Individual differences in internal models explain idiosyncrasies in scene perception

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Abstract

According to predictive processing theories, vision is facilitated by predictions derived from our internal models of what the world *should* look like. However, the contents of these models and how they vary across people remains unclear. Here, we use drawing to directly access the contents of the internal models of individual participants. Participants were first asked to draw typical versions of scene categories, as descriptors of their internal models. These drawings were converted into standardized 3d renders, which we used as stimuli in subsequent scene categorization experiments. Across two experiments, participants' scene categorization was more accurate for renders tailored to their own drawings compared to renders based on others' drawings or copies of scene photographs, suggesting that scene perception is determined by a match with idiosyncratic internal models. These results demonstrate that visual perception can only be fully understood through the lens of our personally unique models of the world.

Introduction

Scene perception is not only achieved through a passive analysis of sensory input. The brain actively creates predictions about the world that are compared against current inputs (Clark, 2013; Friston, 2005, 2010). Such predictions are derived from our own unique internal models of what we think the world *should* look like. How can we characterize the contents and individual differences of these internal models?

The contents of internal models are mainly inferred from carefully manipulating the structure of the visual input and observing the resulting changes in perceptual performance and neural representation. Using this approach, researchers could successfully infer key features of internal scene models, such as the typical spatial distributions of objects (Bar, 2004; Biederman et al., 1982; Kaiser et al., 2019), semantic relationships between objects and scenes (Davenport & Potter, 2004; Oliva & Torralba, 2007; Vo et al., 2019; Wolfe et al., 2011), or the spatial layout of whole scenes (Biederman, 1972; Kaiser et al., 2020; Kaiser & Cichy, 2021).

However, this approach only reveals the contents of internal models that are shared across people – although there is mounting evidence for individual variability in visual perception and neural representation (Charest et al., 2016; de Haas et al., 2019; Gauthier, 2018; Mollon et al., 2017; Tulver et al., 2019; Wang et al., 2012). If we could harness this individual variability, we would be able to predict and explain characteristic differences in the way each of us perceives the world.

Here, we thus develop a novel approach that focuses on distilling out key properties of internal models in individual participants. We achieve this through drawing, enabling participants to provide unconstrained descriptions of typical scenes both quickly and without prior training. Using these drawings as descriptors for internal scene models, we then tested whether individual participants' scene perception can be explained through similarities with their personal internal models.

Our participants first drew typical exemplars of natural scenes categories, as well as copies of photographs of the same categories (which served as a control for familiarity acquired during drawing). They then performed a scene categorization task, in which they viewed carefully constructed scene renders that were created based on the drawings. Across two experiments, participants were more accurate in categorizing renders based on their own drawings, compared to renders based on other people's drawings and renders based on mere copies of scenes. Our results provide compelling evidence that individual differences in internal models explain individual differences in scene categorization.

Materials and Methods

Experiment 1

Participants. 43 participants completed the drawing session, 39 returned for the categorization task. 4 were excluded for performing at chance level (binomial test), leaving a sample of 35 participants (22.6 ± 4.3 years ± SD, 6/29 male/female). Procedures were approved by the ethics committee of the Department of Psychology, University of York and adhered to the Declaration of Helsinki. Experiment 1 was conducted online and participants provided informed consent through an online form. Sample size was based on convenience sampling, with the target to exceed 80% statistical power for a hypothesized medium effect of d = 0.5 in a two-sided t-test. For this target, at least 34 participants are required.

Drawing sessions. The drawing session took part online, using Skype. Participants were tasked with drawing scenes from two categories: living rooms and kitchens (Fig. 1a). Critically, they were instructed to draw what they conceived as the most typical example of the scene category. The definition of typical was given as the most generic and ordinary example they could think of. They were instructed not to draw a scene that they thought looked particularly interesting or attractive. They were further instructed to not simply draw an exact copy of a scene they knew from real life such as their own kitchen or living room (though they were reassured that similarities with known scenes did not need to be deliberate avoided). Participants were given 1 minute to plan and think about what their most typical scene should look like and 3:30 minutes to draw the scene using a pencil, eraser, and ruler. Scene sketches were drawn into a standardized perspective grid, to allow participants to draw in 3d more easily as well as to match viewpoints across scenes. Grids were either drawn or printed by the participant on A4 paper and consisted of a large central rectangle (7.1 cm by 16.5 cm) and 4 diagonal lines going from each corner of the rectangle to the corners of the page. The rectangle was placed 8.5cm from the bottom of the page and 5.4cm from the top of the page.

While drawing, participants were reminded how much time they had left at the halfway point, and when they had a minute remaining. They first drew a practice scene of a bedroom, to get them used to the timings and drawing on the perspective grid. In addition to the living rooms and kitchens, they also drew garden scenes, which were collected for another experiment. The order in which they drew the scene categories was balanced across participants. After completing each drawing, participants also drew a coarse birds-eye view of the scene, in which they labelled all objects in the scene. This was done to help clarify the room's intended 3d layout and to confirm the identity of any ambiguously drawn objects, providing additional information for generating accurate 3d renders later.

After drawing their most typical versions of the scenes, participants drew copies of given photographs of the same scene categories (Fig. 1a). Photographs were chosen to be clear examples of the scene category, but not particularly typical ones. This was done to reduce incidental similarities between the copied scenes and participants' typical drawings. All participants copied the same photographs. The copies were drawn under the same time constraints as the typical drawings, and participants were instructed to capture a similar amount of detail as they used in their drawings of typical scenes. Participants had access to the photograph throughout their drawing time. These copies acted as a control for familiarity effects in the subsequent categorization experiment: Participants will have seen and drawn these scenes, just like their typical versions, but they will not adhere to their internal models of what these scenes typically look like.

Scene renders. We created 3d renders from the drawings by placing suitable candidate objects into an empty room. Scene renders were constructed using The SIMS4. The game includes a comprehensive design kit that allows the user to create a range of 3d environments by placing walls and objects onto a grid-like system (known in the game as "Build Mode"). The use of The SIMS4 allowed us access to a large library of thousands of 3d-modelled candidate objects for building the renders.

To create the renders, first an empty room was built to replicate the view and approximate dimensions of the perspective grid. This room was approximately 6x6 m in size and used wall pieces approximately 3 m high, with the outward facing wall was removed. The scenes were then manually populated with objects by one of the authors, referencing both the scene sketch and birds-eye view plans the participants assembled in the drawing session. The closest matching 3d object was chosen to represent each object in the render. When objects were drawn in very little detail, a relatively generic version of the object was used at the author's discretion. Screenshots of the scenes were taken using the X box live app for Windows. Screenshots were taken from the same distance and angle for every scene render, cropped so that only the room was visible, and resized to 820 by 390 pixels. To control for low-level visual differences between the resulting images, all images were grayscaled and luminance-matched using the SHINE toolbox for MATLAB (Willenbockel et al., 2010).

In total, 88 renders were created: 86 renders were based on the typical drawings of 43 individual participants and 2 renders were based on the 2 control images.

Categorization task. The categorization task was conducted online, using Gorilla (Anwyl-Irvine et al., 2020). Participants were instructed to full-screen the application and sit approximately 60cm from the screen. During the experiment, participants were asked to categorize briefly presented scene renders into kitchens versus living rooms. On each trial, a scene render was flashed for 83ms, followed by a mask presented for 150ms. Masks consisted of a random arrangement of squares, diamonds, and circles. A blank screen was then displayed until the participants responded by either pressing "K" or "L" on their keyboard (to indicate whether the scene was a kitchen or living room). There was no response time limit, but both accuracy and response time were stressed. Trials were separated by a 1-second inter-trial interval.

Participants viewed renders based on their own drawing of a typical scene ("own" condition), based on other participant's drawings of typical scenes ("other" condition), and based on their copied scenes ("control" condition; the control renders were identical for all participants). In total, 88 renders were shown in the experiment, 2 of which corresponded to each participant's own drawings, 2 of which corresponded to the copied scenes, and 84 that corresponded to the other participants' drawings (based on the 43 participants who initially completed the drawing session). Each render was repeated 10 times, for a total of 880 trials. Trial order was randomized. The experiment was split into four blocks. After each block, participants were given a 1:30 min break.

Data analysis. Responses slower than 5 s were discarded. Accuracies and response times were compared using one-way ANOVAs and t-tests. For the response times, only trials with correct responses were analyzed.

Experiment 2

Participants. 36 participants completed the drawing sessions and 35 participants (23.9 ± 2.6 years ± SD, 8/27 male/female) returned for the categorization task. Procedures were approved by the ethics committee of the Department of Education and Psychology, Freie Universität Berlin and adhered to the Declaration of Helsinki. Experiment 2 was conducted in the lab, and participants provided written informed consent. The sample size was not increased compared to Experiment 1, as we expected the lab-based experiment to yield stronger effects than the online experiment.

Drawing sessions. The drawing sessions were similar to Experiment 1 but were conducted in the lab. Participants provided their drawings on an Apple iPad Pro using an Apple Pencil. Drawings were created using the Sketchbook app. A standardized perspective grid similar to the one used in Experiment 1 was provided for each drawing. Specifically, the full drawing display (19.5cm by 26.1cm) consisted of a large central rectangle (8.5cm by 13.5cm) and 4 diagonal lines from each corner of the rectangle to the corners of the page. The rectangle was set with the bottom length 8.5cm from the bottom of the page and top length 2.7cm from the top of the page. Instructions and timings were identical to Experiment 1. Here, however, participants drew typical versions and copies of six scene categories (bathroom, bedroom, café, kitchen, living room, and office). Before making their drawings, participants drew a typical classroom to practice drawing under the experimental constraints.

Scene renders. Scene renders were created in the same way as for Experiment 1.

Categorization task. Here, the categorization task was conducted in the lab, using the Psychtoolbox for Matlab (Brainard, 1997). During the experiment, participants categorized the scenes into the six categories. Renders were presented at central fixation with 7° horizontal visual angle. Trial design was identical to Experiment 1. To accommodate the six response options, participants saw a response screen after the mask, on which they indicated which of the six categories they had just seen, using the "S", "D", "F", "J", "K", and "L" keys on the keyboard.

In Experiment 2, we sought to make the design more efficient by not showing all renders to every participant. We instead grouped participants into groups of 4, and each participant only saw renders based on their own drawings, renders based on the other 3 participants' drawings, and the control renders created from the scene copies. Groups of 4 were chosen so that there was still sufficient variability in visual stimuli across the experiment. Each participant thus saw 5 renders for each of the 6 categories. Each of these 30 stimuli was repeated 40 times across the experiment, for a total of 1200 trials. Trial order was randomized. The experiment was split into 4 blocks. After each block, participants could take a break for as long as they needed.

For some participants, we also recorded EEG during the categorization task, in order to obtain preliminary data for another study.

Data analysis. Accuracies and response times were analyzed in the same way as for Experiment 1.

<u>Data availability</u>

Data, code, and materials for both experiments will be published on the Open Science Framework (OSF) upon publication.

Results and Discussion

In our experiments, participants first completed a drawing session, in which they drew typical versions of scene categories, such as a typical living room (Fig. 1a; see Materials and Methods). These drawings were used as descriptors of their internal models of scenes. They also copied photographs of scenes from the same categories, which later served as a control for familiarity acquired during drawing. For the subsequent experiments, we transformed these drawings into standardized 3d renders (Fig. 1b), thereby leveling out individual differences in drawing skill and style.

We then tested whether scenes designed to mimic individual participants' internal models (described by their own typical drawings) are more accurately perceived than scenes that were designed to mimic other participants' internal models. To this end, we devised a scene categorization task that required participants to accurately categorize the briefly presented and backward-masked scene renders.

In Experiment 1, participants completed an online drawing session where they drew typical versions and copies of living rooms and kitchens. They then performed an online categorization task (Fig. 2a), during which they categorized the scene renders created from participants' drawings into kitchens versus living rooms.

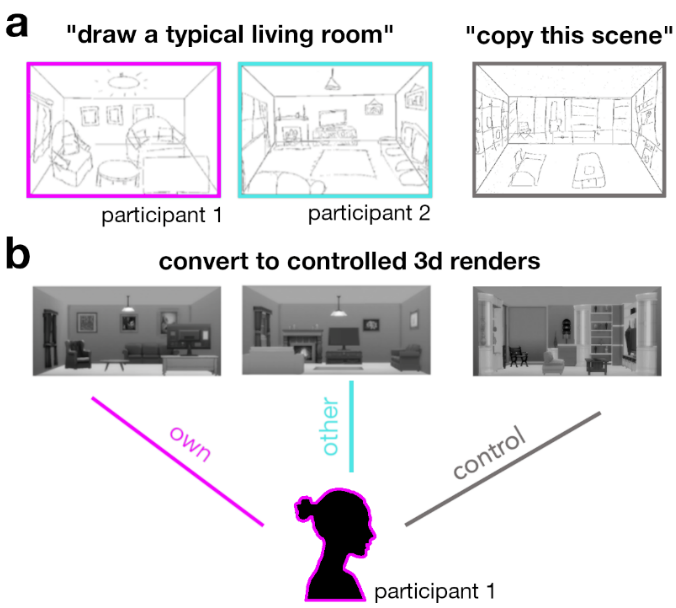

Figure 1. Drawing session and stimuli. a) *Participants drew typical versions of natural scenes and copies of scene photographs.* ***b)*** *Drawings were converted into 3d renders, based on each participant's own typical drawings, other participants' typical drawings, or scene copies.*

To investigate whether scenes that were specifically tailored to participants' personal internal models are more accurately categorized, we compared accuracies between renders based on each participant's own drawing ("own" condition), other participants' drawings ("other" condition), or the copied scenes ("control" condition). Accuracy was significantly different between conditions, $F(2,68) = 4.15$, $p = .020$, partial $\eta^2 = 0.11$ (Fig. 2b), with two significant pairwise comparisons: First, renders in the *own* condition were more accurately categorized than in the *other* condition, $t(34) = 2.18$, $p = .036$, $d = 0.37$, indicating that idiosyncrasies in categorization are indeed related to individual differences in internal models. Second, renders in the *own* condition were also more accurately categorized than in the *control* condition, $t(34) = 2.26$, $p = .031$, $d = 0.38$, indicating that the categorization advantage for renders based on typical drawings cannot be explained with participants acquiring familiarity with their drawings during the drawing session. No difference was found between the *other* and *control* conditions, $t(34) = 1.11$, $p = .28$, $d = 0.19$. Response times were also significantly different between the conditions, $F(2,68) = 3.62$, $p = .032$, partial $\eta^2 = 0.10$. Specifically, the *control* condition yielded greater response times than the *own* condition, at the trend level: $t(34) = 1.87$, $p = .070$, $d = 0.32$, and the *other* condition, $t(34) = 3.18$, $p = .003$, $d = 0.54$. No difference was found between the own and other conditions, $t(34) = 0.26$, $p = .79$, $d = 0.04$.

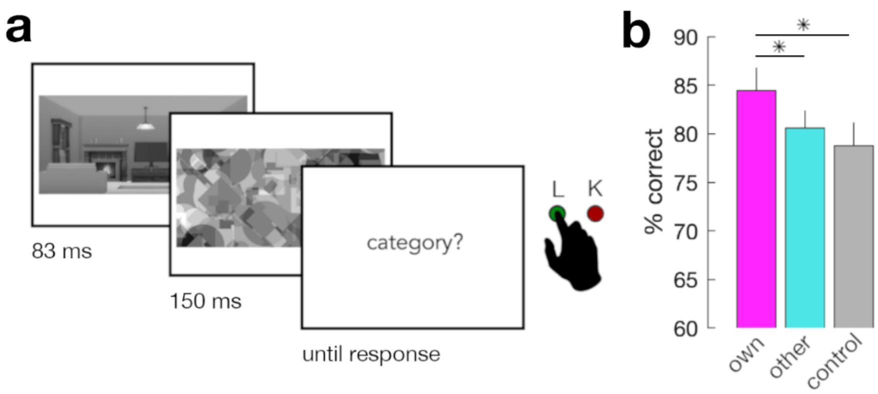

Figure 2. Experiment 1. a) *Participants categorized briefly presented renders into kitchens versus living rooms.* ***b)*** *Categorization was more accurate for renders based*

*on participants' own drawings (own condition) than for those based on other participants' drawings (other condition) or copies (control condition). Error bars represent standard errors of the mean. * indicates p < .05.*

In Experiment 2, we aimed to replicate these results in a lab-based setup and for a wider range of scene categories. Here, participants first drew typical versions and copies for six scene categories: bathroom, bedroom, café, kitchen, living room, and office. In the subsequent categorization task, they again categorized renders based on their own, as well as other participants' drawings into the six categories (Fig. 3a).

Results fully replicated the pattern observed in Experiment 1. Categorization accuracies varied significantly across conditions, $F(2,68) = 8.05$, $p < .001$, partial $\eta^2 = 0.19$ (Fig. 3b), with higher accuracy in the *own* condition, compared to both the *other*, $t(34) = 2.89$, $p = .007$, $d = 0.49$, and *control* conditions, $t(34) = 3.61$, $p < .001$, $d = 0.61$. No difference was found between the *other* and *control* conditions, $t(34) = 1.59$, $p = .12$, $d = 0.27$. This again shows that scenes are categorized more accurately when they are similar to individual participants' internal models of the scene. Response times were not significantly different between the conditions, $F(2,68) = 0.69$, $p = .51$, partial $\eta^2 = 0.02$.

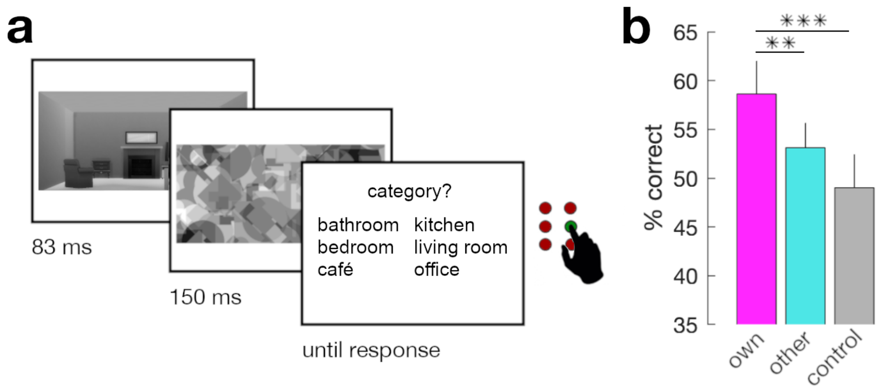

Figure 2. Experiment 2. a) *Participants categorized briefly presented renders into six scene categories.* ***b)*** *Categorization was again more accurate for renders based on participants' own drawings (own condition) than for those based on other participants' drawings (other condition) or copies (control condition). Error bars represent standard errors of the mean. ** indicates p < .01, *** indicates p < .001.*

Together, our results showcase the potential of a new approach to study natural vision that embraces individual variability. Harnessing drawing to describe internal models, we demonstrate that the correspondence between current inputs and participants' personal internal models is a key determinant for how efficiently we perceive the world.

Why internal models systematically differ across participants remains an important open question. Future studies could relate variations in internal models to idiosyncrasies in cortical representation (Charest et al., 2016; Lee & Geng, 2017) and visual exploration behavior (de Haas et al., 2019; Henderson & Luke, 2014), as well as to individual differences in brain anatomy (Llera et al., 2019).

Another open question concerns how visual inputs are matched against the internal models. There is a variety of dimensions along which this match could be computed, such as the objects included in a scene as well as their spatial distribution (Kaiser et al., 2019; Oliva & Torralba, 2007; Vo et al., 2019; Wolfe et al., 2011), the global geometry of the scene (Epstein & Baker, 2019; Kaiser & Cichy, 2021; Oliva & Torralba, 2006), or low- and mid-level features correlated with the content of a scene (Geisler, 2008; Groen et al., 2017; Watson et al., 2014). To shed light on this question, future studies could systematically manipulate inputs to deviate from internal models in targeted ways.

Our study further highlights the potential of drawing for quantifying internal representations. Drawings indeed received renewed attention recently, in studies of scene memory (Bainbridge & Baker, 2020; Bainbridge et al., 2019) and perception (Matthews & Adams, 2008; Morgan et al., 2019; Ostrofsky et al., 2017). Our study suggests that drawings also yield the potential to advance our understanding of the internal models that guide the visual representation of objects, faces, or actions. Furthermore, our drawing method may prove useful for studying the maturation of internal models across development (see Long et al., 2021) or their alterations in disorders of prediction like autism (Pellicano & Burr, 2012).

In sum, our work provides two critical advances for studying natural vision on the individual level. First, our work provides a new drawing-based method for unveiling the contents of internal models in individual participants. This method has the potential to be widely applied to derive explicit predictions about individual differences in vision. Second, our findings shine a new light on why scene perception is in the eye of the beholder. They demonstrate that we all perceive our surroundings through the lens of our individually unique internal models of the world.

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