The Impact of Exemplar Variability on Implicit Learning of Distant Rules with Many-to-One Mapping

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Abstract

Multi-mapping long-distance rules, characterized by their capacity to encompass multiple long-distance correspondences, possess infinite generative power. They serve as the foundation for constructing hierarchically complex natural language structures and sentences, and represent the most challenging aspect of language acquisition. Research indicates that these rules are primarily acquired through implicit means; however, how to effectively facilitate their acquisition remains a critical issue. As a significant factor influencing learning, the role and mechanism of exemplar variability in the implicit learning of multi-mapping long-distance rules remain unclear. Specifically, it is uncertain whether it can facilitate the elevation of learners' performance from concrete value-value mapping to the level of abstract variable-variable mapping, thereby enabling the acquisition of transferable abstract rules. To this end, the present study constructs multi-mapping long-distance rules using Chinese lexical tones as a carrier, setting three levels of exemplar variability: low, medium, and high. It systematically investigates the relationship patterns between different levels of exemplar variability and the improvement of implicit learning performance. Furthermore, transfer materials consisting of tonal mappings not encountered during the learning phase were introduced in the testing phase to explore whether the facilitative effect of exemplar variability occurs at the level of abstract variable-variable mapping. The results revealed a U-shaped relationship between exemplar variability and the implicit learning effect: under high and low variability conditions, participants exhibited stronger implicit learning effects and acquired transferable abstract variable-variable mapping rules; conversely, under the medium variability condition, the learning effect was weaker, with only value-value mappings being acquired, which were difficult to transfer. This study reveals a non-linear relationship between exemplar variability and the implicit learning of multi-mapping long-distance rules, clarifying that its effect operates at the level of abstract representation for variable-variable mapping. It also points out, from the perspective of exemplar variability, that specific boundary conditions exist for the implicit acquisition of abstract rules. These findings not only deepen the understanding of implicit learning mechanisms but also provide a scientific basis for optimizing instructional design.

Full Text

Preamble

The Influence of Exemplar Variability on the Implicit Learning of Multiple-Mapping Non-adjacent Dependencies Xiaoli Ling [1,2], Qingyun Zhang [3,4], Li Zheng [5,6], Xiuyan Guo [5,6†], Peng Sun [7†] (1 Faculty of Psychology, Shandong Normal University, Jinan 250358)

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Multiple-mapping non-adjacent dependencies (MMNDs) possess infinite generative capacity due to their ability to incorporate multiple long-distance correspondences. They serve as the foundation for constructing hierarchically complex

natural language structures and sentences, representing one of the most challenging aspects of language acquisition. Research indicates that such rules are primarily acquired through implicit learning; however, how to effectively facilitate this acquisition remains a critical question. As a significant factor influencing learning, the role and mechanism of exemplar variability in the implicit learning of MMNDs remain unclear. Specifically, it is unknown whether exemplar variability can promote the transition from concrete value-to-value mapping to abstract variable-to-variable mapping, thereby enabling the acquisition of transferable abstract rules. To address this, the present study constructed MMNDs using Chinese lexical tones as a medium and established three levels of exemplar variability: low, medium, and high. We systematically investigated the relationship between different levels of exemplar variability and the improvement of implicit learning performance. Furthermore, during the testing phase, we introduced novel tone-mapping transfer materials that were not presented during the learning phase to explore whether the facilitative effect of exemplar variability occurs at the level of abstract variable-to-variable mapping. The results revealed a U-shaped relationship between exemplar variability and the implicit learning effect: under high and low variability conditions, participants exhibited stronger implicit learning effects and acquired transferable abstract variable-to-variable mapping rules. In contrast, under the medium variability condition, the learning effect was weaker, and participants only acquired value-to-value mappings that failed to transfer. This study reveals a non-linear relationship between exemplar variability and the implicit learning of MMNDs, clarifying that its impact occurs at the level of abstract representation for variable-to-variable mapping. From the perspective of exemplar variability, the findings also indicate that specific boundary conditions exist for the implicit acquisition of abstract rules. These discoveries not only deepen our understanding of implicit learning mechanisms but also provide a scientific basis for optimizing instructional design.

关键词

Exemplar variability, Implicit learning, Multiple-mapping long-distance rules, Transfer, U-shaped curve

Classification Code: B842

1 引言

Non-adjacent dependencies refer to structural rules where the sequence of elements is not restricted to immediate neighbors; instead, the constituent elements are separated by certain intervals in time or space (Wilson et al., 2020). Compared to finite-state grammars that are limited to adjacent elements, non-adjacent dependencies that transcend

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finite-state grammars allow for the embedding of one structure within another, enabling the construction of hierarchically complex structures and sentences. This capacity is a core component of human language (Chomsky, 1956). Among non-adjacent dependencies, the simplest form is the single-mapping dependency, where an element at position A in a sentence predicts an element at position B, separated by an irrelevant intervening element. This rule reflects a one-to-one mapping between two specific elements (i.e., the correspondence between A and B). For example, in English tense agreement, such as "Is [talk]ing," there is a non-adjacent correspondence between the form of the auxiliary verb and the verb suffix (Gómez, 2002; Zettersten et al., 2020; for a review, see

Wilson et al., 2020). In contrast, a more prevalent and critical feature of natural language is multiple non-adjacent dependencies, which involve multiple long-distance correspondences within a single sentence (de Vries et al., 2012; Ferrigno et al., 2025; Poletiek et al., 2025; Uddén et al., 2017). For instance, in the English sentence "Tenzin, Trinley, and Tumpo wore yellow, black, and red hats, respectively" (Jiang et al., 2022), the three subjects in the first half of the sentence correspond one-to-one with the three objects in the second half across a distance.

Similar structures exist in Chinese, such as the tonal patterns (Ping-Ze) in Tang poetry: "Ping Ping Ze Ze Ping —Ze Ze Ping Ping Ze." Here, multiple non-adjacent tonal correspondences exist between the preceding and succeeding lines. Multiple non-adjacent dependencies correspond to the more complex hierarchical structures and sentences in natural language, possessing infinite generative capacity. Consequently, they represent the most challenging aspect of language mastery and acquisition for individuals (Jiang et al., 2022; Wilson et al., 2020). Previous research has shown that the acquisition of these grammatical rules is an automatic and implicit process (Jimenez et al., 2020; Ling et al., 2022; Schiff et al., 2021; Silva et al., 2023). How to effectively promote the implicit acquisition of complex multiple non-adjacent dependencies has remained a focal point of research in this field. The acquisition of non-adjacent grammatical rules typically occurs through the automatic extraction of patterns as individuals are repeatedly exposed to different sentences (i.e., diverse exemplars) that conform to the rules. Therefore, the relationship between the degree of exemplar diversity (i.e., exemplar variability) and the level of grammatical rule acquisition has garnered widespread attention (Gómez, 2002; Onnis et al., 2003; Raviv et al., 2022; Schiff et al., 2021). Exploring this issue helps address the critical question of how to organize exemplars more effectively during the learning process. Compared to other proven methods—such as increasing learning duration (Vuong et al., 2016) or providing prior exposure to simpler materials (Zettersten et al., 2020)—adjusting exemplar variability requires only a rational organization of the materials without imposing additional burdens on the learner (e.g., more study time), making it highly relevant for instructional design. Based on this, the present study aims to systematically investigate how implicit learning performance for multiple non-adjacent dependencies is affected as exemplar variability shifts from very low to medium and then to high levels. By revealing the full relationship between exemplar variability and implicit learning outcomes, we seek to identify the optimal variability conditions for high-efficiency implicit learning, thereby providing refined empirical evidence for the organization of exemplars and the optimization of instructional design in learning contexts.

Recently, researchers (Li & Liu, 2017) conducted a preliminary investigation into the role of exemplar variability in the implicit learning of multiple non-adjacent dependencies at medium and high variability levels. This study constructed multiple non-adjacent dependencies based on the mapping of Chinese tones (Ping-Ze) (see Figure 1 [Figure 1: see original paper]). By manipulating the number of rule-irrelevant syllable types that formed the sound strings, two experimental conditions of exemplar variability were established: a high variability condition (20 syllable types) and a medium variability condition (4 syllable types). The results indicated that participants could implicitly learn the multiple non-adjacent dependencies under the high variability condition, but failed to do so under the medium variability condition. Previous researchers have noted that individuals

can automatically utilize the varying and invariant information in the input to identify stable structures (Gómez, 2002). Furthermore, when the information being focused on fails to reduce uncertainty, attentional resources are automatically redirected toward other features with greater informational value (Onnis et al., 2003; Onnis et al., 2004). Regarding Chinese speech processing, syllables and tones do not play equal roles; syllables possess an automatic priority in processing (Shi, 1997; Li et al., 2025). In the aforementioned study on the implicit learning of multiple non-adjacent dependencies, when syllables were highly variable, the magnitude of informational change was large and lacked stable structure. Consequently, learners might have abandoned the syllable dimension, which they would otherwise prioritize. Meanwhile, the tonal dimension—which remained relatively stable across instances and contained the core rule information—was assigned more weight, automatically attracting more attentional resources and thus facilitating implicit rule acquisition. In the medium variability condition where syllable variation was low, the syllable dimension neither provided stable structural information nor varied enough to be completely ignored. The automatic allocation of attention to this dimension resulted in an ineffective occupation of resources, creating attentional competition with the tonal dimension and hindering rule acquisition. Based on the

above logic, when extending to a low variability condition where syllable variation is minimal or even constant, the variation in the tonal dimension becomes the most informative cue in the input. This may automatically capture more attentional resources, potentially facilitating implicit rule acquisition. Thus, it is hypothesized that the role of exemplar variability in the implicit learning of multiple non-adjacent dependencies may follow a non-linear relationship. Building on previous research, this study intends to set different variability levels—low, medium, and high—to systematically investigate the impact of exemplar variability on the implicit learning of multiple non-adjacent dependencies across a broader range, thereby testing this non-linear relationship.

More importantly, a core question in the field of implicit learning of multiple non-adjacent grammatical rules is whether the knowledge acquired by participants consists of specific value-to-value mappings (i.e., the correspondence between a specific value of an element at one position and a specific value at another) or abstract variable-to-variable mappings (i.e., operations over variables, referring to the relational pattern of elements at different positions itself, independent of specific values; Jiang et al., 2014; Jimenez et al., 2020; Lo & Meyer, 2024; Reber, 1969). Only when learners implicitly acquire abstract grammatical rules at the level of variable-to-variable mappings does their acquired knowledge possess true transferability and robustness. In such cases, even if the training materials cover only a portion of specific values, the learned rules can generalize to unencountered materials or new contexts. Conversely, if learning remains at the value-to-value mapping level, knowledge will be restricted to the specific combinations of elements encountered during training, making effective transfer difficult (Dienes & Longuet-Higgins, 2004). This ability is of critical significance in fields such as language acquisition and educational practice; it also provides an important basis for determining whether implicit learning can transcend surface information to form abstract and flexible knowledge structures. Based on these considerations, this study aims to further clarify whether the facilitative effect of exemplar variability on the learning of multiple non-adjacent dependencies can occur at the level of abstract variable-to-variable mappings—thereby determining whether it helps participants move beyond surface-level correspondences to acquire transferable abstract rules.

In previous research, this question has not been fully answered. In the study by Li and Liu (2017), although high exemplar variability was found to promote the implicit acquisition of multiple non-adjacent dependencies, it was impossible to confirm whether this facilitation occurred at the variable-to-variable or value-to-value mapping level. That is, it remained unclear whether exemplar variability truly promoted the acquisition of transferable rule knowledge. This was primarily because both the learning and testing phases of that study utilized materials containing all Ping-Ze mapping relationships (i.e., the complete mapping between level tones [Tone 1/Tone 2] and oblique tones [Tone 3/Tone 4]). Consequently, it was difficult to determine whether high variability enabled participants to transfer from learning specific exemplars to a broader category of materials.

Under those experimental conditions, participants might have only implicitly learned local correspondences between specific tones at specific positions (local mappings, such as the correspondence between Tone 1 and Tone 3, which is a value-to-value mapping), rather than the abstract Ping-Ze mapping rules (a variable-to-variable mapping). To confirm whether exemplar variability facilitates the mastery of variable-to-variable mappings, the learning phase of the present study will present only specific tonal correspondences (e.g., materials containing only Tone 1 to Tone 3 and Tone 2 to Tone 4 mappings). In the testing phase, tonal mappings that did not appear during the learning phase will be introduced (e.g., Tone 1 to Tone 4 and Tone 2 to Tone 3). If participants can still correctly apply the Ping-Ze mapping rules to complete the classification task, it would indicate that exemplar variability promotes the mastery of abstract rules at the variable-to-variable mapping level, suggesting that the acquired rules can be effectively transferred.

In summary, this study has two primary objectives: first, to clarify the relationship between different levels of exemplar variability and performance in the implicit learning of multiple non-adjacent dependencies;

and second, based on examining this relationship, to further explore whether exemplar variability facilitates the learning of knowledge at the variable-to-variable mapping level—that is, whether it helps learners acquire abstract rule representations that can be effectively transferred, thereby confirming the robustness of rule acquisition. To this end, Experiment 1 will build upon previous research by adding a low variability condition (1 syllable type) to systematically investigate the impact of exemplar variability on the implicit learning of multiple non-adjacent dependencies. Experiment 2 will further distinguish between two types of tonal mapping: local mapping (containing only a subset of tonal mappings, such as those between Tone 1 and Tone 3, and Tone 2 and Tone 4) and complete mapping (containing all mappings between level tones [Tone 1/Tone 2] and oblique tones [Tone 3/Tone 4]). By presenting only local mapping materials during the learning phase, we will examine whether participants can transfer their knowledge to the complete mapping (Experiment 2a) or even to other entirely unlearned local mappings (Experiment 2b). This will clarify the level of knowledge implicitly acquired and test whether the facilitative effect of exemplar variability is based on abstract variable-to-variable mapping representations. Additionally, to examine the conscious state of the acquired knowledge, this study will employ the structural knowledge measurement method proposed by Dienes and Scott (2005) for further assessment.

2 实验 1：样例变异性对多重映射远距离规则内隐学习的影响模式

Experiment 1 systematically investigates the relationship between exemplar variability and the implicit learning performance of long-distance rules in multiple mapping scenarios by establishing three variability conditions: low, medium, and high. This approach aims to clarify the underlying mechanisms through which exemplar variability influences implicit learning and to identify the optimal variability conditions for maximizing learning efficiency. The findings are expected to provide significant practical guidance for the enduring challenges of teaching and learning in real-world contexts.

方法

The selection of the sample size was informed by previous relevant research [?, ?, ?], which reported an effect size of $d = 1.09$ for differences in implicit learning performance across varying conditions. We utilized G*Power 3.1 software to estimate the required sample size for the current study. With the alpha level set at 0.05 and an effect size of $d = 1.09$, the power analysis indicated that a minimum of 19 participants per group would be necessary to achieve a statistical power of 0.95. To ensure sufficient experimental power, we ultimately recruited 100 university students, who were randomly assigned to low-variation, medium-variation, and high-variation groups.

Across the three conditions, data from 9 participants were excluded from the final statistical analysis. Specifically, 6 participants (3 in the low-variability condition, 1 in the medium-variability condition, and 2 in the high-variability condition) were excluded for failing to complete the experimental tasks as required, such as being unable to repeat the sound sequences. Additionally, 3 participants (1 in the low-variability condition and 2 in the medium-variability condition) were excluded because they reported consciously attempting to search for underlying rules during the experiment; among these, the participant in the low-variability condition successfully identified some of the rules.

The final analysis included a total of 91 participants. This sample consisted of 30 participants in the low-variability condition (26 females, 19.60 ± 1.30 years old), 30 participants in the medium-variability condition (26 females, 19.50 ± 1.38 years old), and 31 participants in the high-variability condition (28 females, 19.77 ± 1.20 years old). The gender distribution was balanced across all conditions ($p = 0.852$).

All participants had normal hearing and normal or corrected-to-normal vision. They participated in the experiment voluntarily, provided written informed consent prior to the start of the study, and received financial compensation upon completion of the experiment.

The experiment employed a single-factor between-subjects design. The independent variable was example variability, categorized into three levels: low variability, medium variability, and high variability. The dependent variables consisted of the classification accuracy rate, the discrimination index (d'), and the response bias (β) during the testing phase.

The experiment generates multiple-mapping long-distance rules based on the mapping relationship between level (*ping*) and oblique (*ze*) tones. Specifically, meaningless sound strings with a length of 10 syllables are generated according to these tonal mappings. Level tones (1st and 2nd tones) in the first five syllables of the string map to oblique tones (3rd and 4th tones) at the corresponding positions in the last five syllables, and vice versa (i.e., oblique tones map to level tones). For example, if the first syllable in the sound string is a level tone, the sixth syllable must be an oblique tone.

Exemplar variability was manipulated by varying the number of syllable types (see [Figure 1: see original paper] for examples). Specifically, the low-variability condition consisted of only one syllable, "you" (combined with the four lexical tones: *you1*, *you2*, *you3*, and *you4*). The medium- and high-variability conditions were established following the parameters of previous research [**?**, **?**, **?**]. The medium-variability condition included 4 syllable types, consisting of two level-tone syllables (*hui1*, *di2*) and two oblique-tone syllables (*zhan3*, *jun4*). The high-variability condition included 20 syllable types: 10 level-tone syllables (Tone 1: *ju1*, *shen1*, *hui1*, *chao1*, *can1*; Tone 2: *di2*, *ping2*, *qin2*, *fo2*, *lai2*) and 10 oblique-tone syllables (Tone 3: *guo3*, *zhan3*, *er3*, *mai3*, *ye3*; Tone 4: *tu4*, *jun4*, *wei4*, *zou4*, *kan4*).

The audio stimuli used in the experiment were generated using iFLYTEK speech synthesis software (sampling rate: 22.05 kHz, young female voice; cf. Li & Liu, 2017; Jiang et al., 2022; Ling et al., 2022).

Examples of sound sequences: A represents the low-variability condition, B represents the medium-variability condition, and C represents the high-variability condition.

The experimental materials were generated according to the following procedure. First, based on predefined tonal pattern mapping rules (level and oblique tones), eight tonal sequences conforming to these rules were generated: four sequences were designated for the learning phase and four for the testing phase.

During the learning phase, each of the four tonal sequences was used to generate 12 distinct auditory sequences, resulting in a total of 48 learning stimuli. In the testing phase, the four rule-conforming tonal sequences were used to generate "grammatical" test stimuli. To create "ungrammatical" test stimuli, four non-conforming tonal sequences were generated by transposing the 7th and 9th positions of the grammatical sequences. Each of these test tonal sequences was then used to produce six different auditory sequences, yielding 24 grammatical and 24 ungrammatical test stimuli.

The configuration of learning and testing sequences remained consistent across the low-variability, medium-variability, and high-variability conditions. The only factor that varied between these conditions was the number of unique syllable types used to construct the auditory sequences. All generated auditory sequences were devoid of specific semantic meaning.

In the experiment, all test materials were balanced for repetition structures and chunking across three dimensions—level/oblique tones (Pingze), specific tones, and syllables—to eliminate the potential influence of these factors on classification judgments. Repetition structure refers to whether any element within a sequence is identical to a preceding element in that same sequence [**?**, **?**]. For instance, if a learning sequence (e.g., "BBGXTR") and a test sequence (e.g., "WWSNPZ") share the same repetition structure (e.g., 112345), this similarity might bias grammaticality judgments. To account for this, the test materials in this experiment were designed so that they shared no identical repetition structures with the learning materials across the dimensions of level/oblique tones, specific tones, or syllables.

Furthermore, to exclude the influence of chunking, we balanced the Mean Feature Frequency (MFF), Global Associative Chunk Strength (GACS), and Anchor Associative Chunk Strength (AACS) between grammatical and ungrammatical test sequences across all three dimensions [TABLE:A1]. Mean Feature Frequency is defined as the average frequency with which each individual element in a test sequence appeared in the learning materials. Global Associative Chunk Strength refers to the average frequency with which the bigram and trigram chunks of a test sequence appeared anywhere in the learning materials. Finally, Anchor Associative Chunk Strength refers to the average frequency with which the bigram and trigram chunks located at the beginning and end of a test sequence appeared at the corresponding beginning and end positions of the learning sequences [?, ?].

The experiment consisted of two phases: learning and testing (see [Figure 2: see original paper]). During the learning phase, 48 auditory sequences were repeated three times, resulting in a total of 144 presentations. The sequences were presented in a randomized order within each repetition. Each sequence was preceded by a 500ms prompt tone. To establish a perceptual pause, a 600ms time interval was inserted between the fifth and sixth tones of each sequence. While the auditory sequences were playing, participants were instructed to listen carefully and perform silent rehearsal. Following the playback of each sequence, a fixation cross ("+") was displayed for 5000ms, during which participants were required to perform a complete oral recall of the sequence they had just heard. The entire learning phase···

The stage lasts approximately 30 minutes.

Following the learning phase, participants were informed that the sound sequences they had previously heard all followed a specific underlying rule, and they were asked whether they had noticed any such patterns. During the testing phase, participants were presented with 48 new sound sequences. They were informed that half of these sequences (24) followed the same rule as the learning phase, while the other half (24) did not. Participants were then required to perform a classification task for each sequence.

After each judgment, participants provided a confidence rating ranging from 50% to 100%. In this scale, 50% indicated that the judgment was a complete guess, 100% indicated absolute certainty (i.e., the participant believed they had identified the rule), and values between 50% and 100% represented varying degrees of confidence. Subsequently, participants were asked to categorize the basis of their judgment by selecting one of four options: "Guess," "Intuition," "Memory," or "Rule." According to the criteria established by Dienes and Scott (2005), "Guess" indicated that the judgment was entirely random and lacked any basis, similar to a coin toss. "Intuition" signified a degree of confidence based on a feeling of whether the sequence conformed to a rule, though the participant could not articulate a specific reason. "Memory" indicated that the judgment was based on whether the current sequence felt familiar or remembered from the learning phase. "Rule" indicated that the judgment was based on a specific, identified rule that the participant believed to be correct and could clearly articulate.

Furthermore, upon completion of the entire test, participants were asked to report whether they had noticed any rules and to describe any patterns they perceived. In accordance with established methodological standards (Chan & Leung, 2018; Ling et al., 2022; Reber, 1967; Rebuschat, 2013; Zou & Luo, 2024), any participants who were able to accurately describe the global rule or specific partial rules were excluded from the final analysis.

结果

According to the structural knowledge measurement method (Dienes & Scott, 2005), “guess” and “intuition” serve as indicators of unconscious structural knowledge (implicit structural knowledge), while “rule” and “memory” serve as indicators of conscious structural knowledge (explicit structural knowledge). In this experiment, participants selected explicit structural knowledge in only a small minority of test trials.

Specifically, before the formal testing began, the definitions of the four types of judgment criteria were explained to the participants one by one, with specific illustrations related to the current experiment. To ensure that participants truly understood the relevant concepts, they were required to paraphrase the meanings of the four criteria after the explanation; any misunderstandings identified during this paraphrase were further clarified. Subsequently, participants completed two practice test trials to confirm they could correctly distinguish and apply the four types of judgment criteria. This procedure has been widely utilized and validated in previous research (e.g., Jurchiș et al., 2020; Norman et al., 2019).

In the test trials, explicit structural knowledge was selected in only a small fraction of cases (0.03 ± 0.06), indicating that participants primarily relied on implicit structural knowledge when making classification judgments. Therefore, this study focuses its analysis on classification performance under conditions of implicit structural knowledge (see).

To accurately evaluate participant performance across different conditions, this study analyzed classification accuracy, the discriminability index d', and the response criterion β. According to Signal Detection Theory (SDT), the discriminability index d' provides a more accurate reflection of a participant’ s ability to distinguish between rule-consistent and rule-violating sound strings—effectively measuring the learning effect of the rules. In contrast, the response criterion β reflects a participant’ s strategic bias toward responding “consistent” or “inconsistent” under different conditions, rather than their actual discriminative ability (Macmillan & Creelman, 2005; Stanislaw & Todorov, 1999). In this study, the natural logarithm of the criterion, $\ln(\beta)$, was used as the analytical index. This measure more closely approximates a normal distribution in its statistical properties, with 0 representing a neutral, unbiased decision point (Stanislaw & Todorov, 1999; Fort & Shulman, 2024).

During data processing, when hit rates or false alarm rates reach extreme values (a hit rate of 1 or 0, or a false alarm rate of 0), the corresponding z-scores approach infinity. To address this, the present study adopted a correction method from previous literature: adding 0.5 to each frequency count and then dividing by $N + 1$, where N represents the total number of signals or noise trials in that condition (Snodgrass & Corwin, 1988).

$\ln(\beta)$

$\ln(\beta)$

$\ln(\beta)$

0.54 $\pm$ 0.05

0.22 $\pm$ 0.26

-0.01 $\pm$ 0.12

0.51 $\pm$ 0.05

0.02 $\pm$ 0.26

0.01 $\pm$ 0.18

0.54 $\pm$ 0.06

0.21 $\pm$ 0.30

0.02 $\pm$ 0.12

Classification Accuracy

Accuracy rates in both the low-variability condition ($t(29) = 4.39, p < 0.001, d = 0.80$) and the high-variability condition ($t(30) = 4.11, p < 0.001, d = 0.74$) were significantly higher than the chance level (0.5). In contrast, accuracy in the medium-variability condition did not differ significantly from chance ($t(29) = 0.63, p = 0.534, d = 0.11$). These results indicate that participants successfully acquired the Ping-Ze mapping rules under low- and high-variability conditions but failed to do so under the medium-variability condition. A subsequent one-way analysis of variance (ANOVA) revealed significant differences in accuracy across the three conditions ($F(2, 88) = 4.73, p = 0.011, \eta_p^2 = 0.10$). Specifically, accuracy in the low-variability ($p = 0.011$) and high-variability ($p = 0.008$) conditions was significantly higher than in the medium-variability condition, while no significant difference was found between the low- and high-variability conditions ($p = 0.922$; see [Figure 3: see original paper]).

Classification accuracy of participants across the three variability conditions

(*, $p < 0.05$; **, $p < 0.01$; error bars represent the standard error of the mean)

Discrimination Index and Decision Criterion

In the low- and high-variability conditions, participants' discrimination indices (d') were significantly higher than the chance level (low variability: $t(29) = 4.56, p < 0.001, d = 0.83$; high variability: $t(30) = 3.83, p = 0.001, d = 0.69$). However, the d' in the medium-variability condition did not differ significantly from chance ($t(29) = 0.33, p = 0.744, d = 0.06$). These findings suggest that participants could effectively distinguish between rule-consistent and rule-violating strings in the low- and high-variability conditions, but failed to demonstrate significant discrimination ability in the medium-variability condition. One-way ANOVAs conducted on both indices revealed that the discrimination index d'

differed significantly across conditions ($F(2,88) = 5.11, p = 0.008, \eta_p^2 = 0.10$), with d' in the low-variability ($p = 0.006$) and high-variability

($p = 0.007$) conditions being significantly higher than in the medium-variability condition. There was no significant difference in d' between the low- and high-variability conditions ($p = 0.930$).

The decision criterion $\ln(\beta)$ showed no significant differences across conditions ($F(2,88) = 0.31, p = 0.737, \eta_p^2 = 0.01$), indicating that participants' response biases were consistent across all experimental groups.

Furthermore, to comprehensively examine the impact of different variability conditions on learning outcomes, this study conducted supplementary analyses on all test trials, including those where participants selected implicit structural knowledge and those where they selected explicit structural knowledge. Three indicators—classification accuracy, discrimination index d', and decision criterion β—were calculated based on all test trials. The results showed that the patterns of change for these three indicators across experimental conditions were consistent with the performance observed in implicit trials. This further confirms that participants' judgments in the classification task primarily relied on implicit knowledge (relevant results have been made public in the Science Data Bank, DOI: 10.57760/sciencedb.psych.00831).

讨论

Experiment 1

Experiment 1 established three levels of variation—low, medium, and high—to systematically investigate the impact of exemplar variability on the implicit learning of long-distance rules involving multiple mappings.

1.1 Experimental Design

The experiment employed a single-factor within-subjects design, with the independent variable being the level of exemplar variability (low, medium, and high). The dependent variables were the reaction times and accuracy rates of the participants during the learning and testing phases. By manipulating the diversity of the training exemplars, we aimed to determine whether increased variability facilitates or hinders the abstraction of underlying structural regularities in a complex mapping environment.

1.2 Participants

A total of [NUMBER] university students were recruited for this study. All participants had normal or corrected-to-normal vision and were naive to the purpose of the experiment. Prior to the start of the session, informed consent was obtained from each participant.

1.3 Materials and Procedure

The stimuli consisted of sequences governed by specific long-distance rules. In the low-variability condition, the number of unique exemplars following the rule was restricted, whereas the medium and high conditions introduced progressively more diverse sets of sequences.

The procedure was divided into a learning phase and a testing phase:

1. **Learning Phase:** Participants performed a serial reaction time task (SRTT) where they were required to respond to the position of stimuli on a screen. Unbeknownst to them, the sequences followed a predetermined multi-mapping long-distance rule.
2. **Testing Phase:** To assess implicit learning, participants were exposed to both "old" sequences (following the learned rule) and "new" sequences (violating the rule). A significant difference in performance between these sequence types served as an index of implicit rule acquisition.

[Figure 1: see original paper]

1.4 Data Analysis

Data were analyzed using repeated-measures ANOVA to compare the learning effects across the three variability conditions. We specifically looked for an interaction between the variability level and the sequence type in the testing phase. Post-hoc comparisons were conducted where necessary to clarify the direction of the effects.

The results are expected to clarify how the cognitive system balances the need for consistency (low variability) with the need for generalization (high variability) when extracting long-distance dependencies in implicit learning contexts.

mode of action. The results revealed that participants exhibited significant implicit learning effects under both low-variability and high-variability conditions, with no significant differences observed between these two groups. However, performance in both the low and high-variability conditions was significantly superior to that in the medium-variability condition, where no learning effect was observed. Further analysis using Signal Detection Theory (SDT) indicated that these differences primarily reflected variations in the participants' actual discriminative ability rather than differences in strategic bias. These findings suggest that the relationship between exemplar variability and multiple⋯

The remapping of long-distance rules in implicit learning exhibits a U-shaped curve relationship. These findings suggest that in instructional design or the construction of learning materials, both high consistency and high diversity may facilitate the implicit acquisition of rules, whereas a moderate degree of exemplar variation may actually hinder learning.

It is noteworthy that Experiment 1 was conducted based on previous research [**?**], utilizing "complete mapping" materials during both the learning and testing phases. These materials encompassed all possible mapping relationships between level tones (Tone 1/Tone 2) and oblique tones (Tone 3/Tone 4). Under this experimental design, it is difficult to determine whether high or low variability allows for the transfer of knowledge—acquired from specific learning exemplars—to a broader category of materials. Consequently, it remains unclear whether the facilitative effect of exemplar variability occurs at the abstract level of variable-to-variable mapping.

To address this, Experiment 2a further distinguished between "complete mapping" and "partial mapping" materials. Partial mapping includes only a subset of the correspondences between level and oblique tones (for example, mapping Tone 1 exclusively to Tone 3). By providing participants with specific subsets during the learning phase, this design aims to clarify the extent of rule abstraction.

Present local mapping materials and establish a transfer test where participants must rely on variable-variable mapping relationships to successfully complete classification judgments (including full mapping tests). This approach aims to investigate whether the facilitative effect of exemplar variability can generalize to the abstract level of variable-variable relationships.

3 实验 2a：样例变异性对多重映射远距离规则内隐学习迁移的影响

Experiment 2a utilized sound sequences containing only local mappings (e.g., Tone 1 mapping only to Tone 3, Tone 2 mapping only to Tone 4, and vice versa) as learning materials. The testing phase consisted of two types of tasks: (1) a non-transfer test, which employed the same specific local tone mappings used during the learning phase; and (2) a transfer test, which utilized complete mapping materials encompassing all possible *Ping-Ze* (level-oblique) mapping relationships. In this transfer test, participants must rely on implicitly acquired underlying *Ping-Ze* mapping rules to complete the classification task and demonstrate a transfer effect. The objective of this experiment was to investigate whether participants, after learning specific mappings between particular tones (pitch values), can transfer and generalize this knowledge to a more abstract level of *Ping-Ze* mapping. This aims to clarify whether the facilitative effect of exemplar variability on acquisition can extend beyond the level of specific value-to-value mappings.

方法

The sample size determination method was identical to that used in Experiment 1. A total of 102 college students were recruited and randomly assigned to one of three conditions: low variability, medium variability, or high variability. Data from 9 participants were excluded from the final statistical analysis: 2 participants (high variability condition) were excluded for failing to complete the experimental tasks as required (e.g., inability to repeat sound sequences, lack of concentration); an additional 7 participants (3 in the low variability condition, 3 in the medium variability condition, and 1 in the high variability condition) were excluded because they reported consciously searching for rules during the experiment, 6 of whom (2 in low variability, 3 in medium variability, and 1 in high variability) successfully identified partial rules. The final analysis included 93 valid participants: 31 in the low variability condition (24 females, 19.77 ± 1.45 years old), 31 in the medium variability condition (27 females, 19.77 ± 1.18 years old), and 31 in the high variability condition (28 females, 20.42 ± 1.84 years old). The gender distribution was balanced across conditions ($p = 0.441$). All participants had normal hearing and normal or corrected-to-normal vision. They participated voluntarily, signed informed consent forms before the experiment, and received compensation upon completion.

The experiment employed a 3×2 mixed design, with exemplar variability (low, medium, and high) as the between-subjects variable and test type (non-transfer test and transfer test) as the within-subjects variable.

The dependent variables were the accuracy of classification judgments, the sensitivity index d', and the response criterion β during the testing phase.

Consistent with Experiment 1, the experimental materials consisted of nonsense sound sequences with a length of 10. The difference in Experiment 2a was that the learning phase materials only contained local mappings of specific tones. Specifically, while the first five sounds and the last five sounds still maintained a mapping relationship based on the *Ping-Ze* (level-oblique) dimension, the tonal dimension only included correspondences between Tone 1 and Tone 3, and between Tone 2 and Tone 4 (see [Figure 4: see original paper] for examples). For instance, if a *Ping* (level) tone in the first five sounds was Tone 1, then the *Ze* (oblique) tone at the corresponding position in the last five sounds would be Tone 3, and vice versa (i.e., Tone 3 mapping to Tone 1). During the testing phase, the non-transfer test utilized local mappings of specific tones identical to those in the learning phase, whereas the transfer test included all *Ping-Ze* mapping relationships (i.e., encompassing all possible

mappings between *Ping* tones (Tone 1/Tone 2) and *Ze* tones (Tone 3/Tone 4)). Furthermore, to control for the effects of specific tonal local mappings, another version of the learning materials was created, featuring correspondences between Tone 1 and Tone 4, and Tone 2 and Tone 3, and vice versa. These two versions of learning materials were counterbalanced across participants.

Examples of the two types of test sound sequences, using the high variability condition as an illustration.

A represents the non-transfer test (i.e., local mapping, using the Tone 1–Tone 3 and Tone 2–Tone 4 correspondences as examples); B represents an example of the transfer test (i.e., full mapping).

As in Experiment 1, exemplar variability was manipulated through the variety of syllables, which were unrelated to the underlying *Ping-Ze* rules. The low variability condition consisted of a single syllable, "you" (combined with the four tones: *you1*, *you2*, *you3*, *you4*). The medium variability condition consisted of 4 syllables (2 *Ping* syllables: *ju1*, *hui2*; 2 *Ze* syllables: *guo3*, *you4*). The high variability condition consisted of 20 syllables, including 10 *Ping* syllables (Tone 1: *ju1*, *shen1*, *hui1*, *chao1*, *can1*; Tone 2: *di2*, *ping2*, *qin2*, *fo2*, *lai2*) and 10 *Ze* syllables (Tone 3: *guo3*, *zhan3*, *er3*, *mai3*, *ye3*; Tone 4: *tu4*, *jun4*, *wei4*, *zou4*, *kan4*). The sounds and the method of sequence generation in Experiment 2 were identical to those in Experiment 1. In Experiment 2, the grammatical and ungrammatical test sequences were also balanced for repetitive structures and chunks across the three dimensions of *Ping-Ze*, tone, and syllable (see Appendix, [TABLE:A2]) to eliminate the potential influence of this information on classification judgments.

As in Experiment 1, the experiment consisted of a learning phase and a testing phase. However, in this experiment, a 500ms blank interval was added following the 500ms

cue tone before each learning sequence was presented, providing participants with more preparation time. During the testing phase, participants performed the non-transfer test (local mapping) and the transfer test (full mapping) sequentially, with the order of the tests counterbalanced across participants.

结果

Consistent with Experiment 1, an analysis of the participants' selection ratios for structural knowledge revealed that they chose explicit structural knowledge in only a small minority of the test strings.

Specifically, the selection ratios were 0.11 ± 0.15 for non-transfer tests and 0.10 ± 0.14 for transfer tests. These results indicate that participants primarily relied on implicit structural knowledge when making classification judgments. Consequently, the present experiment focuses its analysis on classification performance under the condition of implicit structural knowledge (see).

$\ln(\beta)$

$\ln(\beta)$

$\ln(\beta)$

0.53 $\pm$ 0.06

0.16 $\pm$ 0.32

-0.02 $\pm$ 0.14

0.55 $\pm$ 0.09

0.25 $\pm$ 0.46

-0.03 $\pm$ 0.18

0.53 $\pm$ 0.06

0.13 ± 0.30

-0.01 ± 0.11

0.53 ± 0.07

0.19 ± 0.39

-0.03 ± 0.18

0.48 ± 0.08

-0.10 ± 0.39

-0.01 ± 0.09

0.54 ± 0.07

0.19 ± 0.34

0.03 ± 0.10

Classification Accuracy

In the non-transfer test, participants' accuracy was significantly higher than chance across all three variability conditions (low variability: $t(30) = 3.04, p = 0.005, d = 0.55$; medium variability: $t(30) = 2.93, p = 0.006, d = 0.53$; high variability: $t(30) = 2.42, p = 0.022, d = 0.43$). In the transfer test, accuracy was significantly above chance in the low variability ($t(30) = 2.63, p = 0.013, d = 0.47$) and high variability ($t(30) = 2.91, p = 0.007, d = 0.52$) conditions, whereas performance in the medium variability condition did not differ significantly from chance ($t(30) = -1.46, p = 0.155, d = -0.26$;

see [Figure 5: see original paper]).

A 3 (exemplar variability: low, medium, high) × 2 (test type: non-transfer, transfer) repeated-measures ANOVA revealed that the main effects of exemplar variability ($F(2, 90) = 1.54, p = 0.221, \eta_p^2 = 0.03$) and test type ($F(1, 90) = 2.79, p = 0.098, \eta_p^2 = 0.03$) were not significant. However, the interaction between exemplar variability and test type was significant ($F(2, 90) = 4.93, p = 0.009, \eta_p^2 = 0.10$). Simple effects

analysis of this interaction revealed that in the non-transfer test, there were no significant differences in performance among the three variability conditions (low vs. medium: $p = 0.403$; low vs. high: $p = 0.690$; medium vs. high: $p = 0.218$). In contrast, during the transfer test, performance in the medium variability condition was significantly lower than in both the low variability ($p = 0.004$) and high variability ($p = 0.003$) conditions, while no significant difference was found between the low and high variability conditions ($p = 0.977$). These results indicate that participants achieved comparable learning outcomes across all three variability conditions in the non-transfer test; however, in the transfer test, participants exhibited transfer effects only in the low and high variability conditions, failing to transfer in the medium variability condition.

(*, $p < 0.05$; **, $p < 0.01$; error bars represent the standard error of the mean)

Discrimination Index and Response Criterion

In the non-transfer test, the discrimination index d' was significantly higher than chance across all three variability conditions (low variability: $t(30) = 2.71, p = 0.011, d = 0.49$; medium variability: $t(30) = 3.09, p = 0.004, d = 0.55$; high variability: $t(30) = 2.48, p = 0.019, d = 0.44$). In the transfer test, d' was significantly above chance in the low variability ($t(30) = 2.76, p = 0.010, d = 0.50$) and high variability ($t(30) = 3.08, p = 0.004, d = 0.55$) conditions, but did not differ significantly from chance in the medium variability condition ($t(30) = -1.43, p = 0.164, d = -0.26$). These results suggest that in the non-transfer test, participants could effectively distinguish between rule-consistent and rule-violating strings across all conditions. In the transfer test, however, significant discrimination was only observed in the low and high variability conditions. A 3 (exemplar variability: low, medium, high) × 2 (test type: non-transfer, transfer) repeated-measures ANOVA on d' showed that the main effects of exemplar variability ($F(2, 90) = 1.46, p = 0.237, \eta_p^2 = 0.03$) and test type ($F(1, 90) = 2.28, p = 0.135, \eta_p^2 = 0.03$) were not significant, while the interaction between exemplar variability and test type was significant ($F(2, 90) = 5.28, p = 0.007, \eta_p^2 = 0.11$). Simple effects

analysis of the interaction showed that in the non-transfer test, there were no significant differences in d' among the three variability conditions (low vs. medium: $p = 0.297$; low vs. high: $p = 0.791$; medium vs. high: $p = 0.192$). In the transfer test, d' in the medium variability condition was significantly lower than in the low variability ($p = 0.003$) and high variability ($p = 0.003$) conditions, with no significant difference between the latter two ($p = 0.937$). Regarding the response criterion $\ln(\beta)$, neither the main effect of exemplar variability ($F(2, 90) = 1.73, p = 0.182, \eta_p^2 = 0.04$) nor test type ($F(1, 90) = 0.44, p = 0.508, \eta_p^2 = 0.01$) was significant. The interaction between exemplar variability and test type was also non-significant ($F(2, 90) = 0.30, p = 0.741, \eta_p^2 = 0.01$), indicating that response bias remained consistent across all conditions.

Consistent with Experiment 1, supplementary analyses were conducted based on all test trials, calculating classification accuracy, the discrimination index d', and the response criterion β

to more comprehensively examine the impact of different variability conditions on learning outcomes. The results revealed that the patterns of these three indicators

across conditions were highly consistent with the performance observed in implicit trials (relevant data have been made available in the Science Data Bank, DOI: 10.57760/sciencedb.psych.00831).

讨论

Experiment 2a utilized local mapping as the learning material and established both a non-transfer test (the same local mapping used in the learning phase) and a transfer test (a more abstract full mapping). This design aimed to further investigate how exemplar variability facilitates the implicit learning of long-distance rules in multiple mappings.

The results indicated that in the non-transfer test, participants in all three variability conditions exhibited significant implicit learning effects, with no significant differences observed between groups. However, in the more abstract transfer test, participants in the low-variability and high-variability conditions demonstrated transfer effects, whereas those in the medium-variability condition did not. Signal detection theory analysis further revealed that these differences primarily stemmed from variations in the participants' actual discriminative ability rather than differences in strategic bias.

The aforementioned results suggest that while participants across all three variability conditions implicitly acquired specific tone-to-tone (value-to-value) mappings, only those in the low- and high-variability conditions were able to transfer and generalize this knowledge to the more abstract level of *Ping-Ze* (tonal category) mapping. This suggests that exemplar variability may not influence the implicit acquisition of simpler rules based on specific tone-to-tone correspondences (i.e., value-to-value mappings), but it does impact the implicit acquisition of deeper, more abstract rules (i.e., variable-to-variable mappings).

It should be noted that although the transfer test in this experiment employed a more abstract full mapping, it still contained some of the local mappings encountered during the learning phase. Specifically, if the local mapping in the learning phase consisted of correspondences between Tone 1 and Tone 3, and Tone 2 and Tone 4, the full mapping in the test phase included all possible combinations—Tone 1 and Tone 3, Tone 2 and Tone 4, Tone 2 and Tone 3, and Tone 1 and Tone 4—resulting in partial mapping overlap. Consequently, Experiment 2b will employ a more rigorous experimental design using full transfer test materials that have no overlap with the local mappings from the learning phase. Under these strictly controlled conditions, participants must rely entirely on the acquired underlying variable-to-variable mapping (*Ping-Ze* mapping) to complete the grammatical classification task and demonstrate transfer effects. This approach allows for a more rigorous investigation into whether exemplar variability truly facilitates the implicit learning of underlying rules at the variable-to-variable level.

4 实验 2b：样例变异性对多重映射远距离规则内隐学习完全迁移的影响

Experiment 2b builds upon the foundation of Experiment 2a by implementing a more rigorous full-transfer test. Specifically, the learning phase of Experiment 2b is identical to that of Experiment 2a, presenting only specific local mapping relationships (e.g., the correspondence between Tone 1 and Tone 3, and between

Tone 2 and Tone 4). However, the testing phase utilizes tone correspondence combinations that were entirely absent during the learning phase (e.g., the correspondence between Tone 1 and Tone 4, and between Tone 2 and Tone 3).

The objective of this experiment is to investigate whether participants can transcend specific tone correspondences when faced with novel value-to-value mappings that conflict with those encountered during the learning phase. By examining whether participants can transfer acquired general rules—namely, abstract relationships at the variable-to-variable level—to entirely novel tone correspondences, this study aims to rigorously determine whether the facilitative effect of exemplar variability on implicit learning can reach the level of abstract variable-to-variable representations.

方法

The sample size selection was identical to that of Experiment 1. A total of 95 college students were recruited and randomly assigned to one of three conditions: low variability, medium variability, or high variability.

Among the participants, seven were excluded because they reported consciously searching for rules during the experiment (one in the low variability condition, three in the medium variability condition, and three in the high variability condition); notably, the three excluded participants in the medium variability condition also reported some of the specific rules. Consequently, 88 participants were included in the final analysis: 30 in the low variability condition (21 females, 19.63 ± 0.85 years old), 29 in the medium variability condition (25 females, 19.97 ± 1.97 years old), and 29 in the high variability condition (24 females, 19.93 ± 1.89 years old). The gender distribution was balanced across all conditions ($p = 0.265$). All participants had normal hearing and normal or corrected-to-normal vision. They participated voluntarily, signed informed consent forms before the experiment, and received financial compensation upon completion.

The experiment employed a single-factor between-subjects design. The independent variable was exemplar variability (low, medium, and high), while the dependent variables were the accuracy of classification judgments, the sensitivity index d', and the response bias β during the testing phase.

The experimental materials were consistent with those used in Experiment 2a. The sole difference was that Experiment 2b utilized a local mapping correspondence during the learning phase (e.g., mappings between Tone 1 and Tone 3, and Tone 2 and Tone 4, and vice versa), whereas a different local mapping correspondence was used during the testing phase (e.g., mappings between Tone 1 and Tone 4, and Tone 2 and Tone 3, and vice versa). That is, although the materials in both the learning and testing phases conformed to the overarching Ping-Ze mapping rules, the specific tonal mapping relationships encountered in the testing phase had not appeared during the learning phase (see [Figure 6: see original paper] for an example). The two types of correspondence relationships in the local mapping materials were counterbalanced between subjects. To exclude the potential influence of surface features on classification judgments, the grammatical and ungrammatical strings in the test phase were balanced for repetitive structures and chunks across three dimensions: Ping-Ze, tone, and syllable (see Appendix, [TABLE:A3]).

Examples of sound strings for the learning phase (tonal mapping: 1-3, 2-4, 3-1, 4-2) and the testing phase (tonal mapping: 1-4, 2-3, 4-1, 3-2), using the high variability condition as an example.

Identical to Experiment 2a.

结果

Following the same procedure as Experiment 1, an analysis of the participants' selection ratios for structural knowledge revealed that they chose explicit structural knowledge in only a small minority of the test strings.

Specifically, the selection ratio for explicit knowledge was 0.03 ± 0.06, indicating that participants primarily relied on unconscious structural knowledge when making classification judgments. Consequently, the analysis focused on classification performance based on implicit structural knowledge (see Table 3).

The classification performance under these conditions is summarized in Table 3 .

$\ln(\beta)$

$\ln(\beta)$

$\ln(\beta)$

0.53 $\pm$ 0.05

0.15 $\pm$ 0.26

-0.01 $\pm$ 0.08

0.51 $\pm$ 0.05

0.05 $\pm$ 0.26

-0.03 $\pm$ 0.10

0.52 $\pm$ 0.04

0.12 $\pm$ 0.22

0.02 $\pm$ 0.09

Classification Accuracy

Participants' accuracy was significantly higher than chance levels in both the low-variability condition ($t(29) = 3.10, p = 0.004, d = 0.57$) and the high-variability condition ($t(28) = 2.85, p = 0.008, d = 0.53$).

In contrast, accuracy in the medium-variability condition did not differ significantly from chance ($t(28) = 0.99, p = 0.330, d = 0.18$). These results indicate that under conditions of complete transfer, participants were able to acquire the underlying abstract rules in the low- and high-variability conditions, but failed to do so in the medium-variability condition.

Classification accuracy of participants across the three variability conditions.

(*, $p < 0.05$; **, $p < 0.01$; error bars represent the standard error of the mean.)

Discrimination Index and Response Bias

In the low- and high-variability conditions, participants' discrimination index (d') was significantly higher than chance (low variability: $t(29) = 3.22, p = 0.003, d = 0.59$; high variability: $t(28) = 3.03, p = 0.005, d = 0.56$). However, there was no significant difference from chance in the medium-variability condition ($t(28) = 1.01, p = 0.323, d = 0.19$). This suggests that participants could effectively distinguish between rule-consistent and rule-violating strings in the low- and high-variability conditions, but showed no significant discriminative ability in the medium-variability condition. A one-way ANOVA revealed no significant differences in d' across the three variability conditions ($F(2, 85) = 1.34, p = 0.268, \eta_p^2 = 0.03$). Similarly, the response bias $\ln(\beta)$ showed no significant differences across the three conditions ($F(2, 85) = 2.02, p = 0.138, \eta_p^2 = 0.05$), indicating that participants' response biases were similar across all conditions.

Consistent with Experiment 1, we further calculated three indicators—classification accuracy, discrimination index d', and response bias β—based on all test trials. These supplementary analyses were conducted to more comprehensively examine the impact of different variability conditions on learning outcomes.

The results showed that the patterns of these three indicators across experimental conditions were consistent with the performance observed in the implicit trials (relevant results have been made public in the Science Data Bank, DOI: 10.57760/sciencedb.psych.00831).

讨论

Experiment 2b utilized a complete transfer test (employing entirely different local mapping correspondences between the learning and test phases) to further clarify the underlying mechanisms of learning.

Specifically, the experiment investigated whether the facilitative effect of exemplar variability on the implicit learning of multi-mapping distant rules occurs at a more abstract rule level. The results indicated that participants in both the low-variability and high-variability conditions continued to demonstrate significant learning effects and discriminative ability during the complete transfer test. In contrast, participants in the medium-variability condition failed to show either a transfer effect or significant discriminative ability. Furthermore, no significant differences in response bias were observed across the various conditions.

These findings suggest that participants are capable of implicitly acquiring underlying abstract rules. Moreover, exemplar variability primarily influences the acquisition of abstract rules at the variable-variable level, enabling learners to transcend specific value-value correspondences and achieve rule transfer.

5 总讨论

This study investigates the impact of exemplar variability on the implicit learning of multiple-mapping long-distance rules and its underlying mechanisms by manipulating three levels of exemplar variability (low, medium, and high) and employing a transfer test. The primary objective was to determine whether exemplar variability facilitates the implicit acquisition of abstract rules. Whether learners can master the abstract level of rules is crucial for language acquisition. The results indicate a U-shaped relationship between exemplar variability and performance in the implicit learning of multiple-mapping long-distance rules. Furthermore, exemplar variability specifically influences the implicit acquisition of abstract rules at the variable-variable level, rather than simple mappings between specific values.

Further analysis of discrimination indices and decision criteria revealed that performance differences across variability conditions were primarily reflected in the participants' actual ability to discriminate between rule-consistent and rule-violating strings, rather than adjustments in their decision criteria. This suggests that exemplar variability does not alter the participants' decision bias but instead genuinely affects their degree of implicit mastery over the abstract structure. These findings not only reveal the mechanisms underlying the implicit learning of multiple-mapping long-distance grammatical rules but also provide significant insights for designing learning materials that facilitate transfer in educational practice.

Experiment 1

Building upon previous research, Experiment 1 introduced a low-variability condition to more comprehensively examine the relationship between exemplar variability and the implicit learning of multiple-mapping long-distance rules. The results showed that participants in both the low-variability and high-variability conditions exhibited significant implicit learning effects, whereas no learning effect was observed in the medium-variability condition. The discovery of this U-shaped effect addresses the limitations of prior studies, which focused only on medium and high variability conditions, and provides a more complete characterization of the relationship between exemplar variability and the implicit learning of multiple-mapping long-distance rules.

The underlying mechanism behind this U-shaped effect may be related to the automatic allocation of attentional resources. Specifically, learners tend to spontaneously focus on stable and regular structural information within their environment [?, ?, ?]. Even in the absence of explicit task instructions, a learner' s attention is naturally drawn to information characterized by statistical regularities or structured features [?, ?, ?]. Furthermore, a substantial body of behavioral and neuroimaging research suggests that the occurrence of implicit learning requires the support of certain attentional resources [?, ?, ?, ?, ?]. Consequently, when participants are required to simultaneously perform tasks that consume these attentional resources···

Implicit learning performance (e.g., statistical learning) significantly declines when attention is diverted (Toro et al., 2005). In the present study, the level/oblique (ping-ze) tonal dimension carries the rule-based information, while the syllabic dimension serves as a source of rule-irrelevant variation. According to the theory of attentional resource competition, systematic differences may exist in the patterns of attention allocation across different levels of variation.

Under low-variation conditions, the syllables remain constant and lack change, thereby consuming fewer processing resources. Consequently, the variations in the tonal dimension naturally become the most informative cues in the input, automatically attracting more attentional resources and facilitating the implicit acquisition of rules. Conversely, under high-variation conditions, the syllabic changes are substantial and lack a stable structure. According to the theoretical perspective of Raviv et al. (2022), high-variation input can signal to the learning system that features with high degrees of change may not be critical and can thus be ignored or abstracted. In this context, features that remain relatively stable across instances are likely to contain core information; these features are assigned greater weight and automatically attract more attentional resources.

Under these conditions, the syllable dimensions associated with such uncertainty are easily identified and suppressed automatically. This process enables individuals to extract tone mappings that remain stable across different exemplars.

mapping relationships, thereby forming more abstract rule representations. In contrast, under the medium variability condition where syllable changes are relatively minor, the syllable dimension is neither a completely stable background nor variable enough to be entirely ignored. This automatically triggers an allocation of attention to that dimension, leading to an ineffective occupation of attentional resources and creating attentional competition with the tone dimension. Such competition weakens the weight assigned to the rule-relevant dimension, making it difficult for individuals to consistently focus limited processing resources on the tonal relationships that carry the rules, which in turn hinders the acquisition of abstract rules. In summary, the observed U-shaped learning effect may reflect the differential allocation of attentional resources across various dimensions of information under different levels of variability: low and high variability conditions facilitate learning through "background stability highlighting rules" and "background chaos promoting abstraction," respectively, whereas medium variability hinders learning due to attentional competition.

It is noteworthy that previous research on implicit learning of long-distance rules with multiple mappings has confirmed that participants can implicitly extract underlying abstract rules of *Ping-Ze* (level-oblique) correspondence. Furthermore, they demonstrate generalization capabilities based on these abstract rules in transfer tests, such as transferring to different tone correspondences [?, ?] and materials of varying lengths [?, ?]. This raises a critical question: does the U-shaped effect of exemplar variability on the implicit learning of long-distance rules occur at the abstract level of variable-to-variable mapping?

To address this question, Experiment 2 of the present study designed two types of testing tasks. The first is a transfer test, where grammatical judgments must rely on the underlying *Ping-Ze* correspondence rules (variable-to-variable mapping). The second is a non-transfer test, where grammatical judgments can be made based on specific tone-to-tone correspondences (value-to-value mapping).

The experimental results provide direct evidence for this inquiry. In the transfer test, participants in the low-variability and high-variability conditions were able to transfer to more abstract, complete mapping rules after acquiring local mapping rules (Experiment 2a). Even when faced with new value-to-value mapping rules that conflicted with the learning phase, these two groups still exhibited transfer learning (Experiment 2b). In contrast, participants in the medium-variability condition showed no learning effect in the transfer tasks.

These results suggest that low and high variability conditions facilitate the implicit acquisition of the underlying abstract rules of *Ping-Ze* correspondence. Under the medium-variability condition, however, interference from syllable-dimension variability prevents learners from effectively focusing on the tonal dimension that contains the rule information. This makes it difficult for participants to extract underlying rules at the variable-to-variable level, leading them to acquire only value-to-value mappings, which in turn causes a decline in transfer performance.

In the non-transfer tests, participants across the low, medium, and high variability conditions exhibited similar implicit learning effects, with no significant differences in learning outcomes between conditions. In this specific test, the learning and testing phases utilized the same local tone mapping rules (i.e., the correspondence between Tones 1 and 3, and Tones 2 and 4). Even if participants in the medium-variability condition struggled to extract variable-to-variable level mappings···

the underlying rules, they can still make judgments based on the value-to-value correspondences encountered during the learning phase, thereby demonstrating implicit learning effects. Taken together, the U-shaped curve effect of exemplar variability on the implicit learning of long-distance rules with multiple mappings is primarily manifested at the variable-to-variable mapping level, rather than the value-to-value mapping level.

In this study, the manipulation of exemplar variability was applied to dimensions unrelated to the underlying rules (such as syllabic elements). This design avoids direct interference with the rules themselves; instead, it guides learners to focus on stable underlying structures by increasing the diversity of surface-level information. This approach provides a feasible framework for future practical teaching or training, suggesting that irrelevant features can be flexibly adjusted to optimize rule acquisition.

Furthermore, exemplar variability can exist not only in dimensions unrelated to the rules but also in rule-relevant dimensions (i.e., the diversity of exemplar features associated with the underlying rules). Whether these two types of variability differ in their ability to facilitate implicit learning, and which pattern of exemplar variability most effectively optimizes the implicit acquisition of rules, remains a significant question for future research.

Further research is required to explore this matter in greater depth.

6 结论

This study systematically investigated the influence of exemplar variability on the implicit learning of long-distance rules with multiple mappings through two experiments, further clarifying the level at which this facilitation effect occurs. The results reveal a U-shaped relationship between exemplar variability and the implicit learning effect of multiple-mapping long-distance rules. Specifically, under conditions of low and high variability, learners more easily implicitly acquired abstract rules at the variable-variable level and demonstrated transferable effects. Conversely, under the medium variability condition, the learning effect was weaker, with learners only acquiring value-to-value mappings, making knowledge transfer difficult to achieve.

The findings of this study have significant theoretical and practical implications. Theoretically, this study is the first to provide a complete characterization of how exemplar variability influences the implicit learning of multiple-mapping long-distance rules, clarifying that this effect operates at the level of abstract variable-variable representations rather than concrete value-value mappings. The abstractness of implicitly acquired knowledge has long been a core theoretical issue in the field of implicit learning; while numerous previous studies have demonstrated that learners can implicitly acquire underlying abstract rules (e.g., Jimenez et al., 2020; Ling et al., 2018; Scott & Dienes, 2010), our results reveal that the implicit acquisition of abstract rules does not occur unconditionally. Instead, specific boundary conditions exist. From the perspective of exemplar variability, the acquisition of abstract rules at the variable-variable level is only facilitated under low or high variability conditions, providing an important theoretical supplement to our understanding of the mechanisms underlying abstraction in implicit learning.

From a practical standpoint, the research results offer direct guidance for instructional design. When designing learning materials, educators should avoid moderate levels of exemplar variability. Instead, they should employ either low or high variability presentation formats to maximize the promotion of learners' mastery and the transfer of abstract rules. This discovery provides a scientific basis for optimizing teaching strategies and improving learning efficiency.

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Effect of Example Variability on the Implicit Learning of Multiple Non-Adjacent Rule LING Xiaoli1,2, ZHANG Qingyun3,4, Zheng Li5,6, GUO Xiuyan5,6, SUN Peng7 (1 School of Psychology, Shandong Normal University, Jinan 250358, China) (2 Shandong Provincial Key Laboratory of Brain Science and Mental Health, Jinan 250358, China) (3 School of Business and Management, Shanghai International Studies University, Shanghai 201620, China) (4 Shanghai Key Laboratory of Brain-Machine Intelligence for Information Behavior, Shanghai 201620, China) (5 Fudan Institute on Ageing, Fudan University, Shanghai 200433, China) (6 Ministry of education (MOE) Laboratory for National Development and Intelligent Governance, Shanghai 201620, China) (7 Mental Health Education and Research Center, Shandong University of Finance and Economics, Jinan 250014, China)

Abstract

Learning multiple non-adjacent dependencies is fundamental to processing the hierarchical structures of natural language and constitutes one of the most challenging aspects of language acquisition. Such dependencies are typically acquired automatically and implicitly; however, how to effectively facilitate their learning remains unresolved. A particularly powerful factor in improving learning and generalization is variability in the input examples. However, its role in the implicit learning of multiple non-adjacent dependencies remains unclear, particularly whether such variability enables learners to move beyond value–value mappings to operations over variables, thereby acquiring transferable abstract rules. Accordingly, this study first examines how different levels of example variability influence implicit learning performance (Experiment 1) and then explores whether the effect of variability operates at the level of abstract variable-variable mappings (Experiment 2).

The study employed multiple non-adjacent rules defined over the tones with which Chinese syllables were spoken. Specifically, the tone types (ping or ze) of the first five syllables predicted those of the final five by an inversion relation in strings of length ten. In Experiment 1, three conditions of variability (low, medium, and high) were established by manipulating the number of syllable

types used in the strings. The experiment comprised a training phase and a test phase. During the training phase, participants listened to a series of tone-syllable strings that followed the multiple non-adjacent rules and repeated them. In the test phase, participants were told that all strings they heard during the training phase followed a grammatical rule, and were asked to judge whether a set of new strings conformed to the learned rule. In Experiment 2, to further examine the level at which variability facilitates learning, two types of materials were constructed. One included only partial tone mappings (e.g., Tone 1–3 or Tone 2–4), while the other included complete tone mappings between level tones (Tones 1/2) and contour tones (Tones 3/4). Unlike in Experiment 1, during the training phase of Experiment 2, participants were exposed only to strings containing partial mappings. They were then tested in a non-transfer test (strings with the same partial mappings as in training), and either a mixed transfer test (strings with complete mappings; Experiment 2a) or a novel transfer test (strings with novel partial mappings that conflicted with training; Experiment 2b).

The results revealed a U-shaped relationship between example variability and implicit learning performance in Experiment 1: participants showed significant implicit learning effects in both the low- and

high-variability conditions, whereas no learning effect was observed in the medium-variability condition.

Performance was greater in the low- and high-variability conditions than in the medium-variability condition.

In Experiment 2, the participants demonstrated implicit learning in the non-transfer test (Experiment 2a) across all variability conditions. However, their ability to transfer this learning to new materials varied significantly by condition. Participants in the low- and high-variability conditions were able to implicitly extract abstract rules from partial mappings and generalize them to complete mappings (Experiment 2a).

Remarkably, this transfer ability was maintained even when participants were confronted with novel partial mappings that directly contradicted the training material (Experiment 2b). In contrast, participants in the medium-variability condition failed to transfer their knowledge to new materials in either transfer tests. This indicates that both low and high variability facilitated the implicit learning of transferable abstract rules (variable–variable mapping level), whereas participants in the medium-variability condition implicitly learned only surface-level value–value mappings.

Taken together, this study provides a comprehensive account of how example variability influences the implicit learning of multiple non-adjacent dependencies. It reveals a nonlinear relationship between example variability and implicit learning and identifies that this effect operates primarily at the level of abstract variable–variable mappings. From the perspective of example variability, the findings further indicate that the implicit acquisition of abstract rules is constrained by specific boundary conditions. The findings not only deepen the understanding of the mechanisms underlying implicit learning, but also provide theoretical implications for optimizing instructional design.

Keywords

relationship

variability, implicit learning, multiple non-adjacent dependencies, transfer, U-shaped

附录

In Experiment 1, the chunking strength ($M \pm SD$) for grammatical and ungrammatical sequences across different dimensions (Ping-Ze, tone, and syllable) is presented as follows:

720.00 ± 0.00

720.00 ± 0.00

360.78 ± 2.21

360.20 ± 2.16

71.58 ± 2.48

71.95 ± 1.95

224.75 ± 0.00

224.75 ± 6.90

48.91 ± 1.98

48.70 ± 2.36

1.67 ± 0.62

1.72 ± 0.67

18.00 ± 0.00

18.00 ± 0.00

4.91 ± 1.78

4.72 ± 1.67

0.19 ± 0.40

0.19 ± 0.33

Note: In the low-variability condition, only the dimensions of Ping-Ze (level and oblique tones) and lexical tone are present; in the medium-variability condition, lexical tone and syllable are treated as a single dimension. MFF, GACS, and

AACS represent Mean Feature Frequency, Global Associative Chunk Strength, and Anchored Associative Chunk Strength, respectively.

In Experiment 2a, the chunk strength ($M \pm SD$) for legal and illegal strings across different dimensions (Ping-Ze, lexical tone, and syllable) is as follows:

720.00 ± 0.00

720.00 ± 0.00

360.00 ± 0.00

360.00 ± 0.00

72.00 ± 0.00

72.00 ± 0.00

224.75 ± 0.00

224.75 ± 11.49

51.51 ± 6.91

51.89 ± 5.53

1.68 ± 0.46

1.69 ± 0.58

18.00 ± 0.00

18.00 ± 0.00

4.97 ± 1.29

4.91 ± 2.11

0.19 ± 0.40

0.16 ± 0.31

720.00 ± 0.00

720.00 ± 0.00

360.00 ± 0.00

360.00 ± 0.00

72.00 ± 0.00

72.00 ± 0.00

224.75 ± 0.00

224.75 ± 11.49

53.04 ± 3.80

52.88 ± 5.60

1.57 ± 0.49

1.61 ± 0.50

18.00 ± 0.00

18.00 ± 0.00

4.72 ± 1.72

4.47 ± 1.54

0.19 ± 0.33

0.22 ± 0.41

Note: In the low-variation condition, only two dimensions are present: Ping-Ze (level and oblique tones) and lexical tone. In the medium-variation condition, lexical tone and syllable are treated as a single dimension. For the local mapping test, Version 1 is used as an example (where lexical tones are mapped as follows: Tone 1 to Tone 3, Tone 2 to Tone 4, Tone 3 to Tone 1, and Tone 4 to Tone 2).

MFF, GACS, and AACS represent Mean Feature Frequency, Global Associative Chunk Strength, and Anchored Associative Chunk Strength, respectively.

In Experiment 2b, the chunk strength ($M \pm SD$) for grammatical and ungrammatical strings across different dimensions (Ping-Ze, tone, and syllable) is as follows:

720.00 ± 0.00

720.00 ± 0.00

360.00 ± 0.00

360.00 ± 0.00

72.00 ± 0.00

72.00 ± 0.00

224.75 ± 0.00

224.75 ± 11.49

50.17 ± 5.65

50.49 ± 5.67

1.77 ± 0.66

1.68 ± 0.60

18.00$±$0.00

18.00$±$0.00

5.03 ± 1.69

4.63 ± 1.65

0.28 ± 0.43

0.28 ± 0.49

Note: In the low-variability condition, only two dimensions are present: level-oblique (ping-ze) patterns and tones. In the medium-variability condition, tones and syllables are treated as a single dimension. Taking Version 1 as an example: during the learning phase, the tonal mapping consists of transitions between Tones 1 and 3, and between Tones 2 and 4 (and vice versa); during the testing phase, the tonal mapping shifts to transitions between Tones 1 and 4, and between Tones 2 and 3 (and vice versa).

MFF, GACS, and AACS represent Mean Feature Frequency, Global Associative Chunk Strength, and Anchored Associative Chunk Strength, respectively.

Note: Figure translations are in progress. See original paper for figures.