Reverse engineering what makes a symbol memorable

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Abstract

Symbols may represent the first form of human visual communication, yet little is known about the cognitive and neural mechanisms supporting memory for these pervasive graphics. By investigating memory for everyday symbols, we can understand how abstract concepts are concretized with simple referents and later processed in visual memory systems. Recently, symbols have been found to be highly memorable, especially relative to words, but it remains unclear what drives their heightened memorability. We identified the key visual and conceptual attributes driving high memorability for symbols. Participants were tested on their memory for conventional symbols (e.g., !@#$%) before sorting them based on visual or conceptual features. Principal component analyses performed on the sorting data revealed which of these features predict memory for symbols. Generative AI was then used to accentuate or downplay these predictive features to create a set of memorable and forgettable novel symbols. A memory test revealed that symbols designed to be memorable were not only better recognized than those designed to be forgettable, but they also afforded superior recall of associated abstract words. This work demonstrates that certain stimulus features drive memory for images beyond distinctiveness or context and offers clear evidence that memory can be intentionally engineered.

Keywords: memorability, symbols, AI image generation, recognition memory, cued recall

Significance Statement

Despite their prevalence, little is known about how everyday symbols (e.g., !@#$%) are processed in memory. We identified visual and conceptual features of symbols that predict how well they will be remembered. Using generative AI, we manipulated these features to create symbols that were designed to be memorable or forgettable. Recognition of symbols designed to be memorable was substantially improved, as was recall of their associated concepts. This work shows that 1) certain visual features predict the memorability of images, 2) these features can be tailored to manipulate memory, and 3) doing so leads to associative recall benefits beyond the image itself. This study offers the first demonstration that memory can be engineered at scale by modifying visual design features.

The year is 1967 and the US government has a problem. Weapons of mass destruction loom large in the minds of the American public as the Cold War quietly rages on, and troop deployments to Vietnam are ever-increasing. All the while, basic standardization of dangerous material warnings is immature throughout the US military, risking life-threatening accidents for personnel. For instance, symbols used to denote the presence of biohazard dangers varied greatly: the US Army used a blue triangle while the US Navy used a pink rectangle (1, 2). To solve this pressing issue, researchers at Dow Chemical Company were tasked with creating a new symbol to represent the presence of biohazards. The researchers sought a novel shape that was unique, easily remembered, yet semantically void to be able to take on new meaning (3). When they asked participants to rate the memorability of several brand-new shapes, one stood out as entirely meaningless but most memorable: ☣.

Symbols are a pervasive part of everyday life. Their importance ranges from mundane (e.g., ▶) to lifesaving (e.g., ☠), and everything in-between. A symbol's usefulness, however, depends on the likelihood that anyone who will encounter it can readily understand its meaning. But what makes a symbol 'effective'? As Baldwin and Runkle surmised with the creation of the biohazard symbol almost 60 years ago, an effective symbol should be naturally memorable. This affords not only the ability to learn a symbol's meaning quickly but also allows its associated concept to be comprehended and retained in memory after just a brief glance (say, while driving along a highway). Symbols are therefore especially useful when it comes to encapsulating and conveying complex abstract ideas using succinct and highly recognizable visual forms. While symbols and words can sometimes be used interchangeably to convey similar ideas, it is possible that symbols differ from their word counterparts in fundamental ways.

Everyday visual symbols (e.g., $) have been shown to be highly memorable relative to their abstract word counterparts (e.g., 'dollar'), as well as concrete words (e.g., 'balloon'; 2). Participants' ability to quickly and accurately remember symbols is on-par with that of more detailed images of objects as well (4). At the same time, symbols are compact, often easy to draw by hand, and—critically—transcend both language and culture. For these reasons, Baldwin and Runkle's symbol went on to be adopted as a universal warning of biohazard dangers, but the study that led to its creation left a critical question unanswered: What made that particular shape so much more memorable than all the other novel shapes that were tested? Perhaps, there is something memorable about its visual features.

In recent years, it has been demonstrated that certain stimuli are almost universally better remembered than others; they have a certain degree of *memorability*. This concept has been demonstrated in pictures of objects (5), human faces (6), scene images (7, 8), and even dynamic stimuli like videos of dance routines (9). Memorability has been shown to impact real-world behavior as well, like naturalistic memory for art pieces in a museum (10), as well as engagement on social media (11). Demonstrating its consistency, item-level memorability has also been found in children as young as 4 years old (12) and in nonhuman primates as well (13). Further, the memorability of pictures can be predicted by deep neural networks like ResMem (14) and MemNet (15) that make use of perceptual and conceptual features found within images.

Recent work has shown that the visual features of an image uniquely contribute to its memorability (5), while others have demonstrated that words with singular meanings and few synonyms tend to be better remembered (16). Some argue that memorability is thought to be 'intrinsic' to the stimulus itself, as performance is largely unaffected by participants' cognitive control, depth of processing, attentional capture, or priming (8, 17). In other words, there is ongoing debate surrounding whether there is a general degree of memorability naturally built-in to each image. While this debate is not the focus of the current study, the notion that certain image properties affect downstream memory performance is critical here.

The use of symbols as a visual stimulus offers a unique way to assess the conceptual and visual characteristics of an image independently, as their meaning is not often tied to their visual form (unlike pictures whereby they are inherently connected). The simple geometric shapes used in symbols also makes them useful from a computer vision standpoint: As compared to pictures, they are comprised of easily quantifiable visual features. Across two experiments, we pioneered a novel method to determine which visual features *predict* the memorability of symbols before manipulating those features with generative AI to *engineer* memorability. We began by determining the visual and conceptual features that predict memorability of conventional symbols. Then, we used generative artificial intelligence to create novel symbols that manipulate memory by accentuating or downplaying these features.

The present work advances our understanding of memory by testing whether item-level memorability is an immutable property of stimuli, or whether it can be systematically explained and causally manipulated. Prior research has largely attributed memorability to high-level semantic categories (5) or has relied on black-box neural networks trained on natural images (18), leaving open the question of how specific image properties shape what endures in memory. By taking advantage of the unique properties of symbols—stimuli that convey complex meaning through simple designs—this study bridges perception and memory, investigating how visual form gives way to semantics and the specific features that govern what 'sticks.'

Symbols provide a uniquely powerful window into the determinants of memory, as they serve as efficient visual gateways to conceptual meaning. Whereas pictures represent the precise objects that they depict and words are muddied by intricate linguistic dependencies, symbols allow for a more general mapping between perceptual form and meaning. This makes them ideal for examining how the visual features of a cue influence the ease of accessing its associated concept in memory. By identifying and harnessing the most memorable properties of conventional symbols, we have the potential to inform data-driven principles of visual design. Such innovations could be applied to enhance memory on a large scale by integrating them into everyday stimuli such as warning symbols, traffic signs, brand logos, fonts, and artwork. Moreover, exploring whether a symbol's memorability can be altered by changes to its form raises the possibility that memory can be optimized through visual content alone, independent of conceptual representations.

Experiment 1: Identification of Memorable Visual Features

As a first step toward engineering memorable symbols, we must first understand which features make a symbol memorable. In this experiment, we determined the memorability of a set of 80 conventional symbols (e.g., !@#$%) and gathered metrics of how participants perceived the high-level conceptual and low-level visual features that comprise them. Finally, we tested which of these conceptual and visual features predict symbol memory.

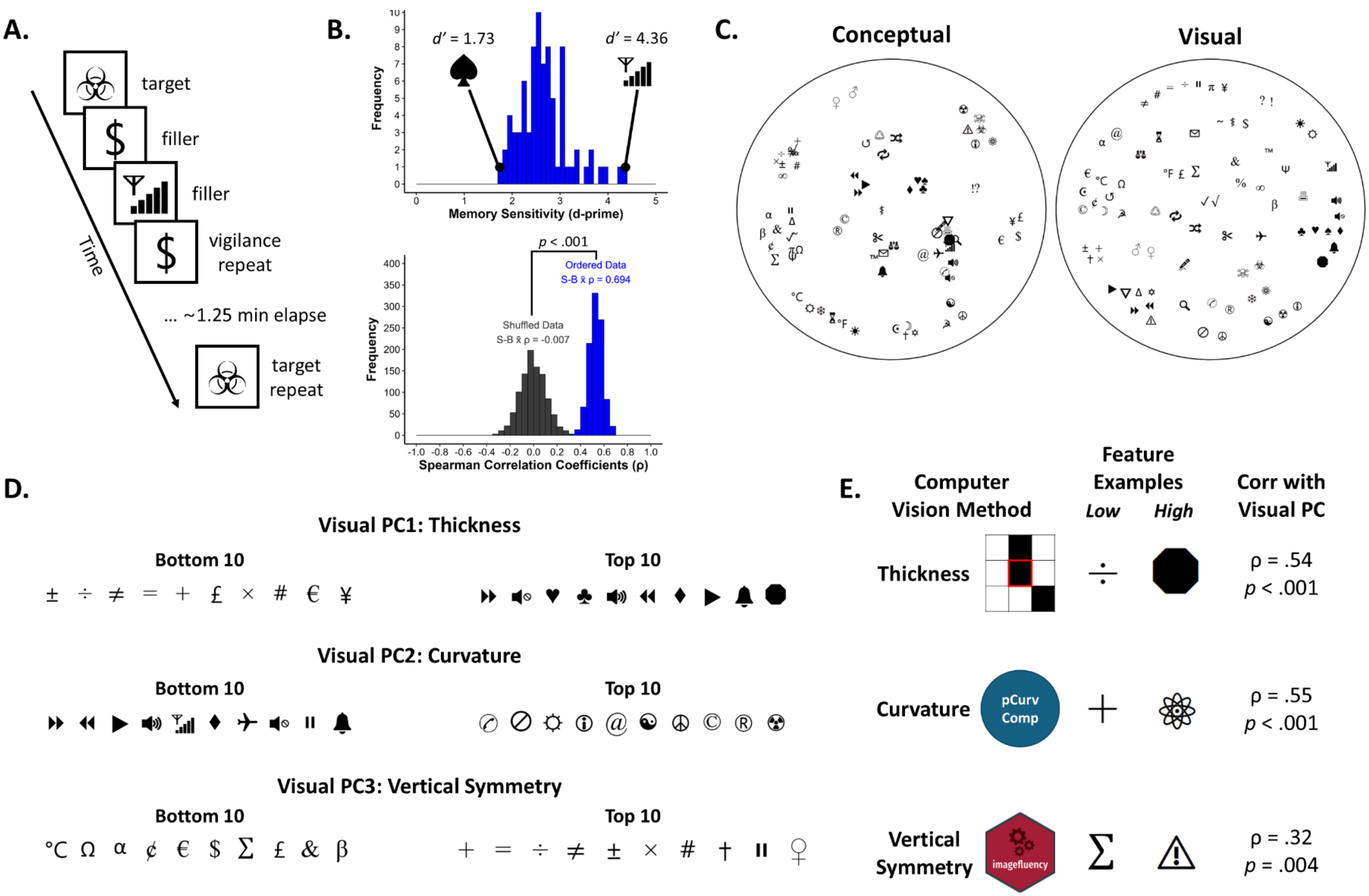

Fig. 1. Procedural Overview of Experiment 1. A. Sequence of trials for the continuous recognition memory test, where participants had to indicate memory for repeated images. Targets were repeated after 1.25 minutes, while vigilance repeats occurred after 0-6 intervening trials to ensure adequate attention was paid to the task. **B.** Results from the continuous recognition memory test showing the high average memorability of conventional symbols with 2 examples (top), as well as the strong reliability of this item-level memory across individuals as demonstrated by 1,000 split-half correlations (annotated by mean Spearman-Brown (S-B) corrected rho (ρ) values; bottom). **C.** Example spatial arrangement method (SpAM) plots from a single participant, demonstrating how they chose to organize symbols based on visual and conceptual similarities. **D.** Top and bottom 10 symbols based on their factor loadings across each visual principal component

(PC), demonstrating that the PCs are capturing thickness, curvature, and vertical (left-right) symmetry (for the full set of symbols, see Fig. 5). **E.** Computer vision-based measures for each of the three visual features, along with example symbols from each end of the feature spectrums, and the correlations between each computer vision methods and relevant visual PCs.

Results

A sample of 248 participants engaged in a continuous recognition memory test (CRT) for a set of 80 conventional symbols (for the full set, see Fig. 5). On each trial, a pseudorandomly selected symbol would appear at the center of the screen. Participants were instructed to press a key whenever they detected a repeated symbol from any trial earlier in the sequence, and to withhold a keypress if the symbol was being presented for the first time. Thirty target items (chosen at random) were repeated after roughly 1.25 minutes had elapsed, whereas 13 other items were randomly selected to serve as attention check trials, repeating after a much shorter delay (< 25 s). D-prime (*d'*) memory sensitivity scores were calculated for each of the 80 symbols in our set to determine their 'memorability', revealing that symbols are highly memorable on average (M = 2.68, SD = 0.54)[1]. We then assessed whether the same symbols were remembered or forgotten across participants using 1,000 repeated rank correlations between random split-halves of participants. The consistency of memorability across participants was indeed reliably above chance, Spearman-Brown (S-B) corrected mean $\rho = .69$, $p < .001$.

After the continuous recognition memory test, participants completed two spatial arrangement method (SpAM; 19) trials whereby they sorted symbols spatially based on the perceived similarity of their visual or conceptual features. This task was designed to capture the perceptual and conceptual attributes that are salient to participants, allowing us to determine whether any of those features predict memory performance. The coordinates of each symbol at the end of the task allowed for calculation of Euclidean distances between each pair of symbols. These distances also served as metrics of each symbol's conceptual and visual distinctiveness, with higher average distance between a symbol and all other symbols representing higher distinctiveness. It should be noted that these metrics serve only as approximations of perceived similarity since psychological confusability is thought to be nonlinearly related to distance (20).

Distinctiveness and Local List Context Do Not Explain Symbol Memorability.

Research on the 'distinctiveness heuristic' has shown that standing out amongst a set of items in a local context should improve memory through more vivid recollection of details (21). Recent work on image memorability, however, has suggested the opposite may be true at larger scales: Global typicality of an image may be associated with better memory (5), perhaps reflective of processing efficiency via template matching to previous experiences (22). To assess this factor in our present study, we tested whether distinctiveness along visual or conceptual dimensions predicted the memorability of a symbol. Both forms of distinctiveness and their interaction were entered into a multiple regression predicting symbol memorability: Visual distinctiveness did not significantly predict memorability, $\beta = -0.02$, $SE = 0.06$, $t(72) = -0.26$, $p = .797$ (Fig. 3A; nor did it predict hit rate or false alarm rate separately, $ps \geq .188$), whereas higher conceptual distinctiveness predicted significantly better memorability, $\beta = 0.14$, $SE = 0.06$, $t(72) = 2.27$, $p = .027$ (Fig. 3B; it also predicted hit rate, $p = .016$, but not false alarm rate, $p = .495$). The interaction

[1] See SI Appendix, Supplemental Results 1 for a breakdown of all recognition memory analyses using hit rate, false alarm rate, and corrected recognition (hit rate minus false alarm rate).

between visual and conceptual distinctiveness was nonsignificant, β = -0.02, *SE* = 0.07, $t(72) = -0.29$, $p = .775$.

We next assessed whether visual distinctiveness influenced memory performance within each participant's local encoding or retrieval context, rather than at the aggregate item level (see SI Appendix, Supplemental Results 5). For each target and repeat CRT trial within a participant, we calculated the average distinctiveness of the symbol relative to (up to 5) preceding symbols. In brief, a series of mixed-effects logistic regressions were used to test whether local distinctiveness and each symbol's average memorability predicted hits above chance using 1,000 cross-validated permutations. There was no influence of local visual distinctiveness context during encoding or recognition on later hits at any trial window size ($bs \leq 0.08$, $ps \geq .074$). Critically, the influence of an item's average memorability predicted hits over and above local distinctiveness context at each window size ($bs \geq 0.29$, $ps \leq .025$; see SI Appendix, Fig. S9). Put simply, even when modeling the influence of each participant's local list context, a symbol's average memorability across people is still uniquely predictive of the same participant's memory for that item.

Taken together, these analyses suggest that—at least for our current set of conventional symbols used in a continuous recognition test—the overall uniqueness of a symbol's design does not affect how well it will be remembered, nor does its distinctiveness relative to preceding items in a local list context.

Visual Features That Impact Memorability.

Spatial arrangement data was next used to assess which features participants were using to sort symbols in the task, and whether any of those features predicted memory for symbols. To do so, we entered the average distances between each pair of symbols across participants into a principal components analysis (PCA; see SI Appendix, Supplemental Methods 3). Using Horn's parallel analysis method (23) to determine the significance of principal components (PCs), we retained 3 visual and 3 conceptual PCs. When entered together into a multiple regression, this PCA-based model significantly predicted symbol memorability, $R^2 = 0.38$, $p < .001$, as did each of the 6 PCs individually.[2]

While the conceptual PCs were intriguing and each uniquely significant ($\beta s \geq |0.25|$, $ps \leq .021$), our focus was on assessing the visual features that predict memorability. This was because our ultimate goal was to test whether memorability can be engineered by changing stimulus features, and while visual designs can be altered, the meaning of a symbol is predetermined by its associated concept. Next, we leveraged computer-vision-based analyses of the symbol images to determine a set of visual features that were significantly correlated with the visual PCs that predicted memorability: thickness, curvature, and vertical symmetry (Fig. 1D and 1E). Thickness was measured as the average proportion of black pixels surrounding each black pixel, vertical symmetry was assessed by comparing mirrored pixels across a vertical median using the *imagefluency* package (24), and curvature was estimated using the *pCurvComp* (25) toolbox which uses neural networks trained to predict human ratings of curvature. Within our multiple regression model of the PCs, we saw that the factor loading on Visual PC1 (representing thickness of a symbol) was negatively predictive of its memorability such that thinner symbols were better remembered, β = -0.38, *SE* = 0.12, $t(69) = -3.01$, $p = .004$. Similarly, the Visual PC2 loading (representing perceived curvature) negatively predicted symbol memorability such that pointier symbols with straighter lines were typically remembered better, β = -0.19, *SE* = 0.07, $t(69) = -2.95$,

[2] For model diagnostics broken down by *d*-prime, hit rate, and false alarm rate, see SI Appendix, Supplemental Results 2.

p = .004. Finally, loading on Visual PC3 (representing vertical symmetry) also negatively predicted symbol memorability such that left-right asymmetric symbols were better recognized by participants, $\beta = -0.11$, $SE = 0.05$, $t(69) = -2.10$, $p = .039$.

Feature Model Outperforms Neural Networks When Predicting Symbol Memorability.

Given that models used to predict memorability already exist, we next tested how our PCA-based model fared against these networks. We ran our set of conventional symbols through both ResMem (14) and MemNet (15), yielding two network-derived estimates of image memorability. These networks were each able to successfully predict the memorability (*d'*) of conventional symbols in linear regressions: ResMem ($R^2 = 0.07$, AIC = 118, $p = .017$), and MemNet ($R^2 = 0.18$, AIC = 109, $p < .001$). Our PCA-based model ($R^2 = 0.38$, AIC = 98, $p < .001$), however, predicted significantly more variance than both ResMem ($F(6,68) = 5.52$, $p < .001$) and MemNet ($F(6,68) = 5.09$, $p < .001$).

Exploring High-Level Features.

Finally, to explore whether higher-level factors relate to memorability, such as the extent to which a symbol resembles an object, or how often it is encountered in daily life, we next assessed whether iconicity, familiarity, or frequency predicted memory for symbols. Ratings of iconicity were collected following the SpAM trials, while data for the latter two factors originated from a previous study that used the same set of stimuli (4). All three factors were entered into a multiple regression predicting symbol memorability. Iconicity (how much a symbol depicts a real object) positively predicted memorability, $\beta = 0.12$, $SE = 0.06$, $t(72) = 2.08$, $p = .041$, while the frequency with which a symbol is encountered in daily life had a negative association, $\beta = -0.24$, $SE = 0.09$, $t(72) = -2.55$, $p = .013$. Familiarity of the tested symbols, however, did not predict memorability, $\beta = 0.04$, $SE = 0.09$, $t(72) = 0.44$, $p = .664$.

Discussion

This experiment determined the features that drive memory for symbols. Results showed that some symbols are better remembered than others, this difference in memorability amongst symbols is highly reliable across participants, and that a symbol's average memorability predicts an individual's ability to recognize it beyond the influence of their unique experiment context. Conceptual (but not visual) distinctiveness was shown to predict the memorability of these symbols, suggesting that symbols benefit from their relative isolation in semantic space. Analysis of visual features via PCA and subsequent computer vision validations revealed that thickness, curvature, and vertical symmetry all negatively predicted symbol memorability. Next, we manipulate novel symbols to either downplay or accentuate these predictive features to see whether we can cause intentional changes in memory through alterations to visual design.

Experiment 2: Engineering Memorable Symbols

After determining thickness, curvature, and vertical symmetry predict the memorability of conventional symbols, next we causally manipulated these features using generative AI to create novel symbols that are designed to be memorable or forgettable. Participants were then tested on their ability to study and later recognize these symbols, and to recall each symbol's associated abstract word. Here, we compared memory performance for memorable and forgettable symbol variants representing the same abstract word to determine if memory can be predetermined via a set of data-driven visual design principles.

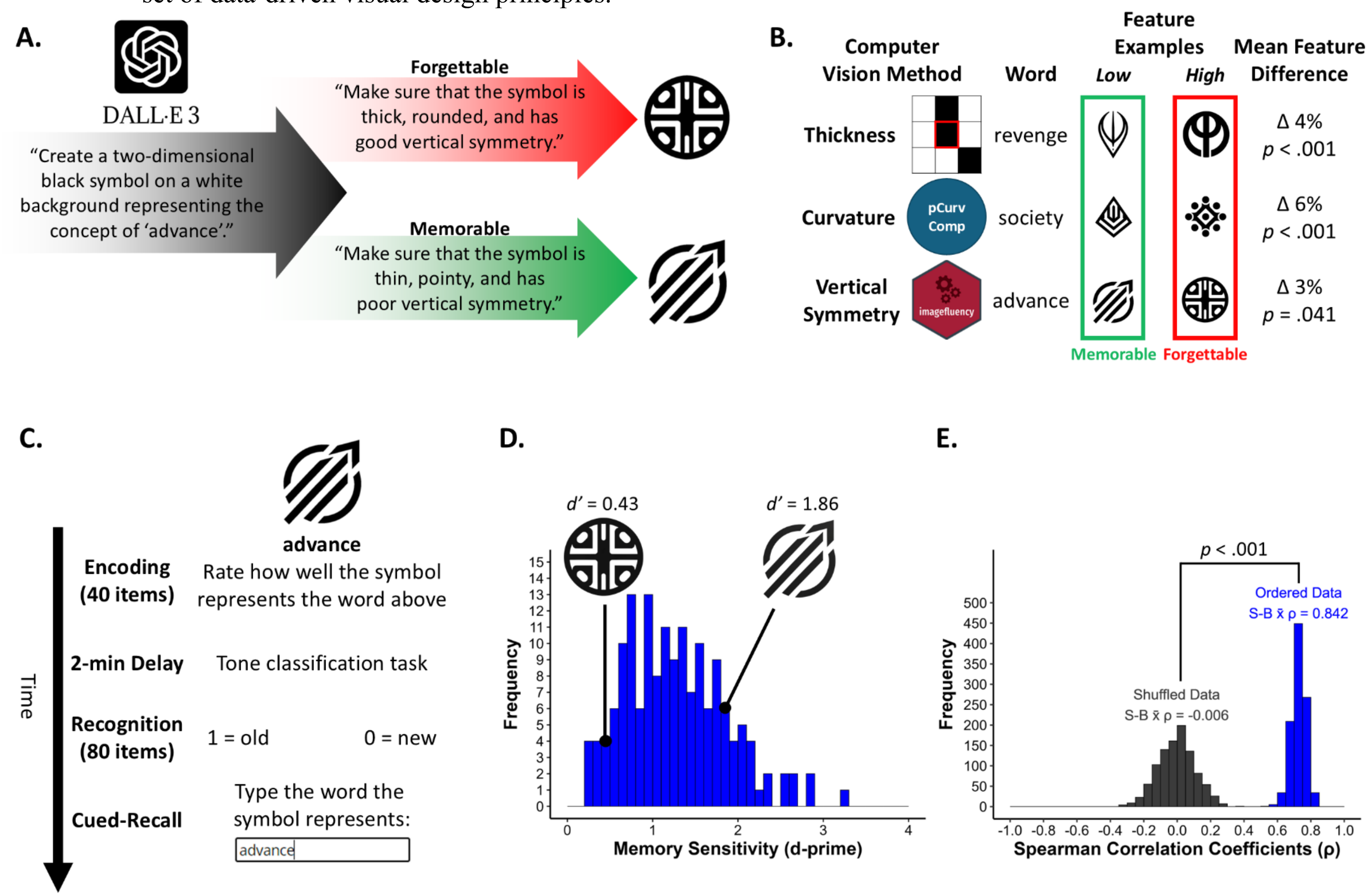

Fig. 2. Procedural Overview of Experiment 2. A. Prompts for memorable and forgettable versions of each symbol submitted to the DALL-E 3 AI image generator. **B.** Computer vision validation metrics for the three manipulated visual features of interest, along with example symbols from each end of the feature spectrums and the average percent difference in these metrics (Δ) between memorable and forgettable symbols. **C.** Example of the experiment paradigm whereby participants linked 40 novel symbols with meaning by rating how well each symbol represented the word below it on a 0-100 scale. The study phase was followed by a 2-min filled delay period. Afterwards, an 80-item test phase took place whereby participants were first presented with an old/new recognition decision for a symbol, which was immediately followed by a cued-recall response that asked participants to enter the word they thought was associated with

the symbol earlier. **D.** Results from the continuous recognition memory test showing the range of memorability of novel symbols, along with forgettable and memorable examples for the word 'advance'. **E.** Histograms depicting 1,000 repeated split-half correlations demonstrating the high reliability of novel symbol memorability across participants, as annotated by mean S-B corrected rho (ρ) values.

Results

In this experiment, 329 participants were presented with a series of novel symbols. Each of the novel symbols was based on an abstract word (acquired from the English Lexicon Project; 26) that did not already have an associated symbol. The DALL-E 3 artificial image generator was used to create a memorable and a forgettable symbol variant of each concept by either emphasizing or downplaying features we previously identified in Experiment 1 to predict memorability. All aspects of the prompts used to generate memorable and forgettable symbols were identical, save for the key feature words that were manipulated: 'thick' vs. 'thin', 'rounded' vs. 'pointy', and 'good' vs. 'poor' vertical symmetry (Fig. 2A).

Participants were shown a subset of 40 novel symbols (from a set of 160) along with the abstract words that were used to create them. Half of the presented symbols were designed to be memorable and the other half forgettable (shown in a random order), with participants only ever seeing either the memorable or forgettable symbol variant of a given concept at encoding, but never both (i.e., item lists were counterbalanced across participants). For each symbol-word pair, participants rated how well the symbol represented the word using a slider scale ranging from 0 to 100, while attempting to remember the symbol and word for a later memory test. The rating task was used to encourage participants to link words and symbols in their minds, ensuring that the novel symbols were encoded with meaning.

After a 2-min delay during which participants completed a tone classification filler task, they then completed a combined old/new recognition with cued-recall memory test. The memory test consisted of 80 symbols, half of which had been presented during the encoding phase—and unbeknownst to participants—the other half were the forgettable or memorable symbol versions of the same concepts (whichever was not presented at encoding). Immediately following each old/new recognition decision for a symbol, participants were asked to type the word they believed had been associated with that symbol during the encoding phase, or to make their best guess based on the design of the symbol if they did not think they had studied it earlier.

As was the case for conventional symbols in Experiment 1, split-half reliability analyses on *d*-prime values revealed that these novel symbols are reliably remembered across individuals, S-B corrected $\rho = .84$, $p < .001$ (Fig. 2E). Memorable symbols specifically were slightly more consistently remembered across participants ($\rho = .86$) relative to forgettable symbols ($\rho = .83$), though this difference was not statistically significant, $Z = 0.74$, $p = .462$.

Validating the Visual Feature Changes.

First, we confirmed via the same computer vision techniques as in Experiment 1 that each of the visual features were changed significantly in the intended directions (*ps* $\leq .041$; see the Method for more details). We attempted to recapture the three features in a model by performing a PCA on the novel symbol visual SpAM data, but this analysis revealed a single principal component that represented the vast majority of explained variance (see SI Appendix, Supplemental Results 3 for more details). Indeed, when entered into a multiple regression with the top three visual and conceptual PCs (as in Experiment 1), Visual PC1 predicted memory accuracy in the expected direction (β = -0.25, p = .001). Thus, while we were able to manipulate the three visual features together, we were unable to later separate them to assess their individual contributions.

Engineered Memorability Predicts Hits Beyond Distinctiveness and Local Context.

Spatial arrangement data for the set of novel symbols was gathered from a separate group of N = 96 participants. A similar analysis of local context as performed in Experiment 1 was conducted (see SI Appendix, Supplemental Results 5), this time adding condition (memorable vs. forgettable) as a binary predictor representing each symbol's intended memorability. Once again, there was no influence of local visual distinctiveness during encoding or recognition on later recognition hits at any window size ($bs \leq |0.03|$, $ps \geq .234$), but in each case a symbol's memorability condition did predict recognition performance ($bs \geq 0.37$, $ps < .001$; see SI Appendix, Fig. S10). This context analysis suggests that the engineered memorability of a symbol allows one to predict hits over and above the local context that the symbol was encountered in. Matching these local context analyses, global visual and conceptual distinctiveness (and their interaction) also failed to predict memory sensitivity in a multiple regression, $ps \geq .456$ (Fig. 3C and 3D).

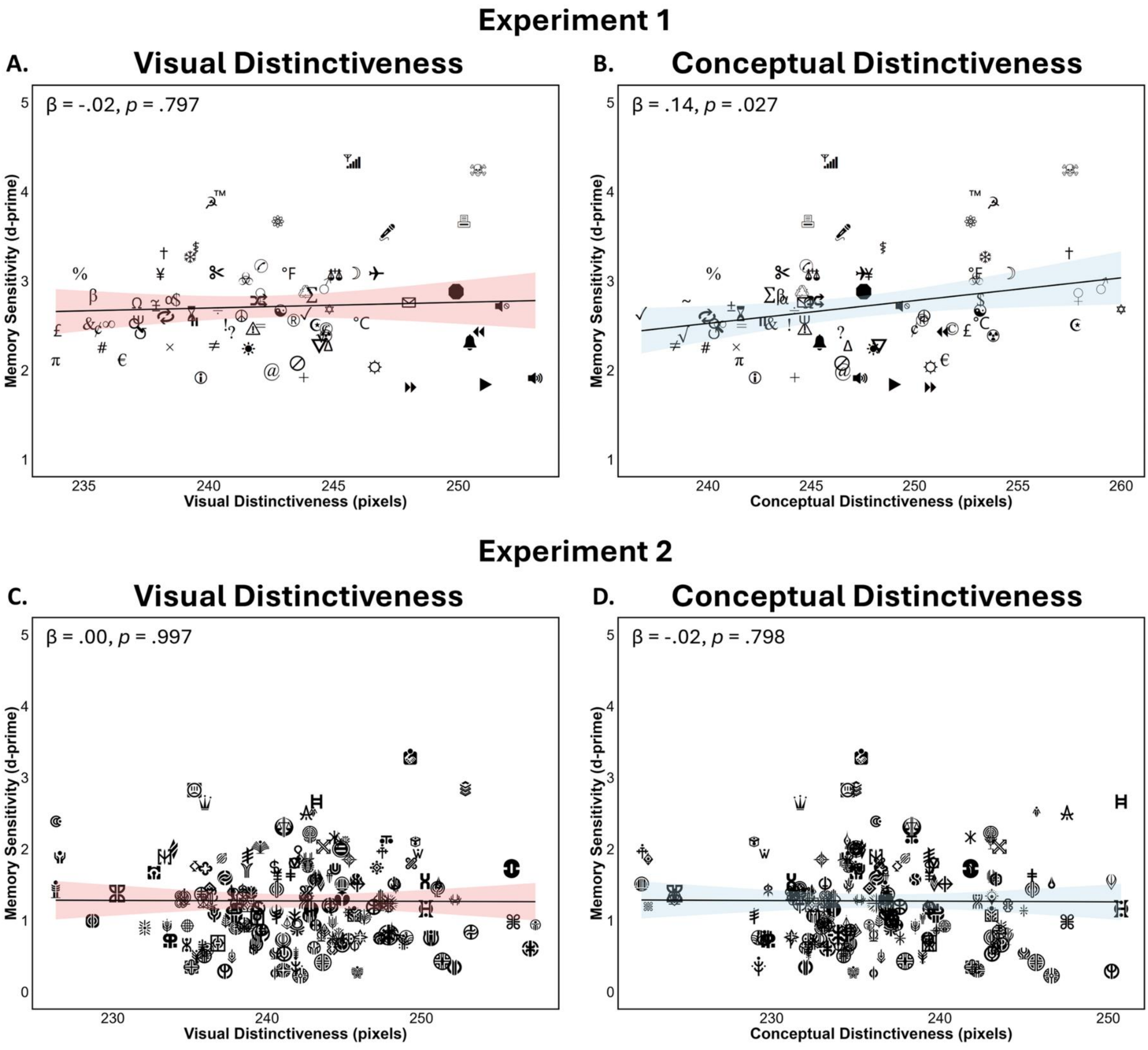

Fig. 3. Relation between distinctiveness and memory in both experiments. Scatterplots showing the relation between symbol memorability and distinctiveness. For conventional symbols in Experiment 1, memorability was unrelated to visual distinctiveness (average Euclidean distance from all other symbols, in pixels; **A**) but was positively related to conceptual distinctiveness (**B**). For novel symbols in Experiment 2, memorability had no relation to either visual (**C**) or conceptual (**D**) distinctiveness.

Engineered Memorable Designs Improve Both Recognition and Associative Memory.

With our design feature alterations confirmed via computer vision metrics, and no context or distinctiveness confounds to be seen, we next evaluated the impact of our key manipulation on memory performance. Memory sensitivity *d*-prime (*d'*) scores from the old/new recognition test were higher for symbols that were designed to be memorable (M = 1.38, SD = 0.72) relative to those designed to be forgettable (M = 1.17, SD = 0.72), $t(328) = 5.49$, $p < .001$, $d = 0.30$, 95% CI = [0.19, 0.41], $BF_{10} > 1{,}000$ (Fig. 4A). Hit rates on the recognition test were significantly higher for memorable (M = .65, SD = .18) relative to forgettable (M = .57, SD = .19) symbols, $t(328) = 8.66$, $p < .001$, $d = 0.48$, 95% CI = [0.37, 0.59], $BF_{10} > 1{,}000$. False alarm rates for memorable (M = .18, SD = .15) and forgettable (M = .19, SD = .16) symbols did not differ, $t(328) = -1.05$, $p = .147$, $d = -0.06$, 95% CI = [-0.17, 0.05], $BF_{01} = 9.37$. Put simply, symbols that were designed to be memorable were recognized at higher rates than those designed to be forgettable, and this difference was primarily driven by the former's propensity to be correctly endorsed as a previously encountered item.

The proportion of correctly recalled target words for each memorability condition was then assessed for all symbols which had been correctly identified on the recognition test as previously studied (i.e., a 'hit' response). The proportion of words successfully recalled when cued with their correctly-recognized symbol was significantly higher if they were tied to a symbol that was designed to be memorable (M = .27, SD = .20) relative to one designed to be forgettable (M = .22, SD = .19), $t(328) = 4.71$, $p < .001$, $d = 0.26$, 95% CI = [0.15, 0.37], $BF_{10} > 1{,}000$ (Fig. 4B). The proportion of words recalled following all other recognition outcomes (misses, correct-rejections, and false-alarms) did not differ between symbol conditions, $ps \geq .679$. Therefore, not only were memorable symbols better recognized, but they also had stronger links to their associated abstract word (even after just a single co-presentation of the pair).

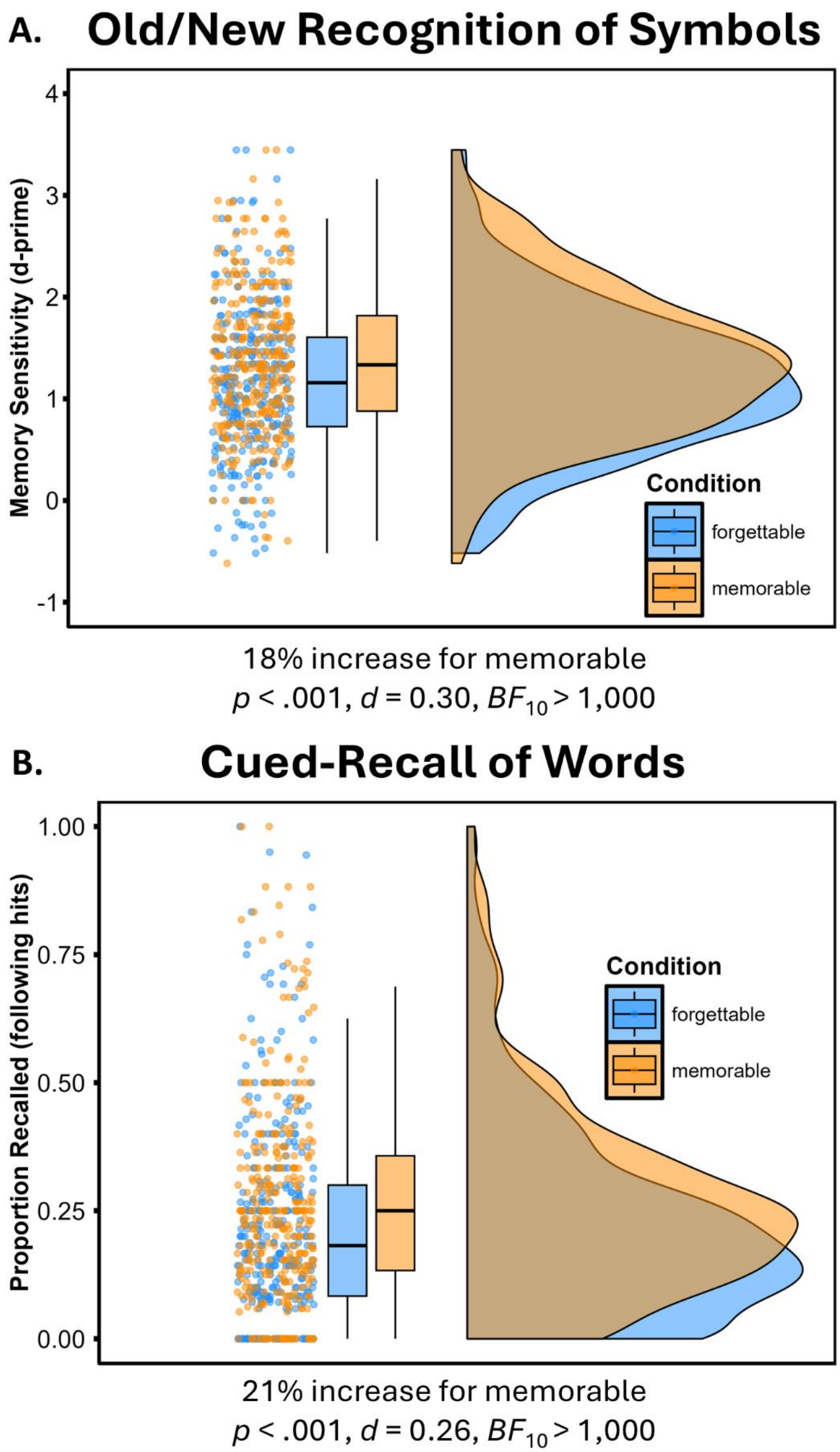

Fig. 4. Critical memory performance results from Experiment 2. A. Average performance on the old/new recognition test, demonstrating a robust memory benefit for symbols that were designed to be memorable. **B.** Average performance on the cued-recall test, showing a memory boost for words that were tied to memorable symbols relative to those tied to forgettable ones.

Symbol Representativeness Partially Mediates the Memory Benefit.

Finally, to investigate a potential mechanism of the memory benefit for memorable novel symbols, we explored whether they may serve as better cues for a given concept. Symbols that were designed to be memorable (M = 38.1, SD = 18.2) were rated as more representative of their associated abstract word relative to symbols designed to be forgettable (M = 34.7, SD = 18.8), $t(328) = 7.20$, $p < .001$, $d = 0.40$, 95% CI = [0.30, 0.50], $BF_{10} > 1{,}000$. This finding was unexpected as symbols were only designed to vary in terms of their low-level visual features. It could be the case that certain visual characteristics are more readily associated with certain meanings. This could be akin to the 'bouba/kiki' effect in the sound symbolism literature whereby individuals are more likely to associate round shapes with the word 'bouba' and pointy shapes with the word 'kiki' (27, 28). Despite this difference in ratings, however, a mediation analysis confirmed that both recognition and cued recall memory remained higher for memorable symbols even when accounting for representativeness ratings (d': $b = 0.191$, $p < .001$; recall: $b = 0.041$, $p < .001$). Representativeness ratings accounted for a small but reliable portion of the effect (indirect effects, d': $b = 0.023$, $p < .001$; recall: $b = 0.005$, $p = .004$), mediating roughly 10% of the total influence of memorability condition on memory performance in each case (see SI Appendix, Supplemental Results 4 for more details).

Discussion

Here we took the features that were shown to predict the memorability of conventional symbols in Experiment 1 and used them to create novel symbols that were designed to be memorable or forgettable. The DALL-E 3 AI image generator was used to form memorable and forgettable symbol variants for a list of abstract words that did not already have symbols, all the while accentuating or downplaying visual features that predicted memory: thickness, curvature, and vertical symmetry. Memorability was shown to be reliable across participants, even for entirely novel symbols. Critically, both recognition and cued-recall memory were substantially improved for symbols that were designed to be memorable. In other words, not only is recognition better for a symbol that was designed to be memorable after just a single encounter, but the associative link to its word counterpart is also bolstered as a result. While we were able to manipulate memorability when all three visual features were altered, the contribution of each individual feature remains unknown. Thus, it remains possible that a single feature change accounted for a large portion of the effect, or that interactions amongst features exist. Nonetheless, this experiment represents the first successful attempt at using generative AI to purposefully engineer memory by manipulating specific visual features.

General Discussion

To determine what drives memorability for visual content, we established a novel, two-step approach using data-driven design changes, implemented with a cutting-edge generative AI model. First, we identified the visual and conceptual features that predict memorability of conventional symbols (e.g., !@#$%). Second, we exploited those features to generate a set of novel symbols that were designed to be memorable or forgettable. Both recognition and cued-recall memory were enhanced for memorable symbols relative to forgettable ones. That is, the ability to later identify a previously seen symbol was improved when that symbol was designed to be memorable by manipulating its visual features, and moreover, these memorable symbols also afforded stronger links to their associated concepts. To our knowledge, this is the first demonstration that certain visual features predict the memorability of an image, and that these features can be intentionally engineered using data-driven alterations to visual design.

This study also offers initial evidence that memorable stimuli serve as highly effective cues for related content, suggesting that their mnemonic benefits may extend far beyond the stimulus itself. Because memorable symbols are easier to later recognize, it is likely that episodic memory for their initial encoding event is also enhanced, and with that comes improvements for connected stimuli: Indeed, our data shows that memorable symbols reliably improve cueing of their co-presented abstract word. The extent to which a symbol is remembered, therefore, may not be restricted to prior encoding of the symbol's visual features, but rather may have further benefits from associative retrieval mechanisms as well.

Recent theories have been put forth arguing that memorability effects may be largely reflective of processing efficiency advantages for memorable stimuli (29–31; for a review see 32). Memorable images have been shown to be quicker to identify (22), benefit from preferential encoding in high-level visual processing regions in the brain (33), and more of them can be stored in working memory at any given time (30). Aligning with this processing efficiency account, it could be that the memorable visual features of symbols we identified (thinness, straight lines, asymmetry) are easier for the human visual system to process, offering efficiency gains that result in superior memory. For instance, straight lines in cardinal directions lead to greater V1 activation (34, 35), as do rectilinear shapes in parahippocampal place area (PPA; 36). There is also evidence to suggest that thinner lines can improve letter character legibility (37) and reading speed (38).

Processing efficiency may also be driven by the extent to which a stimulus is distinct along one or more dimensions. Distinctiveness could benefit processing efficiency due to a lack of interference from competing items in memory. Numerous models have formalized this relationship by contending that memory is driven by distinctiveness relative to other items, and it is interference from competing items in memory (rather than decay) that causes forgetting (e.g., the SIMPLE model; 39). In other words, the more distinct an item is along more dimensions, the better remembered it should be as it stands apart from competing information. Indeed, the general notion that cue diagnosticity predicts successful memory retrieval is shared by many memory researchers (e.g., 40–42).

While both visual and conceptual distinctiveness amongst symbols should theoretically benefit memory, only the latter did for our set of conventional symbols. Indeed, the relative conceptual isolation amongst symbols and their distinct encapsulation of abstract ideas may make them especially memorable as a stimulus category. To illustrate, consider the conceptual distinctiveness of the play symbol (▶) relative to its abstract word counterpart ('play'). Put simply, there is no other symbol with a similar meaning as the play symbol, and it has no substitute. On the other hand, the word ‘play’ has many synonyms in the same context, such as ‘begin’, ‘start’, ‘commence’, etc., and is further burdened by its nature as a homonym (i.e., ‘play’ could also refer to a game, theatrical performance, or strategy). This relative conceptual isolation means that symbols should benefit from reduced interference from competing items during memory storage and retrieval. Indeed, our current data shows that the conceptual distinctiveness of conventional symbols positively predicts their memorability.

Related work on the memorability of words has come to similar conclusions: Words that map to only a single meaning (e.g., ‘pineapple’) are better remembered than those with multiple meanings (e.g., ‘light’) or synonyms (e.g., ‘happy’; 16). On the other hand, research has also shown that words with many semantic neighbours are better remembered (43), as are images of objects that were rated as more prototypical (5). Therefore, it is possible that conceptual distinctiveness benefits processing efficiency in so far as it enhances the diagnosticity of the item. That is, processing efficiency may be driven by the ease with which meaning can be gleaned from a stimulus. The efficiency of this ‘semantic extraction’ may be best supported by items which are prototypical yet conceptually distinct, like symbols.

Given that the memorable and forgettable novel symbols created and tested in this study were based on the same abstract words, their conceptual distinctiveness should be identical. In each case, the symbols were based on abstract words that do not already have a related symbol. Thus when comparing the memorable and forgettable novel symbol versions of the same concept (as we did here), the mnemonic benefit of conceptual distinctiveness should be eliminated (indeed, this factor did not predict memorability for novel symbols). Instead, it is possible that memorable novel symbols benefit from eased semantic understanding, as described earlier: The strength of the link between a symbol and its associated concept could drive part of the performance gains in the current study. Aligning with this idea, we found that symbols that were designed to be memorable were also rated as more representative of the abstract word presented alongside it at encoding. A symbol’s average representativeness rating, however, did not fully explain its memorability nor its associative memory benefit. Nonetheless, this finding perhaps suggests that when a participant is shown a memorable symbol, its visual features lead to perceptual processing efficiencies that cause feelings of metacognitive fluency, biasing the individual to rate the symbol as representative of its co-presented word. Future studies will be needed to precisely determine how certain perceptual features may be processed more efficiently in the brain and may interact with an item’s conceptual distinctiveness to influence memory. Our chief contribution is the demonstrated ability to identify and manipulate visual properties that may modulate the inputs to these underlying mechanisms of memory (e.g., processing efficiency). Integrating engineered feature variation into formal computational models of recognition memory (e.g., global-matching models; 44–48) represents an important direction for future research.

Our goal in this study was two-fold: Identify the features that drive memorability of symbols, and harness that knowledge to define a set of data-driven design principles that can be applied to make any graphic more memorable. An obvious and direct application of this work is the creation of better symbols. These cognitively optimized visual designs could be implemented when creating warning symbols or brand logos that are intuitive and easy for people around the world to learn and remember. We have shown that small changes in visual features can lead to large changes in memory, suggesting that it may even be possible to ‘retrofit’ existing symbols with slight changes in their thickness, curvature, and symmetry to improve performance.

Generative AI provides a promising way to facilitate the modification of existing symbols to make them more memorable. For example, GANs have already been used to modify the memorability of face images (49, 50). Moreover, others have used a GAN-based framework to analyze which high-level visual properties (e.g., brightness, size of objects, centering of objects) predict the memorability of naturalistic images (18). Beyond changing *what* participants study, recent approaches have also shown that the timing of *when* something is presented can improve performance: By inserting memorable or forgettable images depending on one's level of sustained attention (measured in real-time), memory performance can be maximised in any given situation (8). These emerging computational approaches to the study of memorability open the door to future work that could automatically tailor existing and novel visual designs alike to strengthen memory.

In conclusion, the current study identified and manipulated features driving memorability of everyday symbols. First, we demonstrated that certain visual and conceptual attributes are uniquely predictive of later memory for symbols. Namely, key visual attributes predicting improved symbol memory were thinness, pointiness, and vertical asymmetry. These three features were fed into an AI image generator to form a set of novel symbols that either accentuated (memorable) or downplayed (forgettable) these properties. As a result of this causal manipulation, recognition memory was 18% better and cued recall was 21% higher for symbols that were designed to be memorable relative to forgettable. This study clearly demonstrates that image memorability can be altered with simple prompt changes submitted to widely available generative AI models. To our knowledge, this is the first study to demonstrate that memory can be engineered through changes to user-defined visual features. Moreover, these feature manipulations have benefits that extend beyond the image itself, offering improved ability to cue associated content as well. Much like the biohazard symbol's universal implementation following Baldwin and Runkle's 1967 study, this work will serve as the basis for widespread adoption of data-based visual designs that are optimized for human cognition.

Materials and Methods

Data Availability

The procedures and materials for this study were approved by the Institutional Review Board (IRB) at the University of Chicago. All pre-registrations, data, analysis code, experiment programs, and other materials are made available on the Open Science Framework (OSF; https://osf.io/8jtgp/).

Experiment 1

Participants

The final sample consisted of 248 participants aged 18-78 living in the USA (M_{age} = 41.7, SD_{age} = 13.5; 121 female, 118 male, 9 declined to report their sex). See SI Appendix, Supplemental Method 1 for a description of our power analysis and data cleaning steps. In the end, our desired sample size for attaining stable average item memorability was largely achieved, as each symbol served as a memory target for 72 to 116 participants (M = 93, SD = 8.07), and only 4 of the symbols served as targets for fewer than 80 participants.

Materials and Procedure

During the experiment, participants completed four main tasks: first, a continuous recognition memory test with images of conventional symbols, then two spatial arrangement tasks (measuring perceived visual and semantic similarity), next iconicity ratings for each symbol, and finally completion of the Vividness of Visual Imagery Questionnaire (VVIQ; 51). The entire experiment was administered using *jsPsych* (versions 6.1.0 and 7.3.4; 52), hosted on the freely available MindProbe server (https://mindprobe.eu/) using open-source JATOS experiment management software (53). For more details on the experimental procedure, see SI Appendix, Supplemental Methods 2.

Symbol Stimuli. This experiment used a set of 80 symbols that have previously been shown to be highly memorable relative to their word counterparts (4). These symbols (see Fig. 5) were selected based on the criteria that (1) they were mostly physically and conceptually distinct from one another, and (2) they were familiar to people in the target North American population. All symbol stimuli were created by copying the Unicode item from the web, formatting it using the Segoe UI Symbol font in black ink, then editing it to be 110 × 116 pixels on a white background. For more details, see Roberts et al. (4).

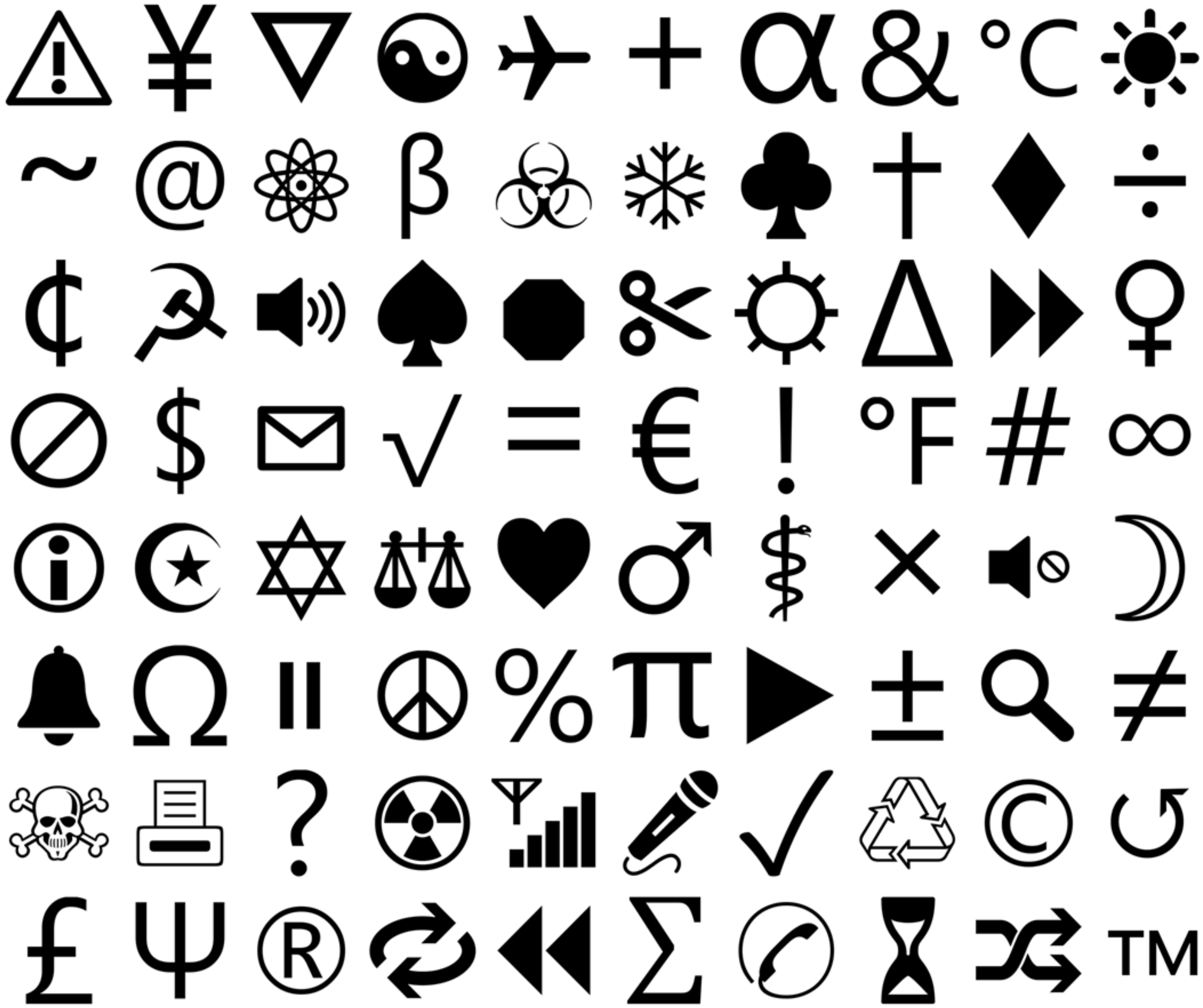

Fig. 5. Conventional symbols used in Experiment 1. Depicted are each of the 80 conventional symbols that were used in Experiment 1. This set of symbols was chosen to contain a variety of different, relatively common symbols that most participants would recognize.

Statistical approach

Memory Scores and Analyses of Memorability. D-prime (*d'*) memory sensitivity scores were used to assess recognition memory performance for each symbol and participant. These scores were calculated using the *psycho* (v. 0.6.1) package for *R*, applying the Hautus (54) correction in cases of extreme hit or false alarm rate values. Hits and false alarms for attention check ('vigilance') trials were not included in these calculations. The average *d*-prime score for each symbol is what we refer to as its 'memorability' (Fig. 1B, top).

To assess the reliability of memorability for each symbol across participants, we used 1,000 repeated Spearman rank correlations between randomly shuffled split-halves of participants. In each iteration, we generated the average memorability score for each symbol in the two halves. Next, we calculated the Spearman correlation of symbol memory rankings between the two halves. We repeated this process 1,000 times in order to obtain the average correlation of symbol memorability across participants. Finally, we applied a Spearman-Brown split-half reliability correction (55) to this average correlation to obtain the final reliability estimate for the memorability of symbols. To assess the statistical significance of this reliability, we used a permutation test by comparing this ordered data to randomly shuffled data across 1,000 iterations (Fig. 1B, bottom).

Computer Vision Analyses. After evaluating the visual PCs by eye, we guessed that the first was capturing the thickness of symbols, the second captured the curvature of symbols, and the third captured vertical symmetry (see Fig. 1D and Fig. S2). To validate whether the PCs indeed represent these visual features, we used computer vision analyses to quantify the degree of thickness, curvature, and vertical symmetry in each symbol.

To quantify the thickness of each symbol, we developed a function to calculate the average proportion of black pixels touching other black pixels in an image. For each black pixel within each symbol image, we counted the number of adjoining black pixels, divided by the number of surrounding pixels. This measure of thickness correlated positively with factor loadings in Visual PC1, $\rho = .54$, $p < .001$, indicating that the latter likely captures the attribute of 'perceived thickness,' and that participants used this feature to sort symbols during the visual SpAM trial.

To assess the curvature of each symbol, we used the newly developed 'pCurvComp' method (25). This approach uses an ensemble model comprised of three deep neural networks (ResNet50, CLIP, and ConvNeXt; 56–58) to extract image features. Then, pCurvComp uses a ridge regression model which is trained on human ratings of perceived curvature for over 27,000 natural object images from the THINGSplus database (59). pCurvComp predicts curvature ratings better than more conventional methods like normalized contour curvature (NCC), as well as recently developed toolboxes designed to evaluate mid-level vision features (25). Indeed, we found that pCurvComp scores (which are more negative with increasing curvature) correlated negatively with factor loadings in Visual PC2, $\rho = -.55$, $p < .001$, indicating that this PC largely captures perceived curvature of symbols.

Finally, we were originally unsure of what Visual PC3 represented so we took an exploratory approach by using the *imagefluency* package (24) for *R* to assess visual factors known to influence cognitive processing. This package provided measures of contrast, complexity, self-similarity, simplicity, vertical symmetry, and horizontal symmetry for each symbol image. Of all these factors, contrast, self-similarity, and vertical symmetry[3] correlated significantly with factor loadings in Visual PC3 (*ps* < .05). After entering all three of these features in a multiple regression, however, only contrast ($p = .028$) and vertical symmetry ($p = .005$) significantly predicted Visual PC3 factor loadings. Because vertical symmetry was a better predictor than contrast, we surmised that Visual PC3 is mostly (but not entirely) capturing vertical (i.e., left vs. right) symmetry, as was confirmed by a positive Spearman correlation between this PC and our computer vision measure of vertical symmetry, $\rho = .32$, $p = .004$.

Outlier Removal and Multiple-Regression Models. Univariate outlier symbols were identified (at the ± 3 *SD* level) across the following metrics: Visual PC1, Visual PC2, Visual PC3, Conceptual PC1, Conceptual PC2, Conceptual PC3, Iconicity, Familiarity, Frequency, Conceptual Distinctiveness, Visual Distinctiveness, and Memorability. Of these, univariate outliers were present only on the Conceptual Distinctiveness metric. These outliers, which were all > 3 *SD* above the average, were the four symbols found in a common set of playing cards: heart, spade, diamond, and club. Thus, it is likely that participants grouped these four symbols together during the

[3] The toolbox was not able to assess vertical symmetry for the tilde symbol (~).

conceptual spatial arrangement task, placing them in their own cluster far away from all other symbols. With these four outlier symbols removed, we then tested a series of linear models to assess which factors would predict memorability of symbols in the current study. We tested the effects of high-level factors (e.g., familiarity), the 6 PCs determined here, and the distinctiveness of symbols. Each regression was formed using the base package *stats* from *R* version 4.3.3.

Experiment 2

Participants

The final sample consisted of 329 participants aged 19-75 living in the USA (M_{age} = 37.5, SD_{age} = 12.1; 168 female, 159 male, 2 declined to report their sex). See SI Appendix, Supplemental Method 1 for a description of our power analysis and data cleaning steps. Participants were randomly sorted into 4 counter-balanced conditions which determined whether they saw the memorable or forgettable symbol version of a given concept, and whether that symbol served as a target or foil item on the recognition test (N = 86 in counterbalance 1, N = 79 in counterbalance 2, N = 75 in counterbalance 3, N = 89 in counterbalance 4).

For the two spatial arrangement tasks that were administered separately, the final sample consisted of 96 participants aged 19-74 living in the USA (M_{age} = 40.2, SD_{age} = 13; 49 female, 47 male). Participants were randomly assigned to sort the memorable or forgettable version of a given symbol during the visual SpAM task (N = 45 in counterbalance 1, N = 51 in counterbalance 2).

Materials and Procedure

During the experiment, participants completed four main tasks: first, a practice phase demonstrating what the experiment will entail, then an encoding phase where participants rated how well symbols represented words, next there was a brief tone classification filler task, and finally there was a combined recognition and cued-recall test for the studied symbols. Matching Experiment 1, this study used *jsPsych* experiment software (version 7.3.4; 52) hosted on the MindProbe server (https://mindprobe.eu/) with JATOS management software (53). A separate group then completed the visual and conceptual SpAM trials. For more details on the experimental procedure, see SI Appendix, Supplemental Methods 2.

Symbol Stimuli. This experiment used a set of 160 novel symbols (see Fig. 6) that were engineered to be memorable or forgettable by highlighting or downplaying certain visual traits. To create these novel symbols, we gathered a list of the top 80 abstract words from the English Lexicon Project (based on concreteness ratings; 26) that also matched the following four criteria: (1) must not already have a symbol referent or is close to a word that does, (2) must not be uncommon such that participants would be unlikely to know the word, (3) must not be too vague or broad to afford creation of a symbol (e.g., the word ‘anything’), and (4) must be a noun or a verb (so as to match the majority of items in Experiment 1). The final wordlist contained items that were 3 to 14 letters long (M = 6.68, SD = 2.20), low concreteness (M = 1.98, SD = 0.42), and above-average frequency (SUBTLWF; M = 70.24, SD = 161.21).

Next, we employed the DALL-E 3 (60) image generator to form novel symbols using the wordlist (see Fig. 2A). We used a Python script to query the model for images via API. Each image generation prompt began with: “Create a two-dimensional black symbol on a white background representing the concept of '{keyword}'.” Then, this standard prompt was followed by one of two sentences, depending on the version of the symbol being created. For memorable symbols, the prompt ended with: “Make sure that the symbol is thin, pointy, and has poor vertical symmetry.”

For forgettable symbols, the prompt stated the opposite: “Make sure that the symbol is thick, rounded, and has good vertical symmetry.” Parameters for the model were to create images 1024 × 1024 pixels in size, using “HD” quality and “vivid” style. Images were then manually reviewed, and any containing color or foreign objects (e.g., a hand, a pencil, etc.) were replaced.

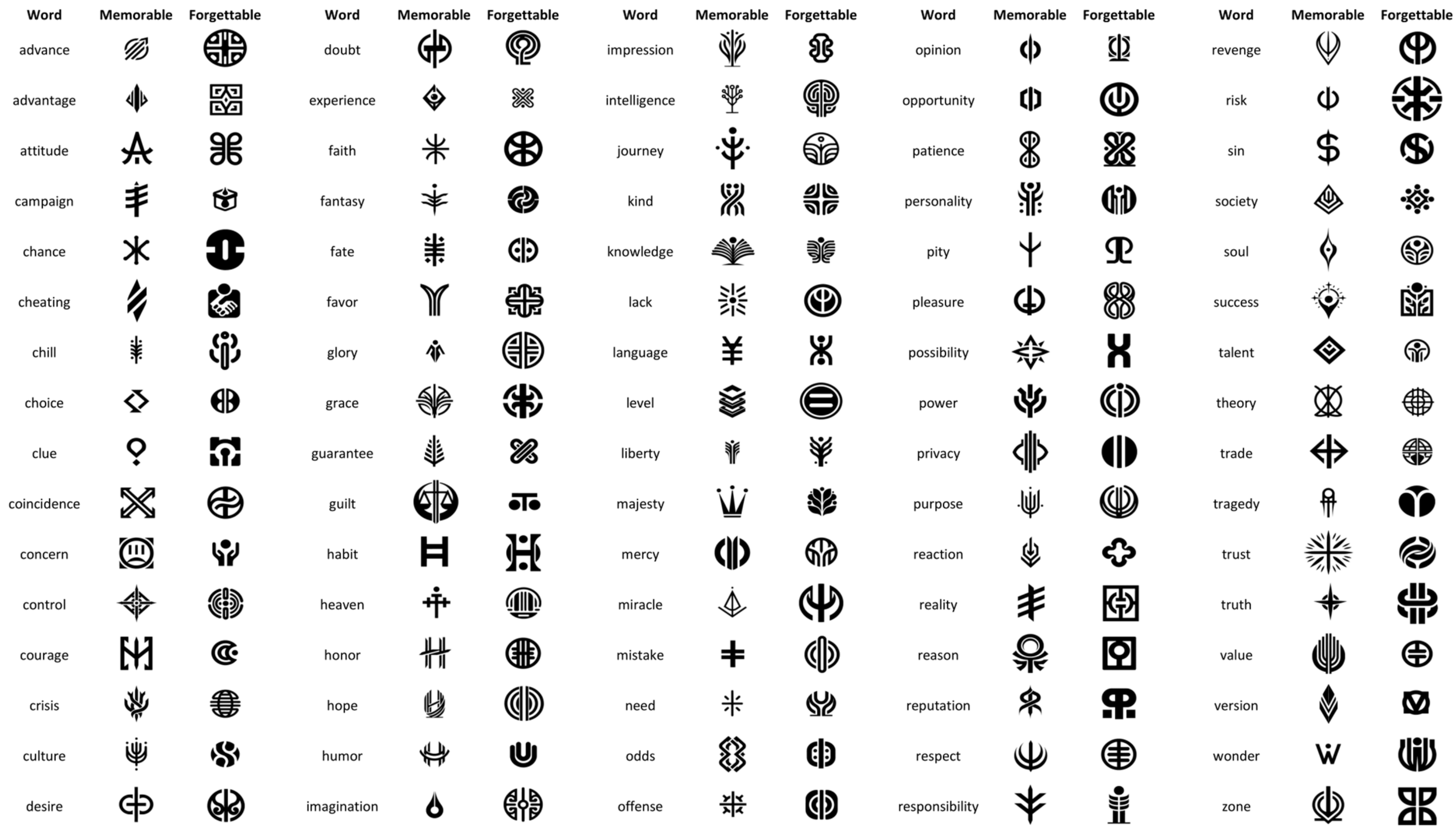

Fig. 6. Novel symbol stimuli generated for use in Experiment 2. Depicted are each of the 160 novel symbols that were created using the DALL-E 3 AI image generator. Symbols are placed next to the abstract word that was used in their generative prompt. Memorable and forgettable symbol variants of each concept are presented side-by-side for comparison.

Statistical approach

Computer Vision Validation. Before the experiment was conducted, we first ensured that our AI manipulation of the three key visual features was successful using the same computer vision approaches described in Experiment 1. Memorable symbols (M = .85, SD = .05, range: .68 to .94) were indeed thinner than forgettable symbols (M = .89, SD = .04, range: .73 to .97), $t(79) = -4.93$, $p < .001$, $d = -0.55$, 95% CI = [-0.84, -0.32], $BF_{10} > 1{,}000$. We also confirmed that memorable symbols (M = 55.4, SD = 4.7, range: 42 to 65) were less curvy—as indicated by higher scores on the pCurvComp metric—than forgettable symbols (M = 52.4, SD = 5.7, range: 41 to 65), $t(79) = 3.78$, $p < .001$, $d = 0.42$, 95% CI = [0.19, 0.69], $BF_{10} = 72$. Finally, memorable symbols (M = .94, SD = .12, range: .44 to 1) had less vertical symmetry than forgettable symbols (M = .97, SD = .07, range: .68 to 1), $t(79) = -1.76$, $p = .041$, $d = -0.20$, 95% CI = [-0.37, 0.01], $BF_{10} = 0.54$ (for full feature distributions, see Fig. S11).

Memory Scores and Analyses of Memorability. Much like in Experiment 1, memory sensitivity (*d*-prime) scores were used to assess recognition memory performance for each symbol. The same method of assessing memorability and its reliability that was used in Experiment 1 was employed here as well. To calculate cued-recall performance for studied items, we assessed whether a participant's typed response either matched the target word associated with the symbol, or if the word that was recalled was present in a dictionary of synonyms for the target word (provided by the *syn* package for *R*; 61). Additionally, we counted a response as accurate if the participant entered one of the following: a plural form of the target word, a past-tense version of the word, different spelling of the target word (e.g., 'humour' instead of 'humor'), or a common misspelling of the target word (e.g., 'honar' instead of 'honor').

Analyses of Memory Performance and Representativeness Ratings. Average performance for memorable and forgettable sets of symbols were compared in participants for recognition and cued-recall memory, as well as representativeness ratings, each using a paired-samples *t*-test (one-tailed). Effect sizes for these *t*-tests (Cohen's *d*) and their 95% confidence intervals were determined with 10,000 bootstraps via the percentile method using the *rstatix* package (v. 0.7.2; 62) for *R*. Bayes factors were calculated using the *BayesFactor* package (v. 0.9.12-4.7; 63) for *R*, enlisting a default Jeffreys-Zellner-Siow (JZS) prior with a Cauchy distribution (center = 0, $r = .707$). Interpretations of Bayes factors follow the conventions of Lee and Wagenmakers (64). Bayes factors in favor of the alternative (BF_{10}) or null (BF_{01}) models are presented in accordance with each preceding report of NHST analyses (i.e., based on a $p < .05$ criterion).

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Author Contributions

BRTR conceptualized the study, programmed the experiments, collected and analyzed the data, and prepared the first draft. BRTR also constructed the visualizations and handled project administration. WAB provided funding and supervision, aided in idea generation and analysis approach, and edited subsequent drafts. Both authors reviewed the manuscript prior to submission.

Competing Interests

We have no competing interests to declare.

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