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The Effects of Verbalizable Features on Category Learning Strategies

Marwan A. Syed
Western University, msyed56@uwo.ca

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Department of Psychology

Western University

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Thesis Advisor: John Paul Minda, Ph.D.

Abstract

The present study investigated the effects of how verbalizable features (easy vs not-easily) are on category learning strategies with respect to the COVIS model, which states there are two competing systems (verbal and implicit) that operate simultaneously when making categorization decisions. A total of 102 undergraduate students took part in the experiment, which was an A-B categorization task conducted in a video game setting. A rule-based approach reflected the verbal system whereas a family resemblance approach reflected the implicit system. The findings partially support the hypothesis and COVIS model in that participants in the easily verbalizable condition were more likely to use a rule-based approach, but no clear evidence was found to support the notion that participants would be more likely to use a family resemblance approach if the features were difficult to verbalize.

The Effects of Verbalizable Features on Category Learning Strategies

Category learning is a fundamental aspect of cognition. Literature has shown that category learning in humans is evident in infants as young as six months old (Grossman, Teodora, Johnson, & Mareschal, 2009) and it is a skill people continue to hone throughout life since they are constantly updating and modifying categories (Minda, Desroches, & Church, 2008). As such, cognitive scientists developed a keen interest in category learning and the factors that influence such a dynamic element of cognition. Although previous research has already explored the effects of some of these factors, such as affect (Isen & Daubman, 1984) and ego depletion (Minda & Rabi, 2015), one factor that is of growing interest, and the focal point of the present study, is the influence of language on category learning. The influence of language on category learning has piqued the interested of many researchers since it is exclusive to humans (Couchman, Coutinho, & Smith, 2010), however, the increasing interest can be better attributed to the increasing body of literature highlighting its effects on category learning.

First, the limitations of past theories of category learning will be addressed and a more appropriate model will be presented. Subsequently, the influences of language on category learning, specifically verbalizable features, will be thoroughly discussed. Finally, the current gap in literature will be addressed through the description of the present study.

Category Learning Theories

The vast majority of early theories of categorization assumed that a single category learning system was used for all categorization problems. For instance, the prototype theory (Reed, 1972) posited that category learning operated via averaging all members of a category into a single prototype to which novel stimuli would be compared to. Although this theory still has practical applications, for example teaching English to Chinese post-secondary students

(Gao, 2018), these theories are limited in that they assume a single category learning system is used for categorization problems that vary significantly in difficulty.

In contrast, the Competition Between Verbal and Implicit Systems (COVIS) theory proposed by Ashby, Alfonso-Reese, Turken, and Waldron (1998) suggests that categorization functions by the means of two systems that run in parallel to provide the most accurate answer. The verbal system, also referred to as the explicit system, is active on a conscious level and operates by generating and testing rule-based hypotheses about category membership based on verbalizable features. On the other hand, the implicit system is based on procedural learning and functions beyond conscious awareness. It is effective when categorizing items with features that are not-easily verbalizable or when rule-based strategies are ineffective. Due to the verbal system’s explicit nature, it is typically the dominant system during category learning. However, when complex rules define category membership in which linear rules cannot be generated, the implicit system is better suited for categorization problems (Ashby & Maddox, 2011).

The findings of a landmark study by Ashby, Queller, and Berretty (1999) in which they sought to explore the effects of non-unidimensional rules in supervised categorization tasks supports the COVIS model of categorization. In the first part of the experiment, participants categorized stimuli that varied in either length or orientation, reflecting the unidimensional rule, or both, reflecting the non-unidimensional rule, without supervision. Participants in the unidimensional rule were able to use their verbal system since both length and orientation were easily verbalizable features from which rules could be formed and had an average accuracy of 91.7%. In contrast, the participants in the non-unidimensional group, who were not able to generate an effective rule based on verbalizable features had an average accuracy of 65.3%. From this Ashby et al. (1999) were able to infer that there is a verbal system which operates independently of the implicit system when rules can be derived from verbalizable features. In the second part of the experiment participants repeated the same task but were given feedback based on their response. The performance of the participants in the unidimensional group did not differ significantly compared to the first part of the study. However, the performance increased drastically for participants in the non-unidimensional condition to 93.3%, which was the highest of all conditions in both tasks. These findings imply that an independent implicit system exists which operates during complex categorization tasks, since the presence of feedback in the non-unidimensional group promoted procedural learning.

Moreover, the COVIS model also suggests that despite the two systems working simultaneously, a strong bias exists towards the verbal system. This notion is supported by a study exploring the role of family resemblance (FR) during categorization (Medin, Wattenmaker, & Hampson, 1987). Using a classic A-B categorization task in which participants were shown cartoon figures which varied in two dimensions on four levels, they found that most participants opted for a rule-based categorization strategy, reflecting the verbal system. In their seven-part study, four of which are relevant to the present paper, nearly all participants chose a rule-based strategy even when utilizing a unidimensional rule was not always accurate, highlighting the bias towards the verbal route of the COVIS model.

Influence of Language

As the underpinnings of category learning and the COVIS model was better understood, focus shifted towards factors affecting category learning, namely language. As mentioned earlier, language has been studied quite extensively due to its significant impact on category learning. This is evident in a study by Lupyan, Rakison, and McClelland (2007) who examined the effect of nonsense labels on category learning. Taking place in a video game setting, participants were put in one of two conditions and instructed to categorize fictitious aliens as ones to be approached or avoided by making responses on a gamepad controller. Participants in the label condition were presented with a non-sense label, for instance ‘leebish’ or ‘grecious’, after each response was made, whereas participants in the control group did not receive a verbal label after making a response. Lupyan et al. (2007) found that during the training phase participants in the label condition achieved 80% accuracy after 30 trials, in contrast the control group took 72 trials. The results from the test phase indicated that performance in the label condition was significantly better than the control, and that these effects remained even after the labels were removed in following trials, demonstrating that even non-sense verbal labels assist with category learning.

Keeping the influence of language on category learning in mind, the effects of language can also be explored with respect to the COVIS model of categorization. A two-part study by Maddox, Glass, O’Brien, Filoteo, and Ashby (2010) investigated the effects of category label and response location shifts on category learning through the lens of COVIS. In the first experiment, 111 participants randomly assigned to either the response switch condition or the control categorized lines based on length and orientation into four groups in which a rule-based approach, reflecting the verbal system of COVIS, would be the optimal strategy. Maddox et al. (2010) found that breaking the association between the stimuli and category label in comparison to the association between the stimuli and the response location created the largest amount of interference in learning. These results imply that when categorizing using the verbal system the category label, reflecting language, plays an essential role in learning categories. In the second part of the experiment, Maddox et al. (2010) tasked 105 participants with completing the same task with the only difference being that using an information-integration approach, reflecting the implicit system, which relies more on procedural learning would be the optimal strategy. Their findings pointed towards a second independent system which was also most impacted when the association between the category label and stimuli was broken, providing further support for COVIS and outlining the effects of language on categorization.

Furthermore, the effects of language, more specifically the ease of naming features, on category learning was explored by Zettersten and Lupyan (2018). In experiments 1 and 2, the duo randomly assigned participants to either the high nameability condition or low nameability condition and instructed them to categorize colour wheels, each with three different colours, into two categories based on similarity. Zettersten and Lupyan (2018) found that participants in the high nameability condition, in which the colours were easier to name, who adopted a rule-based approach learned categories substantially better than those in the low nameability condition. Experiments 3 and 4 investigated whether this effect was exclusive to the nameability of colours, so the duo repeated a similar paradigm involving polygons varying in easy of nameability. Participants were assigned to either the high nameability condition or low nameability condition and tasked with categorizing polygons into two groups. Similar to the colour wheels, Zettersten and Lupyan (2018) found that when the polygons were easier to name and describe categories were learned significantly better. Hence, the findings of Zettersten and Lupyan's (2018) seven-part study support the notion that the ease with which one can name features influences category learning since performance was significantly better in the high nameability condition in which the colours and polygons, respectively, were easy to name.

Brashears and Minda (2018) conducted a two-part study, the former investigating the effects of verbalizable features on category learning and the latter focusing on the effects of direct vs indirect feedback on category learning. Participants completed a categorization task in a video game setting in which they categorized 'monsters' based on five binary features that were either easily verbalizable or not. Participants were put in one of two groups, the first being the easily verbalizable condition in which the optimal strategy would be a rule-based approach reflecting the verbal system and the second being the not-easily verbalizable condition in which procedural learning, or the implicit system, would be the best strategy. As predicted, Brashears and Minda (2018) found that participants who were in the verbalizable condition adopted a rule-based strategy to categorize stimuli whereas participants in the not-easily verbalizable showed no preference for either approach.

Present Study

Although present literature supports the dual system COVIS model (Ashby et al., 1998), highlights the bias towards the verbal system, and illustrates the influence of language on category learning, there is a glaring gap in existing knowledge when it comes to looking at the influence of verbalizable features on category learning exclusively through the lens of the COVIS theory.

Brashear and Minda (2018) first attempted to address this gap and found promising results. Thus, the present study is a direct replication of experiment one from Brashear and Minda's (2018) original study with the central purpose of determining whether the effects of verbalizable features on category learning can be reproduced. It is hypothesized that the findings will mirror Brashear and Minda's (2018) study such that participants who are presented with features that are easily verbalizable will engage in a rule-based approach, representing the verbal system, and individuals in the not-easily verbalizable condition will favour the FR approach. The rationale for this is that individuals will be able to generate and test hypotheses derived from easily verbalizable features with relative ease, whereas individuals will likely rely more on the implicit system and procedural learning when features are not as easy to verbalize.

Methods

Participants

Participants were 102 undergraduate students (35 males and 67 females) ranging in age from 17 to 50 years attending Western University. Participants were recruited from an introductory psychology class via the SONA system, a participation pool provided through the Department of Psychology at Western University, and were compensated with course credit for their participation. Participants had normal or corrected-to-normal vision with no deficits in red-green colour perception. They read the letter of information (Appendix B) and provided written consent (Appendix C) prior to the experimental procedures approved by the Western University Non-Medical Research Ethics Board.

Materials

Stimuli Design and Norming Study

The stimuli used in this study were two sets of digitally created images of fictitious monsters composed of binary features that varied on five dimensions. The first stimulus set (see Appendix D) was comprised of features that were easily verbalizable, such as: two versus four spots, two versus three eyes, orange versus teal ears, square versus triangular tail shape, or red versus green coloured spines. The second stimulus (see Appendix E) set consisted of five binary features as well but were more difficult to describe in comparison to the first set, such as: uneven stripes versus uniform polka dots, thin and vertical versus wide and horizontal eyes, pointed versus flaccid ears, sharp versus rounded noses, and bumpy versus broad spines.

A norming study was conducted to determine if the novel stimulus sets truly differed in terms of their ability to be described in which one would be easy to describe whereas the other would be more difficult. The norming study was split into two phases to verify whether feature descriptors generated from one group of individuals could be used by another group to identify the correct feature within a feature pair. For the first phase, 63 participants recruited through the SONA system at Western University participated in a Qualtrics study. The participants were tasked with describing the individual features of the monsters in a text box after being shown one of four stimulus prototypes in addition to describing each feature being presented separately. For each feature, the list was narrowed down to the two most common descriptors which were then used in the second phase of the norming study.

The second phase of the norming study entailed 30 individuals who also participated in a Qualtrics Study, using Amazon's Mechanical Turk. The participants were shown feature pairs as well as the two most common descriptors and asked which descriptor best fit which feature. A paired samples t-test was then conducted to compare the accuracy between the responses from phase two to the results from phase one. Participants' accuracy in phase two of the norming study were significantly higher for easily verbalizable items (*M* = 0.95, *SD* = 0.09) than for not-easily verbalizable items (*M* = 0.63, *SD* = 0.14), suggesting that the descriptors were more distinct from one another and that participants were better able to distinguish feature pairs from descriptors that were easily verbalizable. Thus, it can be concluded that there was an objective difference between the two stimulus sets in their ability to be verbalized based on their feature.

Table 1

Training Stimulus

Category A	1	2	3	4	5	Category B	1	2	3	4	5
A1	0	0	0	0	0	B1	0	0	0	0	0
A2	0	1	0	0	0	B2	0	1	0	0	0
A3	0	0	1	0	0	B3	0	0	1	0	0
A4	0	0	0	1	0	B4	0	0	0	1	0
A5	0	0	0	0	1	B5	0	0	0	0	1

The binary notation used for the training stimulus sets shown in Table 1 were procured from the original Minda and Ross (2004) study. The two category sets, reflecting the two conditions, created for the training phase were comprised of five items each including the category prototype and four stimuli with single feature variations. One feature was randomly selected and remained unchanged for all stimuli in the category set. This design allowed for category learning to be accomplished through a FR approach, reflecting the verbal system, or through a criterial attribute (CA) approach in which a singular feature could be used to predict category membership, reflecting the implicit system.

Table 2

Testing Stimulus

	1	2	3	4	5		1	2	3	4	5		1	2	3	4	5
Training Items						Exception Items						Single Feature Items					
TA1	0	0	0	0	0	T1	1	0	0	0	0	T11	0	X	X	X	X
TA2	0	1	0	0	0	T2	1	1	0	0	0	T12	X	0	X	X	X
TA3	0	0	1	0	0	T3	1	0	1	0	0	T13	X	X	0	X	X
TA4	0	0	0	1	0	T4	1	0	0	1	0	T14	X	X	X	0	X
TA5	0	0	0	0	1	T5	1	0	0	0	1	T15	X	X	X	X	0
TB1	1	1	1	1	1	T6	0	1	1	1	1	T16	1	X	X	X	X
TB2	1	0	1	1	1	T7	0	0	1	1	1	T17	X	1	X	X	X
TB3	1	1	0	1	1	T8	0	1	0	1	1	T18	X	X	1	X	X
TB4	1	1	1	0	1	T9	0	1	1	0	1	T19	X	X	X	1	X
TB5	1	1	1	1	0	T10	0	1	1	1	0	T20	X	X	X	X	1

Test stimuli shown in Table 2 were also created to be used in the present study. The test stimuli were composed of three subsets containing 10 items each. The first subset of 10 items (TA1-5 and TB1-5) were the training stimuli presented again to evaluate the participant’s accuracy. The second subset of 10 items (T1-10), referred to as exception items, were taken directly from Minda and Ross (2004) and could be members of either Category A or Category B depending on the participant’s categorization strategy. The last subset of 10 items (T11-20) consisted of each individual feature being shown in isolation and was used to assess the participant’s attention towards features that defined category membership with respect to the category prototype.

Procedure

The experiment was conducted using a video game developed in GameMaker Studio 2 on a laptop. Participants were randomly assigned to one of the two stimulus sets, easily verbalizable or not-easily verbalizable, and the CA feature was also randomized. They were then introduced to the game “Monster Farm” in which they would take on the role of a farmer tasked with sorting the monsters residing on the farm into the correct group using the appropriate collar. The instructions presented on the screen informed the participant that the farmer could be controlled using the arrow keys and collars could be selected by pressing either the A or B key. Participants made their responses on a computer via a keyboard which was recorded by the program and saved to a plain text file. The instructions also informed the participant that certain attributes of the monsters may help with categorization.

In the training phase, participants received feedback based on their response. If the participant correctly sorted the monster a check mark would be displayed above the monster’s head until the next trial began, whereas an incorrect response would result in a cross mark. The training phase would last for at least four blocks (60 trials) and would end after the participant completed at least 60 trials and categorized 12 monsters in a row correctly. If participants were unable to meet the criteria within 200 trials or 30 minutes, the researcher would end the experiment and the participant’s data would be excluded from analyses.

Participants who successfully reached the criteria in the training phase would move onto the testing phase. In the testing phase, participants were tasked with categorizing all of the training, testing, and exception stimuli from Table 2, for a total of 30 trials, presented in randomized order without receiving any feedback

Results

Learning Rate Analysis

The first analysis explored the number of trials it took participants to reach the criteria in each condition in order to advance to the testing phase. As mentioned earlier, this required participants to make 12 correct categorization decisions consecutively after a minimum of 60 trials. A Welch's Two Sample t-test was conducted to determine whether the mean number of trials to reach the criterion for the two groups were equal. It was found that there was no significant difference between the learning rate for the two groups $t(96.59) = -1.33$, $p = .188$. The mean number of trials for the easily verbalizable condition ($M = 82.60$, $SD = 44.53$) and the not-easily verbalizable condition ($M = 95.56$, $SD = 52.68$) can be seen in Figure 1.

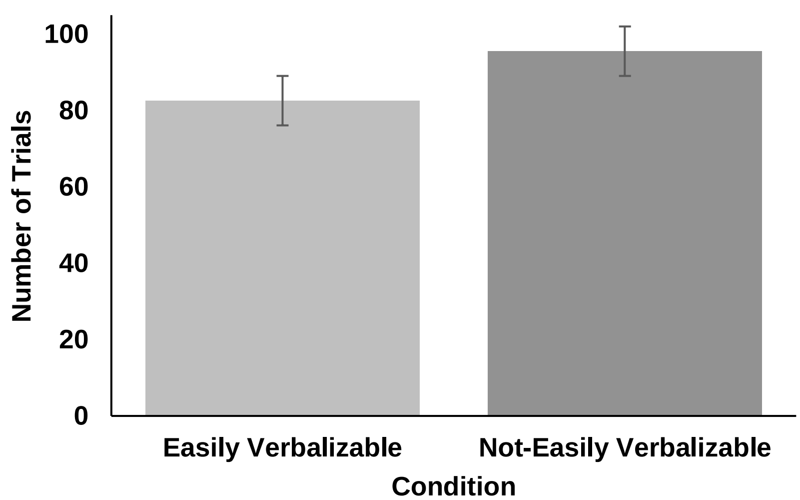

Figure 1. Mean number of trials to reach criterion by condition. Error bars represent standard deviation.

Accuracy Analysis

The second analysis examined the participant's accuracy for the ten training items presented during the testing phase, which were presented in random order in addition to the other 20 items. A Welch's Two Sample t-test found that there was no significant difference between the two groups in terms of accuracy for the training stimulus, $t(87.54) = -1.16$, $p = .250$. The mean accuracy for the easily verbalizable condition ($M = 0.84$, $SD = 0.21$) and the not-easily verbalizable condition ($M = 0.89$, $SD = 0.16$) can be seen in Figure 2.

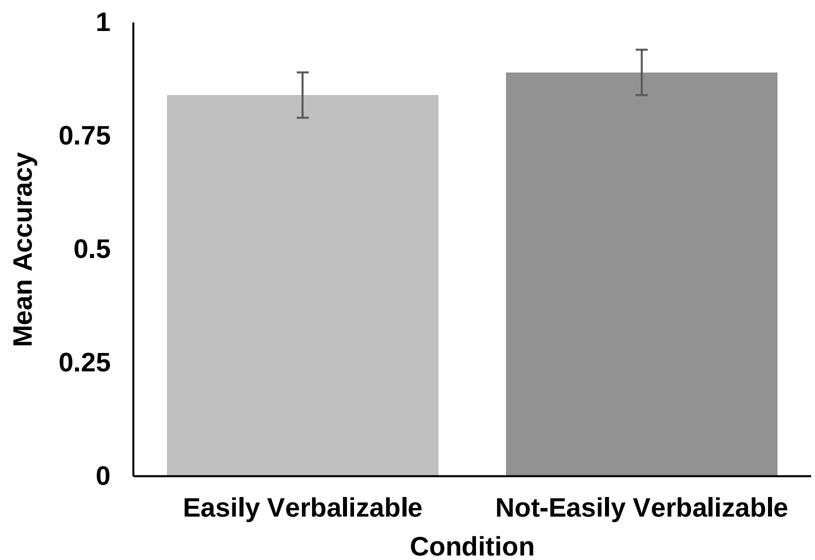

Figure 2. Mean accuracy by condition. Error bars represent standard deviation.

Categorization Strategy Modelling Analysis

The third and final analysis aimed to determine the categorization strategies participants employed when categorizing the exception items during the experiment. The exception items, presented in random order along with the other 20 items during the test phase, were designed to gauge the categorization strategy based on the participants' responses since participants who used the CA to make their decision and participants who used FR to categorize the stimuli would categorize the stimuli in the opposite categories.

The participants' responses were then compared to the predicted results of 12 model responses and assigned a score of either 0 or 1 based on whether the response matched the model or not. These 12 models included responses based exclusively on a CA approach, FR approach, selecting either A or B for all 10 exception items, using a rule-based strategy for a feature other than the CA, and FR approach with a rule-based exception for a feature which was not the CA. The sum of the scores were divided by the 10, the number of exceptions items, and assigned a score ranging from 0 to 1, with 1 reflecting a perfect fit with the respective model.

Microsoft Excel was used to calculate the model fit scores for each participant and presented as a heat map as seen in Figure 3. The A and B models were based on all A or all B responses for the respective models. Using a feature other than the CA is represented by the other rule (OR) models. The exception rule (ER) models were based on rule-based exceptions for features that were not the CA but using a FR strategy otherwise. The model fit scores were colour coded using R with, green reflecting a perfect score of 1, yellow reflecting a score of 0.5, red reflecting a score of 0, and intermediate colours for scores between the assigned values.

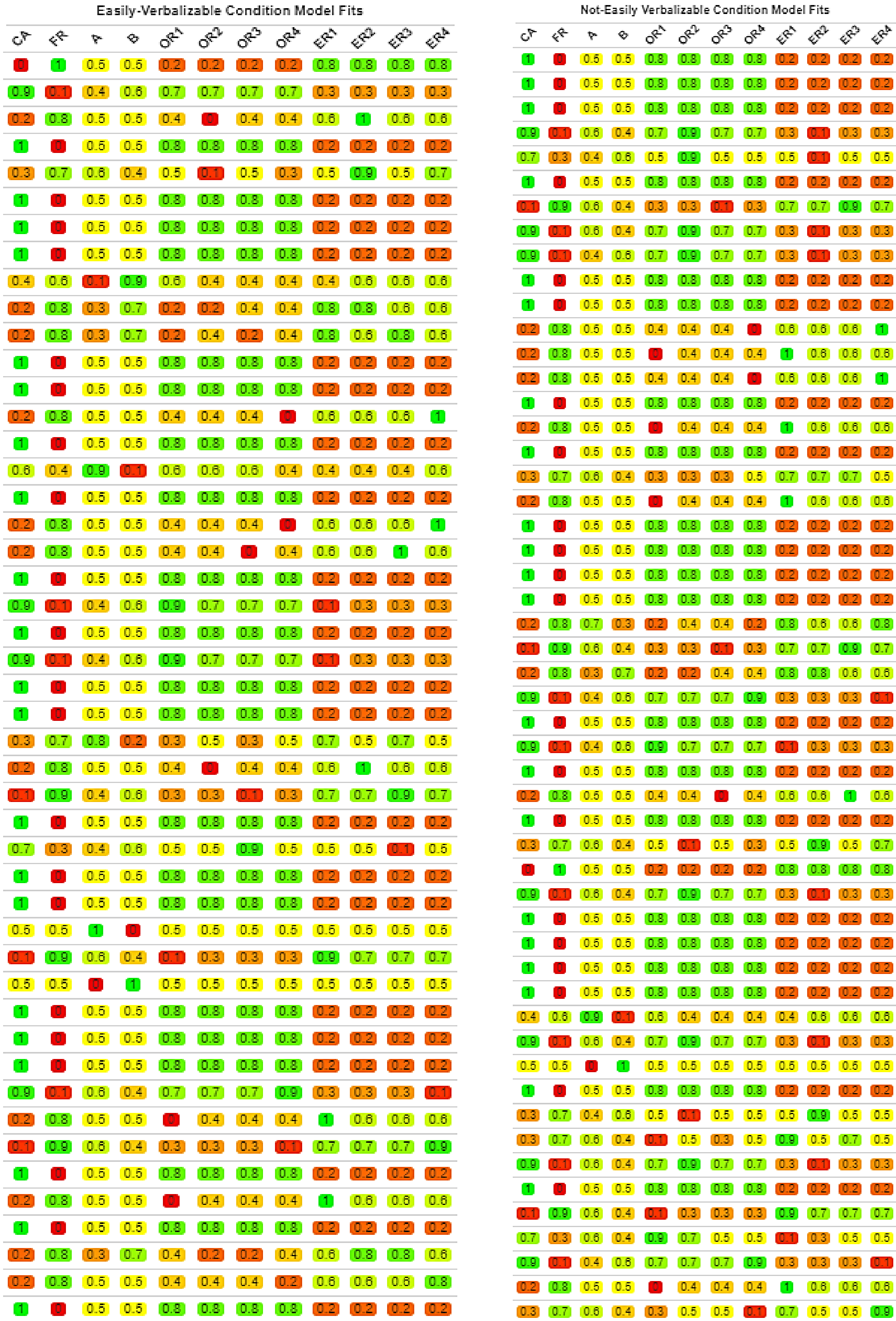

Figure 3. Heat map analysis of model fits.

Subsequently, a mixed 2x2 ANOVA was conducted in which the model type was a within-subject independent variable, condition was a between-subject independent variable, and model fit was the dependent variable. It was found that there was no significant main effect for condition, $F(1,97) < .01$, $p > .99$ nor was there a significant interaction effect, $F(1,97) = .12$, $p = .729$. However, the ANOVA analysis revealed that there was a significant main effect for the model type such that the CA model ($M = 0.66$, $SD = 0.38$) was a better fit in comparison to the FR model ($M = 0.34$, $SD = 0.37$), irrespective of the condition, $F(1, 97) = 18.08$, $p < .001$.

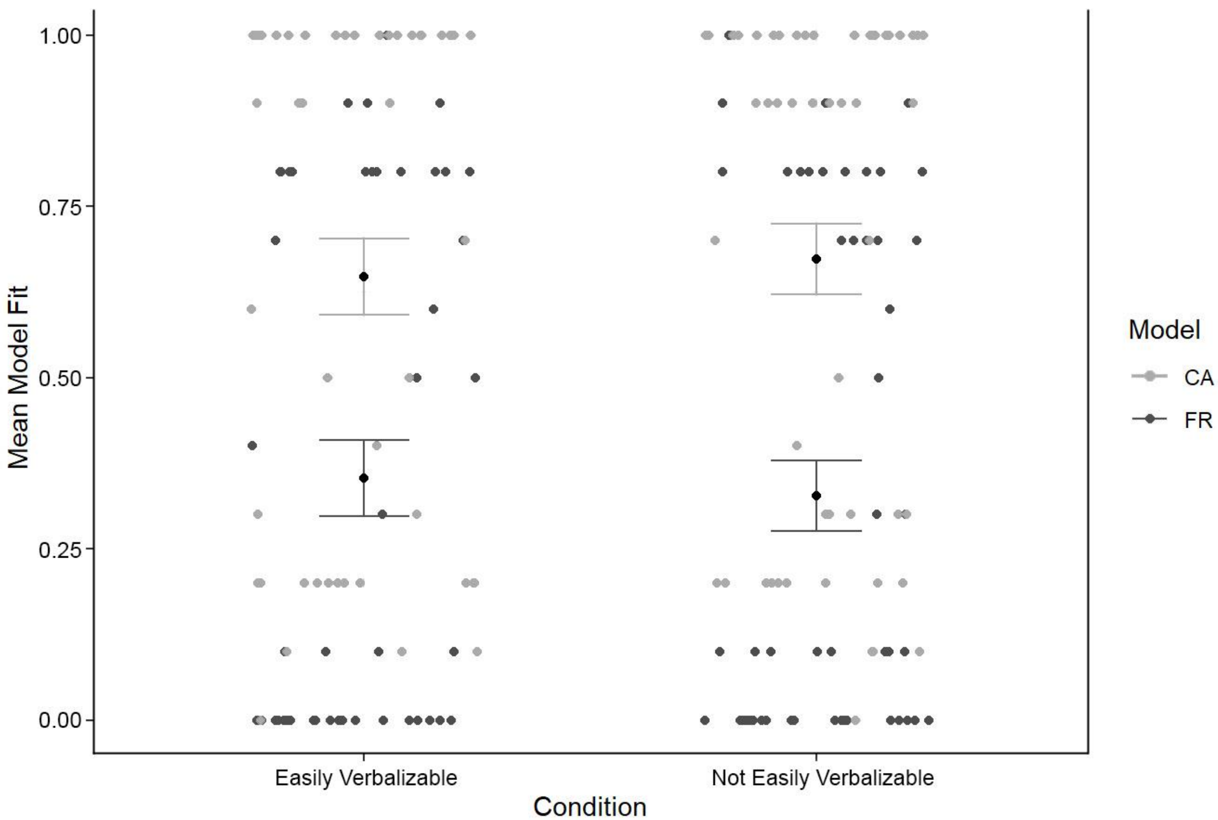

Figure 4. Mean model fit by condition. Error bars represent standard deviation.

Discussion

The purpose of the present study was to replicate experiment one from Brashear and Minda (2018) and investigate if how verbalizable features are influences the categorization strategy used for a novel stimulus set in a video game environment. It was hypothesized that those in the easily verbalizable condition would take a rule-based approach, representing the verbal system, whereas individuals in the not-easily verbalizable are more likely to take a family resemblance approach. The findings of the present study are consistent with existing literature to an extent since it only partially supported the hypothesis.

Through the modelling analysis it was found that participants in the easily verbalizable condition were more likely to use a CA approach. However, individuals in the not-easily verbalizable approach also opted for a rule-based strategy in lieu of a FR approach, which does not support the hypothesis. Moreover, the learning rate and accuracy analyses found that there was no significant difference in the learning rates for the two stimulus sets or and the two groups did not differ significantly regarding accuracy either. This suggests that both the easily verbalizable stimuli and not-easily verbalizable stimuli were equally as easy to learn and retain in this experiment.

Implications

The findings from the current study, specifically pertaining to the modelling analysis, supports the COVIS model first proposed by Ashby et al. (1998). The participants' responses in this study compared to the predicted results of the 12 model responses imply that both a verbal, rule-based approach and implicit, family resemblance approach, were used to categorize the stimuli in this experiment, providing support for the dual system aspect of the COVIS theory. The COVIS theory is further supported by the evidence of a strong bias towards the verbal system in that individuals from both conditions were equally likely to use the conscious, rule-based verbal strategy. This study was unable to find strong evidence for the implicit system being more likely to be used when the features of the stimuli were not-easily verbalizable, since participants in the not-easily verbalizable condition favoured the rule-based strategy much like the individuals in the easily verbalizable condition.

Limitations and Future Directions

The partially supported hypothesis can be attributed to three key limitations in this study. Firstly, it is possible that while the norming study did confirm the belief that the two stimulus sets differed in how verbalizable they were, these differences may not have been strong enough to produce significant results in the present paradigm. Participants in the present study, in contrast to the participants in the norming study, may have been better able to verbalize the not-easily verbalizable stimulus set. Future studies should aim to design features that are more difficult to verbalize and do a replication of the phase two of the norming study to verify that the two stimulus sets do differ in how easy they are to describe and that the findings are generalizable to other groups as well.

Secondly, it is possible that the stimulus set simply had too few dimensions to use a family resemblance approach. Recall that the family resemblance approach is rooted in looking at all the features holistically and generating different categories based on a system of similarities rather than creating an explicit verbal rule using a single feature. Since the program would designate one feature as the CA and be kept uniform throughout the experiment, there were only four other features which could vary to base the family resemblance on. Future studies should strive to add more dimensions to the existing stimulus set or generate another stimulus set that has more than four dimensions which vary.

Finally, the environment in which the task took place may have been a limitation since the video game environment might have been distracting to the participants. While the participants were ultimately completing an A-B categorization task, similar to existing literature, the stimuli or the task itself may have distracted the participants from the task at hand. The monsters in this task are visually similar to *Pokemon* to a degree in that they are fictitious creatures with colourful, unnatural features and the farm setting and 8-bit art style are slightly similar to the games *Terraria* or *Stardew Valley*. These similarities could have caused the participant to recall the other games resulting in them paying less attention to the present task. To account for this potential limitation, future studies should attempt to conduct the experiment in a non video game environment or replicate the present study but with stimulus sets and a setting dissimilar to existing video games.

Conclusion

Nevertheless, further research investigating the effects of language and how verbalizable features are on categorization strategies is imperative to draw concrete conclusions. It is worth noting that the current topic is a growing field of study with little existing literature to establish a robust relationship between how verbalizable features are and its influence on the COVIS theory, specifically in a video game environment. The present study is a direct replication of Brashear and Minda (2018) which was primarily exploratory in nature and endeavoured to further the field of cognitive science. Moving forward, it is essential to remember the basis with which this discussion was held, and continue to research the influence of language and verbalizable features on categorization strategies, the strength of the COVIS model, and the merits of conducting experiments in a video game environment, to contribute to the field of cognitive psychology and gain a better understanding of the mechanisms underlying cognitive processes.

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Appendix A. Ethics Approval Letter

Western
Research

Date: 23 October 2019

To: Dr. John Paul Minda

Project ID: 111628

Study Title: Implicit and Indirect Category Learning

Application Type: NMREB Amendment Form

Review Type: Delegated

Full Board Reporting Date: November 1 2019

Date Approval Issued: 23/Oct/2019

REB Approval Expiry Date: 01/May/2020

Dear Dr. John Paul Minda,

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the WREM application form for the amendment, as of the date noted above.

REB members involved in the research project do not participate in the review, discussion or decision.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario. Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Kelly Patterson, Research Ethics Officer on behalf of Dr. Randal Graham, NMREB Chair

Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).

Appendix B. Letter of Information

Western

Letter of Information and Consent

Project Title: Implicit and Indirect Category Learning
Principal Investigator: John Paul Minda, PhD, Psychology, Western University, jpminda@uwo.ca
Additional Research Staff: Bailey Brashears, Psychology, Western University, bbrashea@uwo.ca

1. Invitation to Participate

You are invited to participate in this study about how people categorize stimuli to solve problems because you have expressed interest in participation in this study and/or have responded to a recruitment announcement. The purpose of this letter is to provide you with information required for you to make an informed decision regarding participation in this research.

2. Why is this study being done?

The purpose of this study is to understand how people categorize different kinds of objects in order to solve problems.

3. How long will you be in this study?

It is expected that you will be in the study for approximately 30 minutes.

4. What are the study procedures?

If you agree to participate, you will play a video game on a computer. In this game you will be presented with “monsters” of varying sizes and appearances and asked to decide which group each “monster” belongs to.

5. What are the risks and harms of participating in this study?

There are no known or anticipated risks or discomforts associated with participating in this study.

6. What are the benefits?

You may not directly benefit from participation in this survey, but the information gathered may provide benefits to society as a whole including a better understanding of how people categorize different kinds of objects and what information they need to properly solve problems.

7. Can participants choose to leave the study?

Participation in this study is voluntary. You may refuse to participate, refuse to answer any questions or withdraw from the study at any time without penalty. If you withdraw from the study your data will not be withdrawn as it is not linked to you and therefore it is not possible to find and remove it.

8. How will participants’ information be kept confidential?

Prior to the publication of the study, all data collected will remain confidential and accessible only to the investigators of this study, Dr. Minda and Bailey

Brashears. Electronic data will be stored on a hard drive in Dr. Minda's locked lab for 7 years after the completion of the study. Bailey Brashears will cease to have access to the data upon her graduation at which time only Dr. Minda will have access to it. However, the anonymized data may be made available to journals and other researchers' future analysis, consistent with open data policies. This data will include demographic information as well as the response collected during the study. No personally identifiable information will be gathered or retained. Your name and signature will be collected on this form but will not be associated or stored with the collected data.

Please note representatives of The University of Western Ontario Non-Medical Research Ethics Board may require access to your study-related records to monitor the conduct of the research at any time while the data is held.

9. **Are participants compensated to be in this study?**

You will be compensated with 0.5 research credits

10. **What are the Rights of Participants?**

Your participation in this study is voluntary. You may decide not to be in this study. Even if you consent to participate you have the right to not answer individual questions or to withdraw from the study at any time. If you choose not to participate or to leave the study at any time it will have no effect on your academic standing. You do not waive any legal right by signing this consent form.

11. **Whom do participants contact for questions?**

If you have questions about this research study please contact Dr. John Paul Minda, (519) 661-2111 ext. 84689, jpminda@uwo.ca.

If you have any questions about your rights as a research participant or the conduct of this study, you may contact The Office of Human Research Ethics (519) 661-3036, email: ethics@uwo.ca.

This letter is yours to keep for future reference.

Appendix C. Consent Form

12. **Consent**

Written Consent

Letter of Information and Consent

Project Title: Implicit and Indirect Category Learning
Principal Investigator: John Paul Minda, PhD, Psychology, Western University, jpminda@uwo.ca
Additional Research Staff: Bailey Brashears, Psychology, Western University, bbrashea@uwo.ca

I have read the Letter of Information, have had the nature of the study explained to me and I agree to participate. All questions have been answered to my satisfaction.

Print Name of Participant	Signature	*Date (DD-MMM-YYYY)*

My signature means that I have explained the study to the participant named above. I have answered all questions.

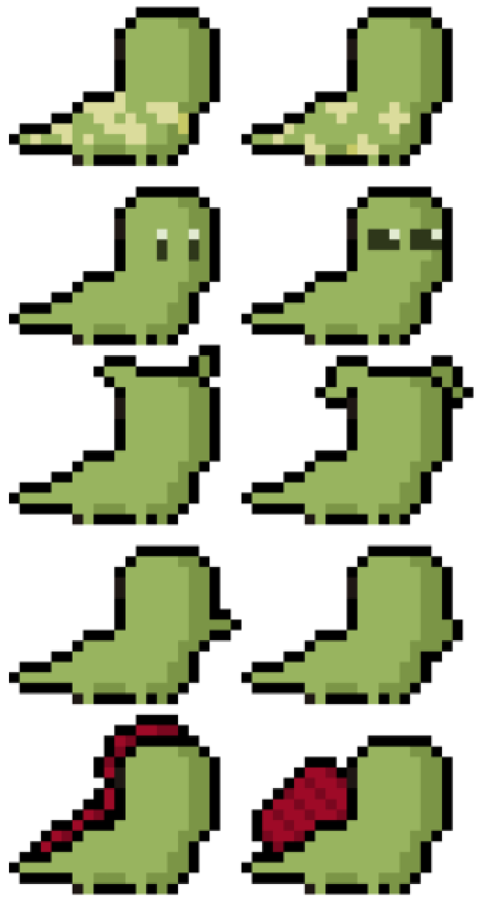
Print Name of Person Obtaining Consent	Signature	*Date (DD-MMM-YYYY)*

Appendix D. Easily Verbalizable Stimulus

The five feature pairs for the easily verbalizable stimulus set. Group A (0) members are on the left side and Group B (1) members are on the right side. Features include: spots, eyes, ears, tail shape, and spine colour.

The two prototypes (left) followed by the single feature variations.

Appendix E. Not-Easily Verbalizable Stimulus



The five feature pairs for the not-easily verbalizable stimulus set. Group A (0) members are on the left side and Group B (1) members are on the right side. Features include: spots, eyes, ears, tail shape, and spine colour.

The two prototypes (left) followed by the single feature variations.