Wheel of fortune: A cross-cultural examination of how expertise shapes the mental representations of familiar and unfamiliar numerals

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Abstract

Numerals are part of our everyday lives and are regularly viewed in less-than ideal conditions. Mistaking one numeral for another is almost an inevitability, and the cost of these confusions could be insignificant or hugely expensive! Numeral confusions can be explained by distances between our mental representations — how we internally represent the external world — resulting from their perceived similarities; yet, how expertise interacts with the mental space of numerals is largely unexplored. We used an identification paradigm to investigate the mental representations of familiar and unfamiliar numerals (4 sets: Arabic, Chinese, Thai, and non-symbolic dots) in a first-language English and a first-language Chinese speaking cohort. Using Luce’s choice model, we removed the undesired effect of response bias and conducted multidimensional scaling analyses. Results showed that expertise with numerals alters distances in the mental space, that unfamiliar numerals are represented identically across cultures, that non-symbolic numerals (dots) may be represented both perceptually and numerically in the mental space, and that Arabic, Thai and Chinese numerals are represented by their perceptual similarities. The findings and methods of this study provide a principled foundation for future investigations into how expertise shapes people’s mental representations.

Keywords: Cross cultural, Chinese numerals, Arabic numerals, Numerical cognition, Multidimensional scaling, Response bias

Declaration

Funding

This work was supported by an ARC Discovery Project Grant DP160102360 to A.E and D.L, the John and Daphne Keats endowment research fund G1700468 to Z.H, P.G, C-T.Y, D.L and A.E, and a Ministry of Science and Technology of Taiwan grant MOST 107-2410-H-006-055-MY2 to C-T.Y.

Conflicts of interest

The authors declare no conflicts of interest in the publication of this work.

Code availability

Data and code are available through the Open Science Framework, osf.io/8sgy3.

Author contributions

All authors contributed to the study conception, ideas for data analysis, manuscript writing and editing. M.B. and P.G. collected data in Australia, and Y-T.H. and C-T.Y. collected data in Taiwan. P.G. and M.B. led the project. P.G. programmed the experiment and analysis, and was the primary author.

Ethics approval

Ethics approval was provided for the Australian cohort by the School of Psychology, the University of Newcastle, Australia (H-2013-0250), and for the Taiwan cohort by the Department of Psychology, National Cheng Kung University, Taiwan (No.2, 2018).

Consent to participate

Participants signed their informed consent before starting the first study session.

Consent for publication

All authors consent to the publication of this manuscript.

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Numerous cultures have independently created numeral systems to accurately communicate quantities, giving rise to advancements in trade, technology, mathematics, and warfare. In today's Western cultures, Arabic numerals, 0 – 9, are commonly used in trade and mathematics, whereas dots are seen on dice and Chinese numerals, 一 – 九 are used on Mahjong tiles. By contrast, Arabic and Chinese numerals are both used for trade and mathematics in countries like Taiwan. Viewing numerals in everyday settings and in less-than ideal conditions makes confusing one numeral for another almost an inevitability. But how and why do we make these confusions? Are numerals confused due to similarities in their innate visual properties — the similar roundness of 3 and 8? Or, does a lifetime's experience affect our perceptual confusions, leading us to confuse numerals by their numerical proximity? As numerals are a fundamental part of modern life, the cost of these errors range from small — confusing \$5 and \$6 — through to life-changing — confusing 3 and 8 on your winning lottery ticket! The present study applied a series of advanced computational methods to examine whether familiar and unfamiliar numerals are confused in similar fashions for first-language English (Australian) and first-language Chinese (Taiwanese) speaking participants.

As a representation of quantity, symbolic numerals have been theorized to inhabit the same mental space — the theoretical cognitive space in which we represent differences in the external world (Eidels & Cassey, 2016) — as the approximate number system (ANS; Dehaene, 2011; Gallistel & Gelman, 1992). The ANS is the predominant account of how quantities greater than four are represented by humans (Dehaene, 2011) and other species (Woodruff & Premack, 1981; Pepperberg & Gordon, 2005; Agrillo, Dadda, Serena, & Bisazza, 2008) and is an inherent system that detects differences in quantity through changes in relative magnitude (i.e., proportional changes between quantities; Gallistel & Gelman, 1992). A related innate system, the object tracking system (Feigenson, Dehaene, & Spelke, 2004; Pylyshyn & Storm, 1988), is purportedly responsible for our ability to rapidly quantify or 'subitize' quantities between 1 – 4

(Kaufman, Lord, Reese, & Volkmann, 1949; Chesney & Haladjian, 2011). These innate perceptual systems have shaped the development of non-symbolic numerals.

Non-symbolic numerals, like tallies and dots, directly represent quantities and easily communicate small values that are within the subitizing range 1 – 4, or by conforming to canonical patterns (Dehaene, 2011). In theory, the mental representations of these non-symbolic numerals are tied to the quantities they physically represent, and should have similar mental representations across cultures. By contrast, larger non-symbolic numerals that engage the ANS are prone to error and thus benefit from a symbolic numeral system (Gallistel & Gelman, 1992). For example, representing one’s flock of sheep using one line per sheep would require a tedious and error-prone counting process, whereas the symbolic representation ‘150’ provides a precise and immediate impression of quantity. Symbolic systems, like Arabic and Chinese numerals, map quantities to unique digits with a sequential ordering and numeric-cardinality, but require expertise to understand (Dehaene, 2011). Without this expertise, symbolic numerals are merely a perceptually distinct item-set that may be confused by their perceptual features. In fact, even with expertise this may still be the case.

According to Shepard, Kilpatrick, and Cunningham (1975), Arabic numerals are confused due to their low-level perceptual similarities. Using numeral confusion scores — the proportion of errors between numeral pairs — Shepard et al. used multidimensional scaling (MDS) to visualize four participants’ internal representations of numbers. Shepard et al. found Arabic numerals were confused along perceptual dimensions of openness/closure and roundness/straightness. These findings have been replicated when asking participants to spatially arrange Arabic numerals by their similarities (Godwin, Hout, & Menneer, 2014). Both studies showed no effect of numerical proximity, and neither study provides insight into how expertise has shaped these mental representations.

Using a similar spatial arrangement task to Godwin et al. (2014), Yeh, Li, Takeuchi, Sun, and Liu (2003) asked expert (Taiwanese and Japanese) and non-expert (English and illiterate Taiwanese) students to arrange Chinese characters by similarity.

Expert students arranged items by configurable structures, treating them as whole objects and focusing on holistic perceptual similarities. Non-expert students arranged items by feature components — line strokes and orientations. Once again, the numeric values had no effect on expert similarity judgements; however, expertise unquestionably altered how characters were perceived. Indeed, similar changes to perceptual processing has been observed in faces (Taubert, Apthorp, Aagten-Murphy, & Alais, 2011), fingerprints (Busey & Vanderkolk, 2005), cars (Gauthier, Curran, Curby, & Collins, 2003), and experimentally controlled objects (Chua & Gauthier, 2019). Yeh et al.’s findings suggest that expert participants identify and represent characters by different perceptual characteristics. Examining how expertise interacts with the perceptual confusion of familiar and unfamiliar numerals has yet to be explored across cultures, and such an investigation would be hugely aided by the latest developments in scaling methods.

Modern multidimensional scaling, MDS, methods were pioneered by Shepard (1962a, 1962b) and Kruskal (1964b, 1964a, see Groenene & Borg, 2014 for a review) and provide the benefit of visualizing item relationships by plotting proximity data, such as confusion scores, as distances in two-or-three dimensions of space. The relative distance between these points is assumed to reflect the psychological distance between internal stimulus representations. When analyzing confusion scores, three considerations must be made: i) the similarity of the stimuli, ii) the visibility of the stimuli, and iii) response bias (Mueller & Weidemann, 2012). Typically, stimulus similarity and visibility are rigorously and experimentally controlled; however, response bias — the pattern of over or under responding with a subset of options — has largely gone unaccounted for. Biased responding results in higher accuracy *for* a given item, but also higher rates of confusion *with* that item (Gilmore, Hersh, Caramazza, & Griffin, 1979). Subsequently, response bias can drastically change confusion patterns and MDS interpretations. Fortunately, techniques exist to deal with this problem.

Luce’s (1963) similarity choice model predicts how response bias, inter-item similarity, and the number of response options impacts the choices we make. This

model factors out the effect of individual response bias, allowing for the examination of theoretically meaningful ‘bias-free’ confusion scores — a property that has affected all previous investigations into numeral confusions. The combination of Luce’s (1963) choice model and MDS have proven invaluable in the past. Townsend (1971) found that bias free MDS spaces provided a better fit to English letter confusions. Townsend concluded that English letters were confused by both perceptual and semantic similarities. This conclusion was only possible after accounting for response bias.

In summary, although numerals are critical to our daily lives, we lack insight into how our experiences and understanding shape our mental representation of numerals. Yeh et al. (2003)’s shows that comparing expert and non-expert participants may provide an invaluable means of addressing this gap. Furthermore, advances in MDS methods suggests that past investigations of numeral representations may have been flawed by not accounting for the effects of response-bias. These three elements provide the impetus for a new psychological investigation.

In the current study, we assessed how expertise (familiarity and everyday usage of a numeral set) affected the mental representations of numerals between expert and non-expert participants, using four numeral sets: non-symbolic dots, Arabic numerals, Chinese numerals and Thai numerals. Two cohorts — one that is first-language Chinese (FL-Chinese) with expertise using Arabic, Chinese and Dot numerals, and one that is FL-English with expertise using Arabic and Dot numerals — provided confusion data for each numeral set. Using Luce’s (1963) choice model, we examined bias-free MDS representations of these four numeral sets, comparing their results between cohorts to describe the effect of expertise on the mental space. We expected dot numerals to show clear effects of numerical proximity and the remaining symbolic numerals to show effects of perceptual similarity. We expected Arabic and Thai numerals to display similar MDS representations — being equally familiar and unfamiliar to our participants — and that Chinese numerals would be represented differently between cohorts due to differences in expertise.

Method

Participants

Participant details are summarized in Table 1. FL-Chinese and FL-English participants were undergraduate student volunteers from the National Cheng Kung University, Taiwan, and the University of Newcastle, Australia, respectively. FL-English participants reported as knowing only English, and FL-Chinese reported as knowing Chinese and English. Five FL-Chinese participants provided their undergraduate ‘Test of English as a Foreign Language’ (TOEFL; Laborda, 2009) scores, displaying an average score of 77.8 (SD = 5.26) out of 120, indicating moderate-to-good English proficiency. For context, the average TOFEL score for English speakers is 91 (Stricker, 2004). All participants reported as having normal or corrected to normal vision, and each participant completed four — Chinese, English, Dots, Thai — 90-minute experimental sessions. Ethics approval was provided for the FL-English cohort by the School of Psychology, the University of Newcastle, Australia (H-2013-0250), and for the FL-Chinese cohort by the Department of Psychology, National Cheng Kung University, Taiwan (No. 2, 2018).

Table 1
Participant details for the first-language (FL) Chinese and English speaking cohorts.

Cohort	<i>N</i>	Mean Age (SD)	Known Languages			Reimbursement	
			English	Chinese	Thai	Session	Total
FL-Chinese	11 (4 female)	21.33 (2.64)	Yes	Yes	No	\$225 NTD	\$900 NTD
FL-English	11 (4 female)	24.45 (1.53)	Yes	No	No	\$75 AUD	\$300 AUD

Stimuli and apparatus

Figure 1 displays the Arabic, Chinese, Thai and dot numerals used for each experimental session. Each numeral was generated in Microsoft Powerpoint 2017 and saved as an image, and was experimentally presented using Python 2.7.14 and the Pygame 1.9.2b package. Arabic numerals were made using calibri-body 80pt font, Chinese numerals using DFKai-SB 80pt font, and Thai numerals with unicode characters and Calibri 80pt font. Canonical dot numerals were made within a 3 x 3 grid

based on playing card patterns. Physical quantities (e.g., dots), are prone to emergent features (Pomerantz & Portillo, 2011; Hawkins, Houpt, Eidels, & Townsend, 2016), such as co-linearity and emergent shapes, and visual covariates of number, such as total area and density. Under ideal conditions, we would present various dot stimuli designed to control for these specific factors (à la, Halberda, Sires, & Feigenson, 2006; Garrett, Howard, Houpt, Landy, & Eidels, 2019). However, as this was not the goal of the current study, we restricted our investigation to a single canonical set of dots, the results of which we compare to the symbolic numeral sets.

ENGLISH	1	2	3	4	5	6	7	8	9
CHINESE	一	二	三	四	五	六	七	八	九
THAI	๑	๒	๓	๔	๕	๖	๗	๘	๙
DOTS	•	• •	• • •	• • • •	• • •	• • • •	• • • • • •	• • • • • • • •	• • • • • • • • • •

Figure 1. Arabic, Chinese, Thai and dot numerals for the range of one to nine (left to right).

Responses were recorded using a standard dell 9RRC7 optical mouse on a Windows 7 operating system with mouse sensitivity set to a default value of 10. Stimuli were presented to the FL-English cohort on a 23inch Dell s2240L (60Hz) monitor with a 16:9 aspect ratio at a display resolution set to 1920 x 1080, and to the FL-Chinese cohort on an 18inch CRT (60Hz) monitor with a 4:3 aspect ratio at a display resolution set to 1280 x 768.

Stimuli were viewed from a distance of 60cm and presented within a noisy field ($\mu = 0$, $\sigma = 0.125$; à la Eidels & Gold, 2014) atop a grey background (RGB values = 240; note these values were identical for red, green and blue and are reported as one-value). Each noisy stimulus subtended a visual angle of 5.53 degrees (5.8cm^2), and was followed by a backwards-mask that subtended a visual angle of 11.61 degrees (12.2cm^2). On a

trial, participants moved a centrally located mouse-pointer to a matching numeral presented within a response-wheel that was divided into nine sectors (Figure 2). Responses were collected when the mouse passed the wheel’s internal-diameter, which subtended 20.04 degrees visual angle (diameter 21.2cm) and which had an outer-diameter of 25.91 degrees visual angle (diameter 27.6cm). At the start of each session, numeral stimuli from one language-set were randomly allocated to the response-wheel sectors and remained fixed in these locations for the duration of the session.

Design and procedure

Participants completed four 90 minute sessions, one for each numeral set, within a two-week period. Session order was randomized using a Latin-square design. In the first session, participants provided signed consent, age, gender, vision status, and reported their proficiency in English, Chinese, and Thai. At the start of each session, participants were provided with task instructions to briefly view a noisy symbol, and using the mouse, identify the best matching symbol on the response-wheel.

Figure 2 illustrates the features of an experimental trial (left) and a response-wheel for each session (right). Each trial began with a blank screen presented for 250ms, followed by a central fixation-cross for 500ms and blank screen for 250ms. The stimulus was then presented for 500ms, followed by a mask for 200ms. The response window began with the presentation of the response wheel and lasted for 8000ms or until a response was made.

At the start of each session, participants completed a practice-calibration block. Using a single staircase procedure, we manipulated the contrast of the signal across trials according to the participant’s responses. A 2-up 1-down rule was applied, such that any two contiguous correct responses produced a step-down and any incorrect response a step-up. Signal contrast began at RGB values 153. Piloting showed this procedure rapidly allowed participants to plateau to their perceptual threshold.

Stimuli were presented at five contrast levels (à la., Eidels & Gold, 2014)

Figure 2. Illustration of a trial with an Arabic numeral stimulus and an Arabic numeral response wheel (left), and example response wheels for the three alternate sessions (right).

determined by their perceptual threshold. This ‘critical contrast level’ was calculated as the mean RGB value over the final 30 calibration trials. The highest (easiest) RGB values were three-steps above the critical contrast; the most difficult one-step below. For example, a critical contrast value of 151 would produce an RGB stimulus range between 150 (hardest) and 154 (easiest), inclusive.

During each session, participants completed a calibration block of 135 trials and 13 experimental blocks of 90 trials. During experimental blocks, each numeral was presented 10 times (twice at each contrast-level) in a randomized order. Mean accuracy feedback was illustrated as a line-plot at the end of each experimental block to maintain engagement. In total, participants completed 130 experimental trial per numeral and 1,170 experimental trials per-session.

Data analysis

Data and code for this study are freely available through the Open Science Framework (Garrett et al., 2021). Trials with no response were removed from the

analysis. Calibration and experimental trials were assessed for accuracy to ensure an appropriately difficult stimulus-signal contrast was achieved. Repeated-measures analysis of variance (ANOVA) and paired-sample *t*-tests were used to statistically compare differences between numeric sets. Where accuracy was matched by RGB signal-contrast level either between participants or between cohorts, between-subject ANOVAs and independent-samples *t*-tests were used. Multiple comparisons were corrected for family-wise error using the Bonferroni method.

For each participant, a 9×9 confusion matrix was generated for each numeral set and Luce's (1963) choice model was applied to remove the effect of response-bias (see Appendix A for a full description of Luce's choice model). Non-metric MDS was applied to these bias-free confusion matrices, and scree analyses were used to determine the optimal number of MDS dimensions for each participant. We produced group MDS plots for each numeral set using the individual differences scaling (Indscal) technique (Carroll & Chang, 1970), that provides a group-fit which differentially weights the fits for each numeral set between cohorts using a K-mean clustering method that produced heat-maps for each numeral set, as well as Procrustes analyses. As the reader will see in the subsequent results, the K-mean heat-maps provide an easy-to-interpret metric of proximity between items in the MDS solution, and can be easily used to decide why items were confused (e.g., by numerical proximity or perceptual similarity). By contrast, the Procrustes analysis provides a goodness-of-fit measure that fits the MDS representation of one cohort to the other.

Results

Accuracy and calibration

Our staircase procedure worked as intended, presenting experimental stimuli near each participant's perceptual threshold and producing the necessary error rates for subsequent MDS analyses. At the end of this calibration phase, overall accuracy was comparable between the FL-Chinese cohort ($\mu = .65$, $\sigma = .12$) and the FL-English cohort ($\mu = .58$, $\sigma = .14$). A full breakdown of the staircase calibration results for both

cohorts is presented in Appendix B.

Figure 3 displays the average accuracy of experimental responses collapsed across participant’s five signal contrast levels in the FL-Chinese (left) and FL-English speaking cohorts (right). As contrast levels are affected by hardware and lighting conditions unique to each cohort, we focused on the distributional ordering of the numeral sets, and disregard the comparison of absolute contrast-levels. In both cohorts, dot numerals were generally the most accurate across contrast-levels, followed by Chinese and English, and Thai numerals were least accurate. Both cohorts’ mean accuracy improved at a similar rate as contrast levels increased, indicating that our contrast-manipulation worked within each cohort. More difficult-to-see numerals (lower signal-to-noise ratio) were more prone to confusions and produced a comparable effect between cohorts. These results are a necessary element for additional MDS analyses, but are not the primary focus of the current paper. As such, a full breakdown of these results are presented in Appendix C, with detailed statistical analyses provided in supplementary materials S1.

Figure 3. Mean accuracy matched by contrast-level for the FL-Chinese speaking cohort (left) and FL-English speaking cohort (right) across numeral sets. Data are collapsed across participants’ five contrast levels, however, more than five levels are displayed as data was pooled across multiple subjects, each with different sensitivities. Only RGB values with multiple data points (i.e., responded to by two-or-more participants) are displayed. Error bars represent one standard-error of the mean.

Response bias

A Pearson rank-order correlation revealed a positive relationship between the frequency of stimulus responses and stimulus accuracy in both the FL-Chinese ($r = .56$, $p < .001$) and FL-English cohorts ($r = .58$, $p < .001$). This suggests numeral identification accuracy was artificially increased (over-responding) or decreased (under-responding) due to response bias, which may have an effect on MDS representations (see appendix C for a full breakdown of response bias by numeral and cohort). Figure 4 displays the biased and bias-free MDS solutions of one participant from the FL-Chinese cohort with MDS axes held constant between plots. This analysis clearly illustrates how removing response-bias reshapes the MDS space by increasing or decreasing the relative proximity of items. We proceeded to create bias-free MDS representations for each participant before performing our group Indscal analysis.

Figure 4. Biased and bias free (Luce's choice model corrected) MDS solutions for FL-Chinese participant S3. Plots display the effect of removing response-bias on the MDS solution in a single person.

Indscal MDS

Scree analyses identified two-dimensions as the best MDS representation for a majority of participants in both cohorts (see Table 2). The remaining participants were best represented by a three-dimensional MDS solution. Scree plots for each participant in each cohort are presented in the supplementary materials, Figure S2.1 to Figure S2.4.

Bias-free MDS plots for individual participants, including three-dimensional representation's not discussed in the main text, are presented in the supplementary materials, Figure S2.5 to Figure S2.12.

Table 2

Number of two-dimensional MDS representations in each numeral set within each cohort. There were a total of 11 participants in each cohort. Remaining MDS representations constituted three dimensions and are presented as supplementary materials.

	Arabic	Chinese	Dots	Thai
First Language Chinese	11	9	8	10
First Language English	8	8	7	11

To assess and compare MDS results, we conducted individual differences scaling solutions on participant's two-dimensional MDS representations. Like all MDS results, Indscal representations require subjective interpretation of which items group together and which items are relatively distant from one-another. To provide a reliable and statistically informed method of diagnosing MDS groupings, we chose to perform a series of K-mean cluster analyses.

For each MDS Indscal solution, a K-mean cluster analysis was performed using 2–6 centroids (i.e., the locations on which MDS representations would cluster). The proportion at which two-items cluster on the same centroid was calculated for each iteration of K. For example, when $K = 2$, the MDS space was divided into two groupings; when $K = 6$, the MDS space was divided into six groupings; if two-numerals (for example, the Arabic digits '3' and '8') were classified within the same cluster on every iteration of $K = 2$ –6, their relative cluster proportion was 1. Conversely, if two numerals never clustered in the same group, then their cluster proportion was 0. Using these cluster proportions, a heatmap was constructed for each representation. This process illustrates which numerals most-commonly grouped together in the Indscal solution, and provides a diagnostic visualization for when items cluster by numerical proximity (e.g., a cluster pattern along the left-to-right diagonal).

Figure 5 displays the group MDS Indscal solutions for the FL-Chinese (panel A) and FL-English cohort (panel B), and their associated K-mean cluster analysis

heatmaps. In both cohorts, dot numerals indicate an effect of numerical proximity in the K-mean heatmaps (left-to-right diagonal clusters). Although we cannot conclude this pattern is entirely due to numerical proximity — quantities are confounded by the covariance of perceptual energy and quantity, a matter we return to during the discussion — it is clear that this pattern of results is missing from the other numeral sets, suggesting Chinese, Arabic and Thai numerals were arranged by properties other than numerical distance (e.g., perceptual similarities). Visual inspection of K-mean heatmaps and MDS solutions reveals similar Indscal representations between cohorts for Arabic and Thai numerals. However, these representations diverge greatly between cohorts for Chinese numerals. To assess the degree of difference between the MDS representations of each cohort, we conducted Procrustes analyses.

Figure 5C displays the Procrustes analysis, fitting the FL-English to the FL-Chinese MDS Indscal solution, with their goodness-of-fit displayed by the sum of squares error (SS_{error}). For interpretation, smaller SS_{error} values indicate a better fit. Results show that dot numerals ($SS_{error} = .05$) and Thai numerals ($SS_{error} = .04$) were represented in a nearly identical fashion between cohorts. Arabic numerals showed a small degree of difference between cohorts ($SS_{error} = .19$), but overall, displayed very similar MDS solutions. By way of contrast, Chinese numerals were represented by an entirely different MDS solution ($SS_{error} = .73$).

Discussion

When asked to identify Arabic, Chinese, Thai and dot numerals under low-contrast settings, both first-language Chinese and first-language English speaking cohorts completed the tasks with error rates appropriate for MDS analyses. After controlling for contrast levels, accuracy in both cohorts was higher for familiar numeral sets, and lowest for unfamiliar (e.g., Thai) numerals. Indscal analyses, combined with K-mean clustering and Procrustes analyses, showed that Arabic, Thai and dot numerals displayed similar mental representational solutions between cohorts. By contrast, mental representations differed greatly between cohorts for Chinese numerals. Dot

Figure 5. MDS Indscal solutions (left) and the proportions at which items clustered (right) for the first-language Chinese (panel A), and first language English (panel B) cohorts. Procrustes analyses (panel C) shows the fit of English-to-Chinese cohort's MDS representations, with lower sum of squares error (SS_{error}) indicating a better fit. Dots are illustrated as Arabic numerals in the MDS plots for clarity of exposition.

numerals appeared to be clustered by their numerical proximity (although, this interpretation may be confounded), whereas the organisation of Arabic, Thai and Chinese numerals in the mental space seems to be governed by other principles (e.g., perceptual similarities), and not numerical distances. These results suggest that familiarity and expertise plays a critical role in how people identify numerals (e.g., Chinese numerals), that non-experts with different cultural backgrounds represent unfamiliar numerals in the same manner (e.g., Thai numerals), that numerical proximity is integral to the representations of non-symbolic numerals (e.g., Dot numerals), and that visual similarity underpins the mental representations of symbolic numerals (e.g., Arabic numerals).

As hypothesised, dot numerals appeared to be represented along dimensions of numerical proximity; however, this interpretation is confounded by the perceptual similarities observed between adjacent items. For example, dot numerals clustered for items 1–3, 4–5, 6–7 and 8–9. These clusters are not only adjacent numerically, but also differ by their absence or presence of a single central dot (see stimuli in Figure 1). Due to this confound, and lacking alternative dot-patterns with which to compare, it is impossible to decide whether these non-symbolic representations were confused by their numeric proximity, their perceptual similarity, or both. What is clear, however, is that both cohorts represented dot numerals in a nearly identical fashion, as evident by the Procrustes analysis.

Thai numerals were unfamiliar to both FL-English and FL-Chinese cohorts, and displayed nearly identical MDS representations. Being unfamiliar, these items were represented by dimensions of perceptual similarity. A subjective interpretation of these findings posits that Thai numerals were arranged by openness/closure and horizontal/vertical curvature. What our results tell is that with no expertise in visually identifying Thai numerals, both FL-English and FL-Chinese cohorts represented Thai numerals identically in the mental space.

In line with the findings of Shepard et al. (1975) and Godwin et al. (2014), Arabic numerals were represented along dimensions of perceptual similarity. Just as in previous

accounts, our results suggest Arabic digits were represented by visual similarities in openness/closure and roundness/straightness. These findings hold for both FL-English and FL-Chinese cohorts; however, we do note that these representations were not as comparable as for dot and Thai numerals. It may be that some degree of difference in expertise still exists between our cohorts. We suggest this is the most likely cause, as we would expect fundamental differences in perceptual strategies to have also been apparent in the Thai and dot MDS representations.

Finally, Chinese numerals, for which expertise differed between cohorts, were represented in entirely different fashions for FL-English and FL-Chinese cohorts. Among FL-English participants, Chinese numerals displayed a clear MDS cluster for items 6–9; yet among FL-Chinese participants, items 2–5 clustered together. Although these clusters are numerically adjacent, neither cohort displayed a consistent effect of numerical proximity for all items, 1–9. Instead, clusters patterns in the Chinese cohort may reflect perceptual similarities caused by the numeral’s logographic origins.

The first three Chinese numerals are logographic in nature, physically representing their numeric values, 一, 二, 三. Numerals 4–5 extend upon these numerals and maintain the horizontal strokes positioned at the top and bottom of the numerals, 四 and 五. These horizontal elements are absent from Chinese numerals 6–9. Instead, Chinese numerals 6–9 only clustered in the FL-English cohort, potentially due to their shared perceptual characteristic of openness (most notable in the bottom half of 六, 八, and 九. Although it is not entirely clear how seven, 七, fits within this framework, it is clear that both FL-English and FL-Chinese cohorts represented items by different perceptual similarities due to their differences in expertise.

Future investigations using our methodology may consider asking participants to describe their visual processing strategy after each block or at the conclusion of the experiment. This may help in classifying individuals with similar MDS representations for group-based inferences and, in the case of comparing expert and non-expert participants, identify what visual features are sought by each group.

Another clear line of future work would be to replicate this study in a FL-Thai

cohort. This may determine whether being unfamiliar with Chinese numerals results in a similar MDS representation to the English cohort, strengthening our hypothesis regarding similar MDS representations among non-experts. Furthermore, it would determine whether Thai numerals produce different MDS representations from our Chinese and English cohorts due to numeric similarities (as with dot numerals) or due to visual similarities. These conclusions would make a compelling contrast to the expert representations of logographic Chinese numerals.

Finally, a future study may assess MDS representations as participants learn a numeral set. This process may prove valuable when determining how people encode, retrieve, and represent numerals as they learn. For example, do mental representations shift in a monotonic fashion, and are they non-linear? How dynamic are these representations? How long does it take for these learned representations to stabilize? The methods we apply in this paper, rapid staircasing, bias-free response-matrices, Indscal MDS analyses, K-mean cluster patterns and Procrustes analyses, can be easily adapted to answer these questions and more.

Our findings suggest familiar and unfamiliar symbolic numerals are confused due to perceptual similarities, and non-symbolic numerals due to both perceptual similarities and numeric proximity. In a first, we assess numeral MDS representations using bias-free confusion matrices and cluster patterns, and show how expertise dictates how and why we perceptually confuse symbolic numerals, and that lacking this expertise, mental representations between English and Chinese speakers are essentially the same.

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Appendix A

Luce's choice model

The following appendix provides a full description of Luce's (1963) choice model, as applied to the confusion data collected in both Chinese and English speaking cohorts. A summary of this model was provided in the main text.

Luce's (1963) choice model describes identification responses as stochastic outcomes driven by the similarity of a stimulus to the others in a choice set, as well as a response-bias parameter — one for each stimulus. By estimating the parameters of the model, researchers can examine the theoretically meaningful similarity scores free from the effect of response-bias that can contaminate the observed data. Formally, the probability of making response j when presented with stimulus i can be expressed as:

$$C_{ij} = \frac{\eta_{ij}\beta_j}{\sum_{k=1}^N \eta_{ik}\beta_k} \quad (1)$$

where C_{ij} is the theoretical similarity matrix for $i = 1, 2 \dots N$, $j = 1, 2 \dots N$. The similarity parameter η is symmetrical along the matrix diagonal i.e., $\eta_{ij} = \eta_{ji}$, and $\eta_{ii} = 1$ for all i . In the current study, we will employ nine unique numerals, resulting in $[N(N + 1)/2] - 1 = 44$ free parameters to be estimated from the data.

We estimated the bias and similarity parameters of Luce's (1963) choice model using the combination of a custom Differential-Evolution Markov chain Monte-Carlo (DE-MCMC) process and maximum likelihood estimation (Myung, 2003). We initialised each of the 50 chains by estimating parameter values from Townsend's (1971) approximation of Luce's model:

$$\eta_{ij} = \sqrt{\frac{P(R_i|S_j)P(R_j|S_i)}{P(R_i|S_i)P(R_j|S_j)}} \quad (2)$$

$$\beta_j = \frac{1}{N} \sum_{k=1}^N \sqrt{\frac{P(R_j|S_j)P(R_k|S_j)}{P(R_j|S_k)P(R_k|S_k)}} \quad (3)$$

where R is the response probability given stimulus S ; then adding uniformly sampled noise. On each iteration, each chain proposed updated parameter estimates by

weighting the previous estimates with the estimates of two randomly selected chains using the weighting formula outlined by Turner, Sederberg, Brown, and Steyvers (2013). The log-likelihood of these new parameters and the previous ones were computed by generating an expected confusion matrix (using the estimated parameters and Luce’s choice model) and comparing to the observed data, with the parameters that maximised the log-likelihood being kept. After 500 iterations the parameters from the chain with the highest log-likelihood were used for further analysis.

Appendix B

Staircase calibration

The following appendix provides a full analysis of our staircase procedure that manipulated stimulus accuracy for all participants in all numeric types. In summary, this procedure was highly effective and successfully produced the necessary confusions scores for MDS analyses.

Figure B1 (top) depicts the calibration block for FL-Chinese participant S1, responding to Arabic numerals. This staircase procedure was typical of most participants (middle panel). The mean contrast level of the final 30 assessment trials (highlighted yellow) determined the critical contrast value — the value from which stimulus-signal levels were determined in the experimental session. Violin plots (bottom) depict the mean and standard-error of contrast values for assessment trials, for each participant and language-type. Critical contrast levels were stable across language-type and participants, except for FL-Chinese participant S2 in the non-symbolic dots condition. This participant’s staircase procedure resulted in the highest (easiest) critical contrast level, indicating their performance was particularly poor during the calibration block. The bottom panel displays similar mean assessment contrast levels in the FL-English participants.

Mean contrast levels

Signal contrast and identification accuracy were successfully manipulated at the start of each session by our modified staircase procedure. In the FL-Chinese cohort, signal contrast levels were approximately equal for Chinese (RGB $\mu = 137.4$, $\sigma = 1.49$), Arabic (RGB $\mu = 137.6$, $\sigma = 1.15$) and non-symbolic dot numerals (RGB $\mu = 137.8$, $\sigma = 3.89$), and highest (easiest) for Thai numerals (RGB $\mu = 140.3$, $\sigma = 1.75$). By contrast, critical contrast levels for the FL-English cohort were lowest for Arabic numerals (RGB $\mu = 134.14$, $\sigma = 1.07$), then non-symbolic dots (RGB $\mu = 134.88$, $\sigma = 1.04$), then Chinese numerals (RGB $\mu = 134.91$, $\sigma = .86$) and finally, Thai numerals (RGB $\mu = 135.5$, $\sigma = .97$).

Figure B1. Staircase procedure for one FL-Chinese participant (top) and violin plots of all participant's assessment trials in the FL-Chinese (middle) and FL-English (bottom) cohorts. Assessment trials determined the critical contrast value for the main experiment. Black lines on each violin plot represent the critical contrast value (mean RGB value over the assessment window) for a given participant, and colored ticks on the y-axis are the mean critical contrast values for each numeral set.

Appendix C

Experimental accuracy

Mean accuracy was comparable between cohorts for each numeric-type, and error rates were sufficient for MDS analysis. On average, the Chinese speaking cohort was more accurate ($\mu = .65$, $\sigma = .12$) than the English-speaking cohort ($\mu = .58$, $\sigma = .14$), a trend that held within each numeric-type.

Across experimental trials, mean accuracy in the FL-Chinese cohort was highest for non-symbolic dots ($\mu = .72$, $\sigma = .14$), then Chinese numerals ($\mu = .66$, $\sigma = .12$), Arabic numerals ($\mu = .62$, $\sigma = .14$), and finally, Thai numerals ($\mu = .59$, $\sigma = .11$). By contrast, the FL-English speaking cohort was most accurate for non-symbolic dots ($\mu = .65$, $\sigma = .12$), Thai numerals ($\mu = .64$, $\sigma = .1$), Chinese numerals ($\mu = .61$, $\sigma = .15$), and finally Arabic numerals ($\mu = .55$, $\sigma = .15$).

A direct comparison of accuracy between cohorts is difficult due to the differences between testing facilities. Each testing facility employed different monitors (CRT vs LCD) and ambient lighting. This produced similar levels of accuracy between the two cohorts, at different signal contrast levels. for this reason, the main text focuses on accuracy matched by contrast-level. However, a detailed analysis is presented for each cohort below.

First Language Chinese cohort

During experimental trials, stimuli were presented at five signal-levels: one step below the critical contrast value (level 1: hardest) and three steps above (levels 3, 4 and 5: easiest). Across language-types, mean accuracy increased linearly with the visibility of the contrast levels (Figure C1.a). Accuracy was lowest at level 1 ($\mu = .48$, $\sigma = .17$) and highest at level 5 ($\mu = .79$, $\sigma = .11$). Across experimental trials, mean accuracy was highest for non-symbolic dots ($\mu = .72$, $\sigma = .14$), then Chinese numerals ($\mu = .66$, $\sigma = .12$), Arabic numerals ($\mu = .62$, $\sigma = .14$), and finally, Thai numerals ($\mu = .59$, $\sigma = .11$).

A repeated measures ANOVA displayed a main effect of contrast level on accuracy ($F(4, 40) = 227.262$, $p < 0.001$, $\eta^2 = 0.958$), but no main effect of language-type on

Figure C1. a) Mean accuracy across five signal contrast-levels, and four language-types. b) Mean accuracy across each experimental block. c) Mean accuracy for each participant by critical contrast level. d) Mean accuracy matched by contrast-level, across language-types. Error bars represent the standard-error of the mean.

accuracy ($F(3, 30) = 2.042, p = 0.13, \eta^2 = 0.17$). There was a significant interaction of language-type and contrast level on accuracy ($F(12, 120) = 1.872, p < 0.05, \eta^2 = 0.158$). Post-hoc paired t -tests displayed significant differences between all combinations of contrast level ($p < .001$), and no significant differences between comparisons of language-type (simple effects are reported in supplementary materials S1., Tables S1.2 and S1.3. These results indicate our chosen signal levels appropriately influenced response accuracy, and that familiarity had no effect on response-accuracy. We will return to this shortly.

Figure C1.b. depicts mean accuracy across experimental blocks and language-type. Mean accuracy was comparable between language-types, and increased marginally with block number, being lowest at block 1 ($\mu = .59, \sigma = .15$) and highest at block 7 ($\mu = .67, \sigma = .15$), before plateauing to block 13 ($\mu = .66, \sigma = .15$). A repeated-measures ANOVA displayed a significant main effect of block number on accuracy ($F(12, 120) = 7.207, p < 0.001, \eta^2 = 0.419$), and did not display a significant interaction of block number and language-type on accuracy ($F(36, 360) = 1.033, p = 0.42, \eta^2 = 0.094$). Post-hoc paired-sample t -tests displayed significant differences in

accuracy between blocks 1 and 9–11 ($p < 0.05$), and blocks 2 and 10 ($p < 0.05$; simple effects reported in the supplementary materials, Table S1.4). These results suggest a small practice effect improved accuracy from early to late blocks.

Figure C1.c. presents mean experimental accuracy across critical contrast levels, separated by participant and language-type. A linear regression found a significant positive relationship between critical contrast and mean accuracy ($r^2 = .525$), suggesting a dependency between contrast and accuracy. To disentangle the effect of language-type and contrast on accuracy, we assessed accuracy matched across RGB values from each participant’s five signal-contrast levels (see C1.d).

Figure C1.d. presents mean accuracy matched across participant’s five contrast-levels, separated by language-type. For example, if for Arabic numerals, participant S1 responded to RGB contrast values 130–134 and participant S2 responded to RGB contrast values 134–137, their accuracy at contrast value 134 would be averaged and depicted in Figure C1.d.

Figure C1.d. displays a positive relationship between contrast and matched accuracy. Matching accuracy for contrast levels when all language-types were presented (*i.e.*, excluding contrast values < 135 and > 140), accuracy was highest for non-symbolic dots ($\mu = .74$, $\sigma = .06$), then Chinese numerals ($\mu = .71$, $\sigma = .09$), then Arabic numerals ($\mu = .66$, $\sigma = .11$) and lowest for Thai numerals ($\mu = .61$, $\sigma = .09$).

We completed a two-way between-subjects ANOVA to assess the effect of language-type and contrast-level on matched accuracy (Figure C1.d). We found a main effect of language-type ($F(3, 141) = 7.458$, $p < .001$, $\eta^2 = 0.08$), and a main effect of contrast-level ($F(5, 141) = 24.252$, $p < .001$, $\eta^2 = 0.42$) on accuracy. There was no interaction effect between contrast level and language-type on accuracy ($F(15, 141) = 0.512$, $p = .93$, $\eta^2 = 0.03$). Post-hoc *t*-tests displayed significant differences between all contrast vales ($p < .05$), except comparisons made between high RGB values: 137 and 138, 138 and 139, 138 and 140 and 139 and 140 (pair-wise tests are reported in the supplementary materials, Table S1.5). This suggests a plateau in accuracy occurring at high RGB contrast values. Post-hoc *t*-tests displayed significant differences in matched

accuracy between Arabic and Thai numerals ($t(3) = 3.969, p < 0.001$) and non-symbolic dots and Thai numerals ($t(3) = 3.988, p < 0.001$); other comparisons did not reach statistical significance (summarised in the supplementary materials, Table S1.6). When accuracy was matched by contrast level, the familiar Arabic and Dot numeric-sets were more accurately reported than the Thai numeric-set. Familiar Chinese numerals tended to be more accurately reported than Thai numerals, however, this was not borne out at the statistical level.

First Language English cohort

During experimental trials, stimuli were presented at five signal-levels, one step below the critical contrast value (level 1: hardest), and three steps above (levels 3, 4 and 5: easiest). As shown in Figure C2.a., across numeric-types, mean accuracy increased linearly with the visibility of the contrast levels, being lowest at level 1 ($\mu = .32, \sigma = .02$) and highest at level 5 ($\mu = .8, \sigma = .03$). On average, accuracy was highest for Chinese numerals ($\mu = .6, \sigma = .21$), then Arabic ($\mu = .59, \sigma = .19$) and non-symbolic dots ($\mu = .59, \sigma = .19$), and finally, Thai numerals ($\mu = .54, \sigma = .19$).

A repeated-measures ANOVA found a significant main effect of contrast level on accuracy ($F(4, 40) = 447.914, p < .001, \eta^2 = .99$), but not a main effect of numeric-type on accuracy ($F(3, 30) = 2.134, p = 0.12, \eta^2 = .18$). There was no interaction effect between numeric-type and contrast level on accuracy ($F(12, 120) = 0.951, p = .5, \eta^2 = .09$). Post-hoc pair-wise t -tests using the Bonferroni correction revealed significant differences between all combinations of contrast level ($p < .001$). By contrast, pair-wise t -tests showed no difference in accuracy between numeric-types, except between familiar items, Arabic numerals and non-symbolic dots ($p < .05$). All simple effects are reported in the supplementary materials, Tables S1.8 and S1.9. These results indicate our chosen signal levels appropriately influenced response accuracy. However, there appears to be no effect of numeric familiarity on response-accuracy. We will revisit this line of inquiry shortly.

Figure C2.b. depicts mean accuracy across experimental blocks, for each

Figure C2. a) Mean accuracy across five signal contrast-levels, and four numeric-types. b) Mean accuracy across each experimental block. c) Mean accuracy for each participant by critical contrast level. d) Mean accuracy matched by contrast-level, across numeric-types. Error bars represent the standard-error of the mean.

numeric-type. Mean accuracy was comparable between numeric-types, and increased marginally with block number, being lowest at block 1 ($\mu = .50$, $\sigma = .14$) and highest at block 13 ($\mu = .62$, $\sigma = .13$). A repeated-measures ANOVA found a significant main effect of block on accuracy ($F(12, 120) = 14.733$, $p < .001$, $\eta^2 = .6$), and no main effect of numeric-type on accuracy ($F(3, 30) = 2.139$, $p = 0.12$, $\eta^2 = .18$). There was no interaction effect of numeric-type and block on accuracy ($F(36, 360) = .975$, $p = .51$, $\eta^2 = .09$). Post-hoc pair-wise analysis revealed significant differences in accuracy between early and late experimental blocks. Block 1 differed significantly from blocks 5–13 ($p < .01$), block 2 from blocks 12–13 ($p < .01$) and block 3 from blocks 9, 11 and 13 ($p < .05$). Simple effects are reported in the supplementary materials, Table S1.10. These results suggest a small practice effect, slightly boosting accuracy in later blocks.

Figure C2.c. presents mean experimental accuracy across critical contrast levels, separated by participant and numeric-type. A linear regression found a significant positive relationship between critical contrast and mean accuracy ($r^2 = .551$), suggesting a dependency between contrast and accuracy. To disentangle the effect of numeric-type and contrast on accuracy, we assessed accuracy matched across RGB

values from each participant’s five signal-contrast levels (see C2.d).

Figure C2.d. presents mean accuracy matched across participant’s five contrast-levels, separated by numeric-type. For example, if for Arabic numerals, participant S1 responded to RGB contrast values 130–134 and participant S2 responded to RGB contrast values 134–137, their accuracy at contrast value 134 would be averaged and depicted in Figure C2.d.

Figure C2.d. displays a positive relationship between contrast and matched accuracy. Matching accuracy for contrast levels when all numeric-types were presented, (i.e., excluding contrast values 130 and 138), accuracy was highest for non-symbolic dots ($\mu = .63$, $\sigma = .22$), then Arabic numerals ($\mu = .59$, $\sigma = .24$), then Chinese numerals ($\mu = .58$, $\sigma = .25$) and lowest for Thai numerals ($\mu = .51$, $\sigma = .21$).

We completed a two-way between-subjects ANOVA to assess the effect of numeric-type and contrast-level on matched accuracy (Figure C2.d). We found a main effect of numeric-type ($F(3, 185) = 15.606$, $p < .001$, $\eta^2 = 0.04$), and a main effect of contrast-level ($F(6, 185) = 148.814$, $p < .001$, $\eta^2 = 0.79$) on accuracy. There was no interaction effect between contrast level and numeric-type on accuracy ($F(18, 185) = 0.003$, $p = .99$, $\eta^2 = 0.01$). Post-hoc pair-wise t -tests displayed significant differences between all contrast values ($p < .001$), except between the highest RGB values, 136 and 137 (all pair-wise tests are reported in the supplementary materials, Table S1.. Post-hoc t -tests displayed a significant differences in accuracy between all numeric-types ($p < .05$), except for comparisons between Chinese and Thai, and Arabic and Thai numerals (all pair-wise tests reported in the supplementary materials, Table S1.. These results show a clear effect of contrast-level on accuracy. After accounting for contrast level, trends indicate that accuracy was higher for familiar items (Dots and Arabic) compared to unfamiliar items (Chinese and Thai), however, this was not borne out by the simple effects.

Supplementary Material S1.

Supplementary statistical analyses

671 The following supplementary materials provide the full statistical analysis of all simple
 672 effects reported in the main paper and the appendices of the main paper.

673 **First language Chinese simple effects**

Table S1.1

Post Hoc Comparisons - Calibration Means

		Mean Difference	SE	t	Cohen's d	p_{bonf}
ENG	DOT	-0.215	1.203	-0.179	-0.054	1.000
	CHN	0.227	0.641	0.354	0.107	1.000
	THI	-2.691	0.638	-4.217	-1.272	0.011
DOT	CHN	0.442	0.974	0.454	0.137	1.000
	THI	-2.476	1.314	-1.884	-0.568	0.534
CHN	THI	-2.918	0.561	-5.200	-1.568	0.002

Table S1.2

Post Hoc Comparisons - Contrast Levels

		Mean Difference	SE	t	Cohen's d	p_{bonf}
L1	L2	-0.087	0.011	-7.985	-2.408	< .001
	L3	-0.182	0.010	-18.390	-5.545	< .001
	L4	-0.253	0.014	-18.701	-5.639	< .001
	L5	-0.313	0.017	-18.382	-5.542	< .001
L2	L3	-0.095	0.010	-9.846	-2.969	< .001
	L4	-0.166	0.012	-14.352	-4.327	< .001
	L5	-0.226	0.015	-14.633	-4.412	< .001
L3	L4	-0.072	0.008	-9.340	-2.816	< .001
	L5	-0.132	0.011	-11.762	-3.546	< .001
L4	L5	-0.060	0.007	-8.183	-2.467	< .001

Table S1.4

Post-hoc comparisons of accuracy by block number.

		Mean Difference	SE	t	Cohen's d	p_{bonf}
Block 1	Block 2	-0.014	0.016	-0.878	-0.265	1.000
	Block 3	-0.034	0.016	-2.195	-0.662	1.000
	Block 4	-0.049	0.011	-4.452	-1.342	0.096
	Block 5	-0.043	0.016	-2.702	-0.815	1.000
	Block 6	-0.070	0.015	-4.839	-1.459	0.053
	Block 7	-0.074	0.016	-4.711	-1.421	0.065
	Block 8	-0.072	0.017	-4.142	-1.249	0.156
	Block 9	-0.068	0.014	-5.013	-1.512	0.041
	Block 10	-0.072	0.014	-5.141	-1.550	0.034
	Block 11	-0.063	0.013	-4.885	-1.473	0.050
	Block 12	-0.067	0.016	-4.156	-1.253	0.153
	Block 13	-0.070	0.015	-4.624	-1.394	0.074
Block 2	Block 3	-0.021	0.011	-1.817	-0.548	1.000
	Block 4	-0.036	0.012	-2.900	-0.874	1.000
	Block 5	-0.030	0.015	-1.959	-0.591	1.000
	Block 6	-0.057	0.016	-3.603	-1.086	0.376
	Block 7	-0.061	0.016	-3.851	-1.161	0.250

Table S1.4 continued from previous page

		Mean Difference	SE	t	Cohen's <i>d</i>	<i>p_{bonf}</i>
	Block 8	-0.059	0.016	-3.612	-1.089	0.371
	Block 9	-0.055	0.015	-3.728	-1.124	0.306
	Block 10	-0.059	0.011	-5.214	-1.572	0.031
	Block 11	-0.050	0.013	-3.732	-1.125	0.304
	Block 12	-0.053	0.017	-3.129	-0.943	0.835
	Block 13	-0.056	0.015	-3.842	-1.158	0.254
Block 3	Block 4	-0.015	0.014	-1.062	-0.320	1.000
	Block 5	-0.009	0.020	-0.435	-0.131	1.000
	Block 6	-0.036	0.019	-1.943	-0.586	1.000
	Block 7	-0.040	0.019	-2.127	-0.641	1.000
	Block 8	-0.038	0.019	-2.025	-0.611	1.000
	Block 9	-0.034	0.017	-1.968	-0.593	1.000
	Block 10	-0.038	0.017	-2.217	-0.668	1.000
	Block 11	-0.029	0.018	-1.630	-0.491	1.000
	Block 12	-0.033	0.021	-1.563	-0.471	1.000
	Block 13	-0.035	0.019	-1.870	-0.564	1.000
Block 4	Block 5	0.006	0.009	0.688	0.207	1.000
	Block 6	-0.021	0.011	-1.982	-0.598	1.000
	Block 7	-0.025	0.010	-2.479	-0.747	1.000
	Block 8	-0.023	0.010	-2.347	-0.708	1.000
	Block 9	-0.019	0.009	-2.145	-0.647	1.000
	Block 10	-0.023	0.009	-2.451	-0.739	1.000
	Block 11	-0.014	0.010	-1.399	-0.422	1.000
	Block 12	-0.018	0.013	-1.383	-0.417	1.000
	Block 13	-0.020	0.012	-1.765	-0.532	1.000
Block 5	Block 6	-0.027	0.010	-2.824	-0.851	1.000
	Block 7	-0.031	0.011	-2.905	-0.876	1.000

Table S1.4 continued from previous page

		Mean Difference	SE	t	Cohen's <i>d</i>	<i>p</i> _{bonf}
	Block 8	-0.029	0.011	-2.567	-0.774	1.000
	Block 9	-0.025	0.008	-3.105	-0.936	0.870
	Block 10	-0.029	0.009	-3.371	-1.016	0.555
	Block 11	-0.020	0.011	-1.901	-0.573	1.000
	Block 12	-0.024	0.012	-2.032	-0.613	1.000
	Block 13	-0.027	0.011	-2.330	-0.702	1.000
Block 6	Block 7	-0.004	0.010	-0.391	-0.118	1.000
	Block 8	-0.002	0.013	-0.141	-0.042	1.000
	Block 9	0.002	0.004	0.623	0.188	1.000
	Block 10	-0.002	0.009	-0.232	-0.070	1.000
	Block 11	0.007	0.011	0.673	0.203	1.000
	Block 12	0.004	0.012	0.305	0.092	1.000
	Block 13	7.576e-4	0.013	0.058	0.018	1.000
Block 7	Block 8	0.002	0.005	0.370	0.112	1.000
	Block 9	0.006	0.010	0.597	0.180	1.000
	Block 10	0.002	0.009	0.208	0.063	1.000
	Block 11	0.011	0.008	1.282	0.387	1.000
	Block 12	0.007	0.007	1.058	0.319	1.000
	Block 13	0.005	0.010	0.457	0.138	1.000
Block 8	Block 9	0.004	0.012	0.329	0.099	1.000
	Block 10	-2.525e-4	0.010	-0.025	-0.008	1.000
	Block 11	0.009	0.010	0.888	0.268	1.000
	Block 12	0.005	0.009	0.623	0.188	1.000
	Block 13	0.003	0.010	0.247	0.075	1.000
Block 9	Block 10	-0.004	0.009	-0.500	-0.151	1.000
	Block 11	0.005	0.011	0.433	0.131	1.000
	Block 12	0.001	0.012	0.106	0.032	1.000

Table S1.4 continued from previous page

		Mean Difference	SE	t	Cohen's <i>d</i>	<i>p</i> _{bonf}
	Block 13	-0.002	0.012	-0.125	-0.038	1.000
Block 10	Block 11	0.009	0.005	1.695	0.511	1.000
	Block 12	0.006	0.011	0.516	0.156	1.000
	Block 13	0.003	0.009	0.311	0.094	1.000
Block 11	Block 12	-0.004	0.011	-0.328	-0.099	1.000
	Block 13	-0.006	0.008	-0.759	-0.229	1.000
Block 12	Block 13	-0.003	0.011	-0.246	-0.074	1.000

Table S1.3

Post Hoc Comparisons - Numeric type

		Mean Difference	SE	t	Cohen's d	p_{bonf}
ARABIC	CHINESE	-0.034	0.068	-0.494	-0.149	1.000
	THAI	-0.133	0.064	-2.089	-0.630	0.380
	DOTS	-0.076	0.063	-1.202	-0.362	1.000
CHINESE	THAI	-0.100	0.048	-2.063	-0.622	0.397
	DOTS	-0.042	0.034	-1.241	-0.374	1.000
THAI	DOTS	0.058	0.057	1.006	0.303	1.000

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Table S1.5
Post Hoc Comparisons - Contrast Steps (RGB)

		Mean Difference	SE	t	Cohen's d	p_{bonf}
135	136	-0.095	0.030	-3.146	-0.780	0.030
	137	-0.184	0.029	-6.277	-1.638	< .001
	138	-0.248	0.030	-8.249	-2.221	< .001
	139	-0.302	0.039	-7.757	-2.787	< .001
	140	-0.315	0.043	-7.398	-3.005	< .001
136	137	-0.089	0.026	-3.482	-0.742	0.010
	138	-0.154	0.027	-5.784	-1.273	< .001
	139	-0.207	0.036	-5.716	-1.735	< .001
	140	-0.221	0.040	-5.490	-1.867	< .001
137	138	-0.064	0.026	-2.499	-0.573	0.204
	139	-0.118	0.036	-3.304	-1.077	0.018
	140	-0.131	0.040	-3.311	-1.231	0.018
138	139	-0.053	0.036	-1.471	-0.493	1.000
	140	-0.067	0.040	-1.664	-0.637	1.000
139	140	-0.014	0.047	-0.288	-0.139	1.000

Table S1.10
Post-hoc comparisons of accuracy by block number.

		Mean Difference	SE	t	p_{bonf}
Block1	Block2	-0.032	0.014	-2.257	1.000
	Block3	-0.059	0.015	-3.992	0.199
	Block4	-0.072	0.015	-4.857	0.052
	Block5	-0.066	0.013	-5.209	0.031
	Block6	-0.082	0.013	-6.336	0.007
	Block7	-0.078	0.011	-6.756	0.004
	Block8	-0.080	0.013	-6.188	0.008
	Block9	-0.096	0.012	-8.144	< .001
	Block10	-0.092	0.012	-7.834	0.001
	Block11	-0.096	0.014	-6.623	0.005
	Block12	-0.096	0.014	-6.747	0.004
	Block13	-0.115	0.017	-6.841	0.004
Block2	Block3	-0.026	0.013	-1.961	1.000
	Block4	-0.040	0.014	-2.799	1.000

Table S1.10 continued from previous page

		Mean Difference	SE	t	p_{bonf}
Block3	Block5	-0.034	0.017	-2.004	1.000
	Block6	-0.049	0.013	-3.660	0.342
	Block7	-0.045	0.012	-3.891	0.234
	Block8	-0.048	0.016	-2.955	1.000
	Block9	-0.063	0.015	-4.334	0.116
	Block10	-0.060	0.016	-3.749	0.296
	Block11	-0.064	0.016	-3.870	0.243
	Block12	-0.064	0.009	-7.064	0.003
	Block13	-0.082	0.013	-6.105	0.009
	Block4	-0.014	0.012	-1.115	1.000
	Block5	-0.007	0.009	-0.806	1.000
	Block6	-0.023	0.009	-2.597	1.000
	Block7	-0.019	0.008	-2.338	1.000
Block4	Block8	-0.021	0.010	-2.127	1.000
	Block9	-0.037	0.007	-5.200	0.031
	Block10	-0.034	0.011	-2.964	1.000
	Block11	-0.037	0.006	-5.826	0.013
	Block12	-0.038	0.008	-4.837	0.053
	Block13	-0.056	0.008	-7.089	0.003
	Block5	0.006	0.014	0.456	1.000
	Block6	-0.009	0.012	-0.772	1.000
	Block7	-0.005	0.010	-0.527	1.000
	Block8	-0.008	0.010	-0.791	1.000
	Block9	-0.023	0.010	-2.409	1.000
	Block10	-0.020	0.014	-1.468	1.000
	Block11	-0.024	0.011	-2.203	1.000
	Block12	-0.024	0.009	-2.758	1.000

Table S1.10 continued from previous page

		Mean Difference	SE	t	p_{bonf}
Block5	Block13	-0.042	0.013	-3.359	0.566
	Block6	-0.016	0.011	-1.430	1.000
	Block7	-0.012	0.011	-1.104	1.000
	Block8	-0.014	0.009	-1.518	1.000
	Block9	-0.030	0.010	-3.108	0.865
	Block10	-0.027	0.010	-2.591	1.000
	Block11	-0.030	0.007	-4.418	0.101
	Block12	-0.030	0.012	-2.495	1.000
Block6	Block13	-0.049	0.011	-4.255	0.131
	Block7	0.004	0.006	0.689	1.000
	Block8	0.002	0.009	0.162	1.000
	Block9	-0.014	0.010	-1.468	1.000
	Block10	-0.011	0.011	-1.020	1.000
	Block11	-0.014	0.009	-1.640	1.000
	Block12	-0.015	0.009	-1.636	1.000
	Block13	-0.033	0.007	-4.881	0.050
Block7	Block8	-0.003	0.007	-0.341	1.000
	Block9	-0.018	0.008	-2.217	1.000
	Block10	-0.015	0.012	-1.200	1.000
	Block11	-0.018	0.008	-2.332	1.000
	Block12	-0.019	0.008	-2.482	1.000
	Block13	-0.037	0.008	-4.783	0.058
Block8	Block9	-0.016	0.008	-1.911	1.000
	Block10	-0.012	0.012	-1.019	1.000
	Block11	-0.016	0.005	-2.959	1.000
	Block12	-0.016	0.011	-1.506	1.000
	Block13	-0.035	0.011	-3.231	0.703

Table S1.10 continued from previous page

		Mean Difference	SE	t	p_{bonf}
Block9	Block10	0.003	0.010	0.344	1.000
	Block11	-2.525e-4	0.007	-0.034	1.000
	Block12	-5.051e-4	0.009	-0.056	1.000
	Block13	-0.019	0.011	-1.684	1.000
Block10	Block11	-0.004	0.011	-0.312	1.000
	Block12	-0.004	0.011	-0.335	1.000
	Block13	-0.022	0.012	-1.815	1.000
Block11	Block12	-2.525e-4	0.010	-0.025	1.000
	Block13	-0.019	0.009	-2.119	1.000
Block12	Block13	-0.018	0.007	-2.729	1.000

Table S1.6

Post Hoc Comparisons - Numeric type

		Mean Difference	SE	t	Cohen's d	p_{bonf}
CHINESE	DOT	-0.073	0.032	-2.259	-0.505	0.153
	ARABIC	-0.042	0.024	-1.735	-0.270	0.510
	THAI	0.059	0.026	2.271	0.393	0.148
DOT	ARIBIC	0.030	0.032	0.951	0.221	1.000
	THAI	0.132	0.033	3.988	1.046	< .001
ARABIC	THAI	0.101	0.026	3.969	0.702	< .001

Table S1.7

Post Hoc Comparisons - Numeric type

		Mean Difference	SE	t	Cohen's d	p_{bonf}
ARABIC	DOTS	-0.098	0.036	-2.746	-0.586	0.073
	CHINESE	-0.059	0.042	-1.424	-0.304	1.000
	THAI	-0.091	0.045	-2.026	-0.432	0.334
DOTS	CHINESE	0.038	0.026	1.469	0.313	0.940
	THAI	0.007	0.038	0.183	0.039	1.000
CHINESE	THAI	-0.031	0.040	-0.794	-0.169	1.000

Table S1.8

Post-hoc comparisons between contrast levels. Level 1 being the lowest signal contrast level (hardest) and level 5 being the highest (easiest). Level 2 is elsewhere referred to as the critical contrast level.

		Mean Difference	SE	t	Cohen's d	p_{bonf}
Level 1	Level 2	-0.113	0.009	-12.34	-3.720	< .001
	Level 3	-0.241	0.014	-17.13	-5.166	< .001
	Level 4	-0.355	0.016	-21.97	-6.623	< .001
	Level 5	-0.440	0.016	-26.89	-8.106	< .001
Level 2	Level 3	-0.128	0.009	-13.97	-4.211	< .001
	Level 4	-0.242	0.011	-21.72	-6.550	< .001
	Level 5	-0.327	0.015	-22.55	-6.798	< .001
Level 3	Level 4	-0.114	0.006	-18.67	-5.629	< .001
	Level 5	-0.199	0.009	-22.75	-6.860	< .001
Level 4	Level 5	-0.085	0.008	-10.29	-3.104	< .001

Table S1.9

Post-hoc comparisons between numeric-types.

		Mean Difference	SE	t	Cohen's d	p_{bonf}
ARABIC	CHINESE	-0.085	0.051	-1.678	-0.506	0.746
	THAI	-0.049	0.063	-0.766	-0.231	1.000
	DOTS	-0.120	0.036	-3.353	-1.011	0.044
CHINESE	THAI	0.037	0.058	0.640	0.193	1.000
	DOTS	-0.035	0.041	-0.839	-0.253	1.000
THAI	DOTS	-0.072	0.044	-1.616	-0.487	0.822

Table S1.11

Post-hoc comparisons of accuracy matched by contrast level, for RGB contrast values 131–136.

		Mean Difference	SE	t	Cohen's d	p _{bonf}
131	132	-0.118	0.028	-4.227	-1.572	< .001
	133	-0.235	0.027	-8.851	-2.504	< .001
	134	-0.361	0.026	-13.731	-3.528	< .001
	135	-0.476	0.027	-17.916	-5.024	< .001
	136	-0.568	0.029	-19.850	-7.684	< .001
	137	-0.621	0.034	-18.528	-8.921	< .001
132	133	-0.117	0.021	-5.654	-1.240	< .001
	134	-0.243	0.020	-11.925	-2.394	< .001
	135	-0.358	0.021	-17.265	-3.757	< .001
	136	-0.450	0.023	-19.309	-5.617	< .001
	137	-0.503	0.029	-17.277	-6.344	< .001
133	134	-0.125	0.019	-6.764	-1.150	< .001
	135	-0.240	0.019	-12.700	-2.306	< .001
	136	-0.333	0.022	-15.312	-3.505	< .001
	137	-0.386	0.028	-13.839	-3.947	< .001
134	135	-0.115	0.018	-6.233	-1.054	< .001
	136	-0.208	0.021	-9.728	-2.037	< .001
	137	-0.261	0.028	-9.452	-2.462	< .001
135	136	-0.092	0.022	-4.262	-0.968	< .001
	137	-0.146	0.028	-5.224	-1.478	< .001
136	137	-0.053	0.030	-1.778	-0.675	1.000

Table S1.12

Post-hoc comparisons of accuracy matched by contrast level, across numeric-types.

		Mean Difference	SE	t	Cohen's d	p _{bonf}
ARABIC	CHINESE	-0.052	0.018	-2.857	-0.261	0.029
	DOTS	0.074	0.019	3.891	0.379	< .001
	THAI	-0.009	0.019	-0.472	-0.043	1.000
CHINESE	DOTS	0.126	0.019	6.779	0.674	< .001
	THAI	0.043	0.019	2.309	0.213	0.132
DOTS	THAI	-0.083	0.019	-4.271	-0.420	< .001

Supplementary Material S2.

Scree analyses and bias-free MDS representations

Scree analyses compare the multidimensional stress values (y-axis) against the number of MDS dimensions (x-axis), and is a subjective method for diagnosing the optimal number of MDS dimensions. This is typified by looking for the first ‘elbow’ in the scree plot, which has been denoted by a colored-egg in each plot. Increasing the number of dimensions beyond this elbow would not meaningfully improve the multidimensional stress values.

Scree Plots - First language Chinese

Supplementary Figure S2.1. Bias-free MDS scree plots for Arabic digits (blue) and symbolic dots (green). The y-axis displays stress values, and the x-axis the number of dimensions. Markers identify the optimal number of dimensions in each scree plot.

Supplementary Figure S2.2. Bias-free MDS scree plots for Chinese (red) and Thai (purple) symbols. The y-axis displays stress values, and the x-axis the number of dimensions. Markers identify the optimal number of dimensions in each scree plot.

683 Scree Plots - First language English

Supplementary Figure S2.3. Bias-free MDS scree plots for Arabic digits (blue) and symbolic dots (green). The y-axis displays stress values, and the x-axis the number of dimensions. Markers identify the optimal number of dimensions in each scree plot.

Supplementary Figure S2.4. Bias-free MDS scree plots for Chinese (red) and Thai (purple) symbols. The y-axis displays stress values, and the x-axis the number of dimensions. Markers identify the optimal number of dimensions in each scree plot.

684 Individual Bias-Free MDS solutions - First Language Chinese

Supplementary Figure S2.5. Individual bias-free MDS solutions for the Arabic digits.

Supplementary Figure S2.6. Individual bias-free MDS solutions for symbolic dots. Dots are represented by Arabic numbers for simplicity.

Supplementary Figure S2.7. Individual bias-free MDS solutions for Chinese symbols.

Supplementary Figure S2.8. Individual bias-free MDS solutions for the Thai symbols.

685 Individual Bias-Free MDS solutions - First Language English

Supplementary Figure S2.9. Individual bias-free MDS solutions for the Arabic digits.

Supplementary Figure S2.10. Individual bias-free MDS solutions for symbolic dots. Dots are represented by Arabic numbers for simplicity.

Supplementary Figure S2.11. Individual bias-free MDS solutions for Chinese symbols.

Supplementary Figure S2.12. Individual bias-free MDS solutions for the Thai symbols.