Title: The hunt for the Age of Acquisition effect: It's in the links!

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Abstract

The Age of Acquisition (AoA) effect is such that words acquired early in life are processed more quickly than later-acquired words. One explanation for the AoA effects is the arbitrary mapping hypothesis (Ellis & Lambon-Ralph, 2000), stating that the AoA effects are more likely to occur in items that have an arbitrary, rather than a systematic, nature between input and output. Previous behavioural findings have shown that the AoA effects are larger in pictorial than word items. However, no behavioural studies have attempted to directly assess the AoA effects in relation to the connections between representations. In the first two experiments, 48 participants completed a word-picture verification task (Experiments 1A and 2A), together with a spoken (Experiment 1B) or written (Experiment 2B) picture naming task. In the third and fourth experiments, 48 participants complete a picture-word verification task (Experiments 3A and 4A), together with a spoken (Experiment 3B) or written (Experiment 4B) word naming task. For each pair of experiments the subtraction of the naming latencies from the verification tasks for each item per participant was calculated (Experiments 1-4C; e.g. Santiago, Mackay, Palma & Rho, 2000). Results showed that early-acquired items were responded to more quickly than late-acquired ones for all experiments, except for Experiment 3B (spoken word naming) where the AoA effect was shown for only low-frequency words. In addition, the subtraction results for pictorial stimuli demonstrated strong AoA effects. This strengthens the case for the AM hypothesis, also suggesting the AoA effect resides in the connections between representations.

Keywords: Age of acquisition; word naming; picture naming; verification; subtraction

Introduction

One of the most robust psycholinguistic measures affecting the retrieval time for picture names, words and multi-word units is the Age-of-Acquisition (AoA) of the stimuli (e.g. Carroll & White, 1973). The AoA effect refers to the age at, or order in which, one learns a word. For example, words that have been acquired early in life are significantly easier (and hence faster) to retrieve than words acquired later in life (e.g. Juhasz, 2005). The effect of AoA has been shown in a wide range of tasks such as picture naming (e.g. Barry, Hirsch, Johnston, & Williams, 2001), naming-to-definition (Navarrete, Pastore, Valentini & Peressotti, 2015), monomorphemic and compound word naming (e.g. Ellis & Morrison, 1995, 1998; Elsherif, Catling & Frisson, 2019), phrasal lexical decision (Arnon, McCauley & Christiansen, 2017) and picture-word verification (e.g. Catling & Johnston, 2009). Reviews by Johnston and Barry (2006) and Juhasz (2005) further discuss the AoA effect using different methodologies, populations and languages.

Theories of AoA

Semantic loci

There are three predominant theories that seek to explain how and why the AoA effects occur: The semantic loci, originally argued by van Loon-Vervoon (1989, cited in Brysbaert, van Wijnendaele & De Deyne, 2000), posits that conceptual knowledge depends on the order wherein the concepts are acquired. This is due to their being a greater number of semantic connections for early-acquired concepts, which are placed at the hub of the network (i.e. the centre), allowing them to be easily accessible (Steyvers & Tenenbaum, 2005). Supporting evidence for the semantic loci have been shown in a semantic fluency task (Sailor, Zimmerman & Sanders, 2011). Sailor et al. (2011) asked 36 elderly controls and 34 Alzheimer's disease patients to produce words based on semantics (e.g. vegetables) or letter (e.g. words that begin with F) fluency tasks. They found that words produced for the semantic fluency task had earlier AoA, whereas words produced for letter fluency task had higher word frequency. Differences between controls and Alzheimer's patients with regard to AoA were found to be larger for semantic fluency than letter fluency. They concluded that AoA effect has an effect on verbal production and has a semantic locus. Further evidence to support the semantic hypothesis has

been provided in studies that use an animacy decision task (e.g. Råling, Hanne, Schröder, Kebler & Wartenburger, 2017), category verification task (Råling, Holzgrefe-Lang, Schröder & Wartenburger, 2015), text reading (Juhasz & Rayner, 2003, 2006) and a semantic Simon task (Ghyselinck, Custers & Brysbaert, 2004). The semantic Simon task has participants decide whether a word is printed in upper- or lowercase letters. Following this decision, they must verbally make a response (i.e. 'living' or 'non-living') that is either congruent with the meaning of the word (e.g. saying living to the stimulus 'VIPER') or incongruent (e.g. saying 'non-living' to the stimulus 'VIPER'). Ghyselinck et al. found that semantic congruency effects were larger in early-acquired words, demonstrating that the meaning of early-acquired words was activated faster. The authors concluded that semantics contributes to the AoA effect.

Multiple Loci account

The semantic loci can be placed under the multiple loci account (Moore, Smith-Spark & Valentine, 2004). The multiple loci account argues that the AoA effect has multiple locations in the processing system for words and objects (i.e. orthographic, semantic and phonological levels). Taking this a step further, Catling and Johnston (2009) suggest the magnitude of the AoA effect accumulates with each additional level used for a specific task. They demonstrated that word-picture verification showed a smaller AoA effect than picture naming, arguing that the former involves perceptual and semantic processing, while the latter includes these two mechanisms, plus phonological output. Attesting evidence for the multiple loci hypothesis has been demonstrated in studies that use picture naming (Kittredge, Dell, Verkuilen & Schwartz, 2008), degraded picture naming (Catling, Dent & Williamson, 2008), eye-tracking (Juhasz & Sheridan, 2019) and an object decision task with articulatory suppression (Holmes & Ellis, 2006). Holmes and Ellis asked participants to repeat the word 'supercalifragilisticexpialidocious' and make a decision as to whether the object was real. Holmes and Ellis argue that if the AoA phenomenon is phonological in nature, the AoA should not be demonstrated. They found that the AoA effect was robust but the strength of the effect was reduced when articulatory suppression took place.

Arbitrary mapping account

The multiple loci account overlaps with the arbitrary mapping (AM) account of AoA (Chang, Monaghan & Wellbourne, 2019; Ellis & Lambon Ralph, 2000; Lambon Ralph & Ehsan, 2006) in that the strength of the AoA effects reflect the arbitrary nature of mapping between input (e.g. orthography) and output (e.g. phonological or semantic representations). In addition, prior to the early-acquired items entering the mental lexicon, the neural network has a high level of plasticity. This plasticity benefits early-acquired items, leading to rich and stable representations that are better consolidated in the mental lexicon. Subsequently, the weights or connections between input and output representations are modified by early-acquired items. This causes the network to lose plasticity. Put simply, early-acquired items have a large effect on the final structure of the network. Consequently, late-acquired items become more difficult to consolidate, producing a recognition and production advantage for early-acquired items over late-acquired items. This leads to larger AoA effects when the mapping between input and output is arbitrary (e.g. between orthography/phonology and semantics, as in picture naming) than when the mapping between input and output is more systematic and regular (e.g. between orthography and phonology, as in word naming; see reviews by Juhasz, 2005; Johnston & Barry, 2006). According to the AM hypothesis, the AoA effect is located primarily in the connections between levels of representation/processing as opposed to one isolated system such as the perceptual system. Similar to the multiple loci account, the AM hypothesis places the AoA effect at multiple locations (e.g. in the connections between perceptual, semantic, and/or phonological representations). To sum up, the AoA effects arises from both representations and connections between these representations (Chang et al., 2019).

Supporting evidence includes picture naming and word naming tasks with the same stimuli (Lambon Ralph & Ehsan, 2006), wherein the AoA effects were found to be larger in picture naming than word naming tasks (pictorial stimuli are argued to have a more arbitrary link between perceptual, semantics and phonology than word stimuli). In addition, when reading aloud, the AoA effect is larger for inconsistent words (more arbitrary relationship between spelling and sound) than consistent

words (Cortese & Schock, 2013; Xue, Liu, Marmolejo-Ramos & Pei, 2017). Computational studies (e.g. Chang et al., 2019) have provided further support, as they showed that words acquired before literacy are more likely to access meaning via sound, showing a reduced AoA effect, while words acquired after literacy depended on orthography-to-semantics mapping, showing an exaggerated AoA effect. Further supporting evidence for the AM hypothesis has been provided with learning tasks that focus on the order of acquisition effect. During these learning tasks, participants must learn items over multiple sessions. The findings show that items that are learned earlier are processed faster than items that are learned later, even when frequency of exposure is controlled (Catling, Dent, Preece & Johnston, 2013; Joseph, Wonnacott, Forbes & Nation, 2014; Stewart & Ellis, 2008). These findings have been thought to occur due to the mapping between input (i.e. orthographic or perceptual, depending on type of stimuli) and output (i.e. semantic and phonological knowledge) being arbitrary in these learning tasks.

Most of the evidence (excluding Lambon-Ralph & Ehsan, 2006 and Catling & Johnston, 2006) supporting the AM hypothesis has utilised just one type of stimuli (i.e. words or pictures). It is important to note that the processes that underlie word and picture naming differ in respect to perceptual input and the linguistic representations of the name. Figure 1 provides a theoretical framework for understanding the mechanisms and representations that define spoken and written object and word naming. The processes that define picture naming are driven primarily by semantic processes: speakers need to recognise the concept that reflects the picture, select a suitable lexical unit and retrieve its relating phonological and articulatory representations (e.g. Indefrey & Levelt, 2004; Levelt, Roelofs, & Meyer, 1999), while word naming involves the mapping of orthographic into phonological and articulatory representations (see review by Ellis, 1993). Word naming can involve semantic and conceptual representation but does not depend on these processes insofar as picture naming, as shown in skilled readers, who can readily read non-words (Rosson, 1983; Theios & Muise, 1977; see review by Ellis, 1984). Picture naming and word reading therefore depend on different cognitive mechanisms and these processes have differential outcomes on the AoA effect. Picture

naming depends more on semantic processing and has more arbitrary mapping between perceptual, semantic and phonological processing than word naming. Picture naming also leads to larger AoA effects than word naming (Lambon-Ralph & Ehsan, 2006). This raises the question as to whether part of the AoA effect shown in the previous literature may be attributable to semantic processes or the connections between perceptual, semantic and phonological representations.

Figure 1. A general model of the processes underlying spoken and written object naming, immediate copying and word naming. The components belonging to the direct lexical pathway are presented against a light grey background and the components linked to the indirect sublexical pathway are illustrated in bold dotted lines. Adapted from Bonin, Meot, Lagarrigue and Roux (2015).

AoA effects in spoken and written production

In behavioural studies, the AoA effect has been repeatedly shown in spoken and written picture naming (e.g. Barry et al., 2001; Bonin, Fayol & Chalard, 2001; Bonin, Chalard, Méot & Fayol, 2002; Carroll & White, 1973; Catling & Johnston, 2006; Perret, Bonin & Laganaro, 2014). However, written modalities have not received as much attention as spoken modalities for AoA effects. Written and spoken object naming share some processing levels but also have some levels of processing that are unique to them, for instance orthographic or phonological output (Bonin & Fayol, 2000). This model is supported by Perret and Laganaro (2012) who found that electrophysiological correlates diverged

around 260ms after picture presentation. They indicated that the two modalities involved similar processes until retrieval of modality specific word orthographic and phonological output. In addition, the AoA was found to occur primarily at the orthographic and phonological output levels. Perret et al. (2014) showed that the AoA effect was limited to modality specific word orthographic and phonological output. Although the AoA effects are shown at these levels, it would be incorrect to assume that these findings would generalize to word targets.

In addition, the AoA effect has been repeatedly shown in spoken word naming. Megastudies have shown that AoA contributes to reading aloud (Brysbaert & Cortese, 2011; Cortese & Khanna, 2007; Cortese & Schock, 2013 but see Burani, Arudino & Barca, 2007 who showed no effect of AoA). However, in contrast to pictorial items, the AoA effect was found to be larger in low-frequency words than high-frequency words (Cortese & Schock, 2013; Lambon-Ralph & Ehsan, 2006). For immediate copying tasks (Bonin et al., 2015), there was no main effect of frequency trajectory (i.e. a measure argued to be similar to the AoA effect; but see review by Brysbaert, 2017). One interpretation for the Bonin et al.'s findings is that the input (i.e. orthography) and the output (i.e. orthography) are identical in terms of representations, thus the AoA effect should be reduced or disappear. However, if this is the case, word frequency should not be present, as it is highly correlated with mapping type and the AoA effect (e.g. see computational evidence by Lambon-Ralph & Ehsan, 2006; Seidenberg, Waters, Barnes & Tanenhaus, 1984) such that frequency effect should be less likely shown for regular one-to-one mapping than that of an arbitrary mapping nature. In addition, if frequency is shown in immediate copying, ergo the AoA effect should be observed. Taken together, the AoA effect is a robust measure for spoken picture and word naming and written picture naming. In addition, the AoA effect is smaller for items with systematic and regular mapping than for items with an arbitrary nature between representations, indicating that the AoA effect is a robust measure and supporting the AM hypothesis. However, the effects for written word naming are more unclear, and would require further assessment to assess the generality of the AM hypothesis to written processes.

The current study

To assess the AM hypothesis, we suggest utilizing the methodology of Santiago, MacKay, Palma and Rho (2000). Santiago et al. assessed the sequential activation processes from word-picture matching to picture naming and subtracted the latencies of word-picture matching from the latencies of picture naming to provide a 'phonological access' value. They concluded that this subtraction should remove the processes involved in perceptual analysis of word and picture naming, so that these corrected latencies provide a measure of phonological retrieval time. Supporting evidence showed that processes involved in object recognition, such as semantics and perceptual properties are factored out during the subtraction between category verification and spoken picture naming, leaving only lexical processes and access to phonological retrieval (e.g. Stadthagen-Gonzalez, Damian, Perez, Bowers & Marin; 2009). Stadthagen-Gonzalez et al. evaluated the properties of category verification and spoken naming, while subtracting the latter from the former on a large set of stimulus pictures and conducting regression analyses that included semantic (i.e. image agreement, familiarity), lexical (i.e. frequency, AoA and word length) and speech planning/motoric output (i.e. number of syllables) predictors. They found that the AoA effect, plus semantic variables were shown for category verification, while the lexical predictors were shown for the naming predictor. Once the naming was subtracted from the verification task, they found that lexical predictors, plus the number of syllables, contributed to the corrected latencies, while the perceptual and semantic predictors were found not to contribute to the corrected latencies. In this way, within the current study, the tasks and subtraction approach will enable the deconstruction of the processes involved in responding to word and picture stimuli, together with the impact of AoA on these individual sub-processes. Importantly, in support of the claims of Stadthagen-Gonzalez et al., that the subtraction methodology does leave us the phonological components of processing, this manipulation has been found to be affected by syllabic output (i.e. indicative of speech or written planning; Santiago, MacKay & Palma, 2002).

The present study used both falsification and verification responses in word-picture verification, as the type of response can provide different outcomes. Stadthagen et al. (2009) found that match

responses are influenced by visual and semantic factors (i.e. image agreement and familiarity), but not lexical variables including word frequency (cf. Jescheniak & Levelt, 1994, who showed that word frequency had no effect on word-picture verification). This indicates that the match responses are more sensitive to semantic, not lexical, predictors and participants base responses on the semantic code, not the retrieval of the name that instantiates the picture. Match response captures all the properties of picture processing not included in lexical access. No-match latencies have been argued to reflect the use of a deadline response criterion for negative responses, albeit AoA was also shown in the no-match latencies (Stadthagen-Gonzalez et al., 2009). Stadthagen-Gonzalez et al. concluded that the more difficult pictures to categorise took longer to activate and access semantic representations than the more easy-to-categorise pictures. Bonin, Chalard, Meot and Barry (2006) replicated the same pattern for matched responses but found that image agreement (argued to be a perceptual process) was shown for non-matched responses. If the AoA effect is shown to be stronger in the verification than falsification responses, it would indicate that the strength of the AoA effect would increase depending on the level of representations accessed, supporting the multiple loci account (Catling & Johnston, 2009; Moore et al., 2004).

There has been very little research of the AoA effect in the connections between representations. The present study used the subtraction between word-picture verification and picture naming (Santiago et al. 2000), to assess AoA effects within the connections between representations that underlie the AM hypothesis. In addition, the subtraction approach was also used in writing tasks to assess the claim that the subtraction approach reflect access to phonological output, since if we find AoA effects in the writing tasks, it would indicate that the subtraction approach may reflect access to output representations, as opposed to only phonological output. We used a semi-factorial design in combination with the stimuli from Lambon-Ralph and Ehsan (2006), as they had assessed both picture and word naming and were matched on several psycholinguistic variables. Moreover, we used three tasks: word-picture verification (Experiments 1A and 2A), object naming in two different modalities, namely spoken (Experiment 1B) and written (Experiment 2B) production and their subtraction to

control for the processes prior to lexical access (i.e. perceptual and semantic; Experiments 1C and 2C). In addition, we used the same tasks and items, with words replacing pictorial stimuli, to assess whether the AoA effect results from regular-systematic mapping or arbitrary mapping. If the AM hypothesis is correct, the corrected latencies (Experiments 1-4C) would show the AoA effects in pictorial stimuli and reduced or no AoA effects would be demonstrated for word stimuli because of the arbitrary nature of the connections between output for pictorial stimuli in comparison with the regular and systematic outputs linked to word stimuli.

Experiments 1 and 2: Pictorial stimuli

Method

Power analysis.

Based on Karimi and Diaz's (2020) analysis of the AoA effects for picture naming, we estimated Cohen's d to be .14 using Westfall, Judd, and Kenny's (2014) formula for effect size calculation (see Brysbaert & Stevens, 2018, for discussion). We used the stimuli (i.e. 80 items) from Lambon-Ralph and Ehsan (2006), thus reducing the number of stimuli from 1901 to 80. Following Westfall et al.'s power analysis for the general linear mixed effects model¹, it was approximated that 10 participants would produce sufficient power ($\beta = .80$) to test the AoA effects. Given that we were also interested in testing the interaction between AoA and word frequency, we required 20 participants in the current study. The number of participants was increased to 48 to ensure that we had enough observations after data trimming (i.e. around 1000 observations per condition; Kain, Bolker & McCoy, 2015).

Participants

To reduce experimenter bias, the data were analysed after all the participants were recruited and a stopping rule was introduced for the two experiments. In the current study, we used 96 British

¹ Westfall et al. (2014) published a theoretical analysis of mixed effects models and made a website (https://jakewestfall.shinyapps.io/two_factor_power/) which allows researchers to calculate the power of an experiment and the number of items/participants required for a well-powered experiment. We estimated the sample size using the following values: Effect size d : .14, residual variance: .63, participant intercept variance: .219, item intercept variance: .15; participant-by-target variance: 0; participant slope variance: .0001; item slope variance: 0.

monolingual undergraduate students aged 18-20 years ($M = 18.20 \pm 0.38$ years; 10 males), who were given course credits. The 96 students were split into two groups of 48 students for Experiments 1 and 2. The experiment was conducted in accordance with the British Psychological Society's ethical guidelines and was approved by the University's ethical committee. All participants had normal or corrected-to-normal vision and signed a consent form to participate in the study.

Materials

In order to partially replicate the study of Lambon Ralph and Ehsan (2006), we followed their design and split our stimuli into early and late AoA and high-frequency and low-frequency words. This also allowed us to assess not only main effects but also interactions. In addition, this should allow easier analysis of the data from the subtraction technique. The 80 pictures that depicted nouns (3-8 letters in length) were taken from Lambon-Ralph and Ehsan's study (see Appendix A). The SUBTLEX-UK corpus (van Heuven, Mandera, Keuleers & Brysbaert, 2014) to obtain all frequencies values. Word frequencies were extracted as Zipf values. From Morrison, Chappell and Ellis' (1997) database, we obtained rated AoA (scaled 1-7; 1 = learned at the age of 0-2 years to 7 = learned at the age of 13 or older and the rating was based on the age they believed they learned the word, in either spoken or written form), objective AoA (used the 75% rule), phoneme length, number of syllables, letter length, visual complexity (scaled 1-5), name agreement (% of agreement), concept familiarity (rated 1-5), rated imageability (rated 1-7), and visual complexity (rated 1-5).

The stimuli consisted of 20 items in each of the following categories: early-acquired and high-frequency words, early-acquired and low-frequency words, late-acquired and high-frequency words and late-acquired and low-frequency words. They were used for both picture naming and word-picture verification and falsification task. Each group was orthogonally manipulated for objective AoA and frequency. During the AoA selection, word frequency was matched between early-acquired and late-acquired groups (SUBTLEX: $t(78) = 1.39$, $p = .16$, $d = 0.31$), while in the frequency selection, the AoA values were matched between high-frequency and low-frequency words (Objective: $t < 1$). In the AoA selection, both sets differed in AoA (objective: $t(78) = 16.47$, $p < .001$, $d = 3.68$) and in the

frequency selection, both sets differed in frequency (SUBTLEX: $t(78) = 7.63$, $p < .001$, $d = 1.71$). In addition, each set was matched for visual complexity (all $t_s < 1$), name agreement (only items with high name agreement were selected; all $t_s < 1$), and letter length (Frequency selection: $t(78) = 1.60$, $p = .11$, $d = 0.35$; AoA selection: $t(78) = 1.60$, $p = .11$, $d = .36$). There was a significant difference for familiarity and imageability between high-frequency and low-frequency items ($t(78) = -3.50$, $p < .001$, $d = 0.79$; imageability: $t(78) = -2.67$, $p = .009$, $d = 0.60$) but not for early-acquired and late-acquired items (familiarity: $t(78) = -1.90$, $p = .06$, $d = 0.43$; imageability: $t(78) = 1.71$, $p = .09$, $d = 0.39$). We therefore included imageability and familiarity as covariates for any significant frequency effects.

Furthermore, we used ratings to assess image agreement (rated from 1-7)² for the pictures between the conditions in the current study. This analysis showed there was no significant difference in image agreement between the conditions (AoA selection: $t(78) = 1.11$, $p = .27$, $d = -0.25$; Frequency selection: $t < 1$). Moreover, there were 80 filler pictures used in same-difference task experiment. They were not included in the data analysis since the fillers were not controlled by variables such as AoA, word length and frequency.

The critical stimuli were 80 items. The 80 items consisted of 20 early acquired and high-frequency pictures, 20 early-acquired and low-frequency pictures, 20 late-acquired and high-frequency pictures and 20 late-acquired and low-frequency pictures. These items were further divided into two (balanced) lists to enable for the assessment of both verification and falsification responses. Each target was presented once per list. For example, list one included ant-ANT and quilt-MOUSE, whereas list two had gun-ANT and mouse-MOUSE. Half of the target pictorial stimuli were paired with different primes that had no orthographic, phonological, same initial phoneme/letter, semantic overlap and half of the targets were paired with the same prime (Appendix B). The present study recorded reaction times for 'YES' and 'NO' responses. Both responses were used as Jescheniak and Levelt (1994) argued that mismatch trials indicate that there might be lexical priming on match trials, whereas Stadthagen-

² Image agreement is the degree of matching between a mental image from a name and a visual representation of the object referred by the name.

Gonzalez et al. (2009) argued that the match latencies assess the visual and conceptual factors important for object recognition.

Procedure

Figure 2. The visual depiction of the methodology for each experiment. Experiment 1 and 2 focuses on the pictorial stimuli as shown in the same-difference and naming task, wherein the target is pictorial, while Experiment 3 and 4 tests the word stimuli as shown in the same difference and naming task, in which the target are words.

The overall procedures are shown in Figure 2. Participants were tested individually in front of a computer screen. They were told the experiment involved a same-difference task (Experiment 1A) and spoken picture naming (Experiment 1B) or same-difference task (Experiment 2A) and written picture naming (Experiment 2B). They were instructed to be as fast as possible without compromising accuracy. E-prime (E-studio, E-Prime 2.0) software was used to collect their responses. Each participant saw a blank screen for 1000ms and a word then appeared for 1000ms. This long presentation duration of word ensures it has been lexically processed by the time the picture appears. This was followed by a focal point for 700ms and finally, a picture for up to 2000ms. Participants were asked to respond to the picture and see whether it matched the earlier presented word by pressing a corresponding key as quickly as possible without comprising accuracy. Reaction times and accuracy for the response to pictures were recorded. After the word-picture verification task was conducted, a

spoken (Experiment 1B) or written (Experiment 2B) picture naming task was administered to the same participants.

Spoken picture naming. Participants were instructed to name the picture as quickly as possible without compromising accuracy. Furthermore, they were told to utter only the name of the picture. A trial began with a fixation cross for 700ms, which was followed by a picture, in which the participant had to respond for up to 2000ms. The stimuli were pseudo-randomly presented. The microphone was 30 cm away from the mouth. Naming latencies and accuracy were recorded.

Written picture naming. Written responses were collected with a pressure-sensitive WACOM Intuos A4 graphic tablet and a WACOM inking digitizer pen. The procedure was identical to the one that followed Experiment 1B. Participants were instructed to provide a written word response to a picture on the graphics tablet for each trial. Participants had to hold the stylus above the graphics tablet. Once a response was made, they were instructed to touch the graphics tablet with the stylus and write naturally. However, we had removed visual feedback for the participant by covering the hand with a box. Perret and Laganaro (2013) found that covering the hand with a box had removed visual feedback and made the latencies between written and spoken production similar. This ensures that any similarities or differences such as the magnitude of the AoA and frequency effects shown result from the modality and not eye movements. After the word had been written, participants were instructed to say which word they had written to identify errors made and remove latencies related to the trial. Written latency and accuracy were recorded.

Data analysis.

We performed two main sets of analyses with two separate dependent variables: Accuracy and reaction time (RT). We did not analyse the accuracy data, as participants across all experiments were at ceiling. Our research questions were concerned with the AoA effect, which shows primarily in latency, rarely in accuracy outcomes. Finally, RTs may lead researchers to important insights into lexical retrieval, as faster RTs reflect more efficient processing (Sanz & Grey, 2015). We only therefore report RT analyses in the main text, the accuracy analysis is reported in the supplementary materials.

For the RT analysis, we included only the RTs associated with correct responses, trimmed, response times below 200ms and responses $\pm 2.5SD$ or above from participant's mean response time for each task.

A general linear mixed effect model was fitted to the data using the `lmer` function in the `lme4` package (Bates, Maechler & Dai, 2010) within R statistical programming open code software (R Development Core Team, 2019, version 3.6.1.). Following, the guidelines of Meteyard and Davies (2020), we therefore checked the assumptions of the GLMM. The raw RTs were negatively skewed. We therefore applied a log transformation on raw RTs when running the statistical models to make the residuals normally distributed. We also applied inverse RTs since they have been argued to result in better performance than log RTs (Brysbaert & Stevens, 2018; see supplementary materials for models using inverse RTs). The residuals were normally distributed with log RTs and positively skewed with the inverse RTs. In addition, visual inspection of residual plots and Q-Q plots for each model did not show any deviations from homoscedasticity and linearity. P-values were obtained by likelihood ratio tests comparing the model with the effect in question against the model without it. To assess model fit, we used the Akaike Information Criterion (AIC; smaller AIC indicative of better model fit).

Following the assessment of the assumptions, we used the approach advocated by Matuschek, Kliegl, Vasishth, Baayen and Bates (2017) to find the appropriate random effects structure for the models to decrease the rates of false positives and negatives³. First, we performed likelihood ratio tests on models with four different random effects structures containing random intercepts for subjects and items but varying in complexity in terms of random slope: by-item and by-subject (i.e. maximal model; Barr et al., 2013) slopes, only by-item slope, only by-subject slope and finally a model without subject- and item slopes in each experiment (Matuschek et al., 2017 discusses this procedure in detail). Using the 'car' package (Fox & Weisberg, 2010), the Variance Inflation Factor (VIF) was calculated for each model to estimate the influence of multicollinearity on the regression coefficient.

³ Initially, we used `drop1` function on the most complex model starting from three-way interaction to the simplest model provided. The models did not differ in terms of their final model output (see supplementary materials).

A VIF larger than 5 indicates moderate influence, larger than 10 is seen as problematic. Following the guidelines of Nakagawa and Schielzeth (2013), marginal and conditional R^2 values were obtained with the `r.squared GLMM()` function of the MuMIn package for each model (Barton & Barton, 2015). The marginal R^2 is an estimate of variance explained by the fixed factors only, while the conditional R^2 explains variance of the whole model (i.e. fixed and random factors).

Following the likelihood ratio test, once the final model was determined, confidence intervals [2.5-97.5%] were generated using the `lme4 confint` function, “profile-likelihood unit” for each predictor. Finally, we used the guidelines of Westfall et al. (2014) to calculate effect size. Similar to a standard Cohen’s d calculation, we computed the mean difference between conditions (i.e. ΔM) by the standard deviation. As opposed to collapsing across participants to produce the mean difference, we used the estimated intercept from the model, and we took the square root of the pooled variance (i.e. the sum of the variance attributed to the intercept of the participant, item and the residual variance for standardization of σ ; Cohen, 1988; Westfall et al., 2014). The data, scripts and materials for all experiments are available at the open science framework at <https://osf.io/ar68v/>.

Results

Name-picture verification⁴

We used the outlier trim mentioned in the data-analysis. This led to 6.15% and 5.36% of the data being removed in total for Experiments 1A and 2A, respectively. Average RTs, SDs, and the proportion of correct responses for each condition, are shown in Table 1.

Table 1. Mean response times and proportion correct for each Experiment, age of acquisition, target response and frequency condition in category verification and falsification.

Frequency	Experiment 1A				Experiment 2A			
	Early-acquired		Late-acquired		Early-acquired		Late-acquired	
	High	Low	High	Low	High	Low	High	Low
Verification								
RT	459(135)	458(135)	483(148)	513(165)	457(157)	468(164)	492(169)	515(173)
P correct	.98(0.15)	.97(0.16)	.96(0.20)	.95(0.21)	.97(0.17)	.98(0.15)	.96(0.20)	.95(0.21)
Falsification								
RT	547(135)	548(133)	573(152)	566(144)	528(136)	524(151)	555(147)	541(144)
P correct	.94(0.23)	.97(0.18)	.96(0.19)	.97(0.18)	.98(0.16)	.97(0.18)	.98(0.16)	.98(0.16)

Note: Response times (RT); Proportion (P); Response times are measured in milliseconds and standard deviations are in parentheses.

⁴Once included familiarity and imageability as covariates, the effects did not affect the interaction of word frequency and response.

The comparison between models for Experiment 1A and Experiment 2A are shown in Tables 2 and 3, respectively, together with the VIF and marginal and conditional R^2 per model. The baseline model (i.e. M0) had only random intercepts and no predictors, as it was the most efficient model. Following the baseline model, we used a stepwise procedure to add terms to find the model that best fitted our data. We first compared the baseline model to models with one of the main effects added as fixed effects and finally, interactions (response, AoA and frequency for Experiments 1A and 2A). The models with the fixed effect of response was added to the null model in both experiments and was found to be a better model in relation to the null model in a likelihood ratio test (Experiment 1A: $\chi^2(1) = 337.62$, $p < .001$, AIC = 971.65; Experiment 2A: $\chi^2(1) = 174.2$, $p < .001$, AIC = 1407.7). Subsequently, the response model was compared to a model with frequency and another model with an added fixed factor for AoA. The inclusion of the predictor of frequency did not improve the model fit, whereas the additional factor of AoA did (Experiment 1A: $\chi^2(1) = 0.70$, $p = .40$, AIC = 972.95 and $\chi^2(1) = 18.90$, $p < .001$, AIC = 954.75 respectively; Experiment 2A: $\chi^2(1) = 0.10$, $p = .76$, AIC = 1409.6 and $\chi^2(1) = 20.15$, $p < .001$, AIC = 1389.5 respectively). Adding all three factors as fixed effects did not contribute to a significantly better model fit compared to the model with the main effects of AoA and response (Experiment 1A: $\chi^2(1) = 0.91$, $p = .34$, AIC = 955.84; Experiment 2A: $\chi^2(1) = 0.15$, $p = .70$, AIC = 1391.4). A model with an interaction between AoA and response improved the model fit compared to the model with the main effects (Experiment 1A: $\chi^2(1) = 4.28$, $p = .04$, AIC = 952.47; Experiment 2A: $\chi^2(1) = 4.47$, $p = .03$, AIC = 1387.0). However, adding the main effect of frequency did not contribute to this model fit (Experiment 1A: $\chi^2(1) = 0.91$, $p = .34$, AIC = 953.56 and Experiment 2A: $\chi^2(1) = 0.15$, $p = .70$, AIC = 1389). The interaction of word frequency and response did not contribute to the model fit with the model containing the interaction of AoA and response in Experiment 1A ($\chi^2(2) = 3.56$, $p = .17$, AIC = 952.90) but did in Experiment 2A ($\chi^2(2) = 8.28$, $p = .02$, AIC = 1382.8).

Table 2. Summary of the stepwise procedure to show the model with the best fit in Experiment 1A. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 item) + (1 subject)	4	1307.27	1332.00					
Log(RT) ~ 1 + R + (1 item) + (1 subject)	5	971.65	1002.6	337.62 (1)	<.001	NA	0.08	0.17
Log(RT) ~ 1 + R + WF + (1 item) + (1 subject)	6	972.95	1010.1	0.70 (1)	0.40	1.00	0.07	0.17
Log(RT) ~ 1 + R + AoA + (1 item) + (1 subject)	6	954.75	991.89	18.90 (1)	<.001	1.00	0.09	0.17
Log(RT) ~ 1 + R + AoA + WF + (1 item) + (1 subject)	7	955.84	999.17	0.91 (1)	.34	1.00	0.09	0.17
Log(RT) ~ 1 + R * AoA + (1 item) + (1 subject)	7	952.47	995.80	4.28 (1)	.04	2.51	0.11	0.18
Log(RT) ~ 1 + R * AoA + WF + (1 item) + (1 subject)	8	953.56	1003.1	0.91 (1)	.34	2.51	0.11	0.18
Log(RT) ~ 1 + R * AoA + R * WF + (1 item) + (1 subject)	9	952.90	1008.6	3.56(2)	.17	2.99	0.11	0.18
Log(RT) ~ 1 + R * AoA + AoA * WF + (1 item) + (1 subject)	9	954.85	1010.5	1.62(2)	.44	2.99	0.11	0.18
Log(RT) ~ 1 + R * AoA + AoA * WF + R * WF + (1 item) + (1 subject)	10	954.18	1016.1	4.29(3)	.23	2.99	0.11	0.18
Log(RT) ~ 1 + R * AoA * WF + (1 item) + (1 subject)	11	953.07	1021.2	7.39(4)	.12	5.50	0.11	0.18

Table 3. Summary of the stepwise procedure to show the model with the best fit in Experiment 2A. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The condition R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 item) + (1 subject)	4	1579.9	1604.7					
Log(RT) ~ 1 + R + (1 item) + (1 subject)	5	1407.7	1438.7	174.2 (1)	<.001	NA	0.04	0.15
Log(RT) ~ 1 + R + WF + (1 item) + (1 subject)	6	1409.6	1446.8	0.10 (1)	.76	1.00	0.04	0.15
Log(RT) ~ 1 + R + AoA + (1 item) + (1 subject)	6	1389.5	1426.7	20.15 (1)	<.001	1.00	0.05	0.15
Log(RT) ~ 1 + R + AoA + WF + (1 item) + (1 subject)	7	1391.4	1434.8	0.15 (1)	.70	1.00	0.05	0.15
Log(RT) ~ 1 + R * AoA + (1 item) + (1 subject)	7	1387.0	1430.4	4.47 (1)	.03	2.48	0.05	0.15
Log(RT) ~ 1 + R * AoA + WF + (1 item) + (1 subject)	8	1388.9	1438.5	0.15 (1)	.70	2.48	0.05	0.15
Log(RT) ~ 1 + R * AoA + R * WF + (1 item) + (1 subject)	9	1382.8	1438.5	8.28 (2)	.02	3	0.06	0.15
Log(RT) ~ 1 + R * AoA + AoA * WF + R * WF + (1 item) + (1 subject)	10	1384.7	1446.7	0.09 (1)	.76	3	0.06	0.15
Log(RT) ~ 1 + R * AoA * WF + (1 item) + (1 subject)	11	1386.1	1454.3	0.52 (2)	.47	5.35	0.06	0.15

The models that included an addition of the interaction of AoA and word frequency and word frequency and response did not contribute to the model fit that contained the interaction of response and AoA in Experiment 1A (χ^2 (3) = 4.29, p = .23, AIC = 954.18). The interaction of AoA and word frequency did not contribute to the model that had an interaction of response and AoA, together with frequency and response in Experiment 2A (χ^2 (1) = 0.09, p = .76, AIC = 1384.7). In addition, a three-way interaction of AoA, word frequency and response was found not to contribute to the model fit of response and AoA in Experiment 1A (χ^2 (4) = 7.39, p = .12, AIC = 953.07) and the interactions of response and AoA, together with word frequency and response in Experiment 2A (χ^2 (2) = 0.52, p = .47, AIC = 1386.1).

Simply put, the data was best described by a model with an interaction between AoA and response for Experiment 1A (AoA: β = 0.04[0.007,0.07], SE = 0.01, t = 2.41, response: β = -0.19[-0.21,-0.16], SE = 0.01, t = -14.85, response * AoA: β = 0.04[0.002,0.07], SE = 0.02, t = 2.07) and AoA and

response, together with word frequency and response for Experiment 2A (AoA: $\beta = 0.04[0.01, 0.08]$, $SE = 0.02$, $t = 2.65$, response: $\beta = -0.17[-0.20, -0.14]$, $SE = 0.02$, $t = -10.59$, word frequency: $\beta = -0.02[-0.05, 0.01]$, $SE = 0.02$, $t = -1.33$, response * AoA: $\beta = 0.04[0.003, 0.08]$, $SE = 0.02$, $t = 2.14$, response * word frequency: $\beta = 0.05[0.02, 0.09]$, $SE = 0.02$, $t = 2.85$) (see Appendix C for the full models of Experiments 1A and 2A).

In the final model for Experiment 1A and 2A, there was a two-way interaction between AoA and response (Tables 2 and 3). Participants showed a smaller AoA effect in the falsification response than in the verification response (Table 1). The full model was split into two sub-models: verification and falsification. Response was removed from the equation and the same procedures for the analyses and random structure from the full model were applied to the sub-models. In the verification sub-model, the AoA effect was significant (Experiment 1A: $\beta = 0.07[0.03, 0.11]$, $SE = 0.02$, $t = 3.72$, $p < .001$, $d = 0.23$, Experiment 2A: $\beta = 0.08[0.04, 0.12]$, $SE = 0.02$, $t = 4.30$, $p < .001$, $d = 0.25$). Early-acquired words were responded more quickly than late-acquired words. In the falsification sub-model, there was a significant effect of AoA (Experiment 1A: $\beta = 0.04[0.01, 0.06]$, $SE = 0.01$, $t = 3.07$, $p = .002$, $d = 0.14$; Experiment 2A: $\beta = 0.04[0.01, 0.08]$, $SE = 0.02$, $t = 2.65$, $p = .008$, $d = 0.16$). In comparison to late-acquired targets, participants were quicker to respond to the early-acquired targets in both verification and falsification responses.

In the final model for Experiment 2A, there was also a two-way interaction between Frequency and response (Table 3). Participants showed a smaller Frequency effect in the falsification response than in the verification response (Table 1). The full model was split into two sub-models: verification and falsification. Response was removed from the equation and the same procedures for the analyses and random structure from the full model were applied to the sub-models. In the verification sub-model, the frequency effect was not significant ($\beta = 0.03[-0.01, 0.07]$, $SE = 0.02$, $t = 1.46$, $p = .14$, $d = 0.09$). In the falsification sub-model, there was no significant effect of frequency ($\beta = -0.02[-0.06, 0.01]$, $SE = 0.02$, $t = -1.24$, $p = .22$, $d = -0.08$).

Spoken and written picture naming

The same outlier rejection from Experiment 1A and 2A was used for Experiments 1B and 2B. This led to 5.93% and 5.52% of the data being removed in total for Experiments 1B and 2B, respectively. Average RTs, SDs, and the proportion of correct responses for each condition, are shown in Table 4.

Table 4. Mean response times and proportion correct for pictorial items, age of acquisition and frequency condition.

Frequency	Experiment 1B				Experiment 2B			
	Early-acquired		Late-acquired		Early-acquired		Late-acquired	
	High	Low	High	Low	High	Low	High	Low
RT	643(181)	640(175)	704(206)	713(214)	665(196)	670(189)	718(219)	723(229)
P correct	.97(0.16)	.99(0.12)	.97(0.17)	.95(0.22)	.98(0.15)	.98(0.13)	.97(0.17)	.96(0.20)

Note. Response times (RT); Proportion (P); Response times are measured in milliseconds and standard deviations are in parentheses.

The comparison between models for Experiment 1B and Experiment 2B are shown in Tables 5 and 6, respectively, together with the VIF and marginal and conditional R^2 per model. The baseline model (i.e. M0) had only random intercepts and no predictors, as it was the most efficient model. Following the baseline model, we used a stepwise procedure to add terms to find the model that best fitted our data. We first compared the baseline model to models with one of the main effects added as fixed effects and finally, interactions (AoA and frequency for Experiments 1B and 2B). The models with the effect of AoA was added to the null model in both experiments was found to be a better model in relation to the null model (Experiment 1B: $\chi^2(1) = 47.46$, $p < .001$, AIC = 386.44; Experiment 2B: $\chi^2(1) = 26.56$, $p < .001$, AIC = 230.87). Subsequently, the AoA model was compared to a model with frequency and AoA. The model with frequency and AoA as main effects did not improve the model fit of AoA as a main effect only (Experiment 1B: $\chi^2(1) = 0.19$, $p = .66$, AIC = 388.25; Experiment 2B: $\chi^2(1) = 0.42$, $p = .51$, AIC = 232.45). A model with an interaction between AoA and frequency did not contribute to the model with only the main effect of AoA (Experiment 1B: $\chi^2(2) = 0.88$, $p = .65$, AIC = 389.57; Experiment 2B: $\chi^2(2) = 0.44$, $p = .80$, AIC = 234.43). Simply put, the data was best described by a model with an effect of AoA (Experiment 1B: AoA: $\beta = 0.10[0.07, 0.12]$, SE = 0.01, $t =$

7.99; Experiment 2B: AoA: $\beta = 0.07[0.05, 0.10]$, SE = 0.01, $t = 5.58$) (see Appendix C for the full models of Experiments 1B and 2B).

Table 5. Summary of the stepwise procedure to show the model with the best fit in Experiment 1B. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 item) + (1 subject)	4	431.90	456.67					
Log(RT) ~ 1 + AoA + (1 item) + (1 subject)	5	386.44	417.40	47.46 (1)	<.001		0.03	0.31
Log(RT) ~ 1 + AoA + WF + (1 item) + (1 subject)	6	388.25	425.41	0.19 (1)	.66	1.00	0.03	0.31
Log(RT) ~ 1 + AoA*WF+ (1 item) + (1 subject)	7	389.57	432.91	0.88 (2)	.65	2.97	0.03	0.31

Table 6. Summary of the stepwise procedure to show the model with the best fit in Experiment 2B. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The condition R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 item) + (1 subject)	4	255.43	280.22					
Log(RT) ~ 1 + AoA + (1 item) + (1 subject)	5	230.87	261.85	26.56 (1)	<.001		0.01	0.38
Log(RT) ~ 1 + AoA + WF + (1 item) + (1 subject)	6	232.45	269.63	0.42 (1)	.51	1	0.01	0.38
Log(RT) ~ 1 + AoA*WF+ (1 item) + (1 subject)	7	234.43	277.81	0.44(2)	.80	2.98	0.01	0.38

Subtraction analysis

To measure the phonological and orthographic access, if any responses were missing from either experiment 1A or 1B and 2A or 2B, this was removed from the other data set (e.g. if the picture of boy was not named in the naming task, it was removed from the same-different task and vice versa). In addition, we used the outlier trim mentioned in the data-analysis. This removed 8.96% of the data in total for Experiment 1C and 7.94% of the data in total for Experiment 2C. The corrected latencies for each specific item was calculated for each of the 48 participants as the following: same-different task was subtracted from spoken picture naming task (Experiment 1) and same-different task was subtracted from written picture naming task (Experiment 2). This was computed to acquire a ‘nominal access for phonology and orthography’ response time. The “corrected” latencies were trimmed, excluding all errors and responses $\pm 2.5SD$ or above from participant’s mean response time. Average RTs, SDs, and the proportion of correct responses for each condition, are shown in Table 7.

Table 7. Mean corrected latencies and proportion correct for each experiment, age of acquisition, frequency and response condition.

Frequency	Experiment 1C				Experiment 2C			
	Early-acquired		Late-acquired		Early-acquired		Late-acquired	
	High	Low	High	Low	High	Low	High	Low
CL	142 (222)	134(214)	170(247)	182(250)	167(261)	177(246)	198(283)	201(295)
P correct	.93(0.25)	.96(0.21)	.93(0.26)	.91(0.28)	.95(0.21)	.95(0.21)	.94(0.24)	.93(0.26)

Note. Corrected latencies (CL); Proportion (P); Response times are measured in milliseconds and standard deviations are in parentheses

The comparison between models for Experiment 1C and Experiment 2C are shown in Tables 8 and 9, respectively, together with VIF and marginal and conditional R^2 per model. The baseline model (i.e. M0) had only random intercepts and no predictors, as it was the most efficient model. Following the baseline model, we used a stepwise procedure to add terms to find the model that best fitted our data. We first compared the baseline model to models with one of the main effects added as fixed effects and finally, interactions (AoA and frequency for Experiments 1C and 2C). The models with the fixed effect of AoA was added to the null model in both experiments and found to be a better model in relation to the null model in a likelihood ratio test (Experiment 1C: $\chi^2(1) = 15.89$, $p < .001$, AIC = 47618; Experiment 2C: $\chi^2(1) = 170.38$, $p < .001$, AIC = 1412.5). Subsequently, the AoA model was compared to a model with frequency and AoA. The model with frequency and AoA did not improve the model fit (Experiment 1C: $\chi^2(1) = 0.06$, $p = .81$, AIC = 47620; Experiment 2C: $\chi^2(1) = 0.17$, $p = .68$, AIC = -701.18). A model with an interaction between AoA and frequency did not contribute to model fit of the model with only AoA (Experiment 1C: $\chi^2(2) = 1.74$, $p = .42$, AIC = 47620; Experiment 2C: $\chi^2(1) = 1.88$, $p = .39$, AIC = 47762). Simply put, the data was best described by a model with an effect of AoA (Experiment 1C: AoA: $\beta = 38.85[20.48, 57.21]$, SE = 9.32, $t = 4.17$; Experiment 2C: AoA: $\beta = 28.76[8.32, 49.18]$, SE = 10.37, $t = 2.77$) (see Appendix C for the full models of Experiments 1C and 2C).

Table 8. Summary of the stepwise procedure to show the model with the best fit in Experiment 1C. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: LA= Lexical access, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
LA ~ 1 + (1 item) + (1 subject)	4	44765	47789					
LA ~ 1 + AoA + (1 item) + (1 subject)	5	47618	47648	15.89 (1)	<.001		.007	.17
LA ~ 1 + AoA + WF + (1 item) + (1 subject)	6	47620	47656	0.06(1)	.81	1.00	.007	.17
LA ~ 1 + AoA*WF + (1 item) + (1 subject)	7	47620	47663	1.74(2)	.42	2.95	.008	.17

Table 9. Summary of the stepwise procedure to show the model with the best fit in Experiment 2C. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
LA ~ 1 + (1 item) + (1 subject)	4	48874	48899					
LA ~ 1 + AoA + (1 item) + (1 subject)	5	48868	48899	7.44 (1)	.006		0.003	0.26
LA ~ 1 + AoA + WF + (1 item) + (1 subject)	6	48870	48907	0.46(1)	.50	1	0.003	0.26
LA ~ 1 + AoA*WF + (1 item) + (1 subject)	7	48872	48915	0.50 (2)	.78	2.96	0.003	0.26

Discussion

In Experiment 1A and 2A, we found an interaction of AoA and response in picture-word verification. Participants showed a larger AoA effect in the verification than falsification task. The pattern aligns with Stadthagen-Gonzalez et al.'s (2009) interpretation that the verification task reflects pre-lexical processes such as the semantic and perceptual mechanisms of object recognition, while no-match response times may involve perceptual processing (Bonin et al., 2006). This indicates that the AoA effect is found at perceptual and semantic level, supporting the hypotheses posited by Moore et al. (2004) and Catling and Johnston (2006).

In Experiment 1B and 2B, we found a main effect of AoA on spoken and written picture naming. Participants responded to early-acquired pictures more quickly than to late-acquired pictures. This finding replicates previous studies that have shown the AoA effect in spoken and written picture naming (e.g., Bonin et al., 2002; Bonin et al., 2001; Lambon Ralph & Ehsan, 2006). This demonstrates that the AoA effect is a robust variable in tasks that occurs in both verbal and written outputs. The AoA effect has been argued to occur in the links between representations (e.g., Ellis & Lambon-Ralph, 2000), and this was assessed in Experiments 1C and 2C⁵. We find a main effect of AoA in the corrected latencies for both spoken and written picture naming. Early-acquired pictures showed smaller

⁵ This is the first time that this method has been used in this particular context, we recognise that further work replicating our main results will be necessary to fully validate our novel application of the subtraction method.

corrected latencies than late-acquired pictures. Stadthagen-Gonzalez et al. (2009) argued that once the mechanisms for object recognition are factored out, the remaining processes for the picture-word verification task and picture naming reflect lexical processes and mechanisms for phonological retrieval. Aligning with the AM hypothesis (Ellis & Lambon-Ralph, 2000), the findings support the notion that the AoA effect occurs in the links to phonological output. Further implications of these findings in relation the AM will be further discussed in the general discussion.

For word frequency, there was an interaction of frequency and response shown, as participants showed a larger frequency effect in the verification than falsification task. This indicates that response criteria produce a stronger influence of word frequency during tasks that necessitates more semantic processing. In Experiment 1C and 2C, we found no main effect of frequency. Taken together, the presence of frequency occurs at the semantic level but not in the connections between the semantic and phonological level.

Experiments 3 and 4: Word stimuli

Although the AoA effects may result from the arbitrary mapping between the levels of representations in pictorial items, the AoA effects are shown to be repeatedly reduced in tasks that have a more regular and systematic mapping such as word naming (e.g. Lambon-Ralph & Ehsan, 2006). In addition, word frequency is stronger than the AoA effect in word naming (Belke, Brysbaert, Meyer & Ghyselinck, 2005). Belke et al. observed that when AoA was placed into the stepwise regression, 56.4% of the variance was accounted for the response times with regard to picture naming, whereas word frequency added .6% to the variance. If word frequency was placed in the regression first, 22.8% of the variance was considered but this increased to 57% when AoA was introduced to the model. For word naming, AoA only explained .7% of the variance and word frequency increased this to 17%. This supports the fact that AoA effects may be reduced in word reading in comparison with picture naming and that word frequency may produce a stronger effect during word reading. This indicates that the AoA effect is more likely to occur in items with arbitrary mappings such as pictorial items but is reduced for words (Lambon-Ralph & Ehsan, 2006). However, previously, the AoA effect has been

shown to be more likely to occur in low-frequency words. Low-frequency words are weakly encoded items and possess a more arbitrary relation between orthography and phonology (Lambon-Ralph & Ehsan, 2006). If corrected latencies reflect the link between these mappings, the AoA effect should show little, if any, effect in general but would occur in low-frequency words.

Method

Participants

Ninety-six British monolingual undergraduate students aged 18-20 years ($M = 18.38 \pm 0.38$ years; 6 males) participated in the study and were remunerated with course credits. The 96 students were split into two groups of 48 students for Experiments 3 and 4. The experiment was conducted in accordance with the British Psychological Society's ethical guidelines and was approved by the University's ethical committee. All participants had normal or corrected-to-normal vision and signed a consent form to participate in the study. None of the students participated in the previous experiment.

Materials and Procedure.

The same materials and procedures were Experiment 1 were used with the following exception: for the category verification and falsification (Experiments 3A and 4A), the primes were pictures and the targets were words. The targets that were spoken (Experiment 3B) and written (Experiment 4B) were words, as opposed to pictures.

Results

Picture-name verification

The same data analyses were used as Experiments 1 and 2, along with the same outlier rejection for each sub-experiment. The outlier rejection led to 6.93% and 6.38% of the data being removed in total for Experiments 3A and 4A, respectively. Only correct trials were included in the RT analyses. Average RTs, SDs, and the proportion of correct responses for each condition, are shown in Table 10.

Table 10. Mean response times and proportion correct for each Experiment, age of acquisition, target response and frequency condition in category verification and falsification.

Frequency	Experiment 3A				Experiment 4A			
	Early-acquired		Late-acquired		Early-acquired		Late-acquired	
	High	Low	High	Low	High	Low	High	Low
Verification								
RT	448(164)	427(154)	461(159)	477(167)	454(169)	459(164)	480(175)	484(174)
P correct	.97(0.17)	.96(0.19)	.96(0.19)	.94(0.24)	.97(0.19)	.97(0.18)	.96(0.20)	.93(0.26)
Falsification								
RT	522(163)	531(159)	550(168)	566(175)	537(154)	548(166)	576(157)	582(171)
P correct	.97(0.19)	.97(0.18)	.95(0.21)	.95(0.21)	.97(0.17)	.97(0.18)	.98(0.16)	.97(0.17)

Note: Response times (RT); Proportion (P); Response times are measured in milliseconds and standard deviations are in parentheses.

The comparison between models for Experiment 3A and Experiment 4A are shown in Tables 11 and 12, respectively, together with the VIF and marginal and conditional R^2 per model. The baseline model (i.e. M0) had only random intercepts and no predictors, as it was the most efficient model. Following the baseline model, we used a stepwise procedure to add terms to find the model that best fitted our data. We first compared the baseline model to models with one of the main effects added as fixed effects and finally, interactions (response, AoA and frequency for Experiments 3A and 4A). The models with the fixed effect of response were added to the null model in both experiments and was found to be a better model in relation to the null model in a likelihood ratio test (Experiment 3A: $\chi^2(1) = 338.01$, $p < .001$, AIC = 1973.4; Experiment 4A: $\chi^2(1) = 382.13$, $p < .001$, AIC = 1577.9). Subsequently, the response model was compared to a model with frequency and another model with an added fixed factor for AoA. The inclusion of the predictor of frequency did not improve the model fit, while the additional factor of AoA did (Experiment 3A: $\chi^2(1) = 0.24$, $p = .63$, AIC = 1975.1 and $\chi^2(1) = 19.92$, $p < .001$, AIC = 1955.5 respectively; Experiment 4A: $\chi^2(1) = 0.35$, $p = .55$, AIC = 1579.5 and $\chi^2(1) = 20.33$, $p < .001$, AIC = 1559.6 respectively). Adding all three factors as fixed effects did not contribute to a significantly better model fit compared to the model with main effects for AoA and response (Experiment 3A: $\chi^2(1) = 0.31$, $p = .58$, AIC = 1957.1; Experiment 4A: $\chi^2(1) = 0.49$, $p = .49$, AIC = 1561.1). A model with an interaction between AoA and response, a model with an interaction between response and word frequency, a main effect of AoA and an interaction between AoA and word frequency, nor with the main effect of response did not contribute to the model fit that contained only main effects of response and AoA (Experiment 3A: $\chi^2(1) = 0.53$, $p = .47$, AIC = 1956.9,

$\chi^2(2) = 2.57, p = .28, AIC = 1956.9, \chi^2(2) = 2.76, p = .25, AIC = 1956.7$, respectively; Experiment 4A: $\chi^2(1) = 0.49, p = .49, AIC = 1561.1, \chi^2(2) = 49, p = .78, AIC = 1940.6, \chi^2(2) = 0.53, p = .77, AIC = 1563$).

Adding the interaction of response and AoA and response and word frequency to the model, the interaction of response and AoA, together with AoA and word frequency nor an interaction of response and word frequency, along with AoA and word frequency did not contribute to the model fit that contained only main effects of response and AoA (Experiment 3A: $\chi^2(3) = 3.10, p = .38, AIC = 1958.3, \chi^2(3) = 3.30, p = .35, AIC = 1958.1, \chi^2(3) = 5.03, p = .17, AIC = 1956.4$, respectively; Experiment 4A: $\chi^2(3) = 0.98, p = .81, AIC = 1564.6, \chi^2(3) = 1.02, p = .80, AIC = 1564.6, \chi^2(3) = 0.53, p = .92, AIC = 1565.0$, respectively).

Table 11. Summary of the stepwise procedure to show the model with the best fit in Experiment 3A. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model df	AIC	BIC	$\chi^2(df)$	p	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 item) + (1 subject)	4	2309.4	2334.1					
Log(RT) ~ 1 + R + (1 item) + (1 subject)	5	1973.4	2004.3	338.01(1)	<.001	NA	0.08	0.16
Log(RT) ~ 1 + R + WF + (1 item) + (1 subject)	6	1975.1	2012.2	0.24 (1)	0.63	1.00	0.08	0.16
Log(RT) ~ 1 + R + AoA + (1 item) + (1 subject)	6	1955.5	1992.5	19.92 (1)	<.001	1.00	0.09	0.16
Log(RT) ~ 1 + R + AoA + WF + (1 item) + (1 subject)	7	1957.1	2000.4	0.31 (1)	.58	1.00	0.09	0.16
Log(RT) ~ 1 + R * AoA + (1 item) + (1 subject)	7	1956.9	2000.2	0.53 (1)	.47	2.54	0.09	0.16
Log(RT) ~ 1 + R * WF + AoA + (1 item) + (1 subject)	8	1956.9	2006.3	2.57 (2)	.28	2.54	0.09	0.16
Log(RT) ~ 1 + R + AoA * WF + (1 item) + (1 subject)	8	1956.7	2006.1	2.76(2)	.25	2.98	0.09	0.16
Log(RT) ~ 1 + R * AoA + R * WF + (1 item) + (1 subject)	9	1958.3	2014.0	3.10(3)	.38	2.97	0.09	0.16
Log(RT) ~ 1 + R * AoA + AoA * WF + (1 item) + (1 subject)	9	1958.1	2013.8	3.30(3)	.35	2.97	0.09	0.16
Log(RT) ~ 1 + R * WF + AoA * WF + (1 item) + (1 subject)	9	1956.4	2012.1	5.03(3)	.17	2.98	0.09	0.16
Log(RT) ~ 1 + R * AoA + AoA * WF + R * WF + (1 item) + (1 subject)	10	1957.9	2019.7	5.56(4)	.23	2.99	0.09	0.16
Log(RT) ~ 1 + R * AoA * WF + (1 item) + (1 subject)	11	1956.7	2024.7	8.78(5)	.12	5.60	0.09	0.16

Table 12. Summary of the stepwise procedure to show the model with the best fit in Experiment 4A. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model df	AIC	BIC	$\chi^2(df)$	p	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 item) + (1 subject)	4	1958.0	1982.8					
Log(RT) ~ 1 + R + (1 item) + (1 subject)	5	1577.9	1608.8	382.13(1)	<.001		0.09	0.20
Log(RT) ~ 1 + R + WF + (1 item) + (1 subject)	6	1579.5	1616.7	0.35 (1)	0.55	1.00	0.09	0.20
Log(RT) ~ 1 + R + AoA + (1 item) + (1 subject)	6	1559.6	1596.7	20.33 (1)	<.001	1.00	0.10	0.20
Log(RT) ~ 1 + R + AoA + WF + (1 item) + (1 subject)	7	1561.1	1604.4	0.49 (1)	.49	1.00	0.10	0.20
Log(RT) ~ 1 + R * AoA + (1 item) + (1 subject)	7	1561.1	1604.4	0.487 (1)	.485	2.53	0.10	0.20
Log(RT) ~ 1 + R * WF + AoA + (1 item) + (1 subject)	8	1563.1	1612.6	0.489 (2)	.78	2.53	0.10	0.20
Log(RT) ~ 1 + R + AoA * WF + (1 item) + (1 subject)	8	1563.0	1612.5	0.53(2)	.77	2.97	0.10	0.20
Log(RT) ~ 1 + R * AoA + R * WF + (1 item) + (1 subject)	9	1564.6	1620.3	0.98(3)	.81	2.99	0.10	0.20
Log(RT) ~ 1 + R * AoA + AoA * WF + (1 item) + (1 subject)	9	1564.6	1620.2	1.02(3)	.80	2.97	0.10	0.20
Log(RT) ~ 1 + R * WF + AoA * WF + (1 item) + (1 subject)	9	1565.0	1620.7	0.53(3)	.92	2.97	0.10	0.20
Log(RT) ~ 1 + R * AoA + AoA * WF + R * WF + (1 item) + (1 subject)	10	1566.6	1628.4	1.02(4)	.91	2.99	0.10	0.20
Log(RT) ~ 1 + R * AoA * WF + (1 item) + (1 subject)	11	1568.5	1636.6	1.03(5)	.96	5.47	0.10	0.20

The models that included an addition of the interaction of AoA and word frequency, word frequency and response and the interaction of AoA and response frequency did not contribute to

the model fit to the model with that contained main effects of response and AoA (Experiment 3A: $\chi^2(4) = 5.56$, $p = .23$, AIC = 1957.9; Experiment 4A: $\chi^2(4) = 1.02$, $p = .91$, AIC = 1566.6). In addition, a three-way interaction of AoA, word frequency and response was found not to contribute to the model fit of response and AoA (Experiment 3A: $\chi^2(5) = 8.78$, $p = .12$, AIC = 1956.7; Experiment 4A: $\chi^2(5) = 1.03$, $p = .96$, AIC = 1568.5).

Simply put, the data was best described by a model with main effects of response and AoA (Experiment 3A: AoA: $\beta = 0.07[0.04, 0.09]$, SE = 0.01, $t = 4.72$, response: $\beta = -0.20[-0.22, -0.18]$, SE = 0.01, $t = -18.85$; Experiment 4A: AoA: $\beta = 0.06[0.04, 0.09]$, SE = 0.01, $t = 4.78$, response: $\beta = -0.20[-0.22, -0.18]$, SE = 0.01, $t = -20.07$) (see Appendix C for the full models of Experiments 3A and 4A).

Spoken and written word naming

The same outlier rejection from Experiment 1B and 2B was used for Experiments 3B and 4B. This led to 2.97% and 2.86% of the data being removed in total for Experiments 1B and 2B, respectively. Only correct trials were included in the RT analyses. Average RTs, SDs, and the proportion of correct responses for each condition, are shown in Table 13.

Table 13. Mean response times and proportion correct for word targets, age of acquisition, and frequency condition.

Frequency	Experiment 3B				Experiment 4B			
	Early-acquired		Late-acquired		Early-acquired		Late-acquired	
	High	Low	High	Low	High	Low	High	Low
RT	510(144)	504(143)	506(159)	518(158)	503(154)	512(148)	516(153)	523(159)
P correct	.997(0.06)	.994(0.08)	.988(0.11)	1.00 (0)	.997(0.06)	.994(0.08)	.996(0.06)	.993(0.09)

Note: Response times (RT); Proportion (P); Response times are measured in milliseconds and standard deviations are in parentheses.

The comparison between models for Experiment 3B and Experiment 4B are shown in Tables 14 and 15, respectively, together with the VIF and marginal and conditional R^2 per model. The baseline model for spoken word naming (i.e. M0) had only random-subject intercepts and no predictors, as it was the most efficient model. Following the baseline model, we used a stepwise procedure to add terms to find the model that best fitted our data. We first compared the baseline model to models

with one of the main effects added as fixed effects and finally, interactions (AoA and frequency for Experiments 3B). The models with the main effect of AoA or main effect of frequency was added to the null model and was found to be a better model in relation to the null model (Experiment 3B: $\chi^2(1) = 0.44$, $p = .51$, AIC = -826.59 and $\chi^2(1) = 1$, $p = .32$, AIC = -827.15, respectively) and including both predictors included in the model does not contribute to the model fit ($\chi^2(2) = 1.44$, $p = .49$, AIC = -825.58). A model with an interaction between AoA and frequency contributed to the model fit more than the null model (Experiment 3B: $\chi^2(3) = 8.57$, $p = .03$, AIC = -830.72). Simply put, the data was best described by the full model of Experiment 3B (AoA: $\beta = -0.014[-0.03, 0.005]$, SE = 0.01, $t = -1.43$; Frequency: $\beta = -0.030[-0.01, 0.01]$, SE = 0.01, $t = -1.17$; AoA*Frequency: $\beta = 0.04[0.01, 0.06]$, SE = 0.01, $t = 2.67$).

In Experiment 4B, the baseline model for written word naming (i.e. M0 in table 15) had random-intercepts with no predictors, as it was most efficient model. Following the baseline model, we used a stepwise procedure to contribute terms to find the model that best fitted our data. We first compared the baseline model to models with one of the main effects added as fixed effects and finally, interactions (AoA and frequency for Experiments 4B). The model with the main effect of AoA was added to the null model and was found to be a better model in relation to the null model (Experiment 4B: $\chi^2(1) = 6.33$, $p = .01$, AIC = -226.70). We included frequency to the model with only AoA and found that the model with frequency and AoA contributed to the model fit ($\chi^2(1) = 5.08$, $p = .02$, AIC = -229.78). A model with an interaction between AoA and frequency did not contribute to the model fit more than a model with main effects of AoA and frequency ($\chi^2(3) = 0.18$, $p = .67$, AIC = -227.96). Simply put, the data was best described by the model of the main effects of AoA and frequency (Experiment 4B: AoA: $\beta = 0.02[0.005, 0.04]$, SE = 0.01, $t = 2.62$; Frequency: $\beta = 0.02[0.002, 0.03]$, SE = 0.01, $t = 2.26$) (see Appendix C for the full model of Experiment 4B).

Table 14. Summary of the stepwise procedure to show the model with the best fit in Experiment 3B. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 subject)	3	-828.15	-809.48					
Log(RT) ~ 1 + AoA + (1 subject)	4	-826.59	-801.69	0.44 (1)	.51		0.00006	0.41
Log(RT) ~ 1 + WF + (1 subject)	4	-827.15	-802.26	1.00 (1)	.32		0.0001	0.42
Log(RT) ~ 1 + WF + AoA + (1 subject)	5	-825.58	-794.47	1.44 (2)	.49	1.00	0.0002	0.42
Log(RT) ~ 1 + AoA*WF+ (1 subject)	6	-830.72	-793.38	8.57 (3)	.04	3.00	0.001	0.42

Table 15. Summary of the stepwise procedure to show the model with the best fit in Experiment 4B. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The condition R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 item) + (1 subject)	4	-222.37	-197.47					
Log(RT) ~ 1 + AoA + (1 item) + (1 subject)	5	-226.70	-195.58	6.33 (1)	.01		.001	.39
Log(RT) ~ 1 + AoA + WF + (1 item) + (1 subject)	6	-229.78	-192.43	5.08 (1)	.02	1	.001	.39
Log(RT) ~ 1 + AoA*WF+ (1 item) + (1 subject)	7	-227.96	-184.39	0.18(1)	.67	2.97	.001	.39

In the final model for Experiment 3B, there was a two-way interaction between AoA and Frequency (Table 14). Participants showed a smaller AoA effect in high-frequency words than low-frequency words (Table 13). The full model was split into two sub-models: high-frequency words and low-frequency words. Frequency was removed from the equation and the same procedures for the analyses and random structure from the full model were applied to the sub-models. The AoA effect was not significant in the high-frequency model ($b = -0.01[-0.03, 0.01]$, $SE = 0.01$, $t = -1.39$, $p = .16$, $d = -0.05$), but was significant in low-frequency model ($b = 0.02[0.03-0.04]$, $SE = 0.01$, $t = 2.30$, $p = .02$, $d = 0.08$). In low-frequency words, earlier-acquired words were named more quickly than late-acquired words.⁶

Additionally, the final model was split into two sub-models: early-acquired words and late-acquired words. Age of acquisition was removed from the equation and the same procedures for the analyses and random structure from the full model were applied to the sub-models. The frequency effect was not significant in early-acquired model ($b = -0.01[-0.03, 0.01]$, $SE = 0.01$, $t = -1.20$, $p = 0.23$,

⁶ The effect of familiarity removed the influence of word frequency from contributing to the latencies of immediate copying. Imageability did not contribute to immediate copying latency.

$d = -0.04$), while it was significant in late-acquired model ($b = 0.03[0.01, 0.05]$, $SE = 0.01$, $t = 2.50$, $p = .012$, $d = 0.09$). In late-acquired words, high-frequency words were named more quickly than low-frequency words (Table 13)⁷.

Subtraction analysis

The same data analysis from Experiment 1C and 2C were used for Experiments 3C and 4C. This removed 6.95% of the data in total for Experiment 3C and 6.43% of the data in total for Experiment 4C. The corrected latencies for each specific item was calculated for each of the 48 participants as the following: same-different task was subtracted from spoken word naming task (Experiment 3) and same-different task was subtracted from written word naming task (Experiment 4). Average RTs, SDs, and the proportion of correct responses for each condition, are shown in Table 16.

Table 16. Mean corrected latencies and proportion correct for experiment, age of acquisition and frequency condition for the subtraction approach for Experiments 3 and 4.

Frequency	Experiment 3C				Experiment 4C			
	Early-acquired		Late-acquired		Early-acquired		Late-acquired	
	High	Low	High	Low	High	Low	High	Low
CL	32.1(213)	26.56(214)	9.26(216)	1.68(237)	15.3(237)	8.18 (231)	-10.8(253)	-7.85(266)
P correct	.96(0.19)	.96(0.20)	.95(0.22)	.95(0.22)	.96(0.19)	.96(0.20)	.96(0.19)	.94(0.23)

Note: Corrected latencies (CL); Proportion (P); Response times are measured in milliseconds and standard deviations are in parentheses.

The comparison between models for Experiment 3C and Experiment 4C are shown in Tables 17 and 18, respectively, together with the VIF and marginal and conditional R^2 per model⁸. The baseline model for written word naming subtraction (i.e. M0) had only random-subject intercepts and no predictors, while for spoken word naming had only random subjects- and items-intercept, each of which was the most efficient model. Following the baseline model, we used a stepwise procedure to add terms to find the model that best fitted our data. We first compared the baseline model to models with one of the main effects added as fixed effects and finally, interactions (AoA and frequency for Experiments 3C and 4C). The models with the fixed effect of AoA was added to the null model in both

⁷ Once familiarity was included, the frequency effect in late-acquired word remained.

⁸ However, it is important to note that the reaction times for Experiments 3A and 3B were very similar, leading to very small corrected latencies around 0ms (Table 16).

experiments and found to be a better model in relation to the null model in a likelihood ratio test (Experiment 3C: $\chi^2(1) = 11.94$, $p < .001$, AIC = 48063; Experiment 4C: $\chi^2(1) = 8.53$, $p = .003$, AIC = 49124). Subsequently, the AoA model was compared to a model with frequency and AoA. The model with frequency and AoA did not improve the model fit (Experiment 3C: $\chi^2(1) = 0.99$, $p = .32$, AIC = 48064; Experiment 4C: $\chi^2(1) = 0.02$, $p = .89$, AIC = 49126). A model with an interaction between AoA and frequency did not contribute to the model fit of the model with only the AoA (Experiment 3C: $\chi^2(2) = 1.00$, $p = .61$, AIC = 48066; Experiment 4C: $\chi^2(1) = 0.21$, $p = .90$, AIC = 49128). Simply put, the data was best described by a model with an effect of AoA (Experiment 3C: AoA: $\beta = -24.68[-37.70, -10.86]$, $SE = 6.81$, $t = -3.57$; Experiment 4C: AoA: $\beta = -21.51[-35.94, -7.08]$, $SE = 7.36$, $t = -2.92$) (see Appendix C for the full models of Experiments 3C and 4C).

Table 17. Summary of the stepwise procedure to show the model with the best fit in Experiment 3C. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: LA= Lexical Access, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	$\chi^2(df)$	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
LA ~ 1 + (1 subject) + (1 item)	4	48073	48097					
LA ~ 1 + AoA + (1 subject) + (1 item)	5	48063	48094	11.94 (1)	<.001		0.003	0.20
LA ~ 1 + AoA + WF + (1 subject) + (1 item)	6	48064	48101	0.99 (1)	.32	1.00	0.003	0.20
LA ~ 1 + AoA*WF + (1 subject) + (1 item)	7	48066	48109	1.00 (2)	.61	2.98	0.003	0.20

Table 18. Summary of the stepwise procedure to show the model with the best fit in Experiment 4C. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: LA= Lexical Access, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	$\chi^2(df)$	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
LA ~ 1 + (1 subject) + (1 item)	3	49131	49149					
LA ~ 1 + AoA + (1 subject) + (1 item)	4	49124	49149	8.53 (1)	.003		0.002	0.21
LA ~ 1 + AoA + WF + (1 subject) + (1 item)	5	49126	49157	0.02 (1)	.89	1.00	0.002	0.21
LA ~ 1 + AoA*WF + (1 subject) + (1 item)	6	49128	49165	0.21 (2)	.90	2.95	0.002	0.21

Discussion

In Experiment 3A and 4A, there was a significant main effect of response type. Participants required significantly less time to verify the word when the picture and word were the same (verification) than when they were different (falsification). This was independent of AoA. In addition, an effect of AoA was shown. Participants responded more quickly to earlier-acquired words than to

late-acquired words. This was independent of response type. The comparison between word-picture verification and picture-word verification are discussed in general discussion.

In Experiment 3B, an interaction for AoA and frequency was demonstrated such that the AoA effects occurred in low-frequency words. This replicates the computational and behavioural findings from Lambon-Ralph and Ehsan (2006). This indicates that the AoA effect is most pronounced for weakly encoded representations that possess a more arbitrary mapping between representations than between more systematic representations as shown in high-frequency words. One possible explanation could be the combined effects of AoA and frequency are argued to reflect the general properties of learning (Ellis & Lambon Ralph, 2000) and the interaction between the two factors depend on the degree of the AoA and frequency manipulations (cf. Brysbaert & Ghyselinck, 2006). In Experiment 4B, we showed that there was an interaction of frequency and AoA. We found that high-frequency words and early-acquired words are responded more quickly than low-frequency words and late-acquired words. This pattern partially replicates the findings of Bonin et al. (2015), who showed frequency affected copying, while frequency trajectory (i.e. a measure argued to be similar to AoA) was not found.

The present study suggests that access to perceptual and semantic representations is required for picture-word verification, whereas the word naming task could potentially utilise two different pathways - either the lexical or non-lexical route (Coltheart et al., 2001). The former involves direct access to the mental lexicon to locate the word. The mental lexicon contains the identity of the lexical representation in terms of orthography, phonology and semantics. The non-lexical route involves decoding letter strings from print to speech using letter-sound rules. Hence, it is clear, the subtraction analysis utilised for experiments 1A and 1B, and 2A and 2B would not be suitable for the word stimuli as they did not necessarily share the same early stages of processing. This was borne out by the findings of very similar RTs for Experiments 3A and 3B, and Experiments 4A and 4B. Therefore, indicating that the subtraction technique would not be suitable for Experiments 3C and 4C, as they

were unlikely to have shared the same early stages of processing (but see appendix D for subtraction for Experiments 3C and 4C).

Additional data analysis across experiments

We used the GLMM to examine differences between modalities (i.e. spoken versus written modality), type of response during category verification (picture-word verification and word-picture verification) and type of response during modality output (i.e. picture naming versus word naming). There was no significant difference between word-picture verification ($M = 514$, $SE = 22.3$) and picture-word verification ($M = 506$, $SE = 24.8$; $b = -0.03$, $t = -1.91$, $p = .06$, $d = -.08$). There was no significant difference between visual spoken ($M = 590$, $SE = 27.9$) and written naming ($M = 602$, $SE = 29.5$; $b = 0.013$, $t = 0.48$, $p = .62$, $d = 0.05$). In addition, word naming ($M = 512$, $SE = 22.0$) were named more quickly than picture naming ($M = 684$, $SE = 29.4$; $b = -0.29$, $t = -11.51$, $p < .001$, $d = -0.99$).

General discussion

The current study utilised a range of tasks to isolate the components of the AoA effect, by assessing different tasks that necessitated access to different levels of representation, specifically in response to pictorial and word stimuli. In the experiments that focus on the pictorial stimuli, the results showed that the age at which a person learned a word affected word-picture verification. Early-acquired pictures were responded more quickly than late-acquired pictures, this AoA effect was larger in the verification than falsification response. Furthermore, verification RTs were significantly faster than falsification RTs.

These observed differences in AoA effects could be simply due to the levels of representation necessitated for each task – The verification task necessitates access to perceptual and semantic processing, whereas those for falsification are likely to be based on perceptual processing alone (Bonin et al., 2006; Stadthagen-Gonzalez et al., 2009). Hence, according to the AM hypothesis and the accumulation hypothesis combined we would expect to see greater AoA effects for the verification

task as it necessitates processing through a greater number of levels of representation and therefore greater numbers of connections between these levels which would be arbitrary in nature. Put simply, the strength of AoA as shown in pictorial targets depends on the connections between representations being accessed (cf. accumulation hypothesis; Catling & Johnston, 2006). To explain the differences in reaction times between the tasks, we would suggest that priming occurs for the Verification tasks where perceptual and semantic levels are primed for the response to the pictorial stimuli by the preceding word stimuli. However, this is not apparent in the picture falsification task where the picture and the preceding word are not related.

For word stimuli, the findings demonstrated that the AoA effect influenced picture-word verification, irrespective of response type. Early-acquired words were responded to more quickly than late-acquired words. One tentative explanation could be that the AoA effect for responses to words could be based on orthographic and/or semantic codes being accessed, whereas the pictorial stimuli activate the perceptual and semantic processes of the picture and then once the word is activated only orthography and phonology is required to be processed. In addition, the mapping between orthography and semantics is regular for word targets. The response type may not depend on the perceptual and conceptual codes to verify the picture and word together, since there is no arbitrariness between orthography and semantics, this would lead to AoA effects being found without response type having an influence. We can conclude that the AoA effect is present at the orthographic/perceptual and semantic representations for word targets. The main conclusion that can be inferred for the difference between the two verification tasks is that accumulation only occurs in pictorial, not word, stimuli. This indicates that accumulation of the AoA effect may occur for arbitrary, not systematic, relations between perceptual and semantics.

In addition, the current study demonstrated strong AoA effects for both spoken and written picture naming (Experiments 1B and 2B). This aligns with Perret et al. (2014), who argued that the AoA effect resides at the output level, respective to modality (i.e. spoken and written production). This is

partially supported, as we found that early-acquired pictures were faster to name and write than late-acquired pictures, which is in line with the findings of Bonin et al. (2001) and Perret et al. (2014).

There was lack of frequency effects shown in spoken and written picture naming. This finding is somewhat surprising, as word frequency has been argued to be one of the most robust determinants of naming latencies and has been included as an important predictor of naming speed and accuracy (e.g. Bonin et al., 2004; see review by Johnston & Barry, 2006). It has been argued that word frequency has been ascribed to the lexical-phonological level processing (Almeida, Knobel, Finbeiner & Caramazza, 2007) and the absence of a frequency effect may be indicative that the task does not need lexical access (Jescheniak & Levelt, 1994). This argument may be incorrect, since word frequency has been shown to be absent once AoA is included as a predictor (e.g. Bonin, Fayol & Chalard, 2001; Morrison, Ellis & Quinlan, 1992) and the AoA effect has been argued to reflect access to the mental lexicon (Alario, Ferrand, Laganaro, New, Frauenfelder & Segui, 2004). In addition, word frequency may not be a reliable measure of naming latencies. A recent Bayesian meta-analysis suggests that the influence of word frequency in picture naming latencies is less relevant than traditionally thought (Perret & Bonin, 2019).

Compared to spoken word naming, there have been few studies that have assessed the AoA effect in visual written word naming, as most studies for written word naming have focused on spelling-to-dictation (e.g. Bonin, Barry, Meot & Chalard, 2004), which does not necessarily allow a comparison between spoken and written word naming. We found that early-acquired words and high-frequency words were reproduced more quickly than late-acquired words and low-frequency words. This partially supports Bonin et al. (2015), who argued that copying may require access to the lexical pathway, (as word frequency effects was also shown). Although Bonin et al. included frequency trajectory (analogous to the AoA effect), they did not include the AoA measure. It is recommended not to make a direct comparison to their study concerning the AoA effect and frequency trajectory, as the latter does not assess the same processes that the former measures (see review by Brysbaert,

2017). The findings of the current study support that the notion that the AoA effect resides at output level, respective to their modality (Perret et al., 2014).

In addition, we found that the AoA effect is stronger in low-frequency words than high-frequency words (Experiment 3B). This interaction is common in the AoA literature (e.g. Cortese & Schock, 2013; Gerhand & Barry, 1999). The interaction between frequency and AoA is easily interpretable in terms of AM hypothesis. Early in development, exposure to words leads to large weight changes (i.e. stronger connections are formed between the input and output units) relative to later weight changes when exposure to words results in relatively small weight changes (i.e. weaker connections are formed between the input and output results). This pattern of weight changes produces an AoA effect, if words are encountered infrequently. However, if the later-acquired word is processed frequently, then the connections between inputs (e.g. orthography) and outputs (e.g. phonology and/or semantics) will be strengthened each time the word is encountered and will reduce the disadvantage due to AoA. In addition, the current findings for spoken word naming partially support Perret et al.'s (2014) notion that the AoA effect is at the output level, as we found the AoA effects in tasks that necessitate output. However, our explanations would be that the AoA effect is not at the level of output representations but in the connection to the output representations, as we found the AoA effects limited to only low-frequency words in spoken word naming. This supports the computational finding of Lambon-Ralph and Ehsan's (2006) - that the AoA effect may reflect a general learning principle, supporting the AM hypothesis.

The findings from the present study, however, do not completely support those of Lambon-Ralph and Ehsan (2006). Lambon-Ralph and Ehsan showed that the AoA effect was present, irrespective of word frequency, whereas the current study demonstrated the AoA effect only in low-frequency words. One explanation could be that we used a different analytic strategy, Lambon-Ralph and Ehsan analysed their findings by collapsing the naming together, while we analysed word naming and picture naming separately. We found that if we collapsed task, the same pattern of findings demonstrated by Lambon-Ralph and Ehsan are replicated (see Supplementary table S1 for model that collapsed by task),

indicating that the difference in terms of results between Lambon-Ralph and Ehsan and the current study result on whether the task was collapsed.

The main contribution of the present study was the utilisation of the subtraction approach from Santiago et al. (2000) and Stadthagen et al. (2009) to assess for the AoA loci of effect by partitioning the different levels of representations and the links between the representations in a range of tasks. We showed that early-acquired pictures had smaller corrected latencies than late-acquired pictures. We suggest the smaller corrected latencies for early-acquired words indicate that the links between representations is more established, and this facilitates the speed to access the representations. For word targets, the reaction times between picture-word verification and word naming were very similar, hence the subtraction approach was deemed not appropriate. This suggests the subtraction technique may only work for pictorial items. This was due specifically to the naming of words being significantly faster than the naming of pictures. We hypothesise that when verifying a target picture with a previously viewed word, a simple path must be taken from perceptual process to semantic processes, whereas for picture naming, phonology/orthography must also be accessed. Simply speaking the subtraction leaves us with phonological/orthographic processing and the links between this and the semantic level of representation and phonology/orthographic representation (i.e. the access times to phonological and orthographic output), when naming a picture.

The subtraction approach from Santiago et al. (2000) was not used for word targets, as the corrected latencies was around 0. One tenable explanation could be that unlike picture naming, word naming is not necessarily semantically mediated (Figure 1). Three routes have been argued to be available for reading aloud: a sublexical route; direct lexical but non-semantic route; and a lexically-semantically mediated route. The sublexical route involves decoding letter strings from print to speech using letter-sound rules, whereas the lexical route entails direct access to the mental lexicon to locate the word. The mental lexicon contains the identity of the lexical representation in terms of orthography, phonology and semantics. The lexical but non-semantic route involves activation of the same lexical phonological and orthographic representation, whereas the lexical-semantic route

includes the additional component of the semantic route. These two lexical routes are similar to the routes used by picture naming (i.e. lexical retrieval). Only the lexical-semantic route involves lexical identification and lexical retrieval that is similar to picture naming. As a result of these three routes being activated, the subtraction was placed around 0ms, making it difficult to use the subtraction approach for word targets.

We interpret our results as being consistent with the AM hypothesis of AoA effects (Ellis & Lambon Ralph, 2000), which assigns the AoA effects to the connections between the multiple loci in the mental lexicon. The influence of the AoA effect in the verification tasks, naming tasks and the connection between verification and picture naming tasks, indicates that the perceptual, semantic, and output stages for pictorial stimuli (i.e. perceptual and semantics) may be affected by the age (or order) at which a word is first learned. AoA effects could result from a general learning principle linked to plasticity that enables faster access to perceptual, phonological, and semantic representations for a specific item (Lambon Ralph & Ehsan, 2006). We are not arguing that the AoA effect does not influence the representations per se but may not be as important as the connections between the representations depending on the stimuli. Dirix and Duyck (2017) recently suggested that the AM and the organisation of the semantic system may contribute to the observed AoA effects in reading such that early-acquired words have a more central place in the semantic lexicon that contributes to the advantage of early-learned words being processed faster than late-acquired words. However, their data is limited to only word targets. This may be a correct interpretation for word targets but there may also be accumulation of AoA that occurs in pictorial but not word targets. In the current study, in low-frequency words, early-learned items have an advantage over late-acquired items in the spoken and written word naming. Pictorial stimuli necessitate access to perceptual, semantic and the output levels of representation, this increases the strength of the AoA effect, thus supporting the accumulation hypothesis of Catling and Johnston (2006). The data support the semantic and AM hypothesis for both words and pictures but in addition also the accumulation hypothesis for pictorial

items. A major contribution of the current study is that a clear theoretical underpinning of the AoA effect depends on the type of stimuli used.

The present findings provide several directions for future research. The literature has already demonstrated that conceptual and/or perceptual codes are used to base decisions for word-picture verification and perceptual, together with other processes, for word-picture falsification (Bonin et al., 2006; Stadthagen-Gonzalez et al., 2009). However, we currently do not completely understand the levels of representation that are utilised in picture-word verification. We show that response type in word-picture verification interacted with AoA. The AoA effect was larger for verification than falsification response. However, for picture-word verification, there was no interaction of response type with AoA. If the orthographic and semantic processes contribute to the picture-word verification task, then an interaction between AoA and response type should be shown. However, this interaction was not demonstrated, indicating there may be different codes used for the decisions made in word-picture verification. An additional step would be to replicate Stadthagen-Gonzalez et al.'s (2009), who used a regression design to assess the levels of representations utilised for the decisions made in both picture-word verification and word-picture verification. Finally, it should be noted that, in general, corrected latencies for AoA may lose sensitivity for word stimuli. Within the current study, it is important to "note that as the sample [size] of each experiment was moderate and the designs were also slightly different" (Elsherif, Sahan, & Rotshtein, 2017, p.26) and need to be cautious around the effects. It would be beneficial to assess these possibilities with larger sample of participants and use other measures such as duration of participants' utterance, silent text reading and reading aloud to corroborate these findings.

To conclude, we found that the AoA of the word and pictorial stimuli drove the verification, spoken and written picture and word naming, and access to phonological/orthographic processing from the semantic representation (as assessed through the subtraction approach). This indicates that the AoA effects differ depending on type of stimuli and that accumulation occurs only for pictorial stimuli when the mapping between orthography and semantics is arbitrary, not regular. Furthermore,

the AoA occurs at the lexical and modality-specific output for word targets but at the perceptual, semantic and modality-specific output level, together with the connection between these representations for pictorial stimuli. This supports Ellis and Lambon-Ralph (2000) suggestion that the connections between the AoA effect results from the arbitrary nature and that the strength of the AoA effects in these connections accumulate. To sum up, the effects of AoA will therefore appear in any spoken and written system, irrespective of the type of modality and stimuli (spoken and written production), that uses non-regular or arbitrary coding to learn, store and retrieve information (see Xue et al., 2017). However, the strength of the AoA effect depends on the extent of arbitrary coding and the number of levels of representations accessed to complete a task.

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Appendix A: Stimuli list and target items for all four experiments

Stimuli	Objective AoA	Image agreement	SUBTLEX -UK Freq	Visual complexity	Name agreement	Phoneme	Syllable	Letter length	Concept familiarity	Rated imageability	Rated AoA	Rated Freq
Early, low frequency												
Slide	22.1	4	4.17	3.95	1	4	1	5	2.9	5.9	2.05	2.45
Balloon	22.1	4.33	4.25	1.25	1	5	2	7	2.86	2.86	1.8	2.9
Banana	23.4	4.61	4.21	1.25	0.91	6	3	6	3.71	3.71	1.7	3.7
Mouse	23.4	4.75	4.41	3	0.82	3	1	5	2.59	2.59	1.95	2.3
Flag	38.5	4.23	4.42	2	1	4	1	4	2.22	2.22	2.8	2.15
Lion	23.4	4.77	4.45	3.25	1	4	2	4	1.91	1.91	2.1	2
Scissors	23.4	4.6	3.92	2.2	1	5	2	8	3.91	3.91	2.5	3.45
Boot	23.4	4.47	4.43	2.05	0.96	3	1	4	4.23	6.05	1.9	4.15
Candle	38.5	4.85	3.79	2.25	1	5	2	6	3.32	6.1	3.25	3.05
Snowman	23.4	4	3.52	2.45	1	6	2	7	2.2	2.2	1.7	2.2
Sock	23.4	4.57	3.77	1.8	1	3	1	4	4.73	6.2	1.65	4.05
Carrot	25.1	4.5	4.08	2.65	1	5	2	6	4.23	6.5	2.25	3.4
Spider	25.1	4.49	4.24	3.15	0.95	5	2	6	3.09	6.45	1.75	3.05
Comb	38.5	4.73	3.59	2	1	3	1	4	3.68	6.15	2.55	3.05
Pram	38.5	3.47	3.5	3.55	1	4	1	4	2.4	5.8	2.15	2.1
Jigsaw	38.5	2.23	3.68	2.35	0.9	5	2	6	3	6.25	2.1	1.95
Giraffe	38.5	4.68	3.78	4.35	0.96	5	2	7	1.55	6.4	2.65	1.85
Duck	22.1	3.85	4.53	3.05	0.82	3	1	4	2.59	6.55	1.7	3.5
Bike	23.4	4.86	4.58	3.85	0.64	3	1	4	4.09	6.6	2	3.65
Frog	23.4	2.85	4.05	3.6	0.91	4	1	4	2.38	6.35	2.1	2.25
Mean	27.91	4.2	4.07	2.7	0.94	4.25	1.55	5.25	3.08	6.34	2.13	2.86
SD	7.16	0.68	0.34	0.89	0.09	1.02	0.6	1.33	0.88	0.24	0.43	0.74
Min	22	2.23	3.5	1.25	0.64	3	1	4	1.55	5.8	1.65	1.85
Max	38.5	4.86	4.58	4.35	1	6	3	8	4.73	6.65	6.65	3.25

Stimuli	Objective AoA	Image agreement	SUBTLEX- UK Freq	Visual complexity	Name agreement	Phoneme	Syllable	Letter length	Concept familiarity	Rated imageability	Rated AoA	Rated Freq
Late, low frequency												
Vase	62.5	2.72	4.27	3.40	1	3	1	4	2.50	6.55	3.45	2.50
Swan	62.5	3.73	3.98	2.65	1	4	1	4	2.23	6.55	2.90	2.45
Ant	62.5	3.78	3.95	3.70	0.86	3	1	3	2.75	5.90	2.30	2.50
Deer	86.5	4.3	4.26	3.35	0.77	2	1	4	1.73	6.25	2.55	1.90
Arrow	62.5	2.7	3.78	1.60	1	3	2	5	3.27	6.30	2.85	2.20
Ski	102.5	4.03	3.88	3.05	1	3	1	3	2.05	5.65	3.35	2.25
Dustbin	68.5	4.52	3.27	2.58	0.55	7	2	7	3.50	5.75	2.50	3.40
Torch	56.5	4.83	4.21	2.65	1	3	1	5	3.45	5.90	2.90	2.65
Whale	56.5	4.88	4.14	2.85	1	3	1	5	3.15	6.35	2.95	2.20
Axe	62.5	4.17	3.85	1.85	1	3	1	3	2.14	6.20	2.85	1.85
Jug	56.5	4.8	4.06	1.85	1	3	1	3	3.23	6.3	2.60	2.40
Fridge	56.5	4.65	4.31	2.40	0.70	4	1	6	4.48	6.2	2.95	4.25
Wizard	56.5	4.3	3.88	4.00	0.95	5	2	6	1.50	6.15	2.75	1.90
Plug	68.5	4.08	3.98	2.50	1.00	4	1	3	3.59	5.70	2.85	3.20
Cooker	56.5	4.1	3.79	3.75	0.65	4	2	6	4.45	5.85	2.35	4.00
Pumpkin	74.5	4.18	3.79	2.60	1	7	2	7	1.77	6.25	3.15	1.75
Genie	62.5	4.73	3.48	3.05	1	4	2	5	1.65	6.35	3.80	1.45
Yo-yo	74.5	3.8	3.09	2.95	1	4	2	4	2.15	6.2	2.60	1.60
Grapes	56.5	4.77	3.79	3.35	1	5	1	6	3.00	6.25	2.7	3.05
Dice	56.5	4.5	3.71	2.65	0.85	3	1	4	3.00	6.65	3.00	1.95
Mean	65.10	4.18	3.87	2.84	0.92	3.85	1.35	4.70	2.78	6.17	2.87	2.47
SD	11.90	0.60	0.32	0.65	0.14	1.31	0.49	1.30	0.88	0.29	0.37	0.76
Min	56.50	2.7	3.09	1.60	0.55	2	1	3	1.50	5.65	2.30	1.45
Max	102.50	4.88	4.31	4.00	1	7	2	7	4.48	6.65	3.85	4.25

Stimuli	Objective AoA	Image agreement	SUBTLEX- UK Freq	Visual complexity	Name agreement	Phoneme	Syllable	Letter length	Concept familiarity	Rated imageability	Rated AoA	Rated Freq
Early, high frequency												
Bed	22.4	4.68	5.12	2.45	1	3	1	3	4.86	6.55	.25	4.70
Sun	23.4	4.8	5.01	1.50	1	3	1	3	4.45	6.70	.45	3.45
Ball	23.4	4.8	5.33	2.25	0.91	3	1	4	3.36	6.40	.25	3.45
Fish	22.1	4.83	5.19	2.95	1	3	1	4	3.09	6.75	.90	3.05
Bread	38.5	3.85	4.69	1.50	0.96	4	1	5	4.68	6.30	.95	4.40
Bus	23.4	4.75	4.74	4.15	0.82	3	1	3	3.95	6.55	.75	3.85
Finger	23.4	4.5	4.53	2.35	1	5	2	6	4.68	6.05	.50	3.35
Bath	23.4	4.15	4.65	3.10	0.95	3	1	4	4.65	6.10	.50	4.10
Watch	38.5	4.67	5.3	2.95	1	4	1	5	4.27	6.30	2.25	4.10
Glasses	23.4	4.86	4.37	2.60	0.86	6	2	7	3.82	6.25	2.40	3.85
Knife	23.4	4.75	4.49	1.95	0.96	3	1	5	4.82	6.45	2.15	4.30
Trousers	25.1	4.58	4.24	2.30	1	6	2	8	4.90	6.2	1.95	3.90
Wheel	25.1	3	4.51	3.35	0.86	3	1	5	2.68	6.45	2.10	2.95
Bowl	38.5	4.57	3.98	1.65	1.00	3	1	4	4.09	5.85	1.50	4.05
Castle	38.5	3.2	4.69	3.45	0.95	4	2	6	3.45	6.50	2.50	2.20
Thumb	38.5	4.48	3.97	2.40	0.95	3	1	5	4.64	6.10	2.00	3.10
Basket	38.5	4.89	4.16	3.85	0.96	6	2	6	2.27	6.20	2.65	3.00
Cake	23.4	3.75	4.81	2.80	1	3	1	4	3.32	6.4	1.80	3.40
Cow	23.4	4.87	4.42	3.85	1	2	1	3	3.18	6.55	1.45	2.90
Pig	23.4	4.25	4.51	2.70	0.96	3	1	3	2.36	6.75	1.65	2.50
Mean	27.97	4.41	4.63	2.71	0.96	3.65	1.25	4.65	3.88	6.37	1.85	3.56
SD	7.11	0.54	0.41	0.77	0.05	1.18	0.44	1.42	0.86	0.24	0.41	0.67
Min	22.10	3	3.97	1.50	0.82	2	1	3	2.27	5.85	1.25	2.20
Max	38.50	4.89	5.33	4.15	1	6	2	8	4.90	6.75	2.65	4.70

Stimuli	Objective AoA	Image Agreement	SUBTLEX- UK Freq	Visual complexity	Name agreement	Phoneme	Syllable	No of letters	Concept familiarity	Rated imageability	Rated AoA	Rated Freq
Late, high frequency												
Boy	56.5	4.21	5.28	3.85	0.95	2	1	3	4.5	6.25	1.4	4.1
Hair	56.5	4.32	5.03	2.88	0.95	2	1	4	4.45	5.75	1.5	4.25
King	56.5	4.87	5.09	3.7	1	3	1	4	3	6.35	2.05	2.05
Desk	86.5	3.18	4.34	3.3	0.91	4	1	4	4.6	6.15	2.8	3.6
Nose	56.5	4.04	4.72	1.35	1	3	1	4	4.63	5.8	1.4	3.6
Judge	102.5	3.29	4.69	4.15	1	3	1	5	2.05	5.6	3.95	2.2
Coat	68.5	4.76	4.41	2.45	1	3	1	4	3.77	5.75	1.9	4
Shirt	56.5	4.48	4.47	2.95	1	3	1	5	4.09	6.3	2.45	3.75
Ship	56.5	4.5	4.77	3.35	0.55	3	1	4	3.35	6.25	2.15	2.55
Jacket	56.5	4	4.29	3.85	0.85	5	2	6	4.12	5.95	2.6	3.6
Chain	56.5	4.66	4.49	2.5	0.96	3	1	5	2.57	5.85	2.95	2.6
Cloud	56.5	4.4	4.77	1.15	1	4	1	5	4.05	6.6	1.9	3.35
Shell	56.5	4.2	4.39	3.9	1	3	1	5	2.75	5.8	2.15	2.15
Cap	68.5	4.15	4.42	2.18	0.91	3	1	3	2.91	5.9	2.45	2.05
Crown	56.5	4.9	4.53	3.75	1	4	1	5	1.68	6.4	2.4	1.8
Pipe	74.5	3.7	4.26	1.95	1	3	1	4	2.2	5.65	3.35	2.05
Fence	62.5	3.8	4.31	3.1	0.91	4	1	5	2.68	5.95	2.25	2.4
Lamp	74.5	4.74	4.09	1.9	0.9	4	1	4	3.73	6	2.85	3.55
Skirt	56.5	3.28	3.81	3.15	0.9	4	1	5	3.55	6.05	2	3.3
Tie	56.5	4.05	4.58	2.65	1	2	1	3	2.91	6.1	2.45	2.9
Mean	63.60	4.18	4.54	2.9	0.94	3.25	1.05	4.35	3.38	6.02	2.35	2.99
SD	12.52	0.51	0.35	0.87	0.1	0.79	0.22	0.81	0.9	0.27	0.64	0.8
Min	56.50	3.18	3.81	1.15	0.55	2	1	3	1.68	5.6	1.4	1.8
Max	102.50	4.9	5.28	4.15	1	5	2	6	4.63	6.6	3.95	4.25

Appendix B: Stimulus pairs for experiments 1-4 for picture-word verification

Early-acquired						Late-acquired					
High Frequency			Low Frequency			High Frequency			Low Frequency		
Target	Verification	Falsification	Target	Verification	Falsification	Target	Verification	Falsification	Target	Verification	Falsification
bed	bed	dam	slide	slide	queen	boy	boy	ram	vase	vase	sink
sun	sun	bar	balloon	balloon	toaster	hair	hair	moon	swan	swan	hive
ball	ball	fork	banana	banana	shower	king	king	lamb	ant	ant	gun
fish	fish	rose	mouse	mouse	quilt	desk	desk	lynx	deer	deer	pool
bread	bread	stool	flag	doll	flag	nose	nose	sign	arrow	arrow	stove
bus	bus	lip	lion	lion	pear	judge	judge	snail	ski	ski	eye
finger	finger	barrel	scissors	scissors	elephant	coat	coat	vine	dustbin	dustbin	termite
bath	bath	rope	boot	boot	drum	shirt	shirt	grain	torch	torch	beard
watch	watch	crate	candle	candle	guitar	ship	ship	bean	whale	whale	violin
glasses	glasses	penguin	snowman	snowman	bagpipe	jacket	jacket	remote	axe	axe	bag
knife	knife	scarf	sock	sock	lake	chain	chain	stork	jug	jug	toe
trousers	trousers	envelope	carrot	carrot	shrimp	cloud	cloud	stick	fridge	fridge	camera
wheel	wheel	bridge	spider	spider	globe	shell	shell	cliff	wizard	wizard	anchor
bowl	bowl	crow	comb	comb	gear	cap	cap	ape	plug	plug	road
castle	castle	seesaw	pram	pram	dove	crown	crown	sailor	cooker	cooker	trumpet
thumb	thumb	horse	jigsaw	jigsaw	wallet	pipe	pipe	cart	pumpkin	pumpkin	whistle
basket	basket	Pliers	giraffe	giraffe	ashtray	fence	fence	chair	genie	genie	clown
cake	cake	belt	duck	duck	shoe	lamp	lamp	tomb	yo-yo	yo-yo	bell
cow	cow	arm	bike	bike	worm	skirt	skirt	goose	grapes	grapes	cobweb
Pig	pig	cup	frog	frog	soup	tie	tie	nut	dice	dice	leaf

Appendix C: Tables of the full model.

Table A.1. The full model output for RTs for name-picture verification (Experiment 1a). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{response} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.27	0.018	6.24	6.31	339.46
Main effects					
AoA	0.04	0.02	0.01	0.08	1.97*
Frequency	-0.002	0.02	-0.04	0.04	0.11
Response	-0.19	0.02	-0.22	-0.15	-10.41*
Interactions					
AoA * Response	0.006	0.03	-0.04	0.06	0.22
Frequency * Response	-0.002	0.03	-0.05	0.05	-0.77
AoA * Frequency	-0.01	0.03	-0.07	0.05	-0.39
AoA * Frequency * Response	0.06	0.04	-0.01	0.13	-1.76

Note: * $p < .05$.

Table A.2. The full model output for RTs for name-picture verification (Experiment 2a). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{response} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.24	0.02	6.19	6.28	299.72
Main effects					
AoA	0.05	0.02	0.001	0.09	1.99*
Frequency	-0.02	0.02	-0.06	0.03	-0.82
Response	-0.17	0.02	-0.20	-0.13	-8.81*
Interactions					
AoA * Response	0.03	0.02	-0.03	0.08	1.01
Frequency * Response	0.04	0.03	-0.01	0.09	1.51
AoA * Frequency	-0.01	0.03	-0.07	0.06	-0.17
AoA * Frequency * Response	0.03	0.04	-0.05	0.10	0.72

Note: * $p < .05$.

Table A.3. The full model output for RTs for picture-name verification (Experiment 3a). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{response} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.21	0.02	6.17	6.25	299.64
Main effects					
AoA	0.06	0.02	0.01	0.10	2.26*
Frequency	0.02	0.02	-0.03	0.07	0.84
Response	-0.17	0.02	-0.21	-0.13	-8.21*
Interactions					
AoA * Response	-0.02	0.03	-0.08	0.04	-0.75
Frequency * Response	-0.07	0.03	-0.13	-0.01	-2.33*
AoA * Frequency	-0.006	0.03	-0.06	0.07	-0.16
AoA * Frequency * Response	0.07	0.04	-0.01	0.16	1.79

Note: * $p < .05$.

Table A.4. The full model output for RTs for picture-name verification (Experiment 4a). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{response} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.25	0.02	6.21	6.29	288.55
Main effects					
AoA	0.07	0.02	0.03	0.12	3.13*
Frequency	-0.002	0.02	-0.04	0.04	0.11
Response	-0.19	0.02	-0.23	-0.15	-9.66*
Interactions					
AoA * Response	-0.01	0.03	-0.07	0.04	-0.54
Frequency * Response	-0.002	0.03	-0.06	0.05	-0.08
AoA * Frequency	-0.01	0.03	-0.07	0.06	-0.21
AoA * Frequency * Response	0.002	0.04	-0.07	0.08	0.06

Note: * $p < .05$.

Table A.5. The full model output for RTs for spoken picture naming (Experiment 1b). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.43	0.03	6.38	6.48	252.75
Main effects					
AoA	0.04	0.02	0.05	0.12	5.03*
Frequency	-0.005	0.02	-0.04	0.03	-0.27
Interactions					
AoA * Frequency	-0.02	0.02	-0.03	0.07	0.82

Note: * $p < .05$.

Table A.6. The full model output for RTs for written picture naming (Experiment 2b). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.46	0.03	6.40	6.52	222.61
Main effects					
AoA	0.08	0.02	0.04	0.11	4.00*
Frequency	0.01	0.02	-0.03	0.05	0.54
Interactions					
AoA * Frequency	-0.13	0.03	-0.06	0.05	-0.13

Note: * $p < .05$.

Table A.7. The full model output for RTs for written word naming (Experiment 4B). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.18	0.03	6.12	6.23	225.16
Main effects					
AoA	0.02	0.01	0.002	0.05	2.14*
Frequency	0.02	0.01	-0.0006	0.04	1.89
Interactions					
AoA * Frequency	-0.007	0.02	-0.04	0.02	-0.42

Note: * $p < .05$.

Table A.8. The full model output for corrected latencies (Experiment 1C). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	143.97	15.88	112.91	175.02	9.06
Main effects					
AoA	26.94	13.21	1.25	52.62	2.04*
Frequency	-9.43	13.07	-34.85	15.98	0.72
Interactions					
AoA * Frequency	23.87	18.69	-12.47	60.20	1.28

Note: * $p < .05$.

Table A.9. The full model output for corrected latencies (Experiment 2C). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	171.04	21.99	127.88	214.19	7.78
Main effects					
AoA	30.74	14.78	1.99	59.50	2.08*
Frequency	8.91	14.71	-19.71	37.52	0.61
Interactions					
AoA * Frequency	-3.94	20.94	-44.67	36.78	-0.19

Note: * $p < .05$.

Table A.10. The full model output for corrected latencies (Experiment 3C). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	31.93	15.61	1.25	62.62	2.05
Main effects					
AoA	-23.92	9.71	-42.81	-5.03	-2.46*
Frequency	-6.36	9.63	-25.10	12.38	-0.66
Interactions					
AoA * Frequency	-0.73	13.71	-27.40	25.95	-0.05

Note: * $p < .05$.

Table A.11. The full model output for corrected latencies (Experiment 4C). Formula $\text{lmer}(\text{Log}(\text{RT}) \sim \text{AoA} * \text{Frequency} + (1 + \text{AoA} | \text{Subject}) + (1 | \text{item}), \text{data} = \text{data}, \text{control} = \text{lmerControl}(\text{optimizer} = "bobyqa", \text{optCtrl} = \text{list}(\text{maxfun} = 2e6)))$.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	14.46	17.86	-20.77	49.68	0.81
Main effects					
AoA	-24.74	17.87	-45.07	-4.41	-2.39*
Frequency	-4.24	10.37	-24.57	16.08	-0.41
Interactions					
AoA * Frequency	6.49	14.73	-22.37	35.35	0.44

Note: * $p < .05$.

Supplementary material

S1. Accuracy results

For the accuracy analysis, we included accurate and inaccurate responses as a binomial dependent variable, and AoA, frequency, and response were included as the main predictors for the category verification task. Response was removed as a main predictor for spoken and written naming, together with the subtraction analysis, leaving only AoA and frequency as the main predictors for these tasks. The R code for the category verification analysis (1), spoken or written naming (2) and subtraction analysis was as follows:

1. `glmer(ACC ~ AoA*Frequency*response + (1|Subject) +(1|item), data =data, family "binomial", control = glmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6)))`
2. `glmer(ACC ~ AoA*Frequency + (1|Subject) +(1|item), data =data, family "binomial", control = glmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6)))`

The results for our accuracy analysis are reported in tables S1.1-S1.12 below. It is important to note, as accuracy is close to or around ceiling, it is important to be cautious about accuracy. As can be seen in table S1.1., there was an interaction of response and AoA such that in verification responses, people responded more accurately to early-acquired words than late-acquired words, while in falsification response, the converse was demonstrated. In tables S1.2-S1.4, there was no effect of any predictors on accuracy.

In table S1.5, there was an interaction of AoA and Frequency such that high-frequency words were responded to less accurately than low-frequency words in early-acquired items, while the converse was demonstrated in late-acquired items. In table S1.6, there were no effects of any psycholinguistic predictors on accuracy. In table S1.7, there was a main effect of AoA such that early-acquired words were responded to more accurately than late-acquired words. In tables S1.8-S1.12 there was no effect of any psycholinguistic predictor on the accuracy of the subtraction approach.

Table S1.1. Accuracy Analysis Results for Experiment 1a.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	0.46	0.37	1.26	.21
Frequency	0.56	0.38	1.50	.13
Response	-0.95	0.37	-2.58	.01
AoA*Frequency	-0.47	0.55	-0.86	.39
AoA*response	-1.17	0.50	-2.35	.02
Frequency*response	-0.73	0.53	-1.38	.17
AoA*Frequency*response	-0.61	0.71	0.86	.39

Table S1.2. Accuracy Analysis Results for Experiment 2a.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	0.001	0.33	0.003	.998
Frequency	-0.30	0.43	-0.75	.45
Response	-0.16	0.41	-0.39	.69
AoA*Frequency	0.30	0.59	-0.51	.61
AoA*response	-0.32	0.55	-0.59	.56
Frequency*response	0.55	0.57	0.97	.33
AoA*Frequency*response	0.76	0.77	0.98	.33

Table S1.3. Accuracy Analysis Results for Experiment 3a.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	-0.27	0.33	-0.81	.42
Frequency	0.06	0.36	0.18	.86
Response	0.13	0.36	0.37	.72
AoA*Frequency	-0.06	0.47	-0.14	.89
AoA*response	0.08	0.48	-0.17	.87
Frequency*response	-0.25	0.50	-0.51	.61
AoA*Frequency*response	0.25	0.66	-0.38	.70

Table S1.4. Accuracy Analysis Results for Experiment 4a.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	0.24	0.43	0.55	.58
Frequency	-0.05	0.40	-0.11	.91
Response	-0.13	0.36	-0.35	.72
AoA*Frequency	-0.12	0.59	-0.20	.84
AoA*response	-0.35	0.52	-0.67	.50
Frequency*response	0.12	0.51	0.24	.81
AoA*Frequency*response	-0.62	0.72	0.87	.39

Table S1.5. Accuracy Analysis Results for Experiment 1b.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	-0.16	0.34	-0.48	.63
Frequency	-0.69	0.39	1.76	.08
AoA*Frequency	-1.20	0.50	-2.39	.02

Table S1.6. Accuracy Analysis Results for Experiment 2b.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	-0.34	0.36	-0.944	.35
Frequency	0.21	0.39	0.54	.59
AoA*Frequency	-0.59	0.50	-1.17	.24

Table S1.7. Accuracy Analysis Results for Experiment 3b.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>Z</i>	<i>p</i>
Age of Acquisition	-1.41	0.66	-2.14	.03
Frequency	-0.70	0.72	-0.98	.33
AoA*Frequency	19.85	63.51	0.31	.75

Table S1.8. Accuracy Analysis Results for Experiment 4b.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	-0.25	0.85	-0.30	.77
Frequency	-0.68	0.80	-0.86	.39
AoA*Frequency	0.08	1.08	0.08	.94

Table S1.9. Accuracy Analysis Results for Experiment 1c.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	-0.10	0.23	-0.44	.66
Frequency	0.41	0.25	1.66	.10
AoA*Frequency	-0.64	0.33	-1.95	.052

Table S1.10. Accuracy Analysis Results for Experiment 2c.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	-0.28	0.22	-1.26	.21
Frequency	0.05	0.23	0.20	.84
AoA*Frequency	-0.27	0.31	-0.89	.38

Table S1.11. Accuracy Analysis Results for Experiment 3c.

<i>Predictor</i>	<i>β</i>	<i>SE</i>	<i>z</i>	<i>p</i>
Age of Acquisition	-0.38	0.23	-1.63	.10
Frequency	0.14	0.24	-0.58	.56
AoA*Frequency	0.12	0.32	0.37	.71

Table S1.12. Accuracy Analysis Results for Experiment 4c.

Predictor	β	SE	z	p
Age of Acquisition	1.22e-05	2.70e-01	0.00	1.00
Frequency	-8.23e-02	2.65e-01	1.60	.11
AoA*Frequency	-4.18e-01	3.64e-01	-1.15	.25

S2. Inverse RT

Table S2.1. Summary of the stepwise procedure to show the model with the best fit in Experiment 1A with inverse Reaction Time (RT). The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model df	AIC	BIC	χ^2 (df)	p	Max VIF	$R^2(m)$	$R^2(c)$
(-1000/RT) ~ 1 + (1 item) + (1 subject)	4	7189.5	7214.3					
(-1000/RT) ~ 1 + R + (1 item) + (1 subject)	5	6837.6	6868.5	353.91 (1)	<.001	NA	0.09	0.16
(-1000/RT) ~ 1 + R+ WF+ (1 item) + (1 subject)	6	6838.9	6876.1	0.66 (1)	.42	1.00	0.09	0.16
(-1000/RT) ~ 1 + R+ AoA + (1 item) + (1 subject)	6	6825.6	6825.6	14.04(1)	<.001	1.00	0.09	0.16
(-1000/RT) ~ 1 + R+ AoA + WF+ (1 item) + (1 subject)	7	6826.8	6870.1	0.80 (1)	.37	1.00	0.09	0.16
(-1000/RT) ~ 1 + R*AoA + (1 item) + (1 subject)	7	6822.9	6808.9	4.67(1)	.03	2.51	0.09	0.16
(-1000/RT) ~ 1 + R*AoA + WF+ (1 item) + (1 subject)	8	6824.1	6873.6	0.80 (1)	.37	2.51	0.09	0.16
(-1000/RT) ~ 1 + R*AoA + R*WF+ (1 item) + (1 subject)	9	6824.6	6880.3	2.30(2)	.32	2.99	0.09	0.16
(-1000/RT) ~ 1 + R*AoA + AoA*WF+ (1 item) + (1 subject)	9	6825.6	6881.3	1.28(2)	.53	2.99	0.09	0.16
(-1000/RT) ~ 1 + R*AoA + AoA*WF+ R*WF+ (1 item) + (1 subject)	10	6826.1	6888.0	2.79(3)	.43	2.99	0.10	0.16
(-1000/RT) ~ 1 + R*AoA*WF+ (1 item) + (1 subject)	11	6826.3	6894.4	4.60(4)	.33	5.50	0.11	0.18

Table S2.2. Summary of the stepwise procedure to show the model with the best fit in Experiment 2A with inverse RT. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model df	AIC	BIC	χ^2 (df)	p	Max VIF	$R^2(m)$	$R^2(c)$
(-1000/RT) ~ 1 + (1 item) + (1 subject)	4	7351.7	7376.5					
(-1000/RT) ~ 1 + R + (1 item) + (1 subject)	5	7152.2	7183.2	201.47 (1)	<.001	NA	0.05	0.15
(-1000/RT) ~ 1 + R+ WF+ (1 item) + (1 subject)	6	7154.2	7191.3	0.05 (1)	0.82	1.00	0.05	0.17
(-1000/RT) ~ 1 + R+ AoA + (1 item) + (1 subject)	6	7134.9	7172.0	19.35(1)	<.001	1.00	0.06	0.17
(-1000/RT) ~ 1 + R+ AoA + WF+ (1 item) + (1 subject)	7	7136.8	7180.2	0.08 (1)	.78	1.00	0.06	0.15
(-1000/RT) ~ 1 + R*AoA + (1 item) + (1 subject)	7	7132.1	7175.5	4.77 (1)	.03	2.51	0.06	0.15
(-1000/RT) ~ 1 + R*AoA + WF+ (1 item) + (1 subject)	8	7134.0	7183.6	0.08 (1)	.77	2.51	0.06	0.15
(-1000/RT) ~ 1 + R*AoA + R*WF+ (1 item) + (1 subject)	9	7127.0	7109.0	9.06(2)	.01	2.99	0.06	0.16
(-1000/RT) ~ 1 + R*AoA + R*WF+ AoA*WF+ (1 item) + (1 subject)	10	7128.9	7190.8	0.23(2)	.63	2.99	0.06	0.16
(-1000/RT) ~ 1 + R*AoA*WF+ (1 item) + (1 subject)	11	7130.7	7198.9	0.08(4)	.78	5.50	0.06	0.16

Table S2.3. Summary of the stepwise procedure to show the model with the best fit in Experiment 3A with inverse RT. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model df	AIC	BIC	χ^2 (df)	p	Max VIF	$R^2(m)$	$R^2(c)$
(-1000/RT) ~ 1 + (1 item) + (1 subject)	4	8336.0	8360.7					
(-1000/RT) ~ 1 + R + (1 item) + (1 subject)	5	7967.7	7998.6	370.28 (1)	<.001	NA	0.09	0.16
(-1000/RT) ~ 1 + R+ WF+ (1 item) + (1 subject)	6	7969.6	8006.7	0.14 (1)	0.71	1.00	0.09	0.17
(-1000/RT) ~ 1 + R+ AoA + (1 item) + (1 subject)	6	7949.4	7986.5	20.33 (1)	<.001	1.00	0.10	0.17
(-1000/RT) ~ 1 + R+ AoA + WF+ (1 item) + (1 subject)	7	7951.2	7994.5	0.19(1)	.66	1.00	0.10	0.17
(-1000/RT) ~ 1 + R*AoA + (1 item) + (1 subject)	7	7949.6	7992.9	1.79 (1)	.18	2.54	0.10	0.17
(-1000/RT) ~ 1 + R*WF + AoA + (1 item) + (1 subject)	8	7950.9	8000.4	2.46 (2)	.29	2.54	0.10	0.17
(-1000/RT) ~ 1 + R + AoA * WF + (1 item) + (1 subject)	8	7951.1	8000.5	2.34(2)	.31	2.98	0.10	0.17
(-1000/RT) ~ 1 + R*AoA + R*WF + (1 item) + (1 subject)	9	7951.2	8006.8	4.24(3)	.24	2.97	0.10	0.17
(-1000/RT) ~ 1 + R*AoA + AoA*WF + (1 item) + (1 subject)	9	7951.3	8006.9	4.15(3)	.25	2.97	0.10	0.17
(-1000/RT) ~ 1 + R*WF+ AoA*WF + (1 item) + (1 subject)	9	7950.8	8006.4	4.62(3)	.20	2.98	0.10	0.17
(-1000/RT) ~ 1 + R*AoA + AoA*WF+ R*WF+ (1 item) + (1 subject)	10	7951.0	8012.8	6.42(4)	.17	2.99	0.10	0.17
(-1000/RT) ~ 1 + R*AoA*WF + (1 item) + (1 subject)	11	7948.7	8016.7	10.69(5)	.06	5.63	0.10	0.17

Table S2.4. Summary of the stepwise procedure to show the model with the best fit in Experiment 4A with inverse RT. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, R = Response, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
(-1000/RT) ~ 1 + (1 item) + (1 subject)	4	7667.4	7692.2					
(-1000/RT) ~ 1 + R + (1 item) + (1 subject)	5	7253.8	7284.7	415.63 (1)	<.001	NA	0.10	0.20
(-1000/RT) ~ 1 + R + WF + (1 item) + (1 subject)	6	7255.6	7292.7	0.20 (1)	0.66	1.00	0.10	0.20
(-1000/RT) ~ 1 + R + AoA + (1 item) + (1 subject)	6	7235.5	7272.6	20.31 (1)	<.001	1.00	0.10	0.20
(-1000/RT) ~ 1 + R + AoA + WF + (1 item) + (1 subject)	7	7237.2	7280.5	0.28(1)	.60	1.00	0.11	0.20
(-1000/RT) ~ 1 + R* AoA + (1 item) + (1 subject)	7	7237.3	7280.6	0.16 (1)	.69	2.54	0.11	0.20
(-1000/RT) ~ 1 + R* WF + AoA + (1 item) + (1 subject)	8	7239.1	7288.6	0.38 (2)	.83	2.54	0.11	0.20
(-1000/RT) ~ 1 + R + AoA * WF + (1 item) + (1 subject)	8	7239.1	7288.6	0.39(2)	.82	2.98	0.11	0.20
(-1000/RT) ~ 1 + R* AoA + R* WF + (1 item) + (1 subject)	9	7241.0	7296.6	0.53(3)	.91	2.97	0.11	0.20
(-1000/RT) ~ 1 + R* AoA + AoA* WF + (1 item) + (1 subject)	9	7241.0	7296.6	0.54(3)	.91	2.97	0.11	0.20
(-1000/RT) ~ 1 + R* WF + AoA* WF + (1 item) + (1 subject)	9	7241.0	7296.7	0.49 (3)	.92	2.98	0.11	0.20
(-1000/RT) ~ 1 + R* AoA + AoA* WF + R* WF + (1 item) + (1 subject)	10	7242.8	7304.7	0.65(4)	.96	2.99	0.11	0.20
(-1000/RT) ~ 1 + R* AoA* WF + (1 item) + (1 subject)	11	7244.8	7312.9	0.65(5)	.99	5.32	0.11	0.20

Table S2.5. Summary of the stepwise procedure to show the model with the best fit in Experiment 1B with inverse RT. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
(-1000/RT) ~ 1 + (1 item) + (1 subject)	4	4568.7	4593.4					
(-1000/RT) ~ 1 + AoA + (1 item) + (1 subject)	5	4522.8	4553.7	47.89 (1)	<.001		0.02	0.29
(-1000/RT) ~ 1 + AoA + WF + (1 item) + (1 subject)	6	4524.7	4561.9	0.07 (1)	.79	1.00	0.02	0.29
(-1000/RT) ~ 1 + AoA* WF + (1 item) + (1 subject)	7	4526.2	4369.5	0.62 (2)	.73	2.97	0.02	0.29

Table S2.6. Summary of the stepwise procedure to show the model with the best fit in Experiment 2B with inverse RT. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
(-1000/RT) ~ 1 + (1 item) + (1 subject)	4	4121.4	4146.2					
(-1000/RT) ~ 1 + AoA + (1 item) + (1 subject)	5	4099.0	4130.0	24.38 (1)	<.001		0.01	0.35
(-1000/RT) ~ 1 + AoA + WF + (1 item) + (1 subject)	6	4100.6	4137.8	0.45 (1)	.50	1.00	0.01	0.35
(-1000/RT) ~ 1 + AoA* WF + (1 item) + (1 subject)	7	4102.3	4145.7	0.69 (2)	.71	2.97	0.01	0.35

Table S2.7. Summary of the stepwise procedure to show the model with the best fit in Experiment 3B with inverse RT. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model <i>df</i>	AIC	BIC	χ^2 (<i>df</i>)	<i>p</i>	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 subject)	3	4738.8	4757.5					
Log(RT) ~ 1 + AoA + (1 subject)	4	4740.8	4765.7	0.01 (1)	.92		0.00001	0.38
Log(RT) ~ 1 + WF + (1 subject)	4	4739.8	4764.7	1.03 (1)	.31		0.0002	0.38

Log(RT) ~ 1 + WF + AoA + (1 subject)	5	4741.8	4772.9	1.04(2)	.59	1.00	0.0002	0.38
Log(RT) ~ 1 + AoA*WF+ (1 subject)	6	4736.7	4774.0	8.13 (3)	.04	3.00	0.001	0.39

Table S2.8. Summary of the stepwise procedure to show the model with the best fit in Experiment 4B with inverse RT. The best model was highlighted in bold in each step and was tested against models with all possible combinations, including main effects and later on, interactions. Abbreviations: RT= Response Time, AoA = Age of Acquisition, WF = Word Frequency, VIF = Variance Inflation Factor, $R^2(m)$ = The marginal R^2 and $R^2(c)$ = The conditional R^2 .

Formula	Model df	AIC	BIC	χ^2 (df)	p	Max VIF	$R^2(m)$	$R^2(c)$
Log(RT) ~ 1 + (1 item) + (1 subject)	4	5581.2	5606.1					
Log(RT) ~ 1 + AoA + (1 item) + (1 subject)	5	5577.6	5608.8	5.57 (1)	.02		.001	.38
Log(RT) ~ 1 + AoA + WF + (1 item) + (1 subject)	6	5574.7	5612.0	4.96 (1)	.03	1	.002	.38
Log(RT) ~ 1 + AoA*WF+ (1 item) + (1 subject)	7	5576.0	5619.5	0.72(1)	.40	2.97	.002	.38

S3. Drop1() minimal model comparison

A general linear mixed model was used on the log reaction time data using the lme4 package (Bates, Maechler & Dai, 2010) within R statistical programming open code software (R Development Core Team, 2017). General linear mixed models were run, including AoA (sum coded with late-acquired words as intercept) and frequency (sum coded with low-frequency words as intercepts) as fixed effects with all slopes and intercepts allowed to vary at random by subjects and items. Originally, we used the Drop1() function to reduce the most complex model (i.e. maximal random model and three-way interactions of fixed predictors such as AoA:response:frequency) to the simplest and best-fitted model. This was the opposite analysis to that of the main manuscript (i.e. the simplest to the most complex model). To ensure the results did not differ between likelihood ratio tests in moving from the simplest to the best fitting and most complex model and the most complex to the best fitting and simplest model, we placed the Drop1() results in supplementary material and likelihood ratio test from simplest to best-fitting and most complex model in the main manuscript. The R code for the most complex models in category verification analysis (1), spoken or written naming (2), and subtraction analysis (3) were as follows:

1. `lmer(Log(RT) ~ AoA*Frequency*response + (1+AoA*Frequency*response|Subject) + (1|item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6)))`

2. `lmer(Log(RT) ~ AoA*Frequency + (1+AoA*Frequency | Subject) +(1|item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6)))`
3. `lmer(LA ~ AoA*Frequency + (1+AoA*Frequency | Subject) +(1|item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6)))`

Table S2.1. The minimal model output for RTs for name-picture verification (Experiment 1a). Formula `lmer(Log(RT) ~ AoA*response + (1+AoA | Subject) +(1|item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6)))`.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.2747	0.01493	6.2454	6.3040	420.17
Main effects					
AoA	0.0359	0.01267	0.0061	0.0657	2.36*
Response	-0.1883	0.01520	-0.2131	-0.1634	-14.86*
Interactions					
AoA * Response	0.0374	0.01803	0.0020	0.0727	2.07*

Note: * $p < .05$.

Table S2.2. The minimal model output for RTs for name-picture verification (Experiment 2a). Formula `lmer(Log(RT) ~ AoA*response + Frequency*response (1 | Subject) +(1|item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6)))`.

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.2387	0.0191	6.2015	6.2760	327.16
Main effects					
AoA	0.0434	0.0164	0.0115	0.0753	2.65*
Frequency	-0.0218	0.0164	-0.0537	0.0102	-1.33
Response	-0.1742	0.0165	-0.2064	-0.1420	-10.59*
Interactions					
Frequency * Response	0.0541	0.0190	0.0170	0.0914	2.85*
AoA * response	0.0407	0.0190	0.0035	0.0779	2.14*

Note: * $p < .05$

Table S2.3. The minimal model output for RTs for picture-name verification (Experiment 3a).
Formula = lmer(Log(RT) ~ AoA + response (1+AoA|Subject) +(1|item), data =data, control =
lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6))).

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.2218	0.01555	6.1879	6.2490	399.90
Main effects					
AoA	0.0657	0.01479	0.0366	0.1764	4.45*
Response	-0.1969	0.01043	-0.2173	-0.1764	-18.88*

Note: * $p < .05$.

Table S2.4. The minimal model output for RTs for picture-name verification (Experiment 4a).
Formula = lmer(Log(RT) ~ AoA + response (1+AoA|Subject) +(1|item), data =data, control =
lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6))).

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.2577	0.01693	6.2244	6.2911	369.63
Main effects					
AoA	0.0624	0.01314	0.0365	0.0883	4.75*
Response	-0.1970	0.09812	-0.2162	-0.1778	-20.08*

Note: * $p < .05$.

Table S2.5. The minimal model output for RTs for Experiment 1b. Formula = lmer(Log(RT) ~ AoA (1
|Subject) +(1|item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl =
list(maxfun=2e6))).

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.4254	0.02386	6.3783	6.4724	269.34
Main effects					
AoA	0.0979	0.01225	0.0738	0.1221	7.99*

Note. * $p < .05$

Table S2.6. The minimal model output for RTs for Experiment 2b. Formula = lmer(Log(RT) ~ AoA (1
|Subject) +(1|item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl =
list(maxfun=2e6))).

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.4639	0.02740	6.4098	6.5180	235.90
Main effects					
AoA	0.0740	0.01326	0.0479	0.1002	5.58*

Note. * $p < .05$

Table S2.7. The minimal model output for RTs for Experiment 3b. Formula = lmer(Log(RT) ~ AoA*Frequency + (1 | Subject), data =data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6))).⁹

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.1967	0.02678	6.1438	6.2550	231.42
Main effects					
AoA	-0.0140	0.00979	-0.0332	0.0052	-1.43
Frequency	-0.0114	0.00973	-0.0305	0.0077	-1.17
Interaction					
AoA * Frequency	-0.0369	0.01381	-0.0098	-0.0639	2.67*

Note: * $p < .05$

Table S2.8. The minimal model output for RTs for Experiment 4b. Formula = lmer(log(RT) ~ AoA + Frequency + (1 | Subject) +(1 | item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6))).¹⁰

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	6.17900	0.02714	6.1254	6.2326	227.66
Main effects					
AoA	0.02077	0.00791	0.0053	0.0363	2.63*
Frequency	0.01789	0.00791	0.0024	0.0334	2.26*

Note: * $p < .05$

Table S2.9. The minimal model output for LA for Experiment 1c. LA ~ AoA + (1 | Subject) +(1 | item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6))).

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	135.78	14.72	106.77	164.79	9.22
Main effects					
AoA	28.866	9.55	10.05	47.70	3.02*

Note: * $p < .05$

Table S2.10. The minimal model output for LA for Experiment 2c. LA ~ AoA + (1 | Subject) +(1 | item), data =data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6))).

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	162.31	21.38	120.09	204.53	7.59
Main effects					
AoA	23.01	9.60	4.11	41.93	2.40*

Note: * $p < .05$

⁹ Familiarity and imageability were included as covariates and did not contribute to the interaction of AoA and Frequency.

¹⁰ The effect of familiarity removed the influence of word frequency from contributing to the latencies of immediate copying. Imageability did not contribute to the immediate copying latency.

Table S2.11. The minimal model output for LA for Experiment 3c. $LA \sim AoA + (1 | \text{Subject}) + (1 | \text{item})$, data = data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6)).

Fixed Effects	Estimate	Std. Error	2.5% LCI	97.5% UCI	t values
(Intercept)	9.69	15.72	-21.33	40.72	0.62
Main effects					
AoA	-25.13	7.93	-40.77	-9.51	-3.17*

Note. * $p < .05$

Table S2.12. The minimal model output for LA for Experiment 4c. $LA \sim AoA + (1 | \text{Subject})$, data = data, control = lmerControl(optimizer="bobyqa", optCtrl = list(maxfun=2e6)).

Fixed Effects	Estimate	Std. Error	95% LCI	95% UCI	t values
(Intercept)	-8.51	17.72	-43.53	26.51	-0.48
Main effects					
AoA	-27.07	7.99	-42.74	-11.40	-3.39*

Note. * $p < .05$

Irrespective of the direction of the GLMM approach taken, the same pattern of results emerged.

S4. Compare between studies

We collapsed the two stimuli together for visual word naming (word and picture) to assess whether our findings replicate Lambon-Ralph and Ehsan (2006) for Experiment 1b and 3b. A general linear mixed model was conducted on the log reaction time data using the lme4 package (Bates, Maechler & Dai, 2010) within R statistical programming open code software (R Development Core Team, 2017). General Linear Mixed models were run, including AoA (sum coded with late-acquired words as intercept) and Frequency (sum coded with low-frequency words as intercepts) as a fixed effect with all slopes and intercepts allowed to vary at random by subject and items. We had collapsed the two stimuli together (word and picture) to assess whether our findings replicate Lambon-Ralph and Ehsan (2006) for Experiment 1b and 2b.

Table S4. The model output for RTs following Lambon-Ralph and Ehsan's approach.

Fixed Effects	Estimate	Std. Error	<i>t</i> values
(Intercept)	6.4276	0.02592	248.01
<i>Main effects</i>			
AoA	0.0878	0.01345	6.53*
Frequency	0.0046	0.01333	-0.34
Stimuli	-0.2310	0.03575	-6.46*
<i>Interaction</i>			
AoA * Frequency	0.0194	0.01903	1.02
AoA * stimuli	-0.1015	0.01519	-6.68*
Frequency * stimuli	-0.0067	0.01505	-0.45
AoA * Frequency * stimuli	0.0173	0.02147	0.81

We found that the AoA effect was demonstrated, irrespective of word frequency, supporting Lambon-Ralph and Ehsan's (2006) findings. In addition, the AoA effect is larger for pictorial stimuli than word stimuli.