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Are efficient learners of verbal stimuli also efficient and precise learners of visuospatial stimuli?

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ABSTRACT

People differ in how quickly they learn information and how long they remember it, and these two variables are correlated such that people who learn more quickly tend to retain more of the newly learned information. Zerr and colleagues [2018. Learning efficiency: Identifying individual differences in learning rate and retention in healthy adults. *Psychological Science*, 29(9), 1436–1450] termed the relation between learning rate and retention as *learning efficiency*, with more efficient learners having both a faster acquisition rate and better memory performance after a delay. Zerr et al. also demonstrated in separate experiments that how efficiently someone learns is stable across a range of days and years with the same kind of stimuli. The current experiments (combined $N = 231$) replicate the finding that quicker learning coincides with better retention and demonstrate that the correlation extends to multiple types of materials. We also address the generalisability of learning efficiency: A person's efficiency with learning Lithuanian-English (verbal-verbal) pairs predicts their efficiency with Chinese-English (visuospatial-verbal) and (to a lesser extent) object-location (visuospatial-visuospatial) paired associates. Finally, we examine whether quicker learners also remember material more precisely by using a continuous measure of recall accuracy with object-location pairs.

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Learning efficiency; memory; learning rate; individual differences; generalisability

Recent work has demonstrated that the speed with which a person learns information is related to how well the person remembers the information over time. Specifically, people who learn material more quickly demonstrate better retention for that material at delays ranging from 5 min to several days (Nelson et al., 2016; Zerr et al., 2018). The relation between speed of learning and goodness of retention at the person level has been referred to as *learning efficiency*: More efficient learning represents quicker, more durable long-term learning. How efficiently someone learns was shown to be stable across days ($r = .68$) for an online sample ($N = 281$; Experiment 1 in Zerr et al., 2018) using different Lithuanian-English word lists, and was also stable ($r = .70$) for 46 people across an average of 3 years (Experiment 2 in Zerr et al., 2018) in substantially different environments (inside an MRI scanner, inside a laboratory, and online).

To date, the only materials used to study efficient learning have been Lithuanian-English (verbal-verbal) paired associates. It has not yet been determined whether the pattern of efficient learning replicates with different types of learning materials; for example, will a relation between a quicker learning rate and greater retention still be observed if participants attempt to learn and remember materials other than verbal-verbal paired associates? Or is the relationship between learning rate and retention negligible when assessed using material that relies less on verbal processing? It is also an open question whether efficient learning is a domain-general or a domain-specific phenomenon; if a person is able to both quickly acquire and successfully retain certain kinds of information, such as verbal-verbal paired associates, will their efficiency in learning generalise to other kinds of materials, such as visuospatial stimuli? The present studies address both questions: (1) Is learning rate significantly correlated with retention for visuospatial materials, and (2) Is an efficient learner an efficient learner regardless of stimulus type?

Generalisability of learning efficiency

Zerr et al. (2018) characterised the relation between learning rate and retention using a multitrial learning and recall procedure (termed the "Learning Efficiency Task" or LET)

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with Lithuanian-English word pairs. In this procedure, items are studied once and then repeatedly tested with feedback. Items correctly recalled are dropped out of subsequent tests, so a person is only tested on items they have yet to recall correctly, and thus each item is recalled exactly once during learning. Lithuanian words were used in this procedure because they appear similar to English words and use a Latin alphabet, but are more unfamiliar to English-speaking participants in the United States compared to other foreign languages, thus making it more difficult for prior knowledge or experience to play a role when learning the paired associates. To examine whether learning efficiency generalises to other kinds of material, the current paper uses materials beyond verbal-verbal paired associates. Specifically, we chose materials that are more difficult to verbalise, as such materials draw upon different brain regions (and different cognitive processes) than verbal materials during intentional encoding (Kelley et al., 1998; McDermott et al., 1999).

The primary aim of these studies is to aid in further theorising about learning efficiency. In particular, the outcomes of both studies will shed light on the relative domain-generalisability or domain-specificity of the mechanisms that enable efficient learning. If people who perform well on the verbal materials do not tend to excel on the visuospatial materials, then the mechanism(s) that allow(s) someone to learn the verbal information quickly and remember it well may be more domain-specific (e.g., verbal ability or crystallized intelligence in the form of a better vocabulary). If, however, there is a substantial degree of overlap in performance between the different materials, then the primary mechanism contributing to efficient learning regardless of stimulus type may be more domain-general (e.g., attention, flexibility in applying learning strategies).

In the present study, Lithuanian-English paired associates represented a verbal-verbal relationship (Zerr et al., 2018), Chinese-English paired associates were adopted to represent a visuospatial-verbal relationship (Kang, 2010), and object-location pairings were selected to represent a visuospatial-visuospatial relationship that reduces the contribution of verbal information (Lew et al., 2016). These materials therefore provide a transition from more verbal to more visuospatial information and, depending upon how the overlap in performance changes as a result of this transition, will contribute to a better understanding of the degree to which learning efficiency—and its underlying mechanisms—is specific to the learning material used or type of processing required (Carroll, 1993).

Chinese-English materials

Chinese characters are logograms, which are relatively non-verbalisable to people who read and speak only phonetic or alphabetic languages (Wang & Thomas, 1992). For learners that have no experience with logographic languages, Chinese characters appear as abstract lines or shapes that represent a visuospatial type of material yet are still relevant for educational activities such as vocabulary learning or the acquisition of a foreign language. These types of stimuli may further limit the number of learning strategies available and presumably make it more difficult to use other verbal means of remembering the pairs, such as writing the pairs down or typing them during the study phase, or rehearsing them during a retention interval. Indeed, pronounceability of verbal materials is a good predictor of learnability, such that materials that are less verbalisable are more difficult to learn and remember (Di Vesta & Ingersoll, 1969; Underwood & Schulz, 1960). Although both Lithuanian-English and Chinese-English stimuli still use English pairings, the difference between the Lithuanian words and Chinese characters make it a sufficient starting point for examining how well learning efficiency generalises to other types of material.

Object-location materials

In addition to Chinese-English pairs, we also sought to assess how well efficient learning generalises to more distinct visuospatial materials that further reduce the use of verbal information. For object-location pairings, participants viewed the locations of everyday household objects within a circle and later attempted to recall these locations with a given level of precision. Object-location paired associates were selected for two principal reasons: First, remembering object locations is important for everyday functioning (e.g., finding keys in a home or a car in a large parking lot), and as a result may capture differences in visuospatial learning that relate to real-world behaviour. Second, recording the spatial precision of recalled locations enables the use of a continuous accuracy measure in addition to a binary one (correct or incorrect). Because memories are not just recollected in an "all-or-none" manner but can vary in their fidelity, continuous measures provide a fine-grained index of the quality of recollection (Harlow & Donaldson, 2013; Harlow & Yonelinas, 2016; Richter et al., 2016).

Are efficient learners also precise learners?

In everyday life, it is often necessary to not only retrieve memories, but also to retrieve memories *precisely*. For instance, when searching for an object, recalling its general location ("My umbrella is somewhere in the house") is not as fruitful as recalling its position more exactly ("I left my umbrella on the top left corner of the coffee table"). Although the quality and precision of visual long-term memory has been found to be surprisingly robust (see Brady et al., 2008, 2013; Lew et al., 2016), individuals presumably vary in the granularity of their recollection. One reasonable hypothesis is that learning speed and memory precision are positively correlated with one another, such that faster learners recall more precisely. However, it could also be the case that the speed of learning is distinct from the ability to learn and recall precisely. Although a growing body of literature suggests that quicker learners can retain more items when an outcome is binary (correct or incorrect), it remains to be seen whether they can also retain items more precisely (fewer pixels between an object's selected and actual location).

The goals of the current studies were: (1) To establish whether quicker learning coincides with better retention for different, more challenging types of material. That is, to the extent that learning efficiency is a meaningful construct, learning rate and retention should correlate for Lithuanian-English stimuli, Chinese-English stimuli, and object-location pairings. (2) To evaluate whether learning efficiency generalises such that learners who demonstrate efficient learning with Lithuanian-English word pairs (a verbal-verbal relationship) also demonstrate efficient learning with Chinese-English word pairs (a visuospatial-verbal relationship) and object-location pairings (a visuospatial-visuospatial relationship). (3) Examine whether quicker learners are also more precise learners.

Study 1

Study 1 examined how generalisable efficient learning is across Lithuanian-English (verbal-verbal) and Chinese-English (visuospatial-verbal) paired associates. If efficient learning is less dependent on a specific domain, then participants' performance should be significantly correlated across types of learning material.

Method

Participants

Participants were 201 Amazon Mechanical Turk (MTurk) workers. Informed consent was obtained from all participants in accordance with standard Washington University human research practices, and participants were compensated \$15 total for completing both sessions of the study. Because MTurk studies take place in uncontrolled environments, at the end of the second session we asked participants whether they had written down any of the words during any of the sessions and whether they had thought about or studied the words in the intervening time; 18 participants were excluded for doing so. In addition, 28 participants were excluded for failing to finish both sessions, 16 for having prior knowledge of either the Chinese language or a similar East Asian language that utilises logograms (e.g., Japanese, Korean, Tibetan, Vietnamese, Filipino), 14 for restarting the task after the study portion, 4 for reporting a neurological disorder, 1 for not having normal (or corrected-to-normal) vision, and 1 for having prior knowledge of the Lithuanian language. Of the final sample of 119 participants, 62 (52.1%) were female, with a mean age of 36.7 years (SD = 10.1, range = 20-64) and 14.9 years of education (SD = 1.9, range = 10-20). Most participants (114 of 116 responses) reported completing the study at home, 1 at work, and 1 at a library. All participants had learned English before age 5 and resided in the continental U.S. or a U.S. territory. Although MTurk studies cannot control as many extraneous variables as experiments conducted in a laboratory, prior work suggests that data collected from online samples can be of comparable quality to that obtained from college students when properly screened (Farrell et al., 2017; Goodman et al., 2013; Paolacci & Chandler, 2014).

Materials

Learning material consisted of 28 Lithuanian-English word pairs (e.g., KNYGA – BOOK) and 28 Chinese-English word pairs (e.g., 风 – WIND; see Table A1 for the complete word lists). The Lithuanian-English word pairs were selected from previous norms (Grimaldi et al., 2010; Zerr et al., 2018). English words from both lists were concrete nouns matched as closely as possible for length (M_D = 0.1, range for both = 3-8), log frequency (M_D = 0.1; Lithuanian-English range = 6.8-11.6, Chinese-English range = 8.2-11.7), number of phonemes (M_D = 0.0, Lithuanian-English range = 1-6; Chinese-English range = 2-5), and number of syllables (M_D = 0.1, range for both = 1-2). These measures were calculated using the English Lexicon Project (ELP) database (Balota et al., 2007; http://elexicon.wustl.edu/). Typographic ligatures and diacritical marks were removed from the Lithuanian words to make them appear more similar to English words, and Lithuanian-English pairs were selected to reduce the incidence of cognates and false friends. All word pairs were displayed in capital letters on a white background in 36-pixel (27-point) font; Lithuanian and English words were presented in Roboto font (sans-serif; Arial font family), while Chinese characters were presented in Lora font (serif; PT Serif font family) to preserve character details. The online tasks administered in this experiment were coded using jsPsych (De Leeuw, 2015; http://www.jspsych.org/), an open-source JavaScript library for web-based experiments.

Procedure

This study occurred across two sessions (Figure 1). Word lists were blocked and counterbalanced such that participants studied and were tested on either all of the Lithuanian-English words before the Chinese-English pairs or vice versa. In the first session, participants first studied either 28 Lithuanian-English word pairs or 28 Chinese-English pairs. Pairs were presented one at a time for 4 s each and were separated by a 1 s interstimulus interval (ISI). Participants were instructed to learn each of the word pairs for a later cued-recall test, and were informed that they would be repeatedly tested on the word pairs until they recalled each word pair once, at which point pairs would be dropped from subsequent tests within the session.

After participants studied each word pair once, they took an initial cued recall test (*Test 1*), which required them to type the English equivalent (e.g., "DRUM") for the Lithuanian (e.g., "BUGNAS") or Chinese cue, presented

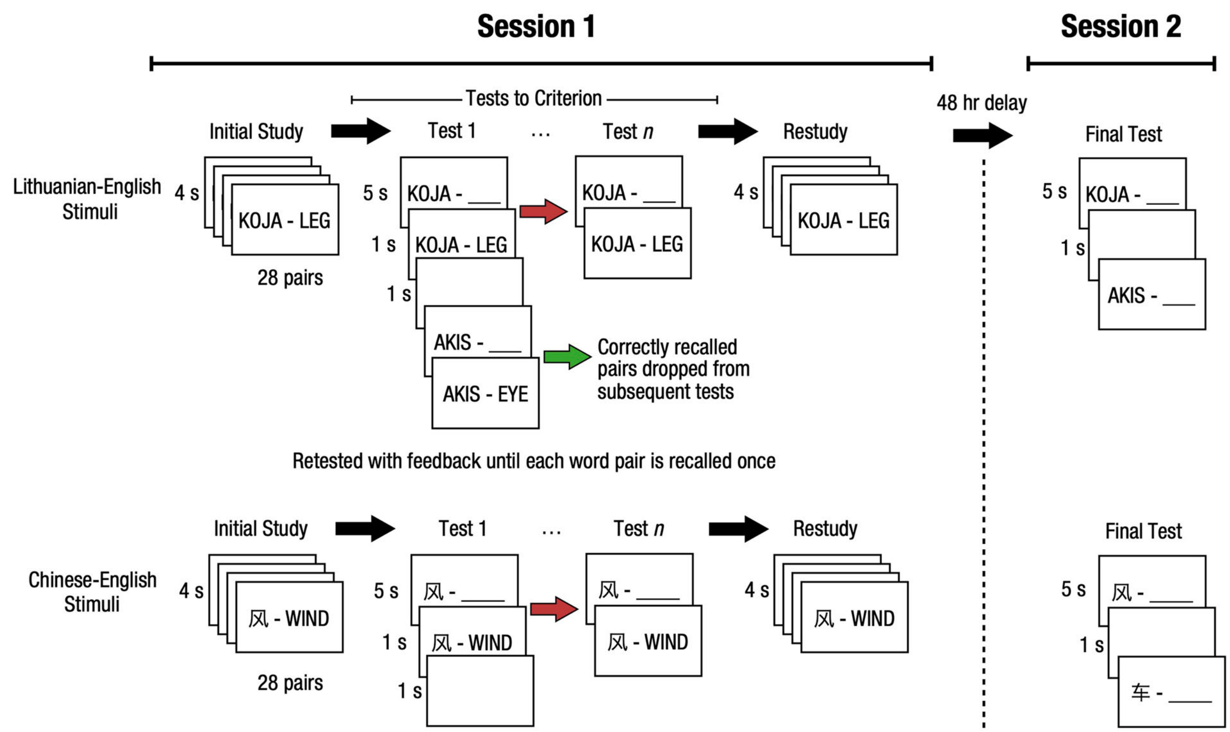

Figure 1. Experimental procedure. In Session 1, participants ($N = 119$) studied either 28 Lithuanian-English word pairs or 28 Chinese-English word pairs (word pairs were blocked, and order was counterbalanced across people). They then took an initial cued recall test (Test 1) with immediate correct-answer feedback. Correctly recalled pairs were dropped from subsequent testing, whereas incorrectly recalled word pairs were presented on the next test (again with feedback) until all 28 Lithuanian-English (or 28 Chinese-English) word pairs were recalled exactly once (Tests to Criterion). A final restudy took place before participants completed the same procedure with the other type of word pairs. Participants then took a final cued recall test (Final Test) without feedback on both types of word pairs 48 hr later.

on-screen for 5 s. Responses were deemed correct if either the full English word or at least the first three correct letters (but no incorrect ones) were provided. Regardless of response accuracy, the correct pairing was displayed for 1 s; this pairing was followed by a 1 s ISI before the next cue appeared. Correctly recalled pairs were dropped from subsequent tests until the final cued recall test in the second session to minimise overlearning.

Participants repeated this testing process on unrecalled word pairs until all 28 word-pairs had been correctly recalled once. Each test block (set of previously-unrecalled test pairs) randomised the presentation order of the paired associates, and each test was separated by 30 s of addition and subtraction mathematics problems (e.g., 7–13 = ?) to limit maintenance of the word pairs in working memory. The number of tests required for each participant to learn all 28 word-pairs (*Tests to Criterion*) was used as an index of learning rate. In the interest of time, the number of tests was limited to a maximum of 22 for each type of material. After a participant reached criterion, all word pairs were presented once more in a random order for a final study session, which was identical to the initial study session. Participants then repeated this procedure with the other type of word pairs (Chinese or Lithuanian). At the conclusion of Session 1, participants provided overall ratings (1 through 5, with 1 being the lowest) of how difficult they thought the task was, how much effort they expended, and how focused they were on the task.

Approximately 2 days later ($M = 51.3$ hr, $SD = 7.2$ hr, range = 41.8-78.8 hr), participants took a final cued recall test on the pairs. The Lithuanian-English and Chinese-English pairs were completed in blocks, so participants were first tested on the 28 Lithuanian-English pairs and then the 28 Chinese-English pairs, or vice versa (this was crossed with ordering in Session 1). The ordering of blocks was counterbalanced across participants. Participants had 5 s to type the English target for the randomly-ordered Lithuanian or Chinese cue that was present on screen before another cue was presented 1 s later. No feedback was provided.

As in Nelson et al. (2016) and Zerr et al. (2018), an overall composite measure of learning and memory performance (*Learning Efficiency Score*) was created by averaging the standardised *z*-scores for each person's Test 1, Tests to Criterion, and Final Test scores (Tests to Criterion was multiplied by −1 because fewer Tests to Criterion indicates a quicker rate of learning). A larger Learning Efficiency Score (LE Score) represents both a quicker rate of learning and better memory performance on a delayed test. LE Scores were calculated separately for each type of stimuli used in the experiment, so each participant had two LE Scores: One for Lithuanian-English material and one for Chinese-English material.

Analysis

For both studies, normality of dependent variables was assessed using the Shapiro–Wilk test; if normality was violated, the non-parametric Wilcoxon Signed Rank (V) test replaced a paired-samples t-test and the non-parametric Mann–Whitney U (U) test replaced an independent-samples t-test. The non-parametric equivalent of Pearson's r—Spearman's rho (rs)—was calculated for ordinal data (i.e., Likert ratings) and response times. Differences were considered significant if $p < .05$.

Results

The Chinese-English word pairs took longer to reach criterion, $V = 1753.5$, $p = .008$, and were not recalled as well as Lithuanian-English word pairs on the initial test, $V = 4610.0$, $p < .001$, although there were no significant differences for the delayed final test, $V = 3847.5$, $p = .072$. Descriptive statistics for task performance are presented in Table 1.

Table 1. Descriptive statistics for experiment 1.

Measure	*M*	*SD*	Median	Min	Max
Test 1 Score					
Lithuanian-English	9.7	5.8	9	0	26
Chinese-English	7.3	4.4	7	0	20
Tests to Criterion					
Lithuanian-English	6.0	2.1	6	2	13
Chinese-English	6.6	2.1	7	3	13
Final Test Score					
Lithuanian-English	13.0	6.3	13	1	26
Chinese-English	11.9	5.6	12	1	24

Note. Test 1 Score and Final Test Score each had a maximum value of 28. Tests to Criterion had a maximum possible value of 22.

Replicating learning efficiency with different stimuli

As shown in Figure 2, the correlation between learning rate (Tests to Criterion) and retention (Final Test scores at a 48-hr delay) was obtained both for the Lithuanian-English pairs, $r = -.28$, $p = .002$, 95% CI [−.44, −.11] and for the Chinese-English stimuli, $r = -.42$, $p < .001$, 95% CI [−.56, −.26]. Additional correlations for task measures are presented in Table 2.

Generalisability of learning efficiency across Lithuanian and Chinese material

As an indicator of generalisability, performance significantly correlated across stimulus type for each of the LET submeasures, including Test 1, $r = .38$, $p < .001$, 95% CI [.21, .52], the number of tests to reach criterion (or learning rate), $r = .37$, $p < .001$, 95% CI [.21, .52], and Final Test scores, $r = .57$, $p < .001$, 95% CI [.43, .68]. The composite LE Score significantly correlated across stimulus type (Lithuanian-English and Chinese-English), $r = .55$, $p < .001$, 95% CI [.41, .67], which is representative of a large effect size (Cohen, 2009). Figure 3 depicts performance for each of these measures across stimulus type.

Intraclass correlation. When using tasks for individual differences research, it is most desirable to have large between-subject variance and minimal within-subject variance. Hedge et al. (2017) recommend examining reliability (or generalisability) of measures by using an intraclass correlation coefficient (ICC), which represents the correlation between repeated measures on the same subject by scaling the data with a pooled mean and standard

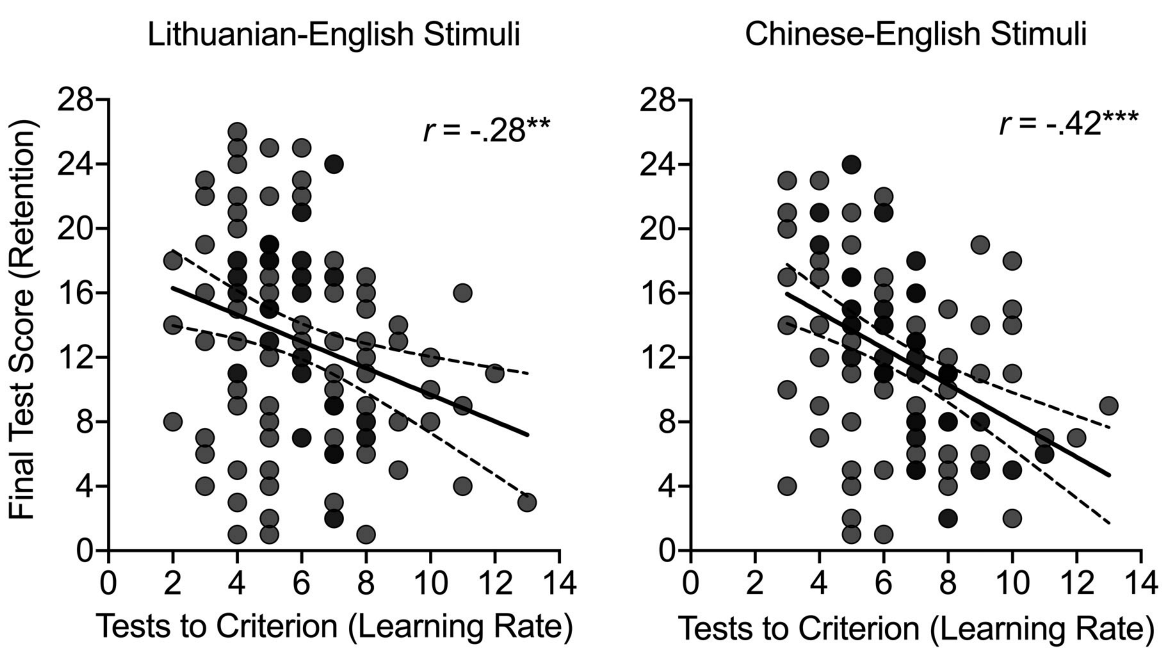

Figure 2. Tests to Criterion (learning rate) and Final Test Score (retention) were negatively correlated for both sets of stimuli, such that quicker learning was related to better retention for both Lithuanian-English stimuli (left) and Chinese-English stimuli (right). Solid lines represent the best-fitting regression line, and dashed lines represent the 95% confidence interval. Darker points indicate overlapping data.

Table 2. Correlation matrix for Learning Efficiency Task measures for Lithuanian-English and Chinese-English word pairs.

		1	2	3	4	5	6	7	8
Lithuanian									
1	Test 1								
2	Criterion	−.59*							
3	Final Test	.28*	−.28*						
4	LE Score	.81*	−.81*	.68*					
Chinese									
5	Test 1	**.38***	−.27*	.46*	.49*				
6	Criterion	−.29*	**.37***	−.41*	−.46*	−.55*			
7	Final Test	.17	−.20*	**.57***	.41*	.54*	−.42*		
8	LE Score	.34*	−.35*	.59*	**.55***	.85*	−.80*	.80*	

Note. * indicates $p < .05$. Criterion represents Tests to Criterion. Bolded values represent generalisability correlations for the same measures with different stimuli.

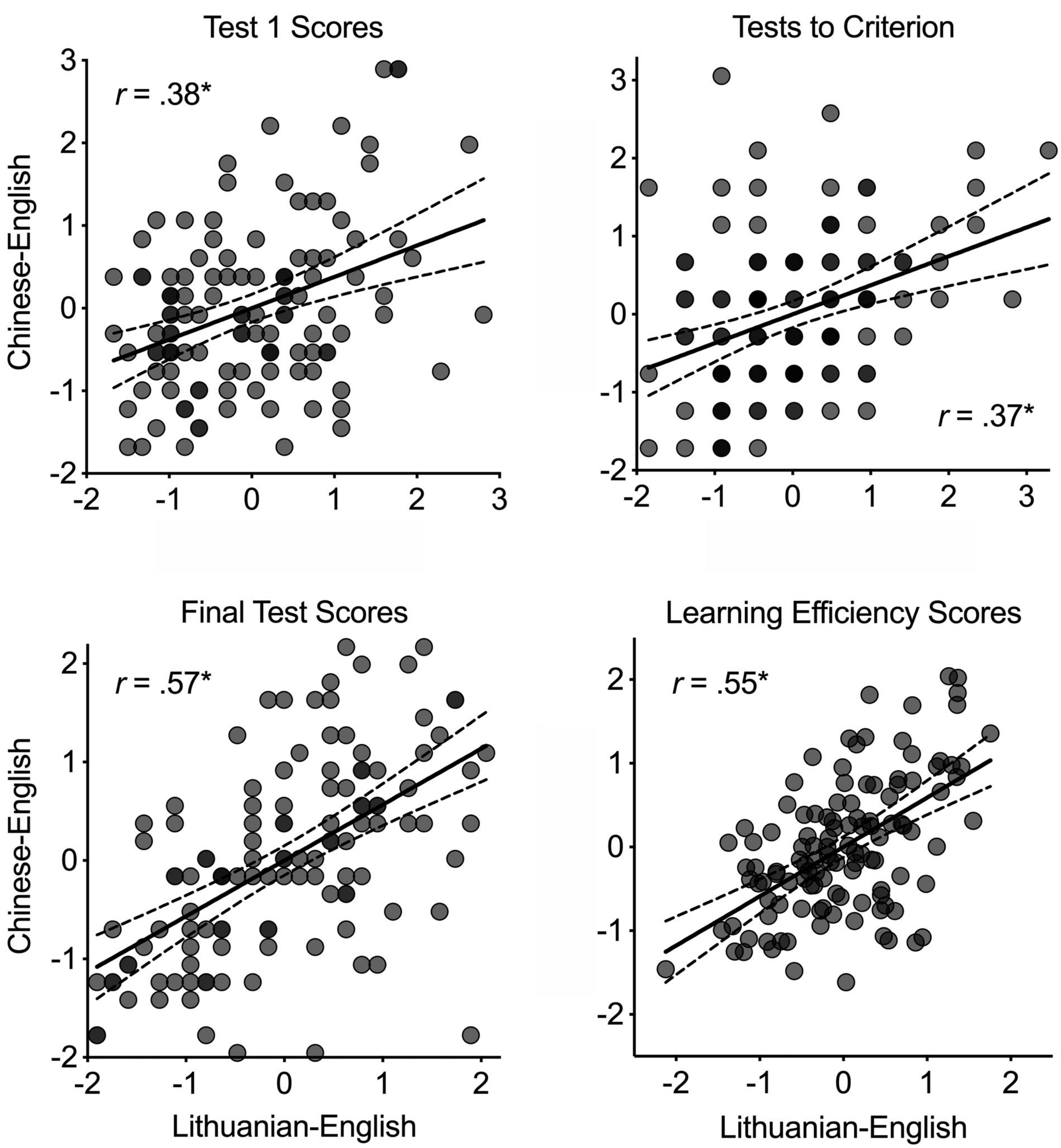

Figure 3. Scatterplots demonstrating generalisable performance across types of learning stimuli for Lithuanian-English and Chinese-English word pairs. Solid lines represent best-fitting regression lines, and dashed lines represent 95% confidence intervals. Each point represents a single person, with darker points indicating overlapping data. Axes represent z-scores.

deviation. An ICC ranges from 0 (large within-person variability and small between-person variability) to 1 (small within-person variability and large between-person variability) and can be thought of as a measure of the percentage of total variation that is attributable to between-person variation. A two-way random ICC for assessing absolute agreement amongst average scores is represented in Equation (1) (Field, 2005; Hedge et al., 2017):

$$ICC = \frac{Between\ subject\ variance - Error\ variance}{Between\ subject\ variance + \left(Within\ subject\ variance - \frac{Error\ variance}{Number\ of\ tasks}\right)} \quad (1)$$

An ICC was calculated (using Equation (1)) for Learning Efficiency Scores from the Lithuanian-English and Chinese-English materials. The two-way random ICC was used because LE Scores represent an average score of several measures. The ICC for LE scores between materials was .71, indicating that LE Scores demonstrated good reliability (or in this case, generalisability) across Lithuanian-English and Chinese-English stimuli. This ICC was significantly greater than a "large" effect size of .5 (Cohen, 2009), $F(2, 118) = 1.74$, $p = .001$, 95% CI [.59, .80]. Another way to describe the ICC of .71 is that there was greater LE Score variability *between* participants on each task than *within* participants across each task. Thus, there was more observed variability between people and less variability within individuals, making it a compelling tool for studying individual differences because people differ from one another and remain stable in their differences.

Neither participants' age nor years of education were correlated with task performance for the Lithuanian or Chinese materials (*ps* > .05). Subjective effort and focus ratings were also not related to performance on either type of material (*ps* > .05). Subjective difficulty ratings were significantly correlated with performance only for the Chinese materials, $r_s = -.35$, $p < .001$, 95% CI [−.50, −.18], such that participants whose learning efficiency was lower on the task rated it as more difficult.

In Session 1, there were significant stimulus order effects that affected scores on Test 1 and Tests to Criterion but did not alter any conclusions. Specifically, participants who received the Chinese-English materials first performed more poorly on the Chinese stimuli than those who received the Chinese-English materials second; this pattern was seen on Chinese-English Test 1, $U = 1295.0$, $p = .012$, Chinese-English Tests to Criterion, $U = 2468.0$, $p < .001$, and overall Chinese-English LE Score, $M_D = -0.4$, $t(117) = -2.8$, $p = .006$. In addition, the generalisability for the Tests to Criterion measure (the correlation between learning speed across each stimulus type) was attenuated in the group who received the Chinese-English stimuli first in Session 1. Specifically, those who received Chinese-English first had a learning speed correlation of $r = .27$, $p = .031$, 95% CI [.03, .49] across stimulus type, whereas those who received Lithuanian-English first had a learning speed correlation of $r = .57$, $p < .001$, 95% CI [.36, .72] across stimulus type. However, this order effect did not significantly affect Final Test scores for either the Chinese-English, $U = 1689.0$, $p = .680$, or Lithuanian-English stimuli, $U = 1447.5$, $p = .089$, and the order of stimulus presentation in Session 2 did not affect Final Test scores for either stimulus type (*ps* > .154).

Study 2

Study 1 found efficient learning generalised across Lithuanian-English (verbal-verbal) and Chinese-English (visuospatial-verbal) paired associates. Study 2 sought to extend this generalisability assessment by comparing performance across Lithuanian-English and object-location pairs. Learning object-location pairs is a particularly intensive visuospatial task as it requires associating images of objects with precise spatial locations and therefore provides a more divergent test of the generalisability of learning efficiency. A secondary aim of Study 2 was to examine whether quicker learners also recall object locations more precisely by including a continuous measure of memory precision (amount of error in pixels) in addition to dichotomous memory outcomes (correct versus incorrect).

Method

Participants

A total of 216 participants were recruited from MTurk and consented in accordance with standard Washington University human research practices. To incentivize completion of the entire study, participants received a flat rate of $12 for completing both study tasks or for exceeding 25 test blocks on either task, at which point the study terminated prematurely. A total of 185 participants completed both sessions, and from these 73 participants were excluded from analyses, including 49 who reported they wrote down or took pictures of the stimuli to help on the memory tests, 17 for having prior knowledge of or exposure to the Lithuanian language, 4 for reporting a learning disability or neurological condition, and 3 for not following directions. Of the final sample of 112 participants included in analyses, 47 were female (42.0%) with a mean age of 34.7 years ($SD = 9.9$, range = 19-66) and a mean of 14.7 years of education ($SD = 2.1$, range = 12-24). Most participants (106) reported completing the study at home, 3 at work, 2 in a coffee shop, and 1 at a library. All participants had learned English before age 5, reported normal or corrected-to-normal vision, resided in the continental U.S. or a U.S. territory, and reported that the input device they used (touchpad or mouse) allowed them to accurately select the locations they intended to.

Materials

The Lithuanian-English materials were identical to those described in Study 1. For the object-location materials, images of 28 everyday objects were presented within a circle. To mitigate confusability, objects were chosen to be semantically and perceptually distinct. Images were obtained from a stock image website (www.freeimages.com) and Google Images (https://www.google.com/imghp) and exported as 60 × 60 pixel JPEGs. Images were cropped tightly to reduce excess white space at the periphery. For each participant, the centre x- and y-coordinates of objects were randomly generated, with the constraint that objects not overlap with each other, the circumference of the circle, or a 50 × 50 pixel fixation cross at the circle centre. The circle measured 900 pixels in diameter. The object-location portion of the task was modified from custom JavaScript code provided by Timothy Lew (used in Lew et al., 2016) and altered to be more consistent with the Learning Efficiency Task.

Procedure

Participants learned the Lithuanian-English and object-location pairings in sequence, and task order was counter-balanced across participants. The Lithuanian-English portion of the task was identical to that of Study 1, except that the maximum number of tests to criterion allotted was increased from 22 to 25 test blocks. This increase was made to allow for more variable performance without subjecting participants to spending too much time on the task.

The object-location portion of the task was structured analogously to the Lithuanian-English portion, with an initial study phase, iterative cued-recall tests until criterion was reached, and a final test. In the study phase, participants viewed 28 object images located within a circle in sequence for 5 s each. They were instructed to remember each object location, with the name of each object displayed in the top left (Figure 4A). Pilot testing indicated that the object-location pairs generally took longer to complete than Lithuanian-English pairs, and so interstimulus intervals were omitted from the object-location portion in the interest of time. In the main testing phase, participants were cued to recall the location of each object indicated by an image and name in the top left of the screen (Figure 4B). To respond, they moved the mouse cursor and clicked a location within the circle, where a 50-pixel diameter crosshair immediately appeared at the selected location. Participants were granted 5 s to respond to each object, and they were instructed that a response would be marked correct if the crosshair was "sufficiently near the centre of the object." Response accuracy was assessed by whether the crosshair overlapped with the object image. Because the objects were square 60 × 60 pixel images and the crosshair was modelled as a round object, the distance threshold for correct responses varied depending on the position of the clicked location relative to the object. After a location was clicked, the correct location of the object appeared for 1 s. Feedback for response accuracy was conveyed via the colour of the crosshair, which turned blue for correct and red for incorrect responses (Figure 4C and 4D, respectively). An accurately scaled image of the experiment is displayed in Figure A1 and pictures of all 28 objects used in the task are displayed in Figure A2.

Objects that were correctly recalled once were dropped from subsequent testing blocks, and testing proceeded until all object locations were dropped. A 30 s distractor of math problems occurred between test blocks. Once criterion was reached (correct recall of each object location precisely one time), participants restudied all object locations as in the initial study phase and then played

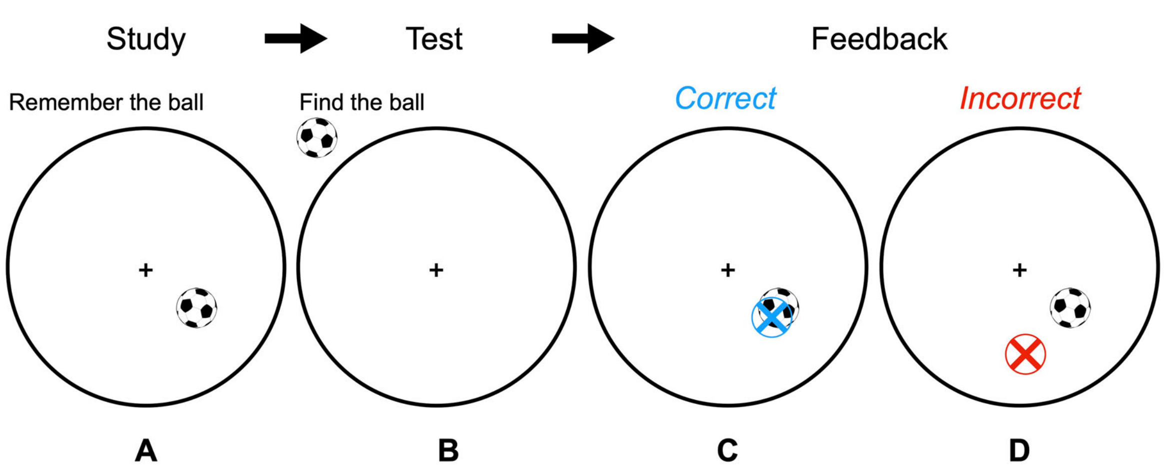

Figure 4. Procedure for the object-location version of the Learning Efficiency Task. Participants attempted to learn the location of 28 different objects within a circle. Each object was presented individually during a study period (A), and participants were later prompted to recall a particular object's location (B) by clicking their cursor within the circle. Immediate correct-answer feedback was presented that showed where the actual location of the object was as well as indicating if the participant was correct (C) or incorrect (D). The object in this figure is enlarged for clarity, and the circles and relative relation of items are shrunken to fit. An accurately scaled image of the experiment can be found in the Appendix (Figure A1).

Tetris for 60 s to prevent maintenance of the object locations in working memory. A final cued-recall test of all 28 object locations was administered, which was identical to the first test block. After completing the task, participants answered a post-task questionnaire, distinct from the one administered in Study 1, that collected basic demographic information and probed subjective task difficulty, subjective performance, effort, focus, and strategy use.

Because participants completed the study within their web browser rather than in a lab setting, display size, display resolution, and viewing distance were not controlled. However, participants were barred from using smartphones or tablets, and they were instructed to maximise their browser window to ensure they could see the totality of the circle and all stimuli. Additionally, because the object-location pairs were not used in the LET, we assessed the reliability of the object-location task in an online MTurk experiment ($N = 84$) across approximately 48 hr ($M = 50.6$ hr, $SD = 15.0$ hr) with different stimuli, finding that the task was indeed sufficiently reliable, $r = .68$, ICC $= .87$, $ps < .001$. Because a task correlates most highly with itself, the upper-bound correlation for performance generalisability across the Lithuanian-English materials and object-location pairings is theoretically $r = .68$ (the degree to which the object-location portion correlated with itself).

Results

Replicating learning efficiency with visuospatial-visuospatial materials

All learning efficiency submeasures were intercorrelated in the Lithuanian-English version of the LET, replicating past findings (Nelson et al., 2016; Zerr et al., 2018). Participants who recalled more on the initial test learned the Lithuanian-English pairs more quickly as indexed by Tests to Criterion, $r = -.65$, $p < .001$, 95% CI [−.75, −.53]. Performance on the initial test related to retention on the final test, $r = .44$, $p < .001$, 95% CI [.28, .58]. Critically, faster learners tended to retain more on the final test, $r = -.69$, $p < .001$, 95% CI [−.77, −.57] (see left side of Figure 5). Comparing these correlation values to those of Nelson et al. (2016) and Zerr et al. (2018) using the Fisher r-to-z transformation, the magnitude of the associations was not found to differ significantly.

The same overall pattern of associations was found for the object-location stimuli. Participants who recalled more objects on the initial test reached criterion more quickly, $r = -.36$, $p < .001$, 95% CI [−.51, −.19] and had better retention on the final test, $r = .52$, $p < .001$, 95% CI [.37, .65]. As with the Lithuanian-English materials, faster learners remembered more on the final test, $r = -.53$, $p < .001$, 95% CI [−.65, −.38] (see right side of Figure 5). The complete correlation matrix of the learning efficiency measures is presented in Table 3.

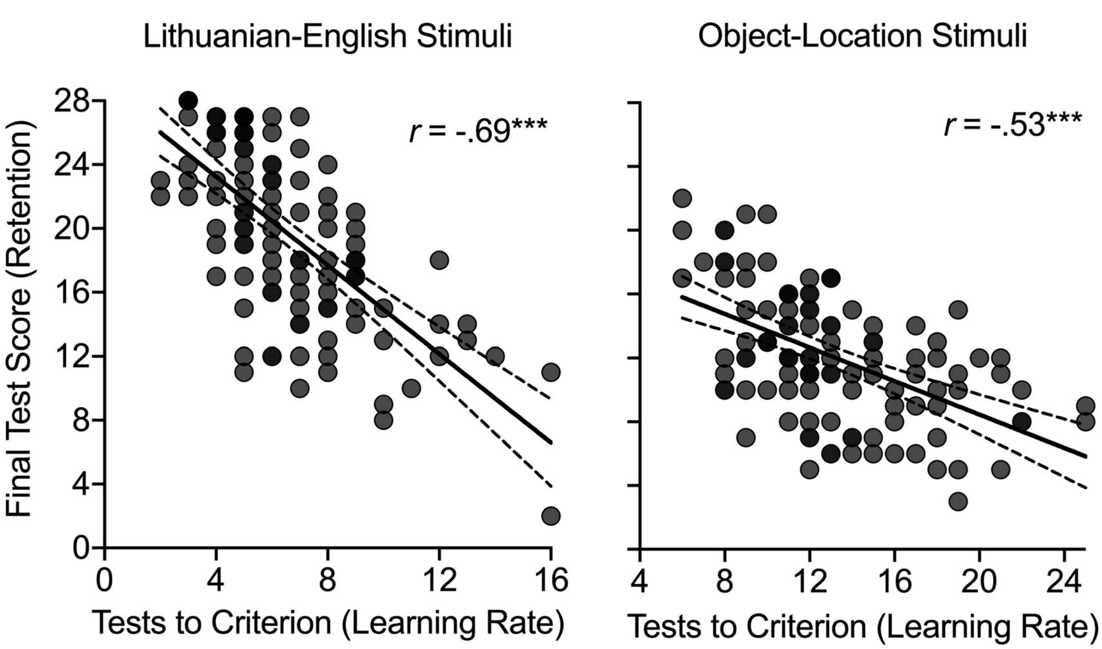

Figure 5. Replicating learning efficiency in different materials. Tests to Criterion (learning rate) and Final Test Score (retention) were negatively correlated for both sets of stimuli, such that quicker learning was related to better retention for both Lithuanian-English stimuli (left) and object-location stimuli (right). Solid lines represent the best-fitting regression line, and dashed lines represent the 95% confidence interval. Each point represents a single person, with darker points indicating overlapping data.

Table 3. Correlation matrix for Learning Efficiency Task measures for Lithuanian-English (verbal-verbal) and Object-Location pairs (visuospatial-visuospatial).

Variable	1	2	3	4	5	6	7	8	9
Lithuanian									
1 Test 1									
2 Criterion	−.65*								
3 Final Test	.44*	−.69*							
4 LE Score	.82*	−.91*	.83*						
Object-Location									
5 Test 1	**.19***	−.24*	.30*	.29*					
6 Criterion	−.14	**.23***	−.25*	−.24*	−.36*				
7 Final Test	.18	−.24*	**.33***	.29*	.52*	−.53*			
8 LE Score	.21*	−.29*	.37*	**.34***	.78*	−.78*	.85*		
9 Final Test Error	−.21*	.26*	−.35*	−.32*	−.50*	.43*	−.82*	−.73*	

Note. * indicates $p < .05$. Criterion represents Tests to Criterion. Bolded values represent generalisability correlations for the same measures with different stimuli.

Generalisability of learning efficiency across more visuospatial materials

To what extent are fast and retentive verbal learners also fast and retentive visuospatial learners? As shown in Figure 6, learning performance as indexed by the learning efficiency submeasures correlated across tasks, including Test 1 recall, $r = .19$, $p = .04$, 95% CI [.01, .37], Tests to Criterion, $r = .23$, $p = .017$, 95% CI [.04, .39], and Final Test recall, $r = .33$, $p < .001$, 95% CI [.16, .49]. The overall Learning Efficiency Scores—the average of the three *z*-score standardised submeasures—also correlated across tasks, $r = .34$, $p < .001$, 95% CI [.17, .49]. A two-way random ICC computed between the two tasks was .51, $F(2, 111) = 2.05$, $p < .001$, 95% CI [.29, .66], indicating that approximately half of the variance in learning efficiency across the two measures is attributable to between-participant variability. Thus, even across two highly disparate tasks, participants' learning efficiency generalises to a large degree.

Generalisability of learning efficiency across studies

Although learning efficiency significantly correlated across materials in each study, it is worth noting that the learning efficiency correlation across tasks in Study 2 ($r_2 = .34$) was significantly smaller than the correlation across tasks in Study 1 ($r_1 = .55$), $Z = -1.98$, $p = .048$. Some attenuation was expected given that the object-location pairings are more distinct from the Lithuanian-English materials than are the Chinese-English materials. Because learning efficiency is an aggregate measure, we also compared its three submeasures across studies to determine if learning rate (test 1 scores, tests to criterion) and retention (final test scores) were attenuated to a similar degree. Correlations from test 1 scores did not significantly differ across studies, $r_1 = .38$, $r_2 = .19$, $Z = -1.56$, $p = .119$, nor did correlations for tests to criterion, $r_1 = .37$, $r_2 = .23$, $Z = -1.16$, $p = .246$. There was, however, a significant difference in correlations between final test scores, $r_1 = .57$, $r_2 = .33$, $Z = -2.28$, $p = .023$.

Descriptive statistics for both the Lithuanian-English and object-location materials are presented in Table 4. Consistent with pilot data collected in the lab, learning object locations proved more difficult than learning Lithuanian words. Participants recalled more words than objects in the initial test, $M_D = 4.0$, $t(111) = 6.84$, $p < .001$, 95% CI = [2.8, 5.2], took fewer tests to reach criterion performance for Lithuanian-English words than objects, $M_D = -6.6$, $t(111) = -15.65$, $p < .001$, 95% CI [−7.4, −5.8], and exhibited greater recall of words on the final test relative to objects, $M_D = 7.6$, $t(111) = 13.95$, $p < .001$, 95% CI [6.5, 8.7].

Spatial precision

To succeed in learning and remembering object-location pairings, participants needed to associate objects with precise spatial coordinates. Spatial precision, operationalised as the Euclidean distance in pixels between selected and target coordinates for each object, is a more fine-grained measure of learning and retention than a binary correct/incorrect classification. A participant may have repeatedly missed an object's exact location yet nevertheless progressively become more precise across blocks as they refined their spatial representation. This subthreshold learning can only be captured by precision data as opposed to binary accuracy (correct/incorrect).

Averaging across participants, responses were more precise on the Final Test ($Mdn = 255.0$) compared to Test 1 ($Mdn = 110.2$), $Z = -9.2$, $p < .001$. The improvement in precision from the first to final test varied considerably between participants ($M = 129.9$, $SD = 64.7$). The degree of this improvement was strongly associated with Test 1 error such that those with greater error scores on Test 1 improved more by the final test, $r = .81$, $p < .001$, 95% CI [.73, .86]. This association may arise because strong Test 1 performers begin closer to their performance ceiling and therefore have diminished opportunity to improve.

Final Test error, in pixels, was found to correlate with Test 1 recall, $r = -.50$, $p < .001$, 95% CI [−.63, −.35], Tests to Criterion, $r = .43$, $p < .001$, 95% CI [.27, .57], and Final Test recall, $r = -.82$, $p < .001$, 95% CI [−.88, −.75], suggesting that it may be another viable measure to characterise learning efficiency. Additionally, Final Test

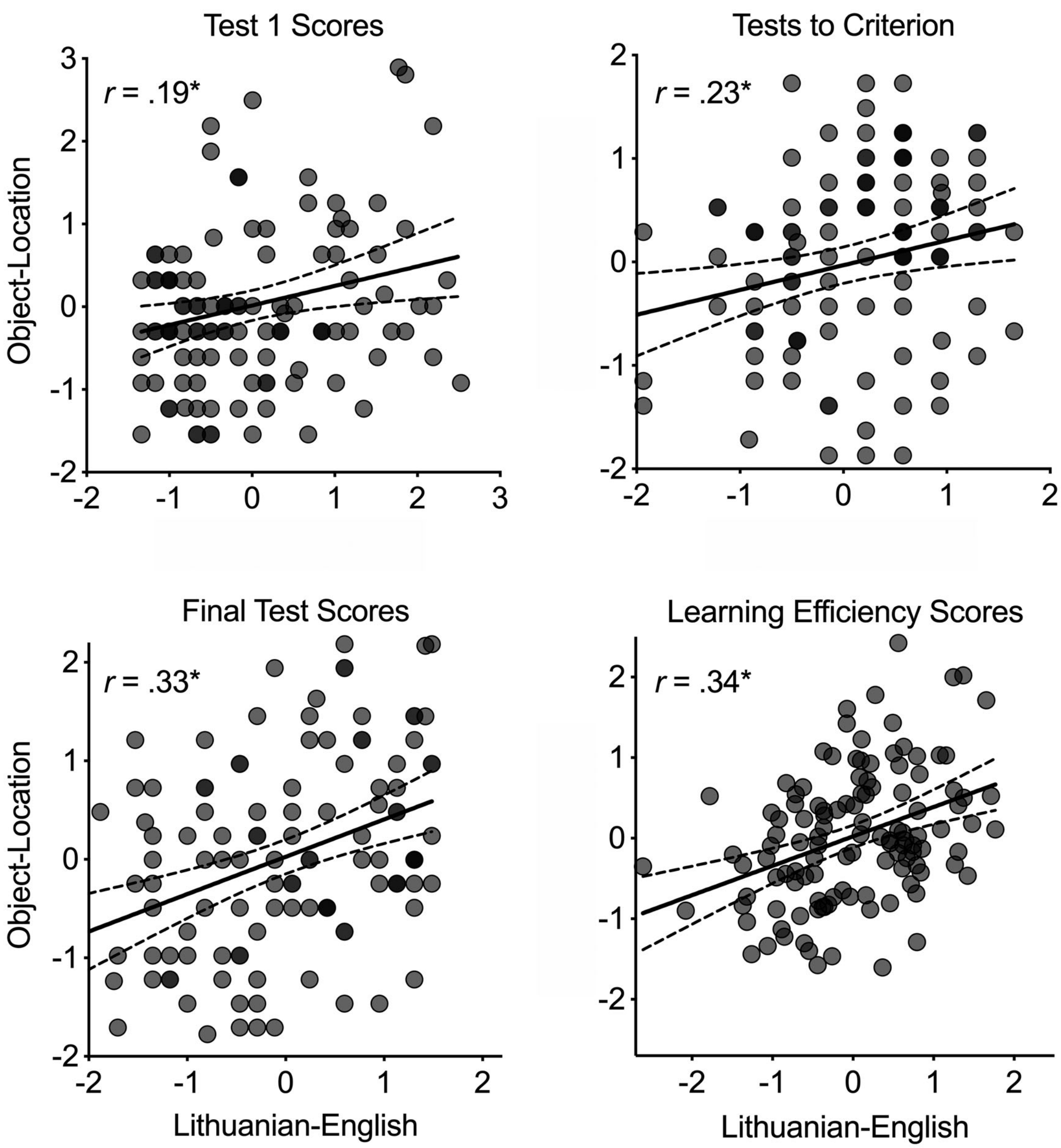

Figure 6. Scatterplots demonstrating generalisable performance across types of learning stimuli for Lithuanian-English and object-location pairs. Solid lines represent best-fitting regression lines, and dashed lines represent 95% confidence intervals. Darker points indicate overlapping data. Axes represent z-scores.

Table 4. Descriptive statistics for learning efficiency measures for Lithuanian-English word pairs and object-location pairs for study 2.

Measure	*M*	*SD*	Median	Min	Max
Test 1 Score					
Lithuanian-English	9.0	6.0	8	1	24
Object-Location	5.0	3.2	4	0	15
Tests to Criterion					
Lithuanian-English	6.6	2.8	6	2	16
Object-Location	13.2	4.2	12	6	25
Final Test Score					
Lithuanian-English	19.6	5.6	20	2	28
Object-Location	12.0	4.1	12	3	22
Final Test Error (pixels)					
Object-Location	119.7	45.0	110.2	50.0	228.5

Note. Test 1 Score and Final Test Score each had a maximum value of 28. Tests to Criterion had a maximum possible value of 25.

error weakly to moderately correlated with the Lithuanian learning efficiency metrics, further supporting the generalisability of learning efficiency across domains (refer to the bottom row in Table 4).

One potential limitation of the precision measure is that, because trials automatically advanced to the next object after 5 s, participants could selectively not respond to objects whose locations they were unsure of. Such selective responding would artificially inflate precision scores. However, an inspection of the data suggests that this practice was infrequent: Across all participants, the mean non-response rate for all trials was 2.4% (SD = 4.9%), and on the final test, participants responded to an average of 27.8 (SD = 0.94) out of 28 objects. When the number of objects responded to on the final test was included as a covariate to the previously reported correlations between Final Test error and the other learning efficiency submeasures, the magnitude of the correlations did not decrease.

Learning strategies

Differences in the selection and application of learning strategies across participants may be one of the factors that account for the association between learning rate and retention. Do efficient learners rely on learning strategies more systematically than less efficient ones? Are there particular strategies that high performers gravitate towards? To shed light on these and related questions, participants responded to questions about their strategy use after learning each type of stimulus. The learning strategy questions were taken from Zerr (2017) and were originally adapted from McDaniel and Kearney (1984). The complete question list is presented in Table 5.

Participants reporting that their strategies did not work more frequently performed worse on the Lithuanian-English task, $r_s = -.51$, $p < .001$, 95% CI [−.64, −.36] (Figure 7A). Similarly, those who more frequently struggled to come up with a strategy tended to have lower scores, $r_s = -.59$, $p < .001$, 95% CI [−.70, −.46] (Figure 7B). Additionally, answers to the strategy *Failure* and *None* questions correlated, $r_s = .66$, $p < .001$, 95% CI [.53, .77], implying that participants who struggled to come up with strategies tended to use less effective ones or implemented them less effectively. This pattern of results replicates findings by Zerr (2017).

Contrary to expectations, those who claimed to persevere with ineffective strategies did not perform significantly worse, and participants reporting frequent strategy switching exhibited no significant advantage (*ps* > .05). *Perseverance* scores were negatively correlated with *Switch* scores, $r_s = -.69$, $p < .001$, 95% CI [−.82, −.54], indicating that participants attended to the questionnaire sufficiently to not provide identical answers to oppositely worded questions. It should be noted that because participants were retroactively answering questions about strategy use after the task, their answers were necessarily "biased" by their own performance.

Strategy differences were also assessed for the object-location pairings with an open-ended question. Participants were asked to describe any strategies or techniques they used to learn the object locations. Of the 112 participants, 108 supplied a typed description of the strategies they employed. The average response length was 23.8 words ($SD = 24.4$), and response length was not

Table 5. Lithuanian-English learning strategy questions.

Strategy	Question	M (SD)
Keyword	How often did you think of an English word that looked similar to the Lithuanian word, and used that similar-looking English word to remember the other English word?	2.8 (1.1)
Other Language	How often did you think of a word in a different language to link to the Lithuanian and English word?	1.7 (1.0)
Physical	How often did you construct sentences to associate the word pairs that described what you physically saw?	2.4 (1.4)
Repetition	How often did you repeat the two words in a pair together over and over (either in your head or out loud) to commit them to memory?	3.6 (1.2)
Failure	How often did your various strategies not work for helping you learn the word pairs?	2.9 (0.8)
None	How often did you struggle or have difficulty trying to come up with a strategy for learning the word pairs?	3.1 (1.0)
Perseverance	If a strategy did not work the first time for a certain word pair, how often did you keep using that same strategy for that word pair?	2.9 (1.1)
Switch	If a strategy did not work the first time for a certain word pair, how often did you switch strategies to something else for that word pair?	2.9 (1.1)

Note. Strategy questions are from Zerr (2017) and were originally adapted from McDaniel and Kearney (1984). 1 = Never; 2 = Rarely; 3 = Sometimes; 4 = Usually; 5 = Always.

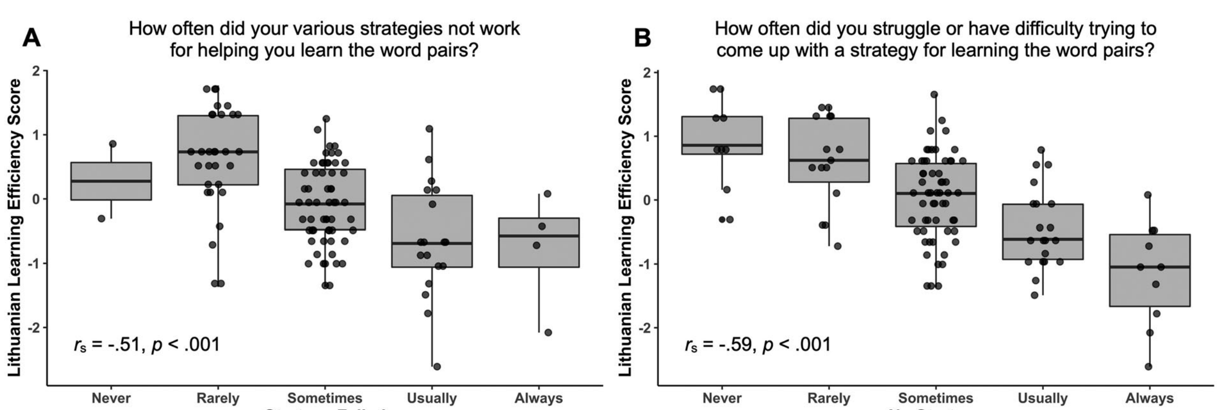

Figure 7. (A and B) Participants who had difficulty finding or implementing effective strategies tended to have lower learning efficiency scores.

significantly associated with object Learning Efficiency Scores, $r_s = .17$, $p = .07$.

Open-ended responses about strategy use were grouped into categories to see if any patterns emerged (more information about these categories can be found in the Supplemental material). Each strategy was independently classified by two raters (CLZ and TS) with an initial agreement of 95.2%, later reaching 100% after discussing the mismatched strategy classifications. Of the 108 participants that responded, 53 participants explicitly indicated they used no strategy, 35 participants used only a single strategy, 17 participants used 2 strategies, 2 participants used 3 strategies, and 1 participant used 5 strategies. The number of overall learning strategies used significantly correlated with overall learning efficiency scores, $r_s = .194$, $p = .045$, 95% CI [.01, .37], such that those who used more strategies tended to be more efficient learners. In particular, using more learning strategies was related to better long-term memory performance on the final test in the form of higher recall scores, $r_s = .244$, $p = .011$, 95% CI [.06, .41], and less error, $r_s = -.223$, $p = .020$, 95% CI [−.40, −.04].

Overall LE Scores did not relate to either participant age or years of education on either the Lithuanian or objects tasks (*ps* > .05). Test 1 scores on the objects task were positively correlated with participant age, $r = .31$, $p < .001$, 95% CI [.13, .47]. Otherwise, the learning efficiency submeasures (Test 1, Tests to Criterion, and Final Test scores) were uncorrelated with both age and education (*ps* > .05).

Subjective focus ratings were not associated with LE Scores on the Lithuanian, $r_s = .08$, $p = .39$, or objects tasks, $r_s = .05$, $p = .62$. Similarly, subjective effort was not related to overall Lithuanian learning efficiency performance, $r_s = .13$, $p = .18$, or objects performance, $r_s = -.02$, $p = .82$. The lack of significant correlations between focus or effort and overall task performance is consistent with Study 1; however, subjective difficulty negatively correlated with Lithuanian-English LE Scores, $r_s = -.54$, $p < .001$, and object-location LE Scores, $r_s = -.21$, $p = .026$, with low-scoring participants rating the task more difficult. This result is in contrast to Study 1, where difficulty ratings were not associated with Lithuanian-English performance. To probe metacognitive awareness, participants were asked to rate their performance on the objects task on a 1–5 rating scale that ranged from "significantly below average" to "significantly above average"; subjective performance ratings were not collected for the Lithuanian task. Subjective performance correlated positively with actual learning efficiency performance, $r_s = .49$, $p < .001$, indicating that participants' self-assessments were reasonably well-calibrated. Unlike Study 1, no effects of task order were found on any of the learning efficiency measures.

General discussion

The primary aims of this study were to establish whether the construct of learning efficiency replicates beyond verbal stimuli and whether a person's learning efficiency generalises across such stimuli, as well as adding a measure of memory precision. To date, learning efficiency has only been tested using Lithuanian-English (verbal-verbal) paired associates (Nelson et al., 2016; Zerr et al., 2018). Therefore, we examined whether quicker learning would relate to better memory performance in more challenging material and whether efficient learners for Lithuanian-English stimuli would also show efficient learning for Chinese-English stimuli (visuospatial-verbal) and object-location pairings (visuospatial-visuospatial). We found that faster learners did retain more when visuospatial-verbal and visuospatial-visuospatial materials were used. Further, learning efficiency generalised across stimuli such that efficient learners of verbal-verbal pairs stimuli tended to be efficient learners of visuospatial-verbal stimuli and (to a lesser extent) visuospatial-visuospatial stimuli. In sum, the present data suggest that much like working memory and intelligence, efficient learning may be neither wholly domain general nor domain specific but rather demonstrates some degree of both characteristics.

Spatial precision, a continuous index of spatial learning, was found to be associated with both visuospatial and verbal learning efficiency measures. Such continuous measures of memory fidelity have the advantage of tracking subthreshold learning that, in theory, may not be captured by binary recollection accuracy scores. However, we found performance on binary scores and precision scores to be highly related ($r = -.82$, $p < .001$). As a result, we found that quicker learners not only tended to retain more items ($r = -.53$, $p < .001$), but also tended to retain these items more precisely ($r = .43$, $p < .001$).

Why might learning efficiency exhibit characteristics of domain-generality?

A natural follow-up question to ask is what underlying mechanisms account for the domain-generality of learning efficiency. Prior work has suggested that usage of learning strategies, crystallized and fluid intelligence, and attentional control may explain variation in learning efficiency (McDermott & Zerr, 2019; Zerr et al., 2018).

Learning strategies

Strategy usage is one factor that may explain the generalisability of learning efficiency. Even though the materials used in the current studies may require different types of strategies to encode them effectively, a person's ability or tendency to implement strategies for new or unfamiliar material may be an important driver of generalisable performance across different domains. Usage of effective strategies at encoding and retrieval is strongly related to recall on a range of memory tasks (Dunlosky et al., 2005; McDaniel & Kearney, 1984; Unsworth, 2019).

For the object-location pairings, participants who used more total strategies tended to have higher learning efficiency scores, and only the *Track with cursor* strategy (following and hovering over object locations with the mouse cursor) produced less overall final test error relative to those who did not use any strategies. Surprisingly, the *Clock or Coordinates* strategies (relating object locations to positions of a clock or geometric coordinates) were not correlated with higher performance as these were anticipated to be the most effective on this task. It may be that using these strategies effectively requires extensive practice or that they only provide a benefit when used appropriately.

Cognitive abilities

Other likely mechanisms of learning efficiency are differences in crystallized (general knowledge) and fluid intelligence and attention. Zerr et al. (2018) found composite scores on the Weschler Adult Intelligence Scale (WAIS-IV; Wechsler, 2008) and Weschler Adult Scale of Intelligence (WASI-II FSIQ-2; Wechsler, 2011) significantly correlated with how efficiently people learned Lithuanian-English paired associates ($r = .44$ and .43, respectively). General knowledge or crystallized intelligence has also been shown to be related to learning and retaining paired-associates (Hundal & Horn, 1977; Kyllonen & Tirre, 1988). Though the stimuli used in Studies 1 and 2 were designed to minimise the influence of prior knowledge, well-informed participants may have used their knowledge repositories to generate better associations or to generate associations more quickly, facilitating encoding and retrieval alike (Bors & MacLeod, 1996).

In addition to intelligence, multiple studies have found that long-term memory abilities are related to, albeit not wholly subsumed by, attentional control (Shipstead et al., 2014; Unsworth, 2019; Unsworth & Engle, 2007; Unsworth & Spillers, 2010), even when partialling out related factors such as working memory capacity. Attentional control is required to focus on to-be-learned information and inhibit external or internally generated distractors. Indeed, efficient learners more robustly deactivate the default mode network during initial encoding (Nelson et al., 2016), a finding in line with the hypothesis that attention to the stimuli (and away from self-focused thoughts) contributes to the across-person differences.

Why might learning efficiency exhibit characteristics of domain-specificity?

Within each study, learning efficiency significantly correlated across materials—Lithuanian-English (verbal-verbal) and Chinese-English (visuospatial-verbal) pairs in Study 1, and Lithuanian-English (verbal-verbal) and object-locations (visuospatial-visuospatial) in Study 2. However, learning efficiency generalised across materials to a stronger degree in Study 1 than in Study 2 as materials shifted from primarily verbal to a mixture of verbal and visuospatial.

Some degree of attenuation in correlation from Study 1 to Study 2 could be expected as materials became less similar. Not only did the object-location pairings provide less verbal information, but the manner in which participants learned and recalled them—by moving their mouse and clicking the screen—was different from the typing required by the Lithuanian and Chinese materials. Thus, some of the decrease in generalisability could be attributable to both the distinctiveness of the materials and how participants interacted with them.

Another likely reason for decreasing generalisability of learning efficiency from verbal to visuospatial information could be due to the contribution of domain-specific mechanisms, such as vocabulary knowledge or verbal ability. Prior data from our lab (described in Zerr et al., 2018, and publicly available data at https://osf.io/kduwn/) using Lithuanian-English materials found more efficient learning coincided with better raw vocabulary scores ($r = .26$, $p = .012$) from the WASI-II (in which participants define a series of vocabulary words; Wechsler, 2011). However, learning efficiency did still significantly generalise across materials in both Study 1 and Study 2, suggesting that the contributions of domain-general mechanisms to efficient learning likely outweigh those of domain-specific ones, though domain-specific mechanisms do help (attenuation from Study 1 to Study 2).

Reconciling learning efficiency with desirable difficulties

At first glance, it may seem paradoxical that learning efficiency and desirable difficulties can co-exist. The desirable difficulties framework postulates that conditions that increase the apparent difficulty of learning and slow the initial rate of acquisition, such as spacing or retrieval practice, may in fact enhance the durability and flexibility of learning (Bjork, 1994; Bjork & Bjork, 2011). In Study 1 and 2, just the opposite was found—slower learning resulted in *reduced* retention. This discrepancy can be reconciled with the observation that not all learning difficulties are desirable. As Bjork and Bjork (2011) note, "many difficulties are undesirable during instruction and forever after … if the learner does not have the background knowledge or skills to respond to them successfully, they become undesirable difficulties" (p. 58). Although difficulties that engender more elaborate encoding and retrieval processes may be desirable within learners, reduced learning rate may be classified as an undesirable difficulty across learners. Indeed, the association between rate of acquisition and degree of retention, which is sometimes negative at the condition-level, can become positive at the item-level (e.g., Woodworth, 1914) and the individual-level (McDermott & Zerr, 2019; Zerr et al., 2018). Failing to account for this reversal, or assuming that the aggregate group effects hold for individuals, would be an ecological fallacy (Robinson, 1950). Thus, the observation that manipulations that slow learning improve retention does not necessarily contradict the observation that slower learners retain less.

Limitations and future directions

One limitation concerns practice effects. In Study 1, participants who began with learning the Chinese-English pairs first took longer to learn them than those participants who learned the Chinese-English pairs second (after having practice on the task by first studying the Lithuanian-English pairs). In other words, those participants who started with the more challenging material had somewhat poorer performance than those who began with the less challenging material. This order effect also attenuated the correlation between learning rate for the two types of material, such that those who began with the more challenging material had lower correlations for learning rate across material types. While these order effects do not change the conclusions that learning efficiency is generalisable across different stimuli, it is worth acknowledging and attempting to mitigate such effects in future studies.

A second limitation concerns the similarity of the generalisability stimuli. Both the Lithuanian and Chinese stimuli were paired with English words, which may have increased the generalisability of learning efficiency due to a common underlying factor or ability (i.e., English vocabulary knowledge or verbal ability as mentioned earlier in the discussion); furthermore, even though the object-location pairings did not explicitly require encoding or retrieving verbal information, the objects were cued with words and the objects themselves were verbalisable. More extensive measures of vocabulary may be required to sufficiently test if vocabulary has any mediating effect on the rate of learning and memory performance. Additionally, future research should use non-verbalisable cues and targets to minimise the influence of prior vocabulary knowledge or language ability.

The current work demonstrates that efficient learning can be observed for both verbal and visuospatial materials such that quicker learning coincides with better retention, and that this construct generalises across these different domains. To further characterise the generalisability of learning efficiency, future work should use a wider variety of stimuli, such as non-verbalisable visuospatial material, fact learning, or more complex, comprehension-based materials (e.g., narrative text). Additionally, future work could extend the robustness of efficient learning even further by employing different types of memory tests, such as recognition or free recall (cf. Underwood et al., 1978), and include additional cognitive measures (attentional control, fluid intelligence) to better understand what mechanisms give rise to efficient learning. Ultimately, a better understanding of individual differences in how quickly people learn and how long they remember may enable the creation of new assessments and interventions to aid learners. To this end, future work should determine whether and how learning efficiency relates to real-world learning outcomes such as classroom grades, and whether targeted interventions can improve performance both in the lab and in applied settings.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data for both studies are available at https://osf.io/qznwk/.

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Appendix

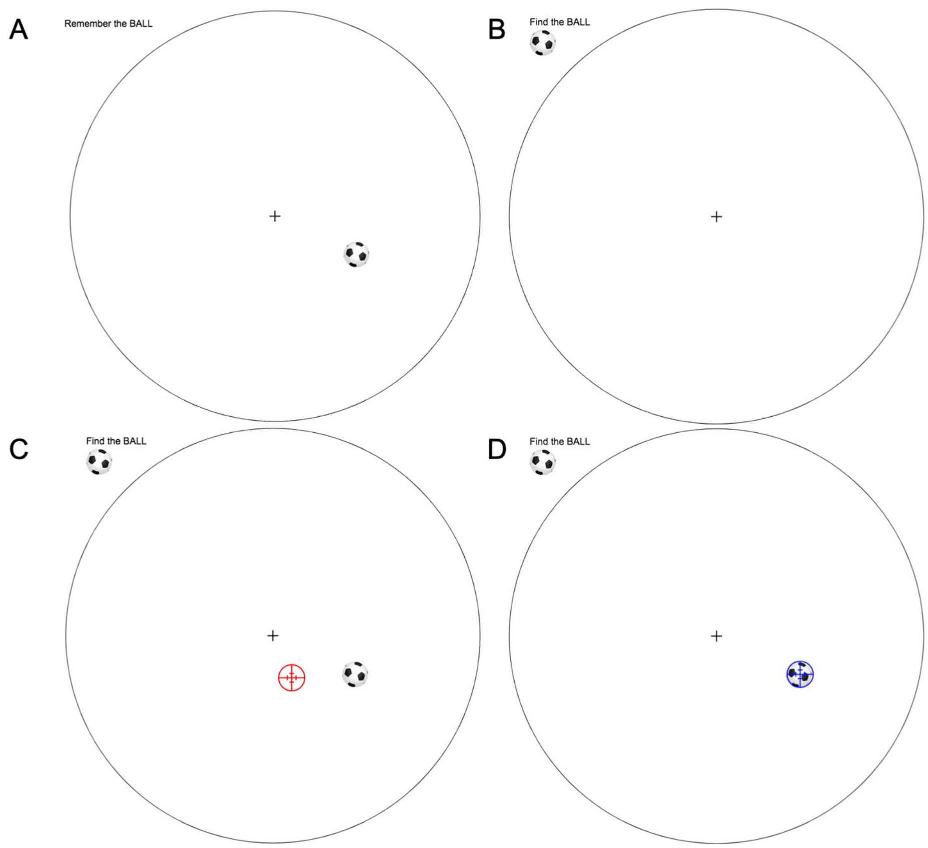

Figure A1. Trial sequence for the object-location stimuli portion of the learning efficiency task with accurate scaling. (A) Participants are instructed to remember the locations of objects in the training phase. (B) During testing, participants are cued to recall each object. (C) Feedback for incorrect responses was provided in the form of a red crosshair at the clicked location. (D) A correct response was designated with a blue crosshair.

Figure A2. The 28 objects used in the object locations task. From top left to bottom right: boot, die, hat, chair, camera, fan, clock, key, bowl, comb, teapot, glasses, bag, lamp, bike, toaster, suitcase, mailbox, scissors, helmet, book, coin, umbrella, headphones, cake, plant, sponge, apple.

Table A1. Paired associates used for experiment 1.

Lithuanian	English	Chinese	English
Obuolys	Apple	箭	Arrow
Tvartas	Barn	豆	Bean
Vonia	Bath	鸟	Bird
Tiltas	Bridge	车	Car
Pastatas	Building	椅	Chair
Pyragas	Cake	牛	Cow
Puodelis	Cup	污	Dirt
Durys	Door	火	Fire
Bugnas	Drum	叉	Fork
Akis	Eye	友	Friend
Zuvis	Fish	金	Gold
Plaukas	Hair	草	Grass
Raktas	Key	手	Hand
Riteris	Knight	心	Heart
Koja	Leg	马	Horse
Turgus	Market	王	King
Pienas	Milk	刀	Knife
Burna	Mouth	月	Moon
Nafta	Oil	山	Mountain
Augalas	Plant	钉	Nail
Lietus	Rain	河	River
Ziedas	Ring	衫	Shirt
Kambarys	Room	天	Sky
Muilas	Soap	曲	Song
Laiptelis	Stair	店	Store
Gatve	Street	风	Wind
Stalas	Table	狼	Wolf
Vanduo	Water	木	Wood