

**Understanding object categorisation through development: the influence of movement
and other developmental heuristics on adult cognition**

A thesis submitted to fulfil requirements for the degree of Doctor of Philosophy

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Statement of originality

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and all sources of information have been acknowledged. This thesis has not been submitted for any degree or other purposes.

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This thesis contains published material, co-authored with other colleagues. Below is a CRediT statement for each experimental chapter, describing the roles for each author

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Ethics statement

All experimental data in this thesis was collected under ethics protocols approved by the University of Sydney Human ethics committee under one of the following protocols: 2019/340, 2020/079, or 2015/985.

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Abstract

For decades, developmental psychologists and cognitive neuroscientists have been studying the same fundamental questions about how perceptual information is transformed into a complex, conceptual understanding of the world. Yet, we still know very little about how they intersect. Is neural object processing in children similar to adults? How do heuristics formed in childhood continue to influence adult cognition? Using methods, theories, and findings from both fields, this thesis investigates how development of categorical processing is reflected in the brain and behaviour of adults and children in five empirical chapters.

Chapters 2, 3, and 4 investigated how our adult conceptual system reflects processes in development. Young adults classified words and images according to whether they were alive, rated their movement characteristics, and rated their similarity. Electroencephalography (EEG) data was also recorded during aliveness and movement judgements. We found that items violating associations between movement and aliveness, plants, and moving natural things, were harder to classify. These results were robust across words and images, and different objects. Capacity for movement was also represented in patterns of brain activity, with an initial identification of potential movement speed, followed by more abstract characteristics like how predictable or independent the motion is. These findings suggest movement provides an important clue to object identity that is processed by the brain and used as a shortcut for judging aliveness.

Chapters 5 and 6 investigated how developmental processes are reflected in the brain, by considering how the brain processes objects without category knowledge (as in development), and by directly comparing categorisation in adults and children. In Chapter 5, we recorded EEG while adults classified animals, plants, and minerals that were camouflaged or unrecognisable. Despite poor classification performance, the true class of objects was distinguishable from patterns of brain activity. The same visual features that were informative

for predicting object category were also correlated with brain activity and used to judge similarity. In Chapter 6, we directly compared neural and behavioural categorisation in adults and 4-year-old children, using EEG and an odd-one-out similarity task. Behavioural similarity judgements were very similar across age groups. Exploratory EEG analyses showed that adults and children had largely comparable patterns of brain activity, but children's brain activity showed no correlations with models of psychological humanness.

Together, the findings suggest that similarity to humans, particularly based on capacity for agentive movement, influences judgements of aliveness and neural representations of objects in both adults and children. The results have important implications for understanding conceptual development and how we study object recognition.

A note to the examiners

Each chapter of this thesis is written as a stand-alone journal article. In keeping with good open science practice, all the data and code will be publicly released with the publications. However, as they are not yet published, the data remains unpublished, but is occasionally mentioned in the text of the manuscript. These items specifically mentioned can be downloaded using the following link, solely for the purposes of examining this thesis:
[REDACTED]

Chapter 3 is already published.

Stimuli, analysis scripts, results and anonymised raw EEG data are publicly available at <https://doi.org/10.18112/openneuro.ds003885.v1.0.7> (Experiment 1) and <https://doi.org/10.18112/openneuro.ds003887.v1.2.2> (Experiment 2). Stimuli, analysis scripts, results and data from the online stimulus validation study are also publicly available at <https://osf.io/jxhcs/>.

Chapter 1: Introduction

The human capacity to recognise an object effortlessly, often in less than a few hundred milliseconds, is a remarkable cognitive ability. Computer scientists have worked for decades to recently replicate human object recognition in *silico*, yet the processes used by computers do not mimic natural development. Babies are not born with labelled images handed to them, but instead must learn by interacting with their environment. How do they accomplish this? What cues do they use to derive order from the objects in the natural world, and how do we continue to use these same cues into adulthood? This thesis aims to investigate how object recognition and categorisation in the brain and behaviour of adults is similar to children, with particular focus on how movement influences judgements of abstract attributes like whether something is alive. Inspired by developmental work showing that children often mis-classify moving natural things as alive, the first part of the thesis explores how movement and aliveness provide clues to object recognition, and how these attributes are processed in the brain. The second part of the thesis examines how object perception changes with age and available semantic information.

What are categories and concepts, and why are they useful?

What does it mean to be able to ‘categorise’ something? According to Bruner et al. (1956, p. 1), to categorise is “to render discriminably different things equivalent, to group objects and events and people around us into classes, and to respond to them in terms of their class membership rather than their uniqueness”. Successful categorisation requires concepts, which are the mental representations corresponding to ‘real-world’ categories (Keil, 2003; Murphy, 2004; Rakison & Lawson, 2013).

The ability to divide up and label the world with concepts has several important functions (Solomon et al., 1999). Conceptual knowledge allows us to make inductive inferences about the world, to identify new items, and efficiently guide behaviour (Oakes & Madole, 2008).

Without conceptual knowledge, every object we encounter would be novel. Instead, categorisation allows us to infer properties of novel objects based on the known attributes of the previous similar items we have encountered. For example, despite the wide variety of visual appearances in dogs, each time you encounter a new dog you are able to make a reasonable prediction at what it's likely to sound like, what it enjoys eating, and where you should pat it. Categorisation is an efficient way of organising information, distilling experience into knowledge that can be applied to facilitate complex interactions with the world and communicate with others.

The adult conceptual system is complex and flexible

Adult categorisation is complex and flexible. Objects don't necessarily fall into a single category; for example, a dandelion flower could be part of the category of 'plants' or 'living things', as well as 'yellow things' or 'things that give me hay fever'. We can form ad hoc categories, such as 'items you have in a bathroom', or 'things with fur' (Barsalou, 1983), and can extract categorical structure even when it's not relevant to the task (Reed et al., 1999). Categories can be based on a wide variety of attributes, including biological groups (e.g., animals, cacti), physical descriptors (e.g., spiky, pink), abstract dimensions (e.g., healthy, evil), utility (e.g., things used for cutting), location (e.g., things found in a kitchen), event (e.g., things to pack for the beach), or size (e.g., big, elongated). We can also flexibly apply category labels based on the context and our own expertise. For example, experts tend to categorise objects from their area of expertise using more specific sub-groupings than members of the general public (Medin et al., 1997; Tanaka & Taylor, 1991).

Categories are often hierarchical

Different levels of categorisation reflect different hierarchical structures in our categorical knowledge. Eleanor Rosch and her colleagues (Rosch, 1978; Rosch et al., 1976) showed that by default, we tend to name objects at the basic level (e.g., dog, tree), rather than the subordinate level (e.g., Golden Retriever, Oak), or the superordinate level (e.g., animal, plant). Because basic level categorisation maximises between-category dissimilarity *and* within-category similarity, it is most useful for making inferences (Rosch et al., 1976). In behavioural classification tasks, basic level processing seems to be the ‘entry level’ (Jolicoeur et al., 1984), or the level at which objects are first categorised (Potter & Haggmann, 2015). Adults are faster in speeded classification tasks when the words are at the basic level (Jolicoeur et al., 1984; Murphy & Brownell, 1985; Murphy & Wisniewski, 1989), and basic-level concepts are used most frequently in free-naming tasks (Rosch et al., 1976). Basic terms are shorter and used more frequently than subordinate or superordinate labels in picture naming (Murphy & Smith, 1982), and in adult speech (Brown, 1958), particularly in speaking to children (Anglin, 1977; Pérez-Granados & Callanan, 1997; Shipley et al., 1983); an adult is more likely to call the neighbour’s pet a ‘dog’ than a ‘chihuahua’ or an ‘animal’. It is not surprising, then, that children tend to acquire basic level words first (Anglin, 1977; Callanan, 1985; Mervis & Crisafi, 1982). Children tend to generalise terminology at the basic level, generalising a label given to a Collie to other dogs, rather than all animals or only Collies (Golinkoff et al., 1995).

Though many categories have some kind of hierarchical structure, how categories are defined also varies across different domains. Adults tend to view membership in ‘natural’ categories (e.g., animals; Gelman & Kalish, 2006) as absolute and pre-determined, but membership in artifact categories (objects created by humans) as more graded and subjective (Diesendruck, 2003; Diesendruck & Gelman, 1999; Estes, 2003; Medin & Ortony,

1989/2009). When participants are asked whether a given item is ‘definitely’ a member of a particular category, they are more likely to say ‘yes’ for natural things than artificial things. For example, a golden retriever is rated as ‘definitely’ a dog more often than a limousine is ‘definitely’ a car, on average, after matching typicality (Diesendruck & Gelman, 1999). Because natural categories are viewed as more homogenous, we are also more likely to generalise animal attributes to novel animals than artifact attributes to novel artifacts (Estes, 2003; S. A. Gelman, 1988). This theoretical understanding of the world influences our categorisation, and can bias interpretation of statistical information (Medin & Shoben, 1988; Murphy & Allopenna, 1994; Spalding & Murphy, 1996, 1999).

How does the categorisation system develop?

The adult categorisation system is clearly flexible and complex. Yet there are clear differences between children and adults in the factors they use to categorise objects (Diesendruck et al., 2003; Hammer & Diesendruck, 2005). So how does this system develop? Theories of conceptual development can be broadly characterised by two frameworks: as a progression of discrete stages, where changes occur as a result of mental restructuring (stage-based theories), or in a more continuous manner where new information is constantly integrated and continuously updated (continuous theories).

Stage-based theories of conceptual development

Stage-based theories, such as those proposed by Piaget (Piaget, 1929/2013), suggest that children form concepts in discrete steps. Piaget suggested that children first claim all things are conscious (ages 0-2), then think things that can move are conscious (ages 2-7), then believe things that can move of their own accord are conscious (ages 7-11), and finally only attribute consciousness to animals (ages 11+). For Piaget, transitions between stages

represented reorganisation of the child's cognitive frameworks. Piaget's theories are also domain-general, meaning that all areas of cognition develop at a similar pace.

Continuous theories of conceptual development

Though there is some evidence for stage-like theories, most modern authors support a more gradual development, based on research indicating that older children increasingly begin to resemble adults in a variety of domains (Ameel et al., 2008; Taylor et al., 2009). Instead of discrete steps, in which jumps in understanding are made by cognitive restructuring, proponents of a more continuous trajectory suggest that systems of categorical knowledge are constantly updated as children acquire new information and experiences (Mandler, 2012).

One of the key arguments for continuous development is the observation that there are remnants of the errors made in childhood in adults, particularly when they are under time pressure. Undergraduate students seem to rely on the associations between movement and aliveness observed in children by Piaget when they are placed under time pressure (Goldberg & Thompson-Schill, 2009). University students tend to make more mistakes and respond more slowly when items violate the association between movement and aliveness (e.g., plants which are alive but do not move, or moving natural things like waves which are not alive but do move) (Goldberg & Thompson-Schill, 2009). Students are also slower and less accurate to verify statements where intuitive theory clashes with scientific theory (Shtulman & Valcarcel, 2012). Teleological thinking (assuming everything has a cause) and essentialist thinking (assuming things in the same category share some kind of underlying 'essence' that makes them similar) are also increased in undergraduates and professional scientists when they are under time pressure (Eidson & Coley, 2014; Kelemen et al., 2013; Kelemen & Rosset, 2009). This reversion to childhood defaults under time pressure suggests development may involve

inhibition rather than replacement of childhood heuristics, supporting a more continuous view of category development.

Though current evidence primarily supports continuous development, there are still disagreements based on what features of objects children use to develop categories. For example, are children relying on perceptual features of objects (e.g., curvature, colour, presence of legs or eyes), or conceptual knowledge (e.g., genetics, similar insides/ organs, object function)? Can infants, with very little conceptual knowledge, form categories? How does the reliance on perceptual features change through development as new knowledge is acquired? Though developmental research has typically used behavioural methods, similar questions have been asked about the integration of perceptual and conceptual features in cognitive neuroscience research on how the brain processes objects from low-level visual attributes into something that is relevant for behaviour. The case for use of perceptual and conceptual features in development is described below, then linked to the parallel debate in cognitive neuroscience.

Categorisation relies on mainly perceptual features

Proponents of a perceptual basis of categorical development suggest that most conceptual features derive from causally related perceptual attributes, particularly for natural categories (Jones & Smith, 1993; Rakison & Butterworth, 1998; Sloutsky et al., 2007; L. B. Smith & Samuelson, 2006). Perceptual features can be anything from whether an object has legs or wheels, whether something has eyes, or it's colour, texture, or shape. In this view, perceptual features are sufficient for classification because naturally existing object categories reflect the correlational structure of the perceptual features in the environment. For example, most animals have eyes, and most things that have eyes are animals. Some of the earliest categories perceived in infancy appear to be grounded in perceptual features, such as

faces (Cohen & Strauss, 1979). Infant categorisation may reflect the ability to detect correlations between features (Quinn et al., 1993), and observable changes in categorisation behaviour throughout development arise from increasing awareness of, or sensitivity to, the most relevant perceptual features. Some authors argue that categorisation in infancy is dominated by shape, which in the absence of conceptual knowledge, is the most distinct feature available to young infants (L. B. Smith & Samuelson, 2006). Children's overextensions of language early in childhood tend to be shape-related; spherical candles and beads are considered balls, but conical-shaped footballs that cannot roll are not (Mervis et al., 2003; Mervis & Mervis, 1982). Self-supervised neural networks, with no access to category labels and only visual features of images, can also derive human-like categories based purely on visual input, suggesting that visual features may be sufficient for category representations in the visual system during development (Konkle & Alvarez, 2022). Visual statistical regularities are, under this view, sufficient to facilitate categorisation even in the absence of conceptual knowledge structure.

Categorisation relies on mainly conceptual knowledge

Though there are clearly perceptual attributes that are shared across categories, a conceptual view suggests that these visual features are stepping stones to inform our conceptual structure which contains richer information beyond visual features. In this view, often characterised as the 'essentialist' view, shape features are only important because they provide a signal to higher-order information about the 'essence' of an object (Medin, 1989; Medin & Ortony, 1989/2009). The 'essence' of an object is based on features that are not necessarily visible, but are diagnostic of membership in a particular category. This 'essence' is important because perceptual features can sometimes be misleading and are therefore not reliable indicators of category (Soja et al., 1991). For example, a cow-shaped mug has similar

visual features to a cow, but clearly should be interacted with in a different manner (Bracci & Op De Beeck, 2016). This view is particularly supported by evidence from preschool-aged children, who often choose to group objects based on non-visible properties (e.g., being able to breathe underwater), rather than perceptual or shape similarity, when pitted against each other ((S. A. Gelman & Diesendruck, 1999, S. A. Gelman & Markman, 1986).). Though visual features alone are sufficient for latent category structure to emerge from a deep neural network, models that are based on semantics from language alone also perform equally well at predicting brain activity, suggesting that concepts also form part of the picture (Conwell et al., 2023).

A combination of perceptual and conceptual, parallel or staggered

Several variations and combinations of a conceptual or perceptual view have also been proposed. For example, Mandler (2000) suggests that perceptual and conceptual features are processed by two separate systems, which develop concurrently. Under this view, perceptual processing is effortless and automatic, and moves from concrete features to abstract knowledge. In contrast, conceptual processing requires deliberation and time to create meaning, and moves from these abstract features to more concrete features. The features might also work together and perform different functions, as Waxman and Gelman (2010, p. 262) summarise: “As infants and young children build a repertoire of concepts and acquire words to describe them, they [use] both perceptual *and* conceptual information, and rely upon both the rudimentary theories that they hold *and* the statistics that they witness.”

Alternately, in line with evidence that both perceptual and conceptual attributes are used for categorisation in adulthood, some researchers have suggested that development represents a transition from reliance on perceptual features in infancy and early childhood to an integration of perceptual features with conceptual, non-obviously visible properties (Quinn

& Eimas, 2000; Sloutsky, 2010). When forced to choose between perceptual and conceptual similarity, 2-year-olds use perceptual attributes, whereas 3- and 4-year-olds tend to rely more on biological information or shared non-visible properties ('essences') (S. A. Gelman & Coley, 1990; S. A. Gelman & Diesendruck, 1999; S. A. Gelman & Markman, 1986, 1987). When children were asked to complete a card-sorting task, children aged 4 used colour or form to create categories, 5-year-olds primarily used the form, and 9-year-olds used mostly conceptual attributes (Melkman et al., 1981). This transition from reliance on perceptual to conceptual features might reflect continuous enrichments of the initial perceptual categories (Quinn & Eimas, 2000), and be influenced by the development of language skills (Waxman, 2003).

A false dichotomy?

Despite the allure of a simple binary theory of reliance on either perceptual or conceptual features, few modern researchers support such dichotomous viewpoints. The overlap between conceptual and perceptual features is complex, and thus many researchers have suggested that the division into purely conceptual or purely perceptual features is a false dichotomy (Madole & Oakes, 1999). Objects could theoretically be classified based on these features alone, on their abstract category alone, or some combination, as these attributes are difficult to disentangle. For example, animate things are more likely to be curved than man-made items (Zachariou et al., 2018).

What other factors influence whether children use perceptual or conceptual features?

To highlight the complexity in discerning how children use and integrate conceptual information and perceptual features, there are also several variables that influence which

theoretical view is supported, such as whether the category is real or constructed, whether objects are labelled or not, and what culture and language is being studied.

Natural categories are different to those created in the lab

In creating artificial categories to learn in a lab setting, scientists have control over features like the variance between and within categories, how much participants know about these categories, and the attributes of each class of stimuli. However, the downside of using these artificially controlled categories is that in real categories pre-existing knowledge might influence decision-making. For example, if you encounter a new animal, you already know what kinds of features might be informative for judging category membership, based on what you already know about typical animal groups have in common (e.g., number of legs, presence of fur/ skin/ feathers, habitat). However, in artificially constructed categories (e.g., alien families), there is often no relevant conceptual knowledge (Lassaline et al., 1992), and there are often several ‘defining features’ (all members must have this attribute) which are absent in categories of real-life objects (Murphy, 2004; Rosch, 1978; E. E. Smith & Medin, 1981). Therefore, results from artificial categories are likely to over-emphasise the importance of perceptual features (Medin et al., 1982; Murphy & Wisniewski, 1989; Wisniewski & Medin, 1991).

Language and culture shape category boundaries

Language may also shape the categories we form. For example, children are sensitive to the part of speech used to label an object. For example, children are sensitive to use of generics (e.g., “Dogs have fur”) and use information presented in this form to generalise, but not information presented using a count noun (e.g., “This dog has fur”). Children also seem to understand that nouns typically refer to a shared taxonomic relationship (e.g., birthday

cake, pie), rather than a shared thematic relationship (e.g., birthday cake, balloon) or a shared shape (e.g., birthday cake, top hat) (Imai et al., 1994). Generally, naming objects increases the likelihood that children will group them with other taxonomically similar items (Markman & Hutchinson, 1984; Waxman & Gelman, 2010), particularly for man-made objects (L. B. Smith et al., 2010). Children also draw more inferences for items that share a label than those that do not (Waxman & Markow, 1995; Welder & Graham, 2001). However, there is also some evidence that naming directs children's attention more towards the shape of the object (Landau et al., 1988, 1992, 1998). Smith et al. (2010) suggest that language is one method in which perceptual regularities are linked to the invisible conceptual categories, by directing attention towards the relevant properties for a particular category.

There are also several cross-cultural and linguistic differences in category acquisition and labelling (Choi & Bowerman, 1991; L. B. Smith et al., 2010), and thus whether perceptual or conceptual features are most important for categorisation. For example, Japanese-speaking children separate substances and objects differently from English-speaking children because of the way verbs are constructed in each language (Imai et al., 1994; Yoshida & Smith, 2003). There is also variation both within and across cultures on how adults label objects for children (Rogoff et al., 1993; Shneidman & Goldin-Meadow, 2012).

Are children flexible, like adults?

The process by which children convert perceptual information into categorical knowledge is complex, and the balance of perceptual and conceptual features depends on the task and language environment. These mixed findings and opposing views might reveal that children, like adults, are flexible and can use different sources of information depending on the context of the task (Hayes & Thompson, 2007; Nguyen & Murphy, 2003; Oakes & Plumert, 2002).

Perceptual and conceptual processing in the brain

This debate surrounding the conceptual and perceptual bases of category development is also mirrored in the cognitive neuroscience of object recognition, in exploring how the visual system processes different categories of objects. Both fields have looked at these same questions using different methods, looking at how different information is prioritised at different stages of development, or at different stages of neural processing. As we attempt to understand the neural substrates of the adult categorisation system, similar debates have arisen to those in the developmental literature about whether the visual system is really processing semantic content, or simply picking up on visual statistical regularities across categories. One lens through which to consider this debate is animacy, or the distinction between animals/humans and other objects. Animacy is an ideal case study, because it has also been well-researched in children, so we have knowledge evidence of its developmental trajectory.

Object recognition in the brain

The human visual system is capable of rapidly and automatically categorising stimuli, ranging from low-level visual features to increasingly abstract concepts (Cichy et al., 2014; Contini et al., 2017; Greene & Fei-Fei, 2014; Mohsenzadeh et al., 2018; Potter et al., 2014; Potter & Hagmann, 2015; Robinson et al., 2019). Distinctions such as whether something is animate (animal/human) are rapidly and automatically processed by the brain (Carlson et al., 2013; Connolly et al., 2012; Ritchie et al., 2015). Patterns of brain activity reflecting higher-order categorical distinctions, including animacy, emerge approximately 100-160ms after stimulus presentation (Contini et al., 2020; Goddard et al., 2016; Grootswagers, Robinson, & Carlson, 2019), even when the stimuli are not task-relevant (Grootswagers et al., 2021).

Study of patients with brain damage provided early evidence that the brain processes different categories of objects in different ways. Some patients were able to name living things, but had difficulty naming non-living objects (Sacchett & Humphreys, 1992). Other patients had the reverse problem: they showed deficits in naming things that are alive, but could name non-living objects (Farah et al., 1991; Warrington & Shallice, 1984). This double dissociation provided early evidence for a categorical organisation of the brain, specifically in processing whether something is animate (Hillis & Caramazza, 1991).

More recent work has found that individual categories of objects are represented distinctly in the brain, both across space and time (Carlson et al., 2013; Cichy et al., 2014; Jordan et al., 2015). For example, the ventral temporal cortex contains areas that respond to specific categories of objects, including faces (Gauthier et al., 2000; Grill-Spector et al., 2004; Kanwisher et al., 1997; McCarthy et al., 1997; Tong et al., 2000), places (Epstein & Kanwisher, 1998), and body parts (Downing et al., 2001; Urgesi et al., 2007). Each of these ‘modules’ seems to be part of a distributed, overlapping cortical representation of categorical information (Haxby et al., 2001; Ishai et al., 2000). With advanced computational methods and multi-variate analysis of functional Magnetic Resonance Imaging (fMRI), magnetoencephalography, and electroencephalography (MEG/ EEG) data, more recent research has focused on finding broad organisational principles which reflect global patterns of brain activity rather than specific regions sensitive to individual characteristics.

Neural processing of animacy

In the ventral visual stream, one such organisational principle is animacy. Animate stimuli are distinguishable from inanimate stimuli in patterns of brain activity from EEG recordings even for very rapid presentations (e.g., 50ms in Robinson et al., 2019), and when subjects are completing an unrelated task (Grootswagers et al., 2021). Differences in neural

processing of animates and inanimates are distributed across the inferotemporal cortex of primates (Bao et al., 2020; Kriegeskorte et al., 2008), human adults (Blumenthal et al., 2018; Coggan & Tong, 2021, 2023; Haxby et al., 2001; Khaligh-Razavi et al., 2018; Konkle & Caramazza, 2013; Sha et al., 2014) and infants (Bayet et al., 2020; Deen et al., 2017). There is also some evidence that animacy is a hard-wired, evolutionarily-adapted mechanism with a corresponding discrete neural system (Caramazza & Mahon, 2003; Caramazza & Shelton, 1998; Mahon & Caramazza, 2011; New et al., 2007).

Are animacy representations more perceptual or conceptual?

As in the developmental literature, there is some debate as to the degree to which representations of animacy in the brain arise from low- and mid-level visual feature similarities between animates (perceptual features), or because of some higher-order abstract attribute like similarity to humans or agency (conceptual features). Mid-level visual features alone (e.g., how curved an object is) explain a considerable proportion of both behavioural judgements of animacy (Schmidt et al., 2017), and neural activity (Nasr et al., 2014; Papale et al., 2020; Yue et al., 2020) beyond object identity and category. As established above, this relationship between visual features and object class is complex and necessarily interrelated because categorical distinctions are, in part, defined by shared visual features. For example, animate things tend to be more curved (Zachariou et al., 2018), and more visually similar than other categories such as tools (Humphreys et al., 1988). The brain may detect these statistics, as infants do, and these may form the basis of neural representations of categories we see in neuroimaging data.

One strategy used to explore the impact of visual features is to reduce or remove object conceptual knowledge by blurring the object but maintaining visual properties such as the spatial frequency and curvature. For example, Long et al. (2016) used texforms ([Figure](#)

1.1), images that have been modified to maintain mid-level features but are no longer identifiable. Even though the texforms were not recognisable, participants could classify by animacy at levels better than guessing, and animate texforms are distinguishable from inanimates in patterns of neural activity

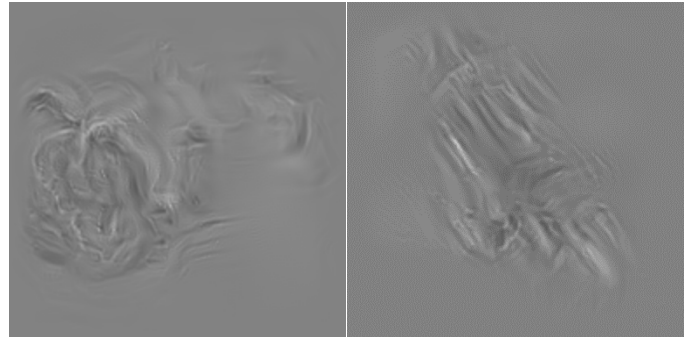


Figure 1.1

Example texforms (Long et al., 2016) On the left is a wristwatch, and on the right is a beetle. Publicly available images obtained from <https://osf.io/69pbd/>

(Grootswagers, Robinson, Shatek, et al., 2019; Long et al., 2016, 2018; Wang et al., 2022).

This suggests that neural representations of animacy can be explained, at least to a substantial degree, by mid-level visual statistics.

Another method of separating perceptual and conceptual information is to use stimuli that are matched for shape across categories, like a coil of rope and a coiled snake. Studies of brain activity using fMRI have revealed that semantic features play a role in object processing beyond carefully controlled visual similarity, particularly in more anterior regions of the ventral visual system (Bracci et al., 2019; Bracci & Op De Beeck, 2016; Kaiser et al., 2016; Proklova et al., 2016). Studies using time-sensitive methods like M/EEG have shown mixed findings, with some findings that animates cannot be distinguished from inanimates when shape is matched (Proklova et al., 2019), and others showing animacy representations for shape-matched hands/gloves and torsos/shirts (Kaiser et al., 2016).

With recent developments in artificial intelligence, another way of looking at the computations of the visual system is to examine how neural networks are able to perform category-classification tasks based on their training regimen. For example, networks that are self-supervised and have no access to category labels perform as well as networks with access to category labels as part of training, suggesting that visual features alone are

sufficient for categorical judgements (Konkle & Alvarez, 2022). Yet, other work has shown that models based on semantic descriptions of scenes perform similarly well at explaining patterns of brain activity than a category-labelling model (Conwell et al., 2023), or even better (Doerig et al., 2022), suggesting the visual system transforms input into rich semantic descriptions, mirroring claims by developmental researchers who have suggested that visual features are a stepping stone to conceptual knowledge (Jones & Smith, 1993).

Children can also distinguish animate movement from early in infancy.

This focus on animacy as a core conceptual feature is also present in development. The capacity to distinguish animates from inanimates develops early in infancy (Poulin-Dubois et al., 1996; Rostad et al., 2012). This is particularly true of animate movement. Infants as young as 7 months can distinguish between animate-like contingent movement and non-goal-directed inanimate movement (Träuble et al., 2014), suggesting that goal-directed movement is an important criterion for distinguishing animates from inanimates. Preschool aged children use goal-directed movement as their primary heuristic for determining if something is alive (Opfer & Siegler, 2004; Richards & Siegler, 1986), but also frequently over-extend this association to claim that natural moving things (like clouds, or the sun) are alive (Piaget, 1929/2013). This tendency to attribute aliveness to moving things has been called animism by Piaget (1929/2013). It suggests that children weight capacity for movement particularly highly in determining what is alive.

Capacity for movement and humanness inform animacy perception

Animacy is clearly an important category in both learning about how children develop and how the brain works. In this thesis, therefore, it serves as a bridge between these two fields. Though there are several factors that influence animacy judgements, in this thesis the

focus is narrowed to focus mainly two elements: whether something can move, and the degree to which it resembles a human. These particular elements were chosen because of the parallels between how they have been studied in development and in the brain. Both capacity for movement and humanness are also related to animacy and can provide important insights into integration of perceptual and conceptual information.

Capacity for movement

Movement, especially movement that is non-Newtonian (Scholl & Tremoulet, 2000) is closely associated with perceptions of animacy, even for simple and non-human stimuli like geometric shapes. In a classic study, Heider and Simmel (1944) showed participants videos of geometric shapes interacting with each other in a contingent manner (e.g., one looks like it is ‘chasing’ the other). Participants interpreted the movements as if the geometric shapes were animate and moving in a goal-directed manner. When adult participants are shown similar videos in an fMRI scanner, areas associated with face processing, such as the fusiform face area, are active, suggesting that processing of movement can provide clues to animacy even in the absence of obvious clues about animacy (Castelli et al., 2000, Schultz et al., 2003). Other nearby regions, such as the superior temporal sulcus, have also been implicated in extracting animacy information from motion characteristics. The superior temporal sulcus is activated both by presentations of biological motion, as well as shapes like those in Heider and Simmel’s experiments that interact in a seemingly contingent manner (Schultz et al., 2005). Perception of movement as contingent, goal-directed, or unpredictable, therefore, seems integral to neural processing of animacy.

The capacity of an object to move, particularly in a goal-directed manner, is also an important criterion that children use to judge whether something is alive (Richards & Siegler, 1986). One place this association between movement and aliveness manifests is in the

difficulty children have in understanding that plants are alive. Children rarely judge plants as living, and plants are rarely named in a child's list of living things (Amprazis et al., 2019; Carey, 1985; Richards & Siegler, 1986). Despite generally understanding of the distinction between animate (animals, humans) and inanimate objects, children do not form the category of 'living things', which includes plants along with animals and humans, until around age 6 or 7 (Anggoro et al., 2005, 2008; Looft, 1974; Nguyen & Gelman, 2002; Stavy & Wax, 1989; Villarroel et al., 2017). These difficulties may arise because the goal-directed movement in plants is less obvious and on a different time scale compared to animals and humans. Very few preschool-aged children are able to identify that plants can move on their own (Margett & Witherington, 2011), and the most frequent justification used by children who claim that plants are not alive is that they are unable to move autonomously (Martínez-Losada et al., 2014; Yorek et al., 2009). When children are taught that plants are capable of goal-directed movement, such as growing towards a light source, they more readily accept that plants are alive (Opfer & Siegler, 2004). Adults have similar difficulty in classifying plants. This tendency to neglect plants in favour of animals has been labelled 'plant blindness' (Schussler & Olzak, 2008; Wandersee, 1986; Wandersee & Schussler, 1999). Students can name and recognise animals more easily than plants (Patrick & Tunnicliffe, 2011), recall animal images more easily than plant images (Schussler & Olzak, 2008), and tend to name more animals than plants when asked to name living things (Torres-Porras & Alcántara-Manzanares, 2019).

Adults also rely on associations between movement and aliveness when they have to make rapid decisions (Goldberg & Thompson-Schill, 2009). Goldberg and Thompson-Schill (2009) found that when they are placed under time pressure, both university students and biology professors have more difficulty in classifying natural things that move, like clouds or lava, compared to still things like stones or sand. This suggests that the associations between movement and aliveness that are so prominent in childhood are still present in adults, and

instead of being completely overwritten, they are merely overridden by scientific knowledge as it is acquired (Kelemen et al., 2013). The degree to which these intuitions are relied upon may depend on the level of familiarity and ease of access of the scientific information (Shtulman & Varacel, 2012); adults tend towards anthropocentric thinking when reasoning under time pressure, and when facing unfamiliar concepts, but not familiar ones (Arenson & Coley, 2018). Other time-pressured tasks suggest that the human brain has developed biases to rapidly detect animate stimuli over the course of evolution, and this is not simply because they move, as the same biases are not seen for cars and other vehicles (New et al., 2007), thus it may be something to do with the degree to which the movement is goal-directed, or autonomous. Alternatively, it may be the naturalness of an item that is important, as even very young infants are able to distinguish biological from non-biological movement (Simion et al., 2008). Adult biases to associate movement with aliveness may also represent a continued bias from infancy to attend to biological motion. This evidence from behavioural work suggests that an object's capacity for movement is closely related to perceptions of animacy. Yet, despite the popularity of animacy as an organising principle of the ventral visual stream, we know very little about how an object's potential movement is processed in the brain, or what characteristics of movement influence decision-making.

Humanness

One reason movement might be an important factor in determining animacy is that the presence of goal-directed movement provides cues to how similar an object is to humans. Animacy is often studied as a binary class: animals and humans are animate, and all other objects (including plants, tools, etc.) are inanimate. However, recent studies have revealed that representations of animacy may be more complex than an animate/inanimate dichotomy. Instead, animacy may be represented on a spectrum according to an object's capacity for self-

initiated movement and agency, or similarity to humans (Connolly et al., 2012; Contini et al., 2020; Grootswagers et al., 2022; Jozwik et al., 2022; Sha et al., 2014; Thorat et al., 2019). In one MEG study, ratings on characteristics such as an object's capacity for pleasure, fear, and emotional regulation were significantly correlated with patterns of neural activity from around 200ms after stimulus onset, with the best model being overall ratings of similarity to humans at later time points 200-300ms after stimulus onset (Contini et al., 2020). Though on the surface, these results provide evidence for a conceptual basis for animacy distinctions, based on humanness or agency, is still remains complex to disentangle semantics from perceptual confounds – things that are more similar to humans are also more likely to have human-like visual features like a face and limbs.

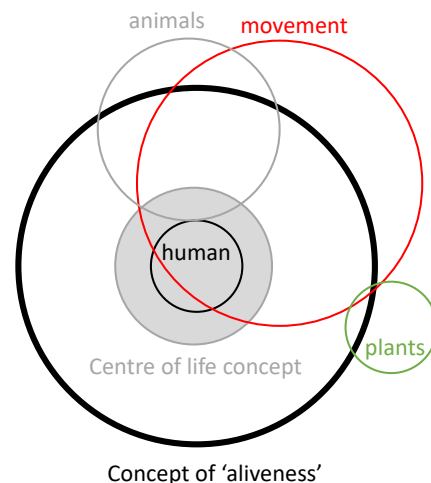


Figure 1.2
The animistic-anthropocentric model of life concept, adapted from Yorek et al. (2009)

There is also evidence that a human-centric model is used in behavioural classification. For both adults and children separately, researchers have proposed that we understand animacy and life status based on a human prototype. Theories of 'life status' in adults such as the animistic-anthropocentric model (Yorek et al., 2009; Yorek & Narli, 2009) propose that our understanding of what is alive centres around characteristics shared with humans, such that humans are seen as 'most alive', followed by animals and then plants (Figure 1.2). This is supported by evidence that teenagers primarily associated the concept of life with humans, then animals, and then plants (Yorek et al., 2009), and primarily listed humans and animals when asked to list 5 living things. Note that movement is also present in this model, where movement is the primary factor in determining similarity to humans.

Evidence for plant blindness discussed above also fits into a human-centric understanding of aliveness, as plants are less similar to humans in many other domains besides movement (e.g., in terms of reproduction, growth, and nutrition needs).

Children also consider aliveness with reference to a human ‘prototype’ (Carey, 1985). When making predictions about the biological behaviour of animals and plants, 5- and 6-year-old children often refer to how humans would react to a particular situation as a reference for making their decisions (Inagaki & Hatano, 1991). Children are more likely to attribute human characteristics, like having a heart or being able to think, to animals that are visually more similar to humans (Carey, 1985). However, children typically see humans as separate from all other animals, even primates. When children are asked to choose the ‘odd-one-out’ from a group of pictures including a person, a chimpanzee, and another animal, children typically choose the human as the ‘odd-one-out’ (Coley, 2007; Johnson et al., 1992), suggesting that the chimpanzee is perceived as more similar to an animal than a human. This human-centric (anthropocentric) view may be strongly influenced by the environment that children grow up in. Children who live in more rural environments show less anthropocentric reasoning, and Native American children show even less reliance on anthropocentric logic (Medin et al., 2010; Ross et al., 2003). These findings suggest that children use humans as a comparison for understanding other animals, but that this may be dependent on their context and exposure to the environment.

Children often claim plants are not alive, but can correctly attribute properties of life

Though children often perform poorly on explicit aliveness classification tasks, particularly ones involving plants (Carey, 1985; Hatano et al., 1993; Meunier & Cordier, 2004; Richards & Siegler, 1986), they have a remarkable grasp of the biological characteristics associated with life by preschool age (Blanchet et al., 2001; Bullock, 1985; R.

Gelman et al., 1983; S. A. Gelman & Gottfried, 1996, 1996; S. A. Gelman & Koenig, 2001; Legerstee, 1992; Mandler et al., 1991; Massey & Gelman, 1988; Rakison & Poulin-Dubois, 2001). Massey and Gelman (1988) asked 3- and 4-year-old children whether a series of ‘animal-like’ objects (e.g., an image of a 4-legged animal stone statue) could move up a hill by themselves. 78% of 3-year-olds and 90% of 4-year-olds responded accurately on their first answer, despite the presence of animate features like eyes and legs in many of the stimuli.

Children also do not attribute animal properties to objects that resemble people, like dolls (R. Gelman et al., 1983), or mechanically moving toys (Carey, 1985), suggesting that if their model of aliveness is based on humans, it is based on something deeper than visual similarity. Simons and Keil (1995) found that children expect sheep and robots to have different insides, even though they were unable to match the insides to the external appearance of the animal. This invisible biological similarity (sometimes referred to in a non-biological sense as their ‘essence’) is understood by children as young as 3, who attribute biological characteristics such as reproducing, breathing, growing, and needing to eat, to animates, but not inanimates (Greif et al., 2006). Specific biological properties of plants are also often understood correctly even when children don’t explicitly classify plants as alive. For example, many preschool age children understand that plants grow (Inagaki & Hatano, 1996), can heal themselves after being damaged (Backscheider et al., 1993), require nourishment (Hatano & Inagaki, 2002; Inagaki & Hatano, 1996) and can die (Anggoro et al., 2008; Nguyen & Gelman, 2002; Waxman, 2005). Thus, children’s understanding of plants seems to depend on how it is queried, and the term ‘alive’ may be misleading for preschool age children.

Understanding of psychological similarity to humans is still developing in children

Children can correctly attribute biological characteristics associated with life, but psychological characteristics are often more confusing, particularly for edge cases like human- or animal-shaped robots. While children rarely attribute biological properties (needing to eat, grow) to humanoid robots, they often attribute them psychological capacities like having thoughts and emotions (Jipson & Gelman, 2007), especially when the robot is seen to interact contingently with a human (Kim et al., 2019). Even when they judge robots as non-living, 6 year old children claimed a robot had emotions (Nigam & Klahr, 2000), and older children aged 7-15 claimed that a robot dog could ‘feel happy’ (Melson et al., 2009). This provides a particularly interesting insight into the influence of conceptual knowledge on neural processing. Given that Contini et al. (2020) found correlations between patterns of activity in the adult brain and psychological factors associated with humanness (e.g., capacity for fear, pleasure, consciousness, thought, and desire), the presence or absence of correlations in children’s brains can provide insight into the role of conceptual knowledge in object recognition in the brain and in development.

Summary

The flexible adult categorisation system develops throughout childhood, most likely in a continuous manner, constantly updating and integrating new information from new experiences and formal education. The debate about the reliance on perceptual compared to conceptual features throughout childhood is mirrored in the adult cognitive neuroscience literature on object representation, particularly in terms of animacy perception. Both fields have shown that categorical organisation of animacy or aliveness is closely related to perception of autonomous movement, and similarity to humans. Yet their intersection remains largely unknown. The current thesis addresses the following question: how is object

recognition and categorisation in the brain and behaviour of adults similar to children? This question is addressed by combining ideas, methods, and theories from the developmental psychology and cognitive neuroscience literature.

Children mainly use movement to judge whether something is alive, and adults seem to rely on similar intuitive scientific reasoning, associating movement and aliveness, when they are placed under time pressure. What elements of movement inform these aliveness judgements? How is movement, a concept so important in understanding aliveness for children, processed by the adult brain? Answering these questions can inform our understanding of how development occurs by searching for traces of development in the adult brain.

The adult brain can effortlessly and rapidly extract complex categorical structures, such as animacy, from visual input. Yet, we know very little about whether the same processes occur in children's brains, whether these occur on the same time scale as adults, and whether they reflect differences in behaviour compared to adults. Addressing these questions can offer important insight into how conceptual knowledge which is still developing in preschool age children influences neural processing, particularly for more abstract psychological properties, which are still developing in preschool age children.

Thesis overview

In five empirical chapters, this thesis investigates how development of categorical processing is reflected in the brain and behaviour of adults and children, outlined in [Figure 1.3](#). The first three chapters (2, 3, and 4) address the relationship between the developing conceptual system and the adult conceptual system. Chapter 2 aims to replicate and extend findings showing that childhood associations between movement and aliveness are suppressed in adults but are still relied upon under time pressure. Chapter 3 looks at how processing of movement might be reflected in brain activity, and how this is related to processing of animacy and aliveness. Chapter 4 investigates which aspects of movement might be represented in the brain, and how capacity for movement influences categorisation behaviour and perceived similarity. The final two chapters address how the developing brain processes objects. Chapter 5 aims to address how perceptual and conceptual processing are reflected in the brain by using unfamiliar objects to reduce the impact of semantic knowledge. Finally, Chapter 6 compares category representations in the brains and behaviour of 4-year-old children to adults.

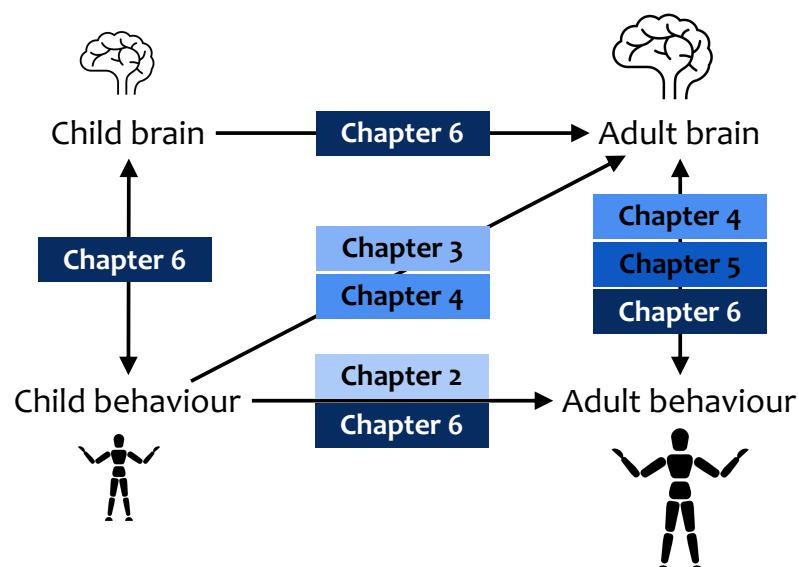


Figure 1.3

Overview of this thesis, looking at how conceptual development is reflected in the brain and behaviour of children and adults.

Chapter 2: The Influence of Movement on Perceptions of Aliveness: A Replication and Extension of Goldberg & Thompson-Schill (2009)

Children often mistake things that appear to move without visible external intervention, such as clouds, for being alive (Piaget, 1929/2013). Goldberg and Thompson-Schill (2009) demonstrated these mistakes are still present in adults under time pressure, suggesting that childhood intuitions are suppressed rather than overwritten (Kelemen et al., 2013). Using a rapid classification task, they showed that adults make more errors when judging if plants and moving natural things are alive (compared to animals, and still or artificial things). However, it is unclear whether participants make more errors on plants because of their lack of movement, because they are less familiar to participants, or because the words chosen for the study refer to many specific flower names which are less frequent than the other plant words. Furthermore, we know very little about the movement characteristics that are actually important for any of these judgements, as they have not been measured and vary widely within each category (e.g., compare how a planet, a clock, and a tiger move). This chapter contains four experiments designed to replicate and extend the original Goldberg and Thompson-Schill (2009) findings, to investigate what aspects of the stimuli might influence these difficulties in judging aliveness for plants and moving natural things. The results replicate Goldberg and Thompson-Schill (2009)'s findings, showing that plants and moving natural things are more difficult to classify as alive. Familiarity and imageability were correlated with accuracy and reaction time in the speeded aliveness classification task. In particular, plants and moving natural things were both less familiar and harder to visualise than other categories. Finally, movement characteristics varied dramatically across categories, such that each seems to have a unique and defining pattern of movement. Moving natural things were perceived to move independently, suggesting that movement has a pervasive influence on adult understandings of aliveness.

Chapter 3: Capacity for Movement is an Organisational Principle in Object

Representations

In Chapter 2, all experiments used the same set of words as Goldberg and Thompson-Schill (2009). It is therefore possible that the pattern of results is unique to that particular selection of objects, which has some quirks, such as a high number of plant words referencing specific flowers. Thus, the first goal of Chapter 3 was to investigate whether the difficulties in speeded classification for plants and moving natural things are robust across different concepts and different modalities, using images instead of words.

Recent neuroimaging evidence has shown that an object's capacity for agency is an important element of object processing in the brain, particularly for animate things (Sha et al., 2014). However, prior work has primarily used animate stimuli that move and inanimate stimuli that are still, making it difficult to disentangle the effect of movement from aliveness or animacy. Thus, in this chapter, the second goal was to look at how capacity for movement impacts neural object processing. Participants viewed static images of moving or non-moving objects that were either natural or artificial while we recorded EEG. In two separate experiments, participants classified the images either according to aliveness or according to capacity for movement. We found that capacity for movement explained significant variance in neural data over and above aliveness, naturalness, or other low-level features like rectilinearity, showing that capacity for movement is an important dimension in the representation of visual objects in humans.

Chapter 4: Capacity for Movement Provides Cues for Categorisation in the Brain and in Behaviour

In Chapter 3, EEG results showed that patterns of brain activity reflected whether a stimulus was able to move or not. However, it is unclear what elements of movement this

model of ‘movement’, which is based on human categorisation decisions, is picking up on. To answer this question, ratings of movement were gathered using similar questions as those in Chapter 2, but based on the images from Chapter 3. We can then explore how each of these attributes correlates with brain activity to examine how the brain might be processing movement. Our results closely resemble the category-level patterns in Chapter 2 using images instead of words, suggesting that movement characteristics may differ systematically across categories and that these patterns are robust across modalities. They also revealed that the correlations between brain activity and movement may be explained by two stages; a first decision of the object’s overall movement speed, followed by judgements of whether that movement is independent, or animate.

We also examined whether movement was behaviourally relevant, given its relevance in the brain. Based on an unconstrained task to pick the ‘odd-one-out’ from three images, would participants recognise the three dimensions (movement, aliveness, naturalness) on which the stimulus set is based? Would they use movement as a factor to choose the odd one out? Participants primarily choose the ‘odd-one-out’ from three images based on naturalness, but also judge based on movement, suggesting that movement is also behaviourally relevant for classification.

Chapter 5: Animal, Plant, or Mineral: Disentangling object concepts from visual features

One of the debates shared across cognitive neuroscience and developmental psychology is the degree to which object recognition relies on perceptual compared to conceptual features of objects. One way of investigating how the brain processes objects in the absence of clear conceptual information, as in childhood, is to use unfamiliar objects. Chapter 5 investigated how mid-level features (e.g., symmetry, aspect ratio, roundedness,

having a clear front and back) are processed in the brain by presenting images that did not clearly fall into a familiar category. Adult participants were shown images of plants, animals, and minerals that were unfamiliar, disguised, or camouflaged while brain activity was recorded using EEG. The results showed that while the true identities of the objects were elusive, both the true class and the perceived class of that object were distinguishable from patterns of brain activity. The same mid-level features that were correlated with brain activity were also used for behavioural similarity judgements, suggesting that visual features are important for object perception in the absence of clear categorical information.

Chapter 6: Object representations in the developing brain

Finally, very little work has been done to examine object representations in children's brains, despite clear differences in behaviour and understanding of aliveness. Thus, the aim of this final chapter was to directly compare conceptual processing in children to adults. Behavioural and neural data (EEG) were collected from children and adults completing the same tasks. Using these edge cases of toys and robots, in addition to plants which are often mistaken for not being alive by children, differences in hierarchical processing were examined for both children and adults. Both age groups also completed an 'odd-one-out' task so we could compare similarity judgements to neural similarity. Importantly, both adults and children completed almost identical versions of the EEG and behavioural task, allowing clear comparisons between age groups. Behavioural classification was remarkably similar across adults and children. However, exploratory EEG analyses revealed that, in contrast to adults, there were no significant correlations between children's brain activity and more abstract psychological aspects associated with being human such as being able to feel pain or pleasure.

Methods

To answer these questions about brain activity, we used EEG in both adults and children. As EEG data from developmental samples is often noisy and practically difficult to collect (Bell & Cuevas, 2012; Rollins & Riggins, 2021), two key methods are used to maximise data quality and analysis while also maximising data integrity: Multi-Variate Pattern Analysis (MVPA) and Rapid Serial Visual Presentation (RSVP).

MVPA is particularly well suited to analysing developmental neuroimaging data because of its sensitivity, and the ability to examine brain activity at different levels of abstraction. MVPA uses machine learning to analyse multi-dimensional recordings of brain activity across time and space. This approach is more sensitive to subtle patterns than traditional univariate methods, making it particularly useful for studying children's potentially noisy data (Williams & Henson, 2018). One common technique in MVPA, decoding, permits investigation of how objects are represented in the brain at different levels of abstraction. Decoding involves using a machine learning classifier trained on labelled chunks of neuroimaging data to predict the identity of unlabelled trials from the same dataset (Haynes, 2015). If the classifier performs better than chance in identifying these trials, it suggests that the patterns of brain activity contain information relevant to distinguishing between the conditions (Grootswagers et al., 2017). As EEG provides time-sensitive recordings, we can determine the timing of information in the brain that distinguishes these categories, revealing potential hierarchical processing of stimuli (Grootswagers et al., 2017). By selecting different labels to feed the classifier (e.g., cat/truck, animate/inanimate, animal/vehicle), the level of abstraction can be manipulated. For example, to examine whether children process basic-level categories before abstract ones, we can train a classifier at each level of abstraction and examine when it can successfully differentiate between the

classes (e.g., animate/inanimate or cat/dog). Accurate decoding provides evidence for differential neural representation of those categories at that level of abstraction.

Though MVPA provides a more sensitive method than univariate analyses, many repeated trials are still required to acquire sufficient power. In children with limited attention spans, collecting sufficient data is challenging. There have now been several demonstrations that the brain extracts a remarkable amount of information from very brief presentations in RSVP (Grootswagers, Robinson, & Carlson, 2019; King & Wyart, 2021; Marti & Dehaene, 2017; Mohsenzadeh et al., 2018; Robinson et al., 2019). Recent demonstrations from adult EEG data have shown that rapid presentations optimise the number of repeats while still gathering the important information (Grootswagers, 2023). These rapid presentations are particularly well-suited for children, whose attention span limits the time available for data collection. The combination of these RSVP streams with MVPA allows us to overcome many of the methodological barriers to investigating conceptual development in the brain.

To gather behavioural similarity ratings from both adults and children, we use an ‘odd-one-out’ task from Hebart et al. (2020). In this task, participants are presented with three images and asked to choose the odd one out. This method of gathering similarity ratings has several advantages in addressing the key aims of this thesis. Firstly, it is a simple task, so both children and adults can complete the exact same task, simplifying comparisons across age groups. Secondly, Hebart and colleagues (2020) have shown that this task can effectively extract the latent dimensions within a stimulus set, as it is unconstrained and does not tell participants which features to focus on. This can provide important insight into what features participants use to judge similarity.

Significance

For decades, developmental psychologists and cognitive neuroscientists have been studying the same fundamental questions about how perceptual information is transformed into a complex, conceptual understanding of the world. Both fields offer important insight into how we understand animacy and what it means to be alive, and how we integrate the most informative information from the visual environment with our existing knowledge.

Integrating methods, theories, and findings across these two fields provides insight into how the developing brain processes objects, and how developmental trends are still reflected in the adult brain.

The unique combination of methods also offers several advantages. By using methods like MVPA and RSVP, methodological barriers to collecting neuroimaging data from children are reduced. Other methods developed in cognitive neuroscience, particularly the odd-one-out triplet task offer an innovative approach to addressing questions about development. The odd-one-out task is simple to complete for both children and adults and substantially simplifies comparing across age groups. Together, these methodological innovations provide unique and important insight into the temporal dynamics of object recognition in children. Though most previous work on object recognition uses stimulus sets that confound animacy with naturalness, the studies on movement in this thesis introduce moving natural things (e.g., waves) to ensure that capacity for movement is balanced across living and non-living things. This inclusion provides unique insights into the role of perceived agency and capacity for movement in object perception and categorisation behaviour.

Furthermore, the methods in this thesis are also designed so that findings are robust and replicable. Two of the studies are repeated on both words and objects, demonstrating that the behavioural outcomes are not based on elements unique to either modality. For investigating movement, EEG data was not only recorded while participants are completing

two different classification tasks, to investigate the impacts of task on neural representations, but also while completing the same irrelevant visual task in both experiments. Comparing data from this identical task across the two experiments establishes the replicability of the results and ensures that comparisons across the two different tasks are valid.

Overall, this thesis offers novel insights into these questions, demonstrating that adults rely on the same simple shortcuts that children do, that these have a neural basis, and that processing the world using these shortcuts may be adaptive. The results have implications for how we understand object recognition in the brain and how we design stimulus sets to test this process, as well as how we understand the relationship between children's behaviour and brain activity.

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Chapter 2: The influence of movement on perceptions of aliveness: a replication and extension of Goldberg & Thompson-Schill (2009)

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Abstract

Children often mistake things that appear to move without visible external intervention, such as clouds, for being alive. Interestingly, these mistakes are also made by adults under time pressure. Goldberg and Thompson-Schill (2009) demonstrated this using a rapid classification task, and showed that adults make more errors when judging if plants and moving natural things are alive (compared to animals, and still or artificial things). Over four experiments, we explored Goldberg and Thompson-Schill's (2009) proposal that connections formed in childhood between movement and aliveness are used in adulthood to make decisions about aliveness. Our results replicated Goldberg and Thompson-Schill's (2009) finding that plants and moving natural things were more difficult to classify by aliveness. In addition, we showed that plants and natural things were also less familiar and harder to visualise than other categories. Participants intuitively believed that moving natural things could move without external intervention, suggesting that associations between movement and aliveness influence even decisions made without time pressure. These results suggest that movement is an important part of our conceptual understanding of aliveness, and how we encode objects in our environment.

The influence of movement on perceptions of aliveness: a replication and extension of Goldberg & Thompson-Schill (2009)

How do you know whether something is alive? For both adults and children, one important determinant of aliveness is whether a thing can move or not, and the degree to which this movement is perceived as autonomous (Richards & Siegler, 1986). Adults understand that even though some things appear to move by themselves, like airplanes in the sky and leaves falling from trees, they are not alive. In contrast, children tend to show what Piaget called “animistic tendencies” and consider non-living things that are natural and moving to be alive. For example, children in Piaget’s studies claimed the sun was alive, because it moved (Piaget, 1929/2013). Indeed, children seem to only consider something to be alive when it can perform goal-directed movement (Opfer, 2002). They also understand that objects that do not move autonomously towards a goal are not alive, including mechanical moving toys (Carey, 1985), and models of vehicles or animals (Massey & Gelman, 1988). Thus, from very early in development our conception of aliveness seems to be closely linked to movement.

One manifestation of the association between movement and aliveness is the difficulty children have in understanding that plants are alive. Children rarely judge plants as living, and plants are rarely named in a child’s list of living things (Amprazis et al., 2019; Carey, 1985; Richards & Siegler, 1986). Despite generally understanding the distinction between animate (animals, humans) and inanimate objects, children do not form the category of ‘living things’, which includes plants along with animals and humans, until around age 6 or 7 (Anggoro et al., 2005, 2008; Nguyen & Gelman, 2002; Stavy & Wax, 1989; Villarroel et al., 2017). These difficulties may arise because the goal-directed movement in plants is less obvious and on a different time scale compared to animals and humans. Very few preschool-aged children are able to identify that plants can move on their own (Margett & Witherington, 2011), and the most frequent justification used by children who claim that

plants are not alive is that they are unable to move autonomously (Martínez-Losada et al., 2014; Yorek et al., 2009). When children are taught that plants are capable of goal-directed movement, such as growing towards a light source, they more readily accept that plants are alive (Opfer & Siegler, 2004). It is clear from these difficulties with plants in childhood that goal-directed movement is crucial in forming our understanding of aliveness.

Adults also tend to neglect living things that don't have obvious movement, like plants. This tendency to neglect plants in favour of animals has been labelled 'plant blindness' (Schussler & Olzak, 2008; Wandersee, 1986; Wandersee & Schussler, 1999). Students can name and recognise animals more easily than plants (Patrick & Tunnicliffe, 2011), recall animal images more easily than plant images (Schussler & Olzak, 2008), and tend to name more animals than plants when asked to name living things (Torres-Porras & Alcántara-Manzanares, 2019). Theories of 'life status' in adults such as the animistic-anthropocentric model (Yorek & Narli, 2009) propose that the concept of motion is crucial for our perception of 'aliveness'. Yorek and Narli (2009) suggest that our understanding of what is alive centres around characteristics shared with humans, such that humans most seen as 'most alive', followed by animals, then plants. Phenomena like plant blindness may arise from misunderstandings of plant movement, again highlighting connections between movement and aliveness.

There are clear parallels in the importance of movement between childhood and adult understanding of what it means to be alive. Developmental theorists have debated whether this transition occurs in discrete stages (e.g., Carey, 2001), or whether it is more continuous and intuitions from childhood are 'overwritten' as scientific knowledge is acquired (e.g., Eimas, 1994). Evidence from undergraduates and professional scientists suggests that childhood intuitions in scientific thinking are persistently present in decision-making, and are suppressed rather than overwritten (Kelemen et al., 2013; Shtulman & Valcarcel, 2012). To

test whether this intuitive association from childhood between movement and aliveness was still present in adults, Goldberg and Thompson-Schill (2009) presented adults with words for living or non-living objects, moving or still objects, and man-made or natural objects, and asked them to judge whether each item was alive or not. Under time pressure, both undergraduate students and biology professors mistakenly classified plants as non-living more often than animals, and mistakenly classified moving and natural things as alive more often than still and artificial things. As a result, Goldberg and Thompson-Schill (2009) concluded that there are ‘roots’ of childhood knowledge that adults use to make decisions when sufficient biological knowledge is unavailable, such as under time pressure.

The underlying reason for these difficulties in classifying plants and natural moving things, however, remains unclear. For example, it is possible that some of the words are simply less familiar for participants, and therefore harder to judge on *any* semantic dimension. Around half of the words in Goldberg and Thompson-Schill's (2009) plant category are specific flower names (such as poinsettia, hyacinth), which are less frequent than the other plant words ([Supplementary Figure 2.1](#)). Furthermore, the movement properties of items in stimulus set varies substantially; compare the movement of a clock, for example, to a planet or a tiger. We also know very little about the characteristics of movement (e.g., autonomy, speed) that influence these judgements of aliveness.

In the current study, we used four tasks to replicate Goldberg and Thompson-Schill (2009) and gain insight into what processes or biases might be driving these findings. We first directly replicated Goldberg and Thompson-Schill (2009)’s aliveness classification task in Australian undergraduates. We then explored three variables that might explain categorical differences in performance on the aliveness classification task: familiarity, imageability, and movement characteristics.

Work in linguistics has shown that word frequency is an important correlate of lexical processing (Brysbaert et al., 2018). Though Goldberg and Thompson-Schill (2009) balanced word frequency across categories of stimuli, the frequency measures (the Hyperspace Analogue to Language (HAL)) were taken from news sources that are almost 30 years old (Lund & Burgess, 1996, as cited in Goldberg & Thompson-Schill, 2009). These older norms may not reflect how *familiar* participants, especially younger undergraduates, are with any given concept. Though familiarity and frequency are often used interchangeably, and are generally correlated, they are not equivalent. They are more similar in corpora based on spoken language like subtitles, but work from written sources shows that “familiarity is necessary for a word to achieve a high frequency, but familiar words are not necessarily frequent” (Tanaka-Ishii & Terada, 2011, p. 96). Many linguistic corpora contain familiarity scores (e.g. Glasgow norms (Scott et al., 2019), Bristol norms (Stadthagen-Gonzalez & Davis, 2006)), but we were unable to find one that covered most or all of the words in this study, as most were missing several of the plant words. To establish familiarity, we simply asked participants to rate their familiarity with each of the concepts in Goldberg and Thompson-Schill’s (2009) word list. We expected some of the plant words to be less familiar, as they were infrequent enough to be excluded from many corpora.

Given almost ceiling level responding in the familiarity ratings, we considered whether there were differences across categories in how easy each of the items were to visualise. In research on word frequency and lexical access, ease of visualisation is often studied as ‘imageability’, and is used as a measure of ‘semantic richness’ (Yap et al., 2012). Though many previous researchers have gathered ratings of imageability as part of a variety of corpora, many of the plant words were absent. Difficulty in visualising items may lead to failure to fully activate semantic knowledge networks and correctly categorise the object (Farah & McClelland, 1991). Words rated lower in imageability are often also low in

familiarity (Kousta et al., 2011), so we expected that these scores would be closely correlated to the familiarity scores. Previous work has also shown that when participants are asked to imagine items in a familiar context, animate things are harder to visualise than inanimate things (Bonin et al., 2015). Hence, we expected animals to be most easy to visualise.

Difficulties in classifying plants and moving natural things may also be explained by differences in the quality of movement across categories. Though Goldberg and Thompson-Schill (2009) state that they use pilot data for ratings of movement, it is unclear what this data was based on. For example, the movement in a clock and the movement of a lion are very different along several domains, including whether the movement is local or global, the speed of the movement, and how much the movement is agentic (self-driven). These differences may provide insight into what characteristics are important in judging aliveness, and how they vary across categories. Some previous work has begun to explore how ‘human-like’ characteristics of an object such as the ability to reproduce, move, and think vary across categories of words (VanArsdall & Blunt, 2022). However, while 80% of the animal words from this experiment were included in VanArsdall and Blunt’s (2022) norms, there was only data for 20% of the plant words. Thus, in our final task, we gathered ratings of different characteristics of movement, how much these kinds of movement are self-driven, and how manipulable the objects are.

To foreshadow, we replicated Goldberg and Thompson-Schill’s (2009) results, showing that moving natural things were responded to more slowly and less accurately. In addition, we found that familiarity and imageability were correlated with both accuracy and reaction time in the aliveness classification task, with plants and moving natural things being less familiar and harder to visualise. We also showed that movement characteristics differ dramatically across categories, and that moving natural things are perceived to have agency in their movement. Our findings suggest that even without time pressure, moving natural

things are still perceived to have autonomous local and global movement, pointing to a pervasive influence of movement on adult conceptions of aliveness.

Methods

To investigate how associations between movement and aliveness developed in childhood influence adult cognition, we used four different tasks. Methods and results for all tasks are written together to avoid unnecessary repetition and to facilitate comparison, as the data for each task is analysed in relation to the others and there is substantial methodological overlap. An independent group of participants completed each task.

Participants

Participant characteristics for all tasks are shown in [Table 2.1](#). All participants were undergraduate students at the University of Sydney, recruited online in return for course credit. All participants reported that English was the first language they learned to read and speak and gave informed consent before commencing the study. The study procedures were approved by the University of Sydney ethics committee. Note that for the movement ratings, data from three participants were incomplete, but contained more than half of the trials. The partial data from these participants was included, but recall data was missing, so recall data and category observation data is from 105/108 subjects. Participants were excluded if they were less than 75% accurate in the aliveness task, as in Goldberg and Thompson-Schill (2009), or if they rated three attention check non-words as more than 25/100 on familiarity or imageability, on average.

Table 2.1.*Participant characteristics.*

	Final N ^ (N excluded)	Mean Age (range)	Gender *	High School biology (%)	University biology (%)
Aliveness classification task	31 (6)	19.84 (18-30)	4 males, 26 females	5 (16%)	15 (48%)
Familiarity ratings	31 (3)	23.25 (18-47)	10 males, 20 females	24 (77%)	18 (58%)
Imageability ratings	35 (4)	20.23 (18-32)	11 males, 23 females, 1 non-binary	19 (54%)	19 (54%)
Movement ratings	108 (4)	20.38 (18 - 46)	39 males, 68 females, 1 non-binary	50 (46%)	69 (63%)

*Where these do not sum to the final N, additional participants answered, “Prefer not to say.”

^ N excluded are not included in the final N, i.e., the total number of participants is the Final N + N excluded.

Materials and procedures

For all tasks, participants completed the experiment online on a laptop or desktop computer, hosted on Pavlovia (Peirce et al., 2019, <https://www.pavlovia.org/>), coded using tools in JSPsych (de Leeuw, 2015), and guided by Grootswagers (2020).

Stimuli

Stimuli were the same across all tasks, taken from Goldberg and Thompson-Schill (2009). The full list can be found in the OSF repository for this study. There were 140 words in total, sorted into 6 categories: plants (30 words, e.g., cactus, gardenia), animals (30 words,

e.g., falcon, octopus), moving artifacts (20 words, e.g., rocket, bicycle), moving natural kinds (20 words, e.g., cloud, monsoon), still artifacts (20 words, e.g., towel, teaspoon) and still natural kinds (20 words, e.g., stone, boulder). Note that only movement is balanced across the stimuli; there are more non-living words (80) than living words (60), and more natural stimuli (100) than artificial stimuli (40). The word lists for animals and plants were equated on mean number of letters, number of syllables, and their frequency in speech using Log transformed HAL Frequency Norms (Balota et al., 2007). The same procedure was also applied to selection of words for the non-living lists (still artifacts, still natural kinds, moving artifacts, and moving natural kinds), such that word length and syllables were roughly equal between lists. To check that participants were completing the task properly, three non-words (“koret”, “malfer”, and “serone”) were also included in all tasks except the aliveness classification task.

Aliveness classification task

All materials and procedures were designed to be as similar as possible to Goldberg & Thompson-Schill (2009). Participants were presented with a single word in the centre of the screen and asked to indicate whether it was alive or not ([Figure 2.1A](#)). The entire experiment typically took less than 15 minutes. All participants responded to all 140 words. Each trial began with a fixation cross in the centre of the screen for a random duration between 500ms and 1000ms ([Figure 2.1A](#)). The fixation was then replaced by the target word, which remained on the screen for 1000ms. If the participant responded within 1000ms, the fixation cross returned to the screen for a random duration between 500ms and 1500ms, and the next trial began. If the participant did not respond, they were shown a time out message “No response recorded” for 1000ms before the next trial commenced. Trials were presented in

blocks of 20 words, separated by breaks in which participants clicked a button on the screen to continue.

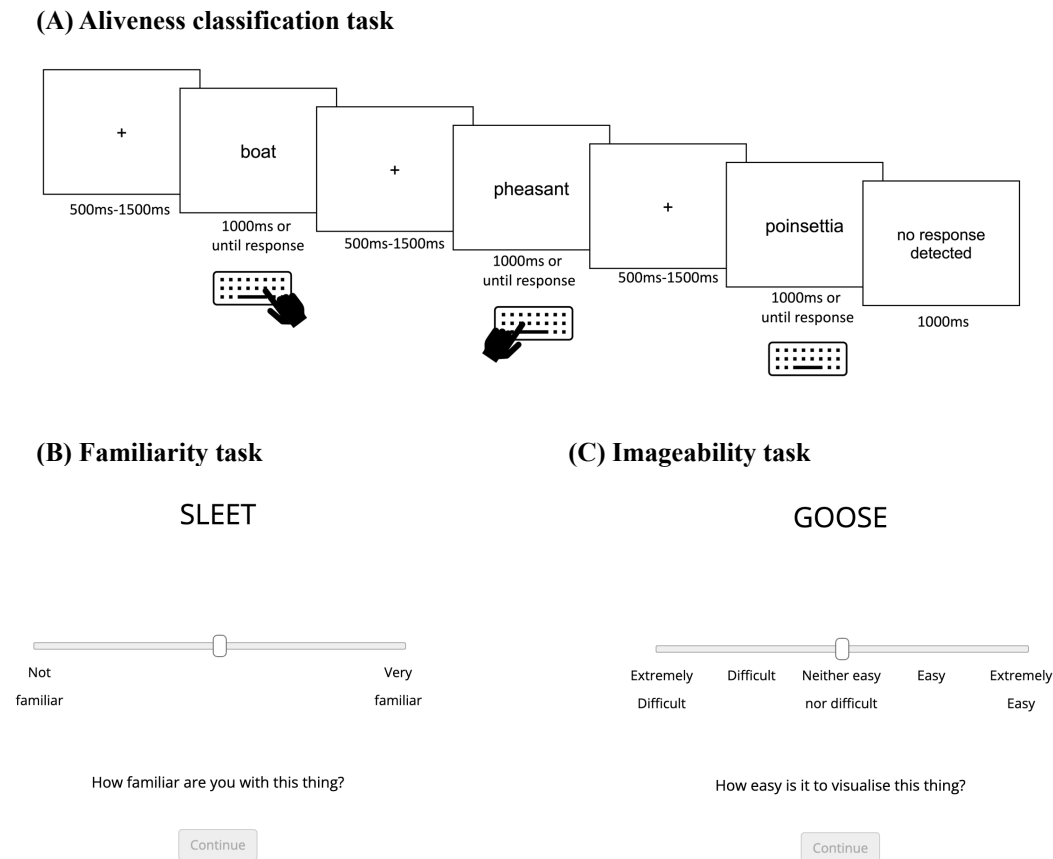


Figure 2.1
Sample sequence of the aliveness task (A), sample rating screen for the familiarity task (B) and imageability task (C).

Familiarity and imageability ratings

For both the familiarity and imageability tasks, participants rated each word, one at a time, on a 0-100 slider. For the familiarity task, participants were asked to rate “...how familiar you are with each word” ([Figure 2.1B](#)). For the imageability task, participants were asked to rate “...how easy each thing is to visualise, or how well you are able to picture an example of the thing in your mind's eye” ([Figure 2.1C](#)). They were told to “Go with your first

impression, don't spend too long on each item.” For the imageability task, participants were also instructed at the beginning of the task “Note that if you don't know what a word means, it might be difficult to visualise”, so it was clear what to do for the three non-words included as an attention check.

Each word was presented one at a time, in the centre of the screen in 30pt font. For each word, participants were presented with a sliding scale representing 0 – 100. For familiarity, 0 was labelled as “very unfamiliar” and 100 labelled as “very familiar” ([Figure 2.1B](#)). For imageability, the scale had ticks at 0, 25, 50, 75, and 100 with the labels “extremely difficult”, “difficult”, “neither easy nor difficult”, “easy”, and “extremely easy” ([Figure 2.1C](#)). Instructions under the slider reminded participants of the task: “How easy is it to visualise this thing?” or “How familiar are you with this thing?” To compare across categories, scores from all participants were collated and averaged for each category.

Movement ratings

One way of distinguishing between different types of movement is to distinguish between movement that involves changing position (global movement), and movement on a local scale, like growing, changing shape, or having moving parts. Participants answered eight questions relating to how each item was able to move, shown in [Table 2.2](#). The familiarity scale was included primarily to serve as the attention check, but also to replicate the findings of the familiarity task.

Table 2.2.

Questions used to obtain movement ratings, all using a 100-point slider.

		Question	Scale labels
Familiarity	1	How familiar are you with this thing?	0: Very UNfamiliar 100: Very familiar
Global movement	2a	How likely is this thing to change position in daily life (including influence of external forces e.g., gravity, wind, a human)?	0: Does not change position 100: Highly likely to change position
	2b	How much does this thing typically change position in one minute, on average (including influence of external forces e.g., gravity, wind, a human)?	0: <1mm 25: 1cm 50: 1m 75: 1km 100: > 100km
	3a	How likely is this thing to change position in daily life, WITHOUT external intervention (i.e., by itself)?	0: Does not change position by itself 100: Highly likely to change position by itself
Intrinsic global movement	3b	How much does this thing typically change position in one minute, on average, WITHOUT external intervention (i.e., by itself)?	0: <1mm 25: 1cm 50: 1m 75: 1km 100: > 100km
Local movement	4a	Without changing position, how likely is this thing to move in daily life? (e.g., grow, change shape, have moving parts)	0: Does NOT move without changing position 100: Definitely moves without changing position
	4b	Without changing position, how much external intervention is required for this object to move? (e.g., grow, change shape, have moving parts)	0: Always requires external intervention to move 100: Can always move without external intervention
Ease of manipulation	5	How easy is it for you to pick up and move this thing?	0: Immobile or difficult to move 100: Easily moveable

To keep the experiment length manageable, each participant saw approximately one quarter of the stimuli from each category, seven animals and plants, and five from the other four categories. Including the three attention check stimuli, each participant rated 37 words.

Each word was shown at the top of the screen, with a series of sliders underneath for the questions in [Table 2.2](#). Participants needed to move the slider (0-100) on every question from its initial starting location at the mid-point (50) to advance to the next word. Across all participants, each word was responded to at least 20 times (range 20-32).

Participants began by viewing a set of instructions, designed to help them understand the intended meaning of the questions. For example, to explain what ‘external intervention’ refers to in questions 2 and 3, participants were shown an animation of two men throwing a pile of leaves in the air and an animation of leaves falling off a tree, and told “For example, an object might change position if it is moved by the wind or gravity, or if a human picks it up or intervenes in some other way.” Local movement was explained as “... movement when the object is stationary, such as changing shape, growing, or having moving parts”. A full copy of the instructions in context can be found in the experiment repository.

At the end of all tasks

At the end of each task, participants were presented with the same questions. First, there was an open text box and participants were asked to “type any words that you can remember from the experiment”. They were not informed in advance that they would be asked to recall the words. For each participant, the average number recalled for each category was calculated, and averaged across participants to estimate the proportion of words recalled across different categories. Participants were also asked, “Did you notice any categories of words appearing in the list?” to investigate whether any categories were obvious from the set of words. Data on category observations is absent for seven subjects in the aliveness classification task due to a technical error. These free text entries from all tasks were fed to the WordCloud library in python (Mueller, 2022) to create a qualitative representation of the frequency with which particular categories are mentioned. Small words (‘there’, ‘were’,

‘some’) were removed, and words less than three letters were also excluded. We also asked participants “Do you have any observations about the words you responded to?” A full list of observations is available in the OSF repository.

Comparing across tasks

To compare how the characteristics studied in each task relate to each other, and might explain accuracies in the aliveness classification task, we looked at Spearman Rank correlations between each of the measures gathered in these tasks ([Figure 2.4](#)). In addition to familiarity and imageability estimates, as well as the movement questions, we also included some measures taken from linguistic databases to investigate how these factors might be related. Age of Acquisition is a measure of the age at which a child can produce a given word, as rated by adults (Kuperman et al., 2012). This measure can also be used to examine Goldberg and Thompson-Schill’s thesis that the same words that are difficult and confusing in childhood remain so in adulthood, as this would predict a positive correlation between age of acquisition and reaction time in the aliveness classification task. The Age of Acquisition data was retrieved from the English Lexicon Project (Balota et al., 2007; Kuperman et al., 2012).

We have also included the frequency on Twitter (TwitterFreqPm) from Worldlex (Gimenes & New, 2016) as an alternate frequency measure to compare to the Log HAL frequency norms that were used by Goldberg and Thompson-Schill (2009) in constructing a balanced stimulus set, particularly given our participant sample is younger and potentially interacting more frequently with Twitter-style text than the news sources that the HAL frequency is based on. Data for both experiments from Goldberg and Thompson-Schill (2009) was retrieved from the supplementary materials available online. Concreteness was also retrieved from the English Lexicon Project, as another measure on which the moving

natural things might differ. Spearman correlations based on experimental data were calculated item-wise, using the average for each item across participants. To test if correlations were above chance, we used a Bonferroni correction for multiple comparisons at $p < .05$, where $p < .00018$.

Statistical inference

Statistics were implemented based on Goldberg and Thompson-Schill (2009), though in addition to the traditional frequentist approach we also examined results under a Bayesian framework. Throughout, results are only interpreted as meaningful when both Bayesian and frequentist approaches indicate evidence for the alternate hypothesis. All Bayesian statistics were run using the BayesFactor package for R, using the default two-sided prior with a width of 0.707. Bayes Factors can be interpreted as odds ratios; a Bayes Factor of 3 indicates three times as much evidence for the alternate hypothesis compared to the null hypothesis. Bayes Factors (BF) are interpreted as according to Jeffreys (1961/1998), where $BF > 30$ is very strong evidence for the alternate hypothesis, $BF > 10$ is strong evidence, $BF > 3$ is some evidence, and $BF < 1/3$ is evidence for the null hypothesis.

Animals and plants were compared using two-sided t-tests, or a Bayesian t-test with a two-sided prior. The effect of movement and naturalness was compared using a two-way ANOVA, or the Bayesian equivalent of an ANOVA (using the anovaBF function of the BayesFactor package), where the effect of a given variable can be calculated by comparing the evidence for a linear model containing that variable to one that does not contain that variable. Comparisons between each category of objects were done using Bayesian t-tests, and Tukey HSD tests, with the family-wise error rate corrected to .05.

Results

To investigate how aliveness judgements are affected by movement, data was collected from four different tasks: a replication of the rapid aliveness classification task from Goldberg and Thompson-Schill (2009), judgements of familiarity and imageability, and ratings of movement characteristics. All raw data and results can be found in the OSF repository for this study.

Replication of results from Goldberg and Thompson-Schill (2009)

First, to ensure replicability of results showing that plants and moving natural things are more difficult to judge by aliveness, we replicated the rapid aliveness judgement task from Goldberg and Thompson-Schill (2009). Our results were remarkably similar to the original study. When judging aliveness, the average accuracy was 82% (range 75 – 92). Many words were near ceiling levels of accuracy, with 65% of words above 80% mean accuracy. Several words were classified accurately by all participants, including octopus, boat, taxi, truck, wagon, dish, vase, ruler, towel, pencil, window, teaspoon, stone, gravel, and diamond. The least accurate words were hemlock (16.13% participants correct), carnation (25.81%), poinsettia (25.81%), and elm (38.71%).

As in Goldberg and Thompson-Schill (2009), accuracy was significantly lower for plants compared to animals, $t(30) = 8.23$, $p < .001$, $BF_{10} = 5.76 \times 10^6$ ([Figure 2.2A](#)), and responses for plants were slower than for animals, $t(30) = 6.31$, $p < .001$, $BF_{10} = 4.73 \times 10^4$ ([Figure 2.2B](#)). There was a main effect of both movement and naturalness on reaction times ([Figure 2.2B](#)). Moving things were responded to more slowly than still things, $F(1,120) = 6.22$, $p = .014$, $BF_{10} = 4.37 \times 10^2$. Natural things were responded to more slowly than artificial

things, $F(1, 120) = 13.59, p < .001, BF_{10} = 1.18 \times 10^6$. The interaction effect was not significant, $F(1, 120) = 1.85, p = .18, BF_{10} = 5.91$.

Movement and naturalness also impacted the accuracy of responding, as shown in [Figure 2.2A](#). Participants responded more accurately to still stimuli compared to moving stimuli, $F(1, 120) = 17.98, p < .001, BF_{10} = 2.33 \times 10^3$. Artificial stimuli were classified more accurately compared to natural stimuli, $F(1, 120) = 43.22, p < .001, BF_{10} = 1.70 \times 10^8$. For accuracy, the interaction term was significant, such that naturalness decreased accuracy for moving stimuli more than still stimuli, $F(1, 120) = 6.01, p = .02, BF_{10} = 1.48 \times 10^1$, reflecting the substantial decrease in accuracy for moving natural stimuli ([Figure 2.2A](#)). Plants were reported incorrectly more often than all other categories except moving natural things, and responses to moving natural things were significantly less accurate than all other categories except plants.

Plants and moving/natural things are less familiar

To investigate other possible factors that might influence judgements of aliveness, we gathered ratings of how familiar participants were with the stimuli from Goldberg and Thompson-Schill (2009). The average familiarity rating ([Figure 2.2C](#)) was 89.03/100, suggesting that the majority of words were familiar to most participants. Many items were scored at near ceiling levels of familiarity; 70% of stimuli were rated above 90/100 for familiarity, and 86% were above 80/100. The least familiar items were poinsettia (11.7/100), hyacinth (23.68/100), hemlock (34.88/100), geyser (44.29/100), elm (47.5/100) and sleet (53.29/100).

For living things, plants were less familiar than animals, $t(30) = 10.78, p < .001, BF_{10} = 1.09 \times 10^9$. For non-living things, moving things were less familiar than non-moving things, $F(1, 120) = 10.56, p = .001, BF_{10} = 5.09 \times 10^7$, and natural things were less familiar than

artificial things, $F(1, 120) = 4.86, p = .029, BF_{10} = 9.42 \times 10^3$. The interaction effect was not significant, $F(1, 120) = 0.019, p = 0.89, BF_{10} = 0.06$. Plants were less familiar than all other categories. Still artificial things were also more familiar than moving natural things.

Plants and moving/natural things are also harder to visualise

Given almost ceiling familiarity with the stimuli, we also gathered ratings of how easy each stimulus was to visualise, a metric used in linguistics as a measure of semantic richness. The mean imageability rating was 80.44/100, indicating that on average participants found most words easy to visualise. 66% of items were rated above 80/100 on ease of visualisation, but only 46% were rated above 90. The easiest item to visualise was grass (98.18/100), and the most difficult items to visualise were poinsettia (13.15/100), hyacinth (14.44/100), hemlock (17.46/100), petunia (30.92/100), and elm (30.95/100). Note that three of these difficult items (poinsettia, hemlock, and elm) were also among the least familiar.

As shown in [Figure 2.2D](#), animals were easier to visualise than plants, $t(38) = 12.27, p < .001, BF_{10} = 2.43 \times 10^{11}$. Artificial things were easier to visualise than natural things, $F(1, 136) = 16.48, p < .001, BF_{10} = 1.65 \times 10^{11}$, and still things were easier to visualise than moving things, $F(1, 136) = 28.64, p < .001, BF_{10} = 1.75 \times 10^{17}$. The interaction effect was non-significant, $F(1, 136) = 0.34, p = .593, BF_{10} = 1.08$. Plants were harder to visualise compared to all other categories, and still artefacts were easier to visualise compared to all other categories except still natural things. Moving natural things were also more difficult to visualise than all other non-living items (moving artificial, still natural, and still artificial).

Movement characteristics vary systematically across categories

To investigate how differences in movement characteristics across categories may explain the difficulty classifying plants and moving natural things as alive, participants

answered a series of questions about whether the movement is local or global, the speed of the movement, and how much the movement is agentive (self-driven). All movement results are shown in [Figure 2.3](#). For brevity, not all statistical tests are reported here, as many of the outcomes are similar; for example, stimuli that were designated as ‘moving’ were rated as more likely to move, and move more quickly, than those designated as ‘still’ by Goldberg and Thompson-Schill (2009) in all questions ([Figure 2.3](#)). Statistics for all comparisons and ANOVAs are contained in the supplementary materials ([Supplementary Table 2.1](#) and [2.2](#)).

A question about familiarity was included to validate the attention check and replicate the familiarity task. As in the familiarity task, moving things were less familiar, as were natural things. Plants were less familiar than all other categories, and moving natural things were less familiar than all other categories except plants.

Adults show attentional preferences for movement that is agentive (New et al., 2007), and agentive movement is also differentiated in language: both adults and children understand “did X move?” to mean “did X move by itself?” (Gelman & Koenig, 2001). As agency is clearly an important element of movement for classification, we asked participants separately about any kind of movement, and specifically about intrinsic, agentive, or self-driven movement. When considering movement from any source, including external intervention like a human or gravity, artificial things were more likely to move overall, and move more quickly than natural things ([Figure 2.3](#)). However, when only considering intrinsic (self-driven) movement, the pattern was reversed; natural things were more likely to move independently, and move more quickly, than artificial things. Local movement was more similar to intrinsic global movement, such that natural things were more likely to move locally, and this movement was more independent.

One notable finding is that the moving natural things (e.g., waves) were perceived to move independently. Moving natural things were more likely to change position independently, and move more quickly independently than all other categories except animals. They were also rated more likely to have local movement, and this local motion was perceived to be more self-driven compared to all other categories except animals.

How much an object is ‘action-oriented’, whether it is manipulable, and whether it moves or is stable, appears to be processed automatically by the visual system of the brain (Magri et al., 2021; Mahon et al., 2007), suggesting the way an object is manipulated is relevant to how it is processed and categorised by the brain. Therefore, we also queried the motor-relevance of objects by asking about how easy items were to manipulate. We found that still things were easier to manipulate than moving things, and artificial things were easier to manipulate than natural things. Most importantly, each category had a unique constellation of these characteristics, as shown by the different patterns across categories shown in [Figure 2.3](#).

More familiar and imageable items are easier to judge in the aliveness task

To investigate whether factors like imageability and familiarity predicted performance in the aliveness task, we looked at the correlation between these attributes. Performance in the aliveness classification task was correlated with both familiarity and imageability, such that things that were familiar and easier to visualise were responded to more accurately and more quickly. This can be seen at the category level in the similar pattern of results across [Figure 2.2A](#), C, and D. As expected from the similarity in response patterns, familiarity and imageability are also closely correlated. In addition, words with an earlier age of acquisition were also responded to more accurately and more quickly in the aliveness classification task, and were more familiar and easy to visualise ([Figure 2.4](#)). Together, these relationships

suggest that less familiar words that are acquired later in life are more difficult to classify as alive or not, providing support for Goldberg and Thompson-Schill's proposal that associations in childhood impact on adult categorisation behaviour.

Interestingly, concreteness was significantly correlated with reaction time, but not accuracy, in the aliveness classification task, such that more concrete things were responded to more quickly. As only reaction times for correct responses were included in measures of reaction time, this suggests that less concrete things are harder to classify as alive or not. The concrete things are also generally more familiar, and easier to visualise. However, the correlation between all of these measures is moderate (maximum $\rho=0.45$), reaffirming previous findings that though imageability and concreteness are related, they are not completely overlapping concepts (Kousta et al., 2011).

Individually, movement attributes are not predictive of accuracy in aliveness judgements

There were few significant correlations between the movement characteristics and performance on the aliveness task. Words with higher likelihood and independence of local movement were responded to less accurately in the aliveness classification, and were also recalled more often. Words with higher likelihood of intrinsic local movement were also more likely to be recalled. This is possibly driven primarily by animals, which were responded to accurately in the aliveness classification task, and also rated highly on local movement. Local movement may be the best correlate of accuracy in the aliveness task because the same division between living and non-living is reflected in both tasks: ratings of local movement reflect the divide between living and non-living things, with animals and plants primarily rated as more likely to have local movement and still artefacts and natural things as less likely to have local movement.

Overall, these correlations reveal that though there are differences in movement across different categories, a large portion of the results in both Goldberg and Thompson-Schill's (2009) results and our replication can be attributed to the effects of familiarity and imageability, as well as word frequency, concreteness, and average age of acquisition.

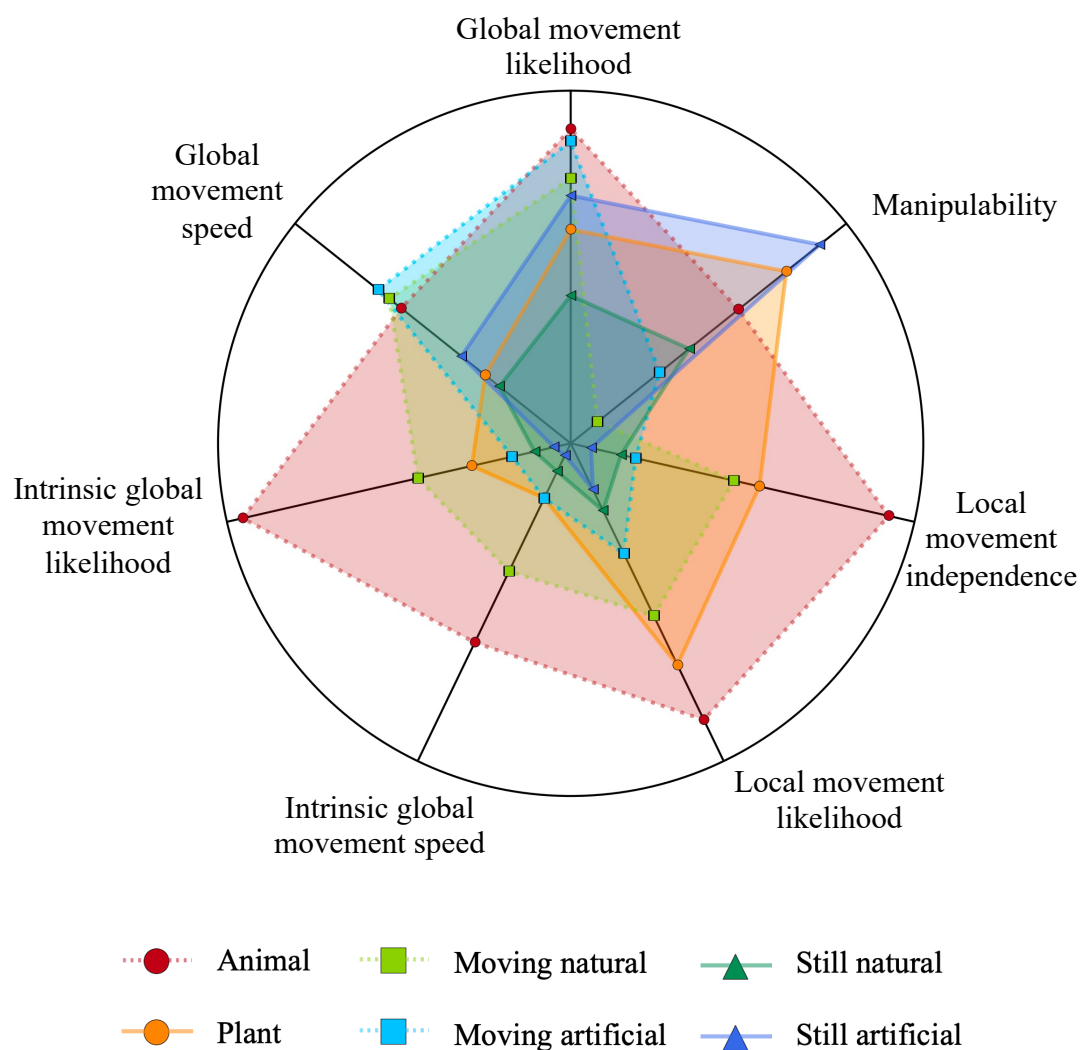


Figure 2.3

Movement characteristics by category. Each characteristic is shown on a spoke of the plot, with each category shown in a different colour. For the non-living things, natural things are in green and artificial things are in blue, moving things are squares (dashed lines) and still things are triangles (solid lines). Note the differences in shape between categories.

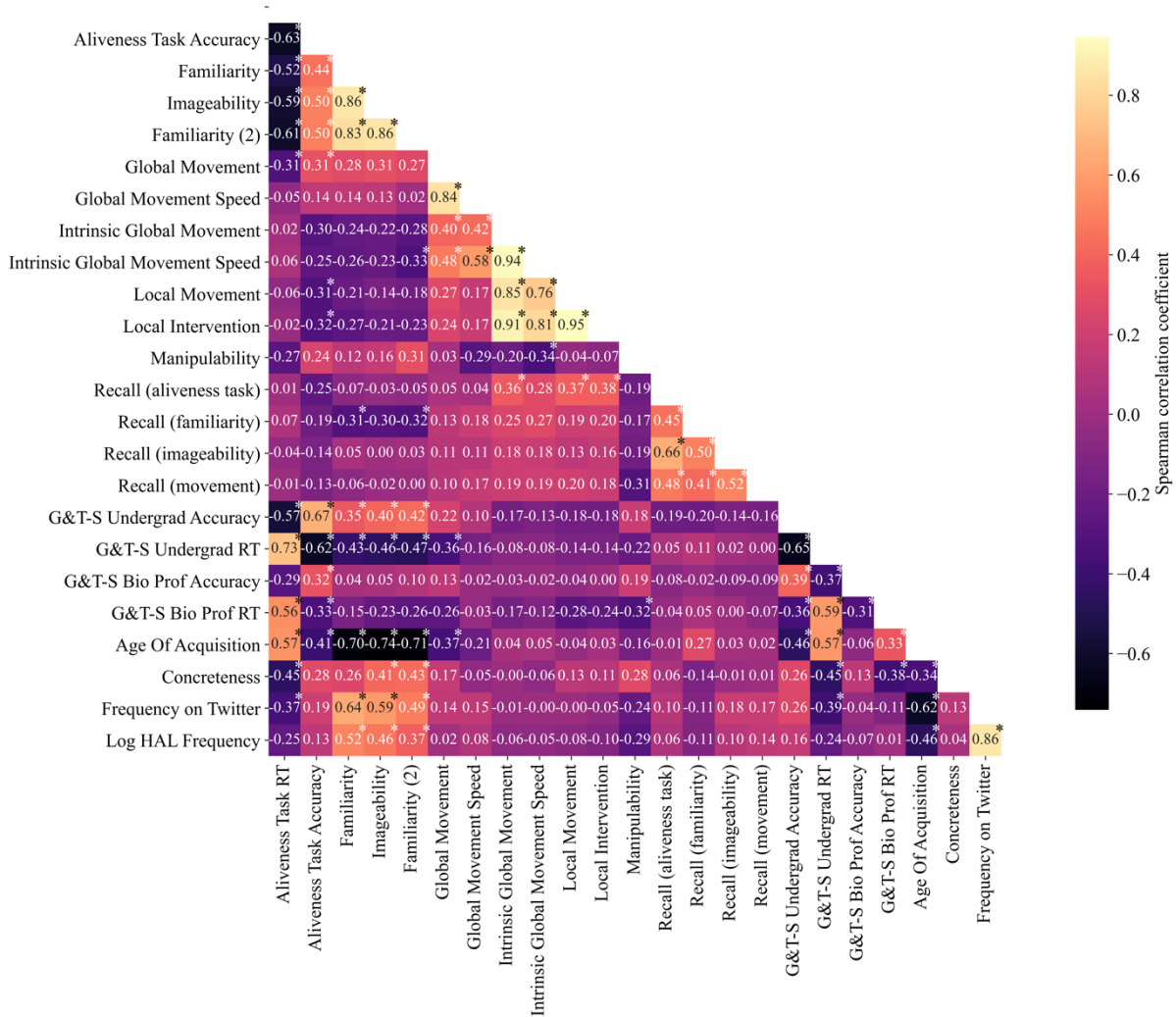


Figure 2.4
 Correlations between the results of all four experiments, and other relevant measures. Spearman rank correlations were calculated item-wise. Boxes with an asterisk (*) indicate correlations that were significant after a Bonferroni correction for multiple comparisons ($p < .00018$). G&T-S refers to the results from Goldberg and Thompson-Schill’s (2009) experiments with this same stimulus set.

Memorability

Participants were asked to recall as many words as they could at the end of the experiment. Results from recall are shown for each experiment and on average in [Figure 2.2E](#), and statistics are shown in [Table 2.3](#). In all tasks, participants recalled more words that move than words that were still. For all tasks except for familiarity ratings, natural things

were more also recalled more frequently than artificial things. For the aliveness classification task and the imageability task, plants were recalled more frequently than animals.

Table 2.3.

Summary of results for free recall memory tests at the end of each task

	Mean number of items recalled (range)	Plants vs animals	Main effect movement	Main effect naturalness	Interaction (movement x aliveness)
Aliveness classification	18.74 words (8-39)	Plants $t(30) = 2.67$, $p = 0.012$, $BF = 2.3$	Moving $F(1,120) = 14.19$, $p < .001$, $BF = 2.11 \times 10^2$	Natural $F(1,120) = 24.57$, $p < .001$, $BF = 2.38 \times 10^4$	Significant $F(1,120) = 5.66$, $p = .019$, $BF = 9.39$
Familiarity	11.81 words (0-40)	-	Moving $F(1,120) = 6.38$, $p = .012$, $BF = 12.88$	-	-
Imageability	21.82 words (4-66)	Plants $t(38) = 2.55$, $p = .015$, $BF = 1.37$	Moving $F(1,136) = 4.12$, $p = 0.044$, $BF = 6.00$	Natural $F(1, 136) = 8.41$, $p = .0043$, $BF = 1.92 \times 10^2$	-
Movement	10.66 words (0-26)	-	Moving $F(1,412) = 18.85$, $p < .001$, $BF = 4.48 \times 10^3$	Natural $F(1,412) = 13.41$, $p < .011$, $BF = 2.21 \times 10^2$	-

Discussion

Over four experiments, we explored findings by Goldberg and Thompson-Schill (2009) suggesting that adults rely on associations between movement and aliveness that are developed in childhood when making decisions about whether something is alive or not. We first replicated their results in Australian undergraduates, then demonstrated that familiarity and ease of visualisation differ across categories. Specifically, words that participants have difficulty classifying by aliveness, plants and moving natural things, are also less familiar and harder to visualise. We also show that associations between movement and aliveness are reflected in intuitions about the characteristics of movement in plants and moving natural things. Participants perceive moving natural things to move with agency, and these moving natural things are less manipulable than other object categories. Overall, the findings suggest movement is an important part of object processing and our conceptual understanding of what it means to be alive. Differences in manipulability and global movement may explain why plants and moving natural things are more difficult to classify by aliveness.

Plants and moving natural things are less familiar and harder to visualise

The familiarity and visualisation ratings showed that words that were difficult to classify as living also tended to be less familiar and harder for participants to visualise. These measures also showed a similar pattern across categories to the aliveness classification task ([Figure 2.2](#)). Though ratings of familiarity for the available stimuli in previous corpora are fairly similar across classes (e.g., ranging from 5/7 to 5.87/7 in the Glasgow Norms; Scott et al., 2019), almost half of the plant words are absent from these corpora, suggesting that some of the effects here may be driven by the words obscure enough to not be in corpora containing the most frequent words.

Though these findings point to a systematic effect of word familiarity and imageability on accuracy and reaction time in the aliveness classification, it is unclear whether this is a result of the individual word choice, or something that is more intrinsic to a particular category. Individuals could be poor at classifying plants as alive because they are unfamiliar with them, but they could be unfamiliar with them because they are not the typical examples of living things. For example, it is possible that participants do not perceive these plants and moving natural things as ‘objects’ but as part of the environment, thus paying less attention to them and being less familiar with their attributes (Torres-Porras & Alcántara-Manzanares, 2019). A lack of knowledge about, and exposure to, these items may then make it more difficult to retrieve semantic information required to judge aliveness (Monsell et al., 1989), leading to the decreased accuracy. Other linguistic and conceptual factors may also influence ratings of familiarity and imageability. For example, the decrease in imageability for moving natural things may also be a result being less concrete (e.g., fog, mist), as previous research has shown that concreteness is closely related to imageability (Kousta et al., 2011). One way to address this in future research would be to use images instead of words as stimuli.

Plants lack global movement, separating them from human-centric concepts of aliveness

The categories that were substantially different to others across all experiments are those which defy conventional associations between movement and aliveness, plants and moving natural things. These are the same items that participants had difficulties in the aliveness task. Plants were not only harder to visualise and less familiar than other categories, but were also more memorable. As expected, plants show similar likelihood of local movement to animals but less and slower global movement ([Figure 2.3](#)). In addition to being less familiar, plant words tended to have a later age of acquisition ([Supplementary Figure](#)

[2.2](#)). This is consistent with the hypothesis that developing an understanding that plants are living occurs later in development because the animals pose a more immediate potential threat (New et al., 2007), and plants do not move, so decisions (e.g., whether to eat a given plant) are less urgent. It also supports theories of aliveness based on a human prototype (Carey, 1985; Yorek et al., 2009), so things that don't change position with speed are further away from humans and therefore harder to classify (Posner & Keele, 1968; Rosch & Mervis, 1975) .

Participants are aware that the plant words are difficult

Participants were cognisant of their own difficulties in classifying plants as living. When asked if they had any observations after the aliveness classification task, several participants commented on the difficulty with plants, with one noting that “[i]t was difficult for me to categorise plants as living organisms...”, and another observing that “I often did not include plants as living”. Some participants also identified the difficulty with moving natural things in their comments, with one participant noting, “I seemed to respond ‘living’ to a number of non-living but natural features associated with nature and living things...”. Many participants were aware of their own difficulties, indicating that some of these effects were consistent enough to be conscious to participants.

Moving natural things are perceived to have agentic movement

Moving natural things were difficult to classify in the aliveness task, less familiar, more difficult to visualise, and more memorable. Interestingly, participants rated moving natural things as having substantially more agentic movement compared to other non-living things ([Figure 2.3](#)), despite instruction to consider forces like gravity and wind as ‘external intervention’. This was the case both for global movement (changing position), and for local

movement (having moving parts, growing, changing shape). Developmental researchers have suggested that these items are difficult for children because there is no clear agent intervening, and therefore they appear to move by themselves (Gelman & Gottfried, 1996; Poulin-Dubois & Heroux, 1994; Richards & Siegler, 1986; Sharp et al., 1985). It is possible the same factors are driving adult intuition here, with some adults relying on ‘intuitive biology’ (Atran & Medin, 2008; Coley et al., 2017) to judge agency when there is no obvious intervening agent, even without time pressure.

Memory was best for plants, animals, and moving natural things

Prior work using free recall tasks has shown a clear advantage for animate recall (Bonin et al., 2014; Popp & Serra, 2018; VanArsdall et al., 2017), even when participants are not told they would be tested on recall, as in the current study (Bonin et al., 2015; Leding, 2018). However, we found that while animals were often recalled well, plants and moving natural things were also frequently recalled by participants ([Figure 2.2E](#)).

Though the results are slightly different across each experiment, this general pattern suggests that in addition to animates, we may also encode items that violate our assumptions of animacy more strongly (i.e., plants, which are alive but don’t move, and moving natural things that move, but aren’t alive). One possibility, given that the categories that were recalled best were also difficult on the aliveness task, less familiar and harder to visualise, is that these words are just viewed and processed for longer. However, memorability was not significantly correlated with viewing time in any task. While recent large-scale memorability work has shown that animacy is a good predictor of recall, it still only explains a small amount of variance in what we remember, and elements like size and usefulness for human survival also predict recall (Madan, 2021). Few other factors were significantly correlated with memorability. Familiar items were recalled better in the familiarity task, and items with

global intrinsic movement and local independent movement were recalled better the movement task ([Figure 2.4](#)). Overall, while memorability ratings show that animates are remembered well, items that violate traditional associations between movement and aliveness also seem to be recalled well.

Theoretical implications

Our results provide support for theories of continuous conceptual development from childhood to adulthood (e.g., Eimas, 1994), and for models of aliveness such as the animistic-anthropocentric model (Yorek & Narli, 2009) which have a human-centric conception of ‘life status’ and include movement as a key variable influencing similarity to humans.

Neuroimaging studies have shown that models of animacy (including humans/ animals, excluding plants) capture neural activity better than models of aliveness (including plants) (Jozwik et al., 2022). Our movement results suggest that this could be because plants move on a different global scale and frequency, the same explanation as others have provided for plant blindness (Wandersee & Schussler, 1999). Processing movement alongside aliveness may be adaptive as it informs how we interact with an object - manipulability judgements revealed that moving things were harder to pick up and move compared to still things.

Our results also provide evidence for continuous conceptual development, by showing that intuitions from childhood may be suppressed by formal scientific education, but are not erased (Kelemen et al., 2013). In addition to replicating findings showing that movement continues to influence judgements of aliveness under time pressure in undergraduate students, we also showed that students believe that moving natural things can move independently. This dismissal of invisible forces relies on an intuitive physics, and demonstrates a pervasive influence of intuition even when there is no time pressure. Additionally, words with an earlier age of acquisition were also responded to more accurately

and more quickly in the aliveness classification task, and were more familiar and easy to visualise.

Qualifications

Though our results provide some potential explanations for the effects in Goldberg and Thompson-Schill (2009) and affirm models of human-centric reasoning on aliveness, they must be considered with some caveats. Firstly, we only considered a small number of potential variables that could explain, or mediate, differences between categories. For example, real-world object size is related to manipulability, and has been shown as an important organising factor in the neural processing of objects (Konkle & Caramazza, 2013; Long et al., 2019), and therefore may mediate some of the relationships seen here. This seems likely, given that manipulability judgements varied so substantially across categories, and real-world size is closely related to whether an object is manipulable and stable (Magri et al., 2021).

Secondly, our study is entirely based on this specific set of words used by Goldberg and Thompson-Schill (2009), and future research should verify if the effects are still present for a different set of words or for images to determine if these effects are robust beyond this particular set of stimuli, particularly given our findings suggest there are several words that are unfamiliar and potentially problematic in this word list. This, however, may be a challenging task. When we tried to re-run the experiment with different words, or simply replace those revealed to be problematically unfamiliar, we found that there were many fewer ‘general’ or basic-level words describing plants, and this proved a very difficult task. Indeed, in participants’ observations, ‘flowers’ were noted as a stimulus category more often than plants more generally ([Figure 2.2F](#)). The decreased familiarity with plants may indeed be reflected in, and reinforced by, the sparsity of terms in English to describe plants, particularly

as Western non-farming cultures tend to identify plants in categories like ‘trees’ rather than by specific names (Berlin, 1972). One way to resolve this, and minimise potential linguistic influences or differences in imageability, would be to use images instead of words in future work.

Conclusion

Overall, our findings replicate Goldberg and Thompson-Schill (2009) and show that movement and aliveness are intrinsically linked in our understanding of the world. Moving natural things (e.g., planets, clouds) are perceived to have agency in their capacity for both local and global movement. The same items that children tend to make errors on, natural moving things like the sun and ocean, are even difficult for adults to perceive as moving in a non-agentive way. Differences in global movement may explain why plants are often neglected in our concept of living things. Together, our findings suggest that in the absence of top-down scientific knowledge, not only do we rely on associations between movement and aliveness that are developed in childhood, but these ‘roots’ of childhood understanding are more pervasive than originally proposed and occur even in the absence of time pressure. Future work should look to replicate these findings with different stimuli to ensure the effects are not specific to the particular objects used here.

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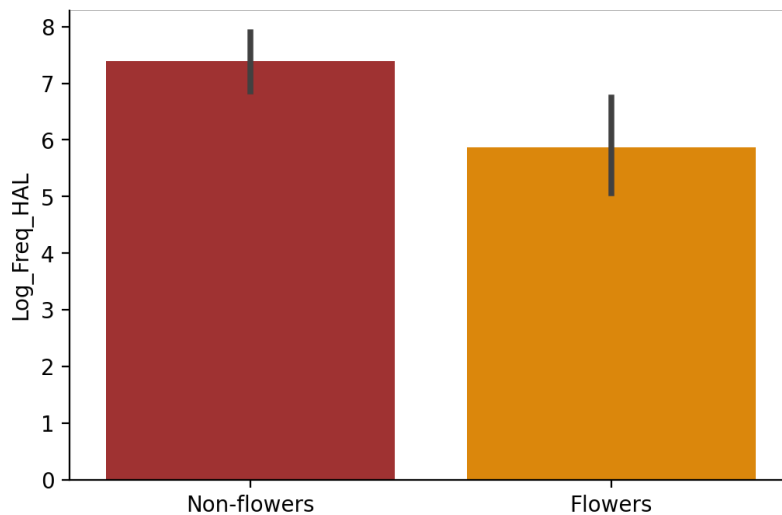
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Supplementary Materials

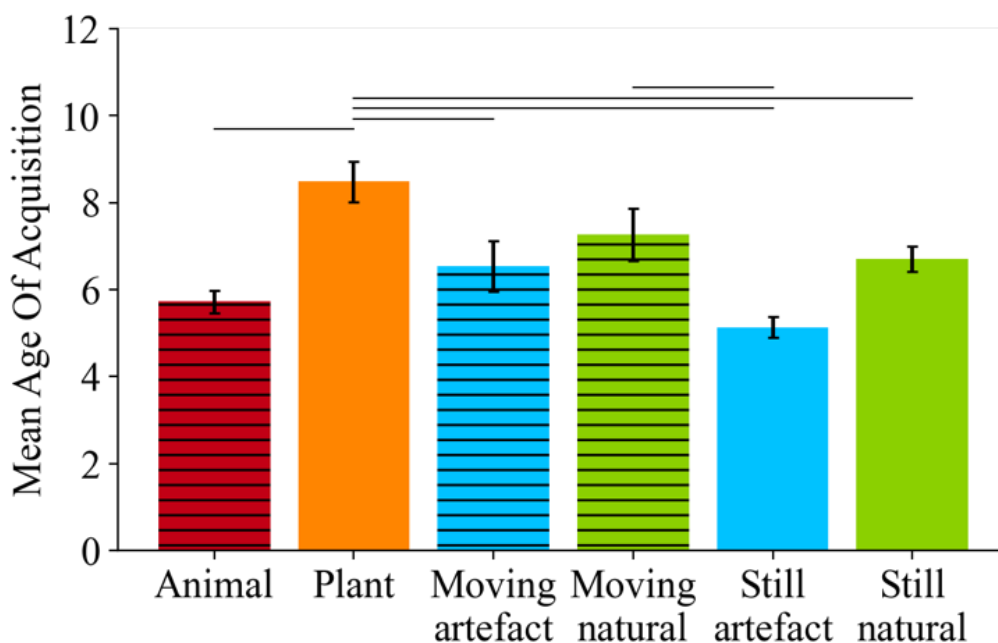
Supplementary Figure 2.1

Many of the words in the plant category describe specific kinds of flowers. Participants were more likely to write ‘flower’ as a category of stimulus than ‘plant’ (Figure 2.2F). We ran some quick checks to determine if flowers were quantitatively different from the other plants. There are no differences on age of acquisition ($t(29) = 0.58, p = .56$), imageability ($t(29) = 1.89, p = .07$), or familiarity ($t(29) = 0.99, p = .32$). However, flowers are less frequent than the rest of the plants, $t(29) = 2.97, p = 0.0060$.



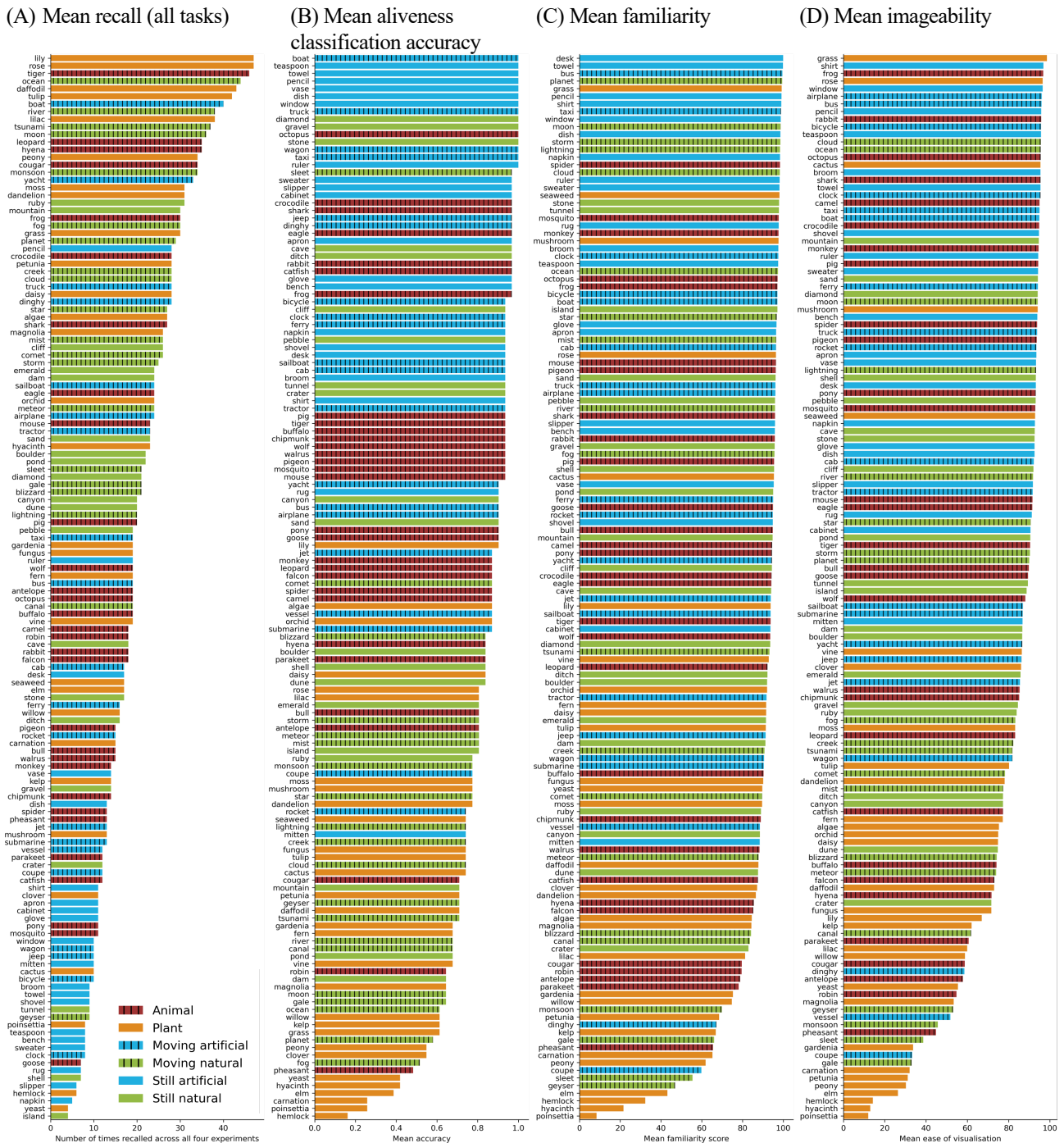
Supplementary Figure 2.2

Age of Acquisition is a measure of the age at which a child can produce a given word, as rated by adults (Kuperman et al., 2012). Compared to all other categories, except moving natural things, plant words are acquired significantly later.



Supplementary Figure 2.3

Within categories, there is considerable variation between items, with some items being difficult in all the experiments. For example, *window* and *pencil* are in the top 10 items for accuracy on the aliveness classification task (A), familiarity (B) and imageability (C). Poinsettia, hemlock, elm, and hyacinth are also all in the bottom 5 for the aliveness task (A), familiarity (B) and imageability (C). The gradient below visually displays the trend across tasks for the majority of stimuli to be responded to at ceiling level, with a few items driving categorical differences.



Supplementary Table 2.1

To increase clarity and brevity in the manuscript, statistics with the same outcomes for the movement task were only reported once. In the below table, results from a t-test for living and ANOVA for non-living items for every question are shown, focusing on just the non-living items, for movement and naturalness.

Question	Animals vs plants	ANOVA naturalness	ANOVA movement	ANOVA interaction
Familiarity	t(104) = 9.19, p<.00001, BF10 = 2.3829e+12	F(1,412) = 17.68, p=3.2e-05, BF10 = 2.5012e+06	F(1,412) = 38.29, p<.00001, BF10 = 1.3749e+14	F(1,412) = 0.70, p=0.403339, BF10 = 6.5483e-01
Likelihood of global movement	t(104) = 11.67, p<.00001, BF10 = 5.5163e+17	F(1,412) = 88.61, p<.00001, BF10 = 1.2362e+19	F(1,412) = 144.30, p<.00001, BF10 = 2.9840e+29	F(1,412) = 21.14, p<.00001, BF10 = 1.2710e+05
Speed of global movement	t(104) = 19.25, p<.00001, BF10 = 6.5187e+32	F(1,412) = 28.99, p<.00001, BF10 = 9.1975e+05	F(1,412) = 490.38, p<.00001, BF10 = 1.7255e+74	F(1,412) = 11.38, p=0.000812, BF10 = 2.2302e+02
Likelihood of intrinsic global movement	t(104) = 22.41, p<.00001, BF10 = 1.6882e+38	F(1,412) = 74.74, p<.00001, BF10 = 9.0917e+15	F(1,412) = 144.39, p<.00001, BF10 = 9.1673e+28	F(1,412) = 33.50, p<.00001, BF10 = 2.8903e+08
Speed of intrinsic global movement	t(104) = 25.12, p<.00001, BF10 = 3.1384e+42	F(1,412) = 61.05, p<.00001, BF10 = 2.3057e+14	F(1,412) = 152.82, p<.00001, BF10 = 5.0527e+32	F(1,412) = 26.01, p<.00001, BF10 = 1.1966e+07
Likelihood of local movement	t(104) = 8.00, p<.00001, BF10 = 6.8939e+09	F(1,412) = 32.72, p<.00001, BF10 = 3.1392e+07	F(1,412) = 152.74, p<.00001, BF10 = 2.3283e+32	F(1,412) = 8.84, p=0.003118, BF10 = 8.2351e+01
Independence of local movement	t(104) = 14.05, p<.00001, BF10 = 5.7299e+22	F(1,412) = 100.62, p<.00001, BF10 = 6.5206e+21	F(1,412) = 160.88, p<.00001, BF10 = 5.8077e+32	F(1,412) = 29.93, p<.00001, BF10 = 6.5243e+07
Manipulability	t(104) = -8.03, p<.00001, BF10 = 7.8486e+09	F(1,412) = 551.47, p<.00001, BF10 = 4.7283e+70	F(1,412) = 937.72, p<.00001, BF10 = 6.4438e+99	F(1,412) = 61.93, p<.00001, BF10 = 6.2094e+12
Recall	t(104) = -0.24, p=0.812386, BF10 = 7.7280e-08	F(1,412) = 13.41, p=0.000283, BF10 = 2.2100e+02	F(1,412) = 18.85, p=1.8e-05, BF10 = 4.4759e+03	F(1,412) = 3.71, p=0.054855, BF10 = 2.6697e+00

Supplementary Table 2.2

Statistics comparing movement characteristics across all categories

Category 1	Category 2	Familiarity	Likelihood of global movement	Speed of global movement	Likelihood of intrinsic global movement	Speed of intrinsic global movement	Likelihood of local movement	Independence of local movement	Manipulability	Recall
Animal	Plant	p<0.00001**, BF10 = 2.3829e+12 **	p<0.00001**, BF10 = 5.5163e+17 **	p<0.00001**, BF10 = 6.5187e+32 **	p<0.00001**, BF10 = 1.6882e+38 **	p<0.00001*, *, BF10 = 3.1384e+42 **	p<0.00001**, BF10 = 6.8939e+09 **	p<0.00001**, BF10 = 5.7299e+22 **	p<0.00001**, BF10 = 7.8486e+09 **	p = 1.0000, BF10 = 7.7280e-08
Animal	Moving artificial	p = 0.9664, BF10 = 3.9618e-05	p = 0.8074, BF10 = 4.7534e-04	p = 0.0015*, BF10 = 1.1888e+07 **	p<0.00001**, BF10 = 2.6777e+49 **	p<0.00001*, *, BF10 = 1.0122e+37 **	p<0.00001**, BF10 = 7.5380e+25 **	p<0.00001**, BF10 = 3.0538e+47 **	p<0.00001**, BF10 = 7.2504e+20 **	p = 0.0417*, BF10 = 3.9850e+00
Animal	Moving natural	p = 0.0265*, BF10 = 9.0516e+02 **	p<0.00001**, BF10 = 1.2216e+05 **	p = 0.1621, BF10 = 4.1971e-02	p<0.00001**, BF10 = 4.7395e+26 **	p<0.00001*, *, BF10 = 5.1308e+09 **	p<0.00001**, BF10 = 1.3500e+17 **	p<0.00001**, BF10 = 1.7355e+22 **	p<0.00001**, BF10 = 9.0940e+42 **	p = 0.4650, BF10 = 2.7077e-03
Animal	Still artificial	p = 0.0013*, BF10 = 2.3539e+10 **	p<0.00001**, BF10 = 4.0153e+07 **	p<0.00001**, BF10 = 3.1814e+19 **	p<0.00001**, BF10 = 2.3744e+64 **	p<0.00001*, *, BF10 = 7.5639e+63 **	p<0.00001**, BF10 = 2.0878e+42 **	p<0.00001**, BF10 = 1.1877e+60 **	p<0.00001**, BF10 = 1.5269e+27 **	p<0.00001**, BF10 = 1.9426e+11 **
Animal	Still natural	p = 0.9949, BF10 = 6.6468e-06	p<0.00001**, BF10 = 3.7477e+28 **	p<0.00001**, BF10 = 3.7540e+31 **	p<0.00001**, BF10 = 1.0053e+53 **	p<0.00001*, *, BF10 = 1.9287e+49 **	p<0.00001**, BF10 = 3.6617e+39 **	p<0.00001**, BF10 = 1.5021e+48 **	p<0.00001**, BF10 = 1.2401e+08 **	p = 0.0106*, BF10 = 3.5162e+00
Plant	Moving artificial	p<0.00001**, BF10 = 6.7120e+07 **	p<0.00001**, BF10 = 4.1288e+16 **	p<0.00001**, BF10 = 1.2520e+39 **	p = 0.0002**, BF10 = 7.7317e+02 **	p = 1.0000, BF10 = 4.2134e-08	p<0.00001**, BF10 = 8.8879e+14 **	p<0.00001**, BF10 = 2.0598e+19 **	p<0.00001**, BF10 = 7.5570e+29 **	p = 0.0234*, BF10 = 6.6231e+00
Plant	Moving natural	p = 0.0049*, BF10 = 3.8604e+02 **	p<0.00001**, BF10 = 2.5399e+05 **	p<0.00001**, BF10 = 1.4433e+27 **	p<0.00001**, BF10 = 4.2310e+05 **	p<0.00001*, *, BF10 = 1.5835e+13 **	p<0.00001**, BF10 = 5.6349e+04 **	p = 0.1029, BF10 = 5.6171e-04	p<0.00001**, BF10 = 4.5735e+52 **	p = 0.3451, BF10 = 1.6885e-02
Plant	Still artificial	p<0.00001**, BF10 = 1.6251e+21 **	p = 0.0045*, BF10 = 1.9793e+01 *	p = 0.0004**, BF10 = 2.4051e+04 **	p<0.00001**, BF10 = 1.6462e+17 **	p<0.00001*, *, BF10 = 1.4338e+16 **	p<0.00001**, BF10 = 3.0092e+32 **	p<0.00001**, BF10 = 1.6767e+31 **	p<0.00001**, BF10 = 2.5778e+09 **	p<0.00001**, BF10 = 3.6454e+10 **
Plant	Still natural	p<0.00001**, BF10 = 1.0484e+14 **	p<0.00001**, BF10 = 2.7566e+12 **	p = 0.1778, BF10 = 1.4486e+00	p<0.00001**, BF10 = 2.4530e+11 **	p = 0.0057*, BF10 = 8.5414e+08 **	p<0.00001**, BF10 = 1.3525e+32 **	p<0.00001**, BF10 = 8.1485e+22 **	p<0.00001**, BF10 = 2.2932e+26 **	p = 0.0054*, BF10 = 3.6356e+00

Moving artificial	Moving natural	p = 0.2078, BF10 = 6.6656e-01	p = 0.0072*, BF10 = 5.3000e+01 **	p = 0.6555, BF10 = 6.9629e-05	p<0.00001**, BF10 = 6.9065e+12 **	p<0.00001*, *, BF10 = 6.0028e+10 **	p<0.00001**, BF10 = 1.6745e+06 **	p<0.00001**, BF10 = 1.5785e+16 **	p<0.00001**, BF10 = 7.2948e+15 **	p = 0.8729, BF10 = 2.9412e-05
Moving artificial	Still artificial	p<0.00001**, BF10 = 6.1161e+09 **	p<0.00001**, BF10 = 5.2210e+08 **	p<0.00001**, BF10 = 1.4907e+31 **	p = 0.0001**, BF10 = 4.0296e+07 **	p<0.00001*, *, BF10 = 3.6971e+09 **	p<0.00001**, BF10 = 2.1514e+10 **	p<0.00001**, BF10 = 5.1851e+09 **	p<0.00001**, BF10 = 1.9563e+45 **	p = 0.0008**, BF10 = 9.4092e+04 **
Moving artificial	Still natural	p = 0.7645, BF10 = 7.0095e-04	p<0.00001**, BF10 = 4.0119e+31 **	p<0.00001**, BF10 = 4.6478e+37 **	p = 0.1497, BF10 = 2.7158e-01	p = 0.0065*, BF10 = 1.2831e+03 **	p<0.00001**, BF10 = 1.6765e+03 **	p = 0.4464, BF10 = 1.3047e-02	p<0.00001**, BF10 = 2.9181e+02 **	p = 0.9980, BF10 = 2.3209e-07
Moving natural	Still artificial	p<0.00001**, BF10 = 1.2038e+13 **	p = 0.4181, BF10 = 7.0141e-04	p<0.00001**, BF10 = 7.2883e+17 **	p<0.00001**, BF10 = 3.9209e+23 **	p<0.00001*, *, BF10 = 2.9192e+23 **	p<0.00001**, BF10 = 3.5029e+23 **	p<0.00001**, BF10 = 7.7007e+25 **	p<0.00001**, BF10 = 1.6672e+69 **	p<0.00001**, BF10 = 1.9395e+06 **
Moving natural	Still natural	p = 0.0045*, BF10 = 3.7688e+04 **	p<0.00001**, BF10 = 3.6138e+17 **	p<0.00001**, BF10 = 1.4525e+28 **	p<0.00001**, BF10 = 2.3310e+19 **	p<0.00001*, *, BF10 = 1.7176e+21 **	p<0.00001**, BF10 = 1.1394e+22 **	p<0.00001**, BF10 = 3.4309e+21 **	p<0.00001**, BF10 = 8.9519e+29 **	p = 0.6262, BF10 = 2.6768e-04
Still artificial	Still natural	p = 0.0094*, BF10 = 7.2644e+05 **	p<0.00001**, BF10 = 1.0883e+17 **	p<0.00001**, BF10 = 1.6156e+10 **	p = 0.3132, BF10 = 1.0045e+04 **	p = 0.2937, BF10 = 2.9882e+03 **	p = 0.3598, BF10 = 4.4708e-02	p = 0.0212*, BF10 = 8.8621e+05 **	p<0.00001**, BF10 = 9.3516e+40 **	p = 0.0045*, BF10 = 3.1321e+02 **

Chapter 3: Capacity for movement is an organisational principle in object representations

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Abstract

The ability to perceive moving objects is crucial for threat identification and survival. Recent neuroimaging evidence has shown that goal-directed movement is an important element of object processing in the brain. However, prior work has primarily used moving stimuli that are also animate, making it difficult to disentangle the effect of movement from aliveness or animacy in representational categorisation. In the current study, we investigated the relationship between how the brain processes movement and aliveness by including stimuli that are alive but still (e.g., plants), and stimuli that are not alive but move (e.g., waves). We examined electroencephalographic (EEG) data recorded while participants viewed static images of moving or non-moving objects that were either natural or artificial. Participants classified the images according to aliveness, or according to capacity for movement. Movement explained significant variance in the neural data over and above that of aliveness, showing that capacity for movement is an important dimension in the representation of visual objects in humans.

Capacity for movement is an organisational principle in object representations

The ability to categorise objects is crucial for efficiently interacting with our environment and vital for survival. Knowing that objects in the same category share properties promotes efficient decision-making, such as aiding in deciding which animals to approach and which to flee, or determining which plants are edible and which are poisonous. Generalising object properties to new objects in the same category is an efficient way to make use of our limited memory capacity and this generalisation permeates all interactions with the visual world.

One way of investigating human categorical knowledge is to examine how the brain distinguishes objects in the visual world. The human visual system can automatically categorise stimuli, from low-level visual features to individual object identity to increasingly abstract conceptual categories in fractions of a second (Cichy et al., 2014; Contini et al., 2017; Mohsenzadeh et al., 2018; Potter et al., 2014; Potter & Haggmann, 2015; Robinson et al., 2019). Categorical distinctions such as animacy are rapidly and subconsciously processed by the brain (Carlson et al., 2013; Cichy et al., 2014; Connolly et al., 2012; Contini et al., 2017; Grootswagers et al., 2018; Konkle & Caramazza, 2013; Ritchie et al., 2015). The representations of higher-order categorical distinctions like animacy have been localised to the inferotemporal cortex (Haxby et al., 2001; Kriegeskorte et al., 2008), and are observable from patterns of brain activity from approximately 100-160ms after stimulus onset (Contini et al., 2020; Goddard et al., 2016; Grootswagers, Robinson, & Carlson, 2019; Grootswagers et al., 2021). In addition to higher-order conceptual processing, some of this separation can be explained by differences in low and mid-level visual features between animate and inanimate stimuli (Grootswagers, Robinson, Shatek, et al., 2019; Long et al., 2018; Wang et al., 2022). Even at rapid presentation rates, and when subjects are completing an unrelated task, animate stimuli are distinguishable from inanimate stimuli in patterns of electroencephalography (EEG) recordings (Grootswagers et al., 2021). This automatic identification of animacy has also been shown behaviourally in children as young as 7 months old (Träuble et al., 2014), leading to suggestions that learning about animacy early in development is evolutionarily

adaptive (Aslan & John, 2016). Neuroscience research has supported this idea, demonstrating that both the adult brain (Bao et al., 2020; Konkle & Caramazza, 2013; Kriegeskorte et al., 2008) and the infant brain (Bayet et al., 2020; Deen et al., 2017) represents whether something is animate as part of core visual processing (DiCarlo et al., 2012).

However, more recent research has shown that the structure of object representations in the brain is more complex than a simple animate/inanimate dichotomy and may be influenced by an object's ability to move independently. Recent neuroimaging work has shown that movement and agency are important in animacy judgements, and visual stimuli may be better represented in the brain as a spectrum, according to their similarity to humans (Contini et al., 2020) or their capacity for agency and goal-directed movement (Connolly et al., 2012; Grootswagers et al., 2022; Jozwik et al., 2021; Sha et al., 2014; Thorat et al., 2019). These findings suggest that motion, particularly animate motion, is an important property of object processing in the brain. Brain regions active when perceiving motion are also active when viewing a still photograph taken mid-motion, also known as implied motion (Kourtzi & Kanwisher, 2000). Studies of implied motion have shown that the speed of implied motion has differential effects on brain activity based on the category of the object being shown, suggesting that movement is an important factor in category distinctions (Lu et al., 2015). Collectively, these findings suggest that the brain represents both movement and aliveness.

Behavioural work further demonstrates how movement and aliveness are used to categorise objects. Theoretical models of life status, such as the animistic-anthropocentric construction model (Yorek & Narli, 2009), suggest that our conception of what is alive is shaped by similarity to humans, particularly in terms of the overlapping concept of motion, with animals most similar to humans, then plants and then other non-living things. Most things that are alive can move, yet movement and aliveness are not the same: not all moving objects are alive (e.g., cars, clouds), and not all objects that are alive move on a time scale that humans can see (e.g., plants). The co-occurrence of movement and aliveness is so common that it is often a cause for classification error. For example, adults often mistake natural moving things (e.g., waves) for being alive when under

time pressure to make a decision (Goldberg & Thompson-Schill, 2009). This co-occurrence makes it difficult to interpret prior neuroimaging literature on how the brain might represent movement, given it is so often confounded by aliveness. Is movement a relevant characteristic of an object for the brain to process, and if so, is this solely because it most commonly co-occurs with animacy? Investigating these cases that violate the intuitive association between aliveness and movement can provide insight into how these characteristics are coded by the brain.

In the current study, we investigated the relationship between movement and aliveness in neural categorisation by taking advantage of unusual cases of natural movement that are often misclassified by children, and adults under time pressure. We used naturalistic static image stimuli, including typical animate and inanimate stimuli as in prior research, and also included natural moving objects (e.g., waves, fire) and plants (e.g., trees, vines). These natural stimuli that violate the association between movement and aliveness (i.e., they are moving but not alive, or alive but not moving) allow us to investigate how movement and aliveness are processed in the brain. We first ran an online study to clarify behavioural classifications of the stimuli. Then, in two experiments, we gathered EEG data while participants classified images according to whether they were alive or not (Experiment 1), or whether they could move or not (Experiment 2). Using multi-variate pattern analysis techniques, we examined similarities and differences in the temporal dynamics of visual processing and decision-making based on a stimulus' capacity for movement, and whether it is alive or not. These methods were used to examine if, and when, movement (including natural, non-agentive movement such as from fire, or waterfalls) is represented in the brain, and whether this is dependent on the categorisation task being completed. We find that capacity for movement explains significant variance in the EEG data, even after controlling for low-level visual factors and aliveness. The findings suggest that movement is an important organisational principle for object representation in the brain.

Methods

This section reports two EEG studies (Experiments 1 and 2) with very similar methodology. Stimuli, analysis scripts, results and anonymised raw EEG data are publicly available at <https://doi.org/10.18112/openneuro.ds003885.v1.0.7> (Experiment 1) and <https://doi.org/10.18112/openneuro.ds003887.v1.2.2> (Experiment 2). Stimuli, analysis scripts, results and data from the online stimulus validation study are also publicly available at <https://osf.io/jxhcs/>.

To investigate how aliveness and movement are represented in the brain, we recorded electroencephalography (EEG) in two experiments, each consisting of a categorisation task in which participants classified images, and passive viewing, in which participants viewed stimuli in rapid streams. The structure of both experiments was identical, including the passive viewing blocks. The only difference was the categorisation task. In Experiment 1, participants classified images based on “whether they are alive or not”. In Experiment 2, participants classified images based on “whether they can move or not”. Different participants completed each experiment. Unless stated otherwise, the description of the methods below applies to both EEG experiments.

Participants

In Experiment 1, 24 undergraduate psychology students (15 women, 9 men) at the University of Sydney, Australia, participated in exchange for course credit. The mean age was 19.58 (range 18-26), and all participants but one were right-handed. In Experiment 2, a separate group of 24 undergraduate psychology students (16 women, 7 men, 1 non-binary person) at the University of Sydney participated for course credit. One additional subject was excluded from Experiment 2 with incomplete data as a result of a technical error during data collection. The mean age was 19.71 (range 18-26), and all participants but one were right-handed. All participants in both experiments had normal or corrected-to-normal vision, were neurologically healthy, and were not colour-blind. Informed written and oral consent was obtained from all participants prior to participation. The study was approved by the University of Sydney Ethics Committee.

Stimuli

Stimuli were 400 realistic colour images collected from free online image databases (www.pixabay.com, www.pexels.com) under Creative Commons 0 licenses, and were used in all studies. All text in images (e.g. brand names on cars) was blurred manually using GIMP (v2.10.14, 2020), then each image was cropped and resized to 256 by 256 pixels. Stimuli were gathered in six categories based on those in Goldberg and Thompson-Schill (2009): animals, plants, still artificial things, still natural things, moving artificial things, and moving natural things (shown in [Figure 3.1A](#)). For animals (bee, cat, dog, dolphin, eagle, horse, lemur, pigeon, tiger, whale) and plants (cactus, clover, fern, flower, grass, lemon tree, moss, palm tree, tree, vine), there were 10 objects. For all other categories, still artificial things (bench, clothes peg, headphones, lock, mug), still natural things (cliff, crystal, rock, sand, shell), moving artificial things (boat, bus, car, helicopter, train), and moving natural things (fire, hot spring, river, waterfall, waves), there were five objects. The extra plant and animal categories were included to ensure there was an equal number of images that were alive and not alive, as well as equal numbers of moving and still images. Within each category (e.g., cat, bench), there were 10 different images (e.g., cat1, cat2, ... cat10). There were 400 images in total, each classified according to aliveness (200 living and 200 non-living), movement (200 moving and 200 still), and naturalness (300 natural and 100 artificial). For objects that are able to move, the stimulus was shown in motion in the image (e.g., birds and helicopters shown flying, see [Figure 3.1A](#)), though all stimuli were static images.

Apparatus

Images were shown in the centre of a 1920x1080 pixel Asus gaming monitor with a refresh rate of 60Hz. Participants responded using the two outermost buttons on a four-button button box produced by The Black Box ToolKit Ltd (layout as shown in [Figure 3.1C](#), [3.1D](#)). They were seated 55cm away from the screen and stimuli subtended approximately 5° of visual angle. EEG was

recorded at 1000Hz on a 128 channel BrainVision ActiCap system (Brain Products GmbH), with electrodes located in positions consistent with the 10-5 extension of the 10-20 system (Oostenveld & Praamstra, 2001). Data were recorded with an online reference of FCz.

Stimulus validation and model generation

To validate the stimulus set and generate behavioural models to compare to the EEG data, we ran an online experiment using Amazon's Mechanical Turk platform, guided by Grootswagers (2020), programmed using jsPsych (de Leeuw, 2015) and hosted on Pavlovia (Peirce et al., 2019, <https://www.pavlovia.org/>). Stimuli, analysis scripts, results and data are publicly available at <https://osf.io/jxhcs/>. Categorisation responses served to ensure that people generally agreed upon stimulus category and were used to construct independent behavioural models.

Mechanical Turk (MTurk) workers were recruited from the U.S.A. and Canada to complete the 15-minute experiment in return for cash payment. Participants were randomly allocated to answer one of three questions about each of the 400 stimuli: (1) "Is the thing in the image alive, or not alive?", (2) "Can the thing in the image move, or is it still?", or (3) "Is the thing in the image naturally occurring or man-made?" Data was gathered from 50 participants for each question. Participants were shown one image at a time and instructed to press the 'F' and 'J' keys on their keyboard to indicate their response for that image. The instructions stated that participants should "try to be fast and accurate." Each image appeared after a 500ms fixation cross and remained on the screen until participants responded ([Figure 3.1B](#)).

To ensure we were only using data where participants were completing the task properly, we removed seven subjects whose overall accuracy (based on expected classification) was less than 50%. We also removed 15 participants who responded in less than 100ms on more than 25% of images, as participants are unlikely to be making valid responses in such a short time period. These exclusion rates are within the range expected from online samples (Thomas & Clifford, 2017). After these exclusions, there were 42 participants who classified by aliveness, 48 participants who

classified by movement capacity, and 38 participants who classified by naturalness. For these included participants, any trial that had a reaction time more than 3 standard deviations longer than the mean of all trials pooled across all participants (on average, less than one trial per participant) or less than 100ms (on average, less than one trial per participant) was also removed.

To investigate how neural activity was related to behavioural classifications of the stimuli, we used Representational Similarity Analysis (RSA) to generate models of categorical and visual attributes of the images (Kriegeskorte et al., 2008). Behavioural models were generated from responses of online participants by averaging the percentage of responses towards the affirmative decision ('alive', 'moves', or 'natural') for each image and calculating the Euclidean distance between each pair of images. This 400 x 400 matrix was then averaged over all images within a category to create a 40 x 40 Representational Dissimilarity Matrix (RDM). These RDMs are shown in [Figure 3.2A](#), [3.2B](#) and [3.2C](#).

EEG Experiment procedure

Participants in both EEG experiments completed 8 blocks of trials, alternating between a passive viewing task (4 blocks) and a categorisation task (4 blocks), and always beginning with passive viewing.

Categorisation task

To see how focusing on aliveness and movement affected neural processing, participants completed a categorisation task ([Figure 3.1D](#)). Each trial consisted of a fixation cross for a random duration between 500ms and 1000ms, followed by an image in the centre of the screen for 100ms. Participants had 1000ms from stimulus offset to respond on the button box. For Experiment 1, participants decided whether the image was alive or not alive. For Experiment 2, participants decided whether the stimulus could move or not. The response mapping changed over each block, such that the side of the button corresponding to 'alive' or 'able to move' switched between left and right

every block, and the order of the mapping was counterbalanced across participants. When a participant responded, the fixation spot filled in to indicate that a response had been recorded ([Figure 3.1D](#)). If there was no response in this time, the screen displayed “Too late!”, and advanced to the next trial. For each of the four categorisation blocks, trials (single image presentation and response, as described above) were chunked into 10 sequences. One sequence contained 40 trials, so that each sequence contained one image from each category (e.g., one dog, one fire). Thus, across the 10 sequences in each block, all 400 images were shown. Each sequence lasted approximately 1-2 minutes, and participants were told to take a break between sequences and advance at their own pace.

Passive viewing task

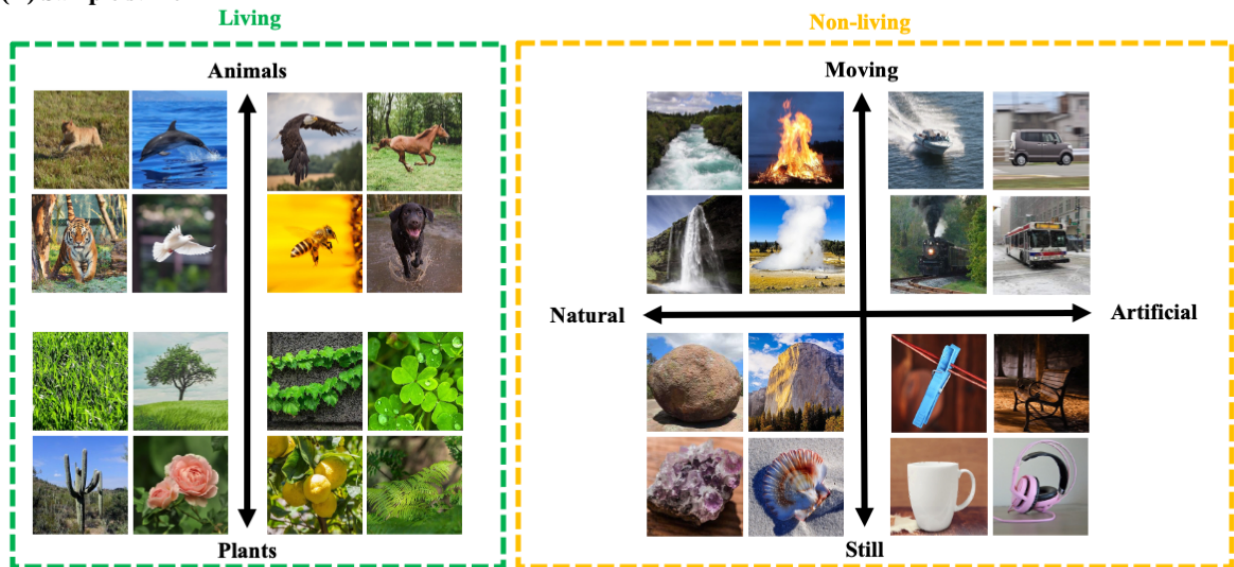
In passive viewing blocks, participants viewed a series of rapid presentation sequences and responded by pressing a button when a fixation spot changed colour ([Figure 3.1C](#)). Images were shown for 100ms each, followed by a 50ms inter-stimulus interval. This non-category related task was included to provide baseline neural activity for each image in order to assess whether movement was processed as a higher-order characteristic, or a lower-level visual attribute. The collection of the same passive task across both experiments also allows the experiments to be directly compared.

In each of the four passive viewing blocks, participants were shown three repetitions of each image during passive viewing sequences, equating to 12 total repetitions of each stimulus across the experiment. These were split into 15 short sequences of 80 images each (~12 seconds each), to minimise fatigue and eye blinks. All 400 images were displayed in the first five sequences, then shuffled and repeated over the next five, and shuffled and repeated over the final five sequences. This ordering ensured that no image appeared twice in the same sequence, and that images were distributed within each block.

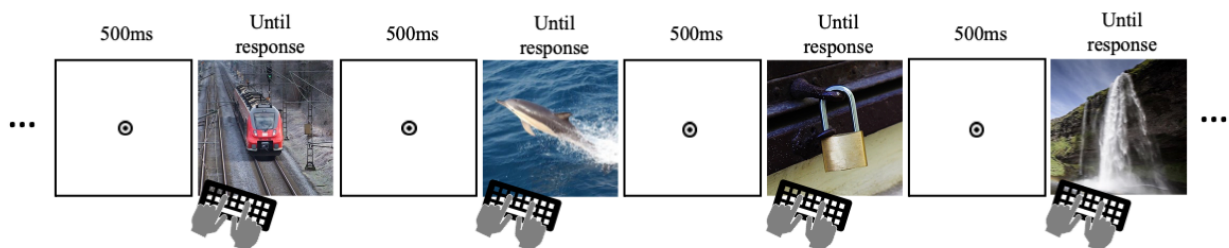
Participants were instructed to press a button as quickly as possible whenever they saw the fixation spot (a bullseye, two concentric black circles, shown in [Figure 3.1](#)) change colour to red. There were two to four randomly located colour changes in the middle 60 presentations of each

sequence of 80 images. The concentric circles of the bullseye were used to ensure there was sufficient contrast with all stimuli to distinguish colour changes. This task ensured that participants maintained a central fixation and paid sufficient attention to the screen but were not explicitly focused on the semantic properties or categories of the images.

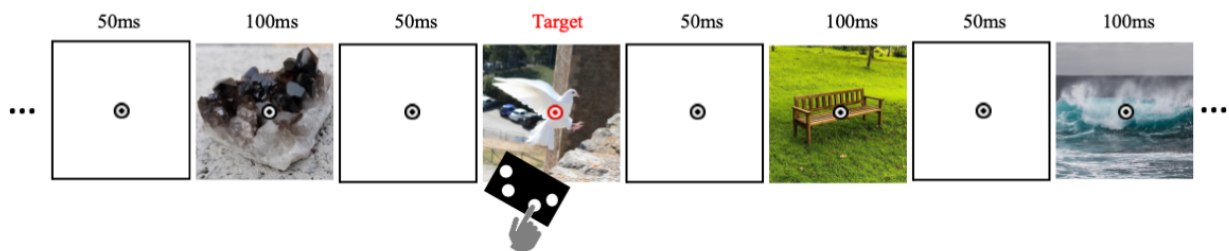
(A) Sample stimuli



(B) Online stimulus validation (alive/not alive, moves/still, natural/artificial)



(C) Experiments 1 and 2: EEG (passive viewing)



(D) Experiment 1: EEG categorisation (alive/not alive) and Experiment 2: EEG categorisation (moves/still)

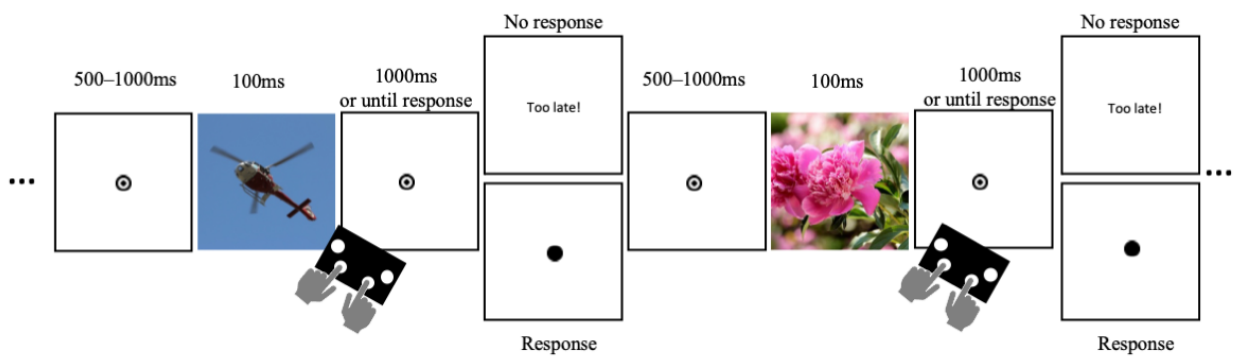


Figure 3.1

Experimental paradigm for our online stimulus validation, and Experiments 1 and 2 with EEG. Sample stimuli are shown in (A). For the online stimulus validation experiment shown in (B), participants classified images by either aliveness, capacity for movement, or naturalness. During passive viewing trials of both EEG experiments in (C), participants viewed a rapid stream of images and responded to the fixation spot changing to red by pressing a button. During categorisation trials for both EEG experiments in (D), participants rapidly categorised images. In EEG Experiment 1, participants responded based on whether each image depicted something that was alive or not alive. In EEG Experiment 2, participants responded based on whether each image showed something that could move or could not move. Note that all images are magnified here for clarity; for presentation they occupied a smaller proportion of the screen.

EEG Data Analysis

EEG pre-processing

We used a minimal pre-processing pipeline, based on prior work (Grootswagers et al., 2021; Grootswagers, Robinson, & Carlson, 2019; Grootswagers, Robinson, Shatek, et al., 2019; Robinson et al., 2019; Shatek et al., 2019). Using custom scripts for EEGLab (Delorme & Makeig, 2004) in MATLAB (The MathWorks Inc., version 2020a), data were re-referenced to an average reference, low pass filtered at 100Hz, high pass filtered at 0.1Hz, then down-sampled to 250Hz. Epochs of data were created from 300ms before each stimulus appeared on the screen to 1000ms after stimulus onset.

Decoding image category

To investigate how the different object categories are represented in the brain, we used multivariate decoding applied to the EEG data in response to each image. All decoding analyses were run in MATLAB using functions from the CoSMoMVPA toolbox (Oosterhof et al., 2016), using all 128 channels from each participant. To test if individual images (e.g., tree1, cat1) and categories (e.g., plant, animal) were distinguishable from the EEG recording, we conducted pairwise decoding analyses. All analyses were conducted timepoint by timepoint relative to when each image was displayed. At the individual image level (e.g., tree1, cat1), we trained a Linear Discriminant

Analysis (LDA) classifier on each pair of images from all but one block and tested on those same images from the left-out block. This was repeated over all pairs of images, for each block as the test data. Separate analyses were conducted for categorisation and passive viewing. At the category level (e.g., plant, animal), we conducted a similar pairwise analysis still leaving two images out to test on, but also excluded these two images from the training set. For example, to compare plants and animals, a classifier was trained on blocks 1-3 using all plants and animals except a pair of images (e.g., tree1 and cat1), and then tested on these left-out images (tree1, cat1) from remaining block (block 4). This process was repeated so each pair of images was left out in each block, then averaged over all pairs.

Representational Similarity Analysis

To investigate how movement and aliveness are represented in the brain, we used Representational Similarity Analysis (RSA) to relate neural activity to behavioural responses as well as lower-level visual features that might differ across categories (Kriegeskorte et al., 2008). Behavioural Representational Dissimilarity Matrices (RDMs) were calculated for aliveness, movement and naturalness based on the online stimulus validation study, and low-level visual models were calculated for colour, rectilinearity and patterns of shadow using a greyscale model. For the colour model, each pixel of each image was allocated values within CIELab colour space, and these values were averaged over all images in a category to form a single vector of values for each category. The Euclidean distance between categories could then be calculated. For the greyscale model, each pixel of each image was converted to a single greyscale value. These values were averaged over all images in a category, and the Euclidean distance between categories was calculated to form the 40 x 40 RDM. To control for rectilinear differences in animacy, we also included a measure of rectilinearity from Nasr et al. (2014), calculated using publicly available code from [https://github.com/cechava/Rectilinearity_Toolbox]. As with the colour and greyscale measures, we

calculated the amount of rectilinearity in of each image, then averaged across each category. We then calculated the Euclidean distance between each category to form a model of rectilinearity.

To calculate RDMs for the neural data, we used an LDA classifier at every time point to compute decoding accuracy for each pair of categories (e.g., cats vs rocks), resulting in a 40x40 neural dissimilarity matrix for each time point. This classifier used the same partitioning structure as category decoding above, in which each pair of images was left out as the testing set for each block

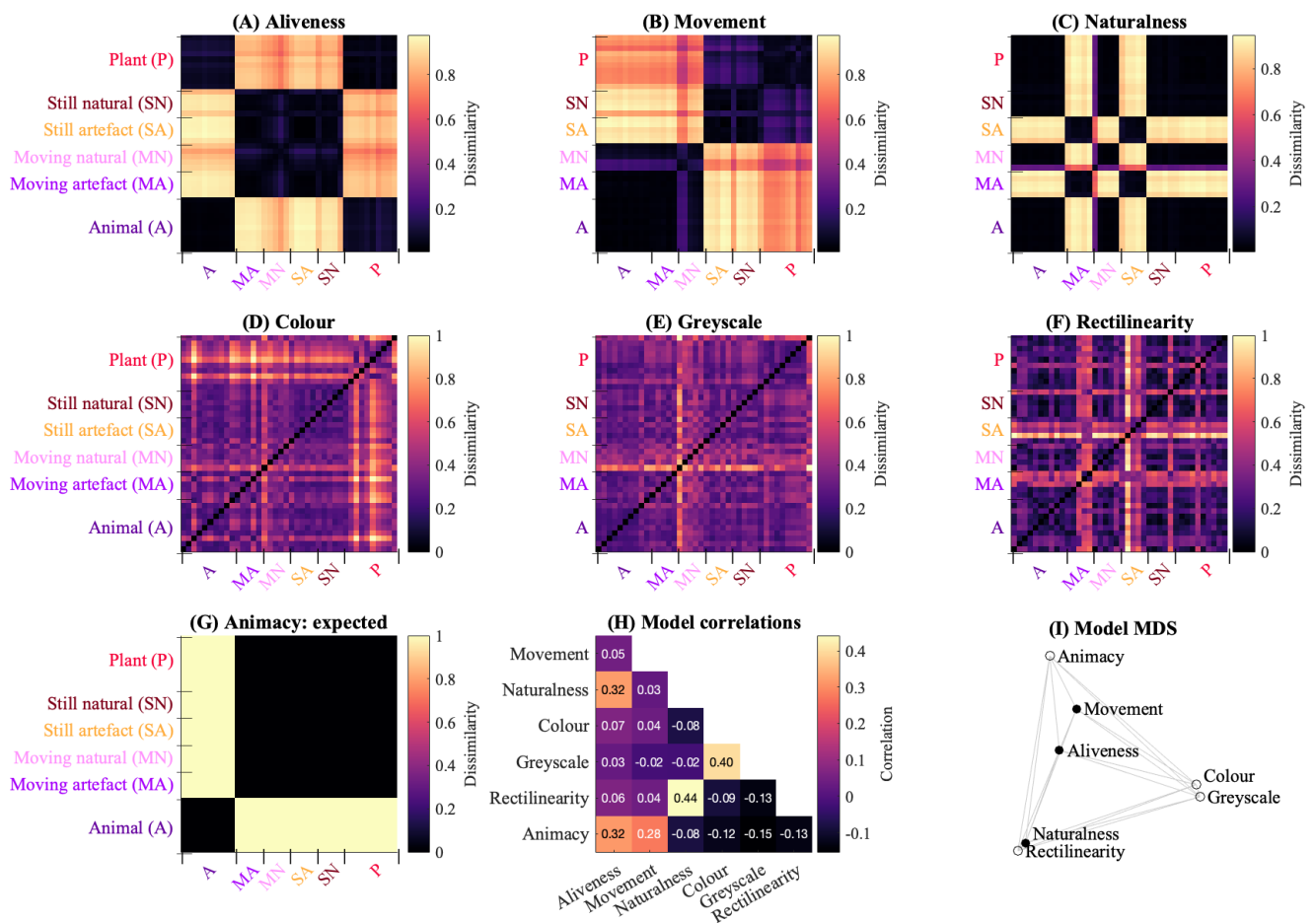


Figure 3.2

Representational dissimilarity matrices (RDMs) generated from behavioural ratings of stimuli and image-level analysis of stimuli. Areas that are more purple indicate low dissimilarity (more similar). Areas that are more orange indicate high dissimilarity (less similar). Each category (e.g., cat, tree) is shown in a single row/column. Panels (A), (B), and (C) illustrate models generated from behavioural ratings of the stimuli from an online stimulus validation task. Panels (D), (E), and (F) show models generated by analysis of the low-level features of the stimuli, and panel (G) shows the experimenter-derived expected animacy model. Model correlations between these models are shown in (H), and the relationships between the models are shown using Multi-Dimensional Scaling (MDS) in (I). Abbreviations on panels (A) – (G) indicate categories; Plants (P), Still Natural (SN), Still Artefacts (SA), Moving Natural (MN), Moving Artefacts (MA), and Animals (A).

and for each pair of categories. Separate neural RDMs were created for passive viewing and categorisation trials.

Linear modelling

To investigate how categories of aliveness and movement account for neural responses to objects, we ran a series of general linear models to see which characteristics best explained the neural processes over time in both the categorisation and passive viewing tasks. For the categorisation data, eight predictor variables were included: aliveness, naturalness, movement, colour, greyscale, rectilinearity, animacy, and stimulus-driven neural responses from the passive viewing trials. All of these models (except the passive viewing neural models) are shown in [Figure 3.2](#). These eight predictor variables were used to run separate linear models for each time point, with outcome variable as the neural RDM of the categorisation task at that time point. This process was repeated with the passive viewing data as the outcome variable, including the first seven predictor variables: aliveness, naturalness, movement, colour, greyscale, rectilinearity, and animacy.

The behavioural models of movement, aliveness, and naturalness ([Figure 3.2A-C](#)) were included in the GLMs to assess how these different image categories influenced neural responses. We also included low-level visual models of colour, greyscale and rectilinearity ([Figure 3.2D-F](#)), as prior evidence has shown that distinct patterns of neural activity arise at least to some extent as a result of similar low- and mid-level visual features such as rectilinearity (Grootswagers, Robinson, Shatek, et al., 2019; Long et al., 2018; Wang et al., 2022). We also included a binary model of animacy (animals coded as 1, all other categories coded as 0; [Figure 3.2G](#)), and the neural RDM of the passive viewing trials. For each time point, the passive viewing RDM was taken from the same time point as the categorisation task RDM (outcome variable) to account for stimulus-driven neural processes during the categorisation tasks. The combination of these models can highlight how stimulus movement and aliveness uniquely contribute to neural responses.

To ensure that multicollinearity was sufficiently low to interpret the output of the model, we calculated the variance inflation factors for each model based on a downloaded MATLAB function (Vasilaky, 2021). A measure of multicollinearity, the variance inflation factor indicates the impact on the variance of the model of adding a particular variable, compared to if it were independent to all the other variables (Montgomery et al., 2012). A variance inflation factor of one would indicate that the variable is independent from the other elements in the model, with factors close to one indicating fewer potential issues with multicollinearity and higher factors indicating more higher multicollinearity (Thompson et al., 2017). The variance inflation factors for all variables were low (ranging from 1.01 for movement to 1.40 for naturalness), indicating low multicollinearity between the models.

Neural network

To investigate whether the characteristics associated with movement are associated with lower-level visual processing, or more abstract categorical processing, we compared neural data to different layers of a neural network. CORnet (Kubilius et al., 2018, 2019) is a deep neural convolutional network designed as a model for the human visual system, where each convolutional layer represents a different area of the visual system. Feature weights for each image were extracted from the layers representing V1, V2, V4 and Inferotemporal cortex (IT). The distance between the feature weights for each image was calculated to form a 400 x 400 RDM, which was then averaged to 40 x 40 so it was the same size as the neural RDMs. This process was repeated over each brain region (layer). To examine which layer of CORnet most closely resembled neural activity over time, we examined the correlation between each layer and the neural data for each time point.

Statistical analysis

We used Bayesian inference to examine differences in accuracy and reaction time across stimulus categories. For all comparisons, we used the BayesFactor package in R (Morey et al., 2018).

Following recommendations in Teichmann et al. (2021), we used a JZS prior (Rouder et al., 2009) with a scale factor of 0.707. This is the default prior and scaling in the BayesFactor package because it makes minimal assumptions about the expected effect size, and serves as a “non-informative default” (Rouder et al., 2009, p. 232).

To calculate statistics for the differences in behavioural classification between animals and plants, we used the Bayesian equivalent of t-tests (Rouder et al., 2009). We also used Bayesian linear models to determine if naturalness and capacity for movement influenced reaction times or accuracy. Models were built to express all combinations of each variable, in addition to participant ID. To determine whether naturalness and movement had an effect on reaction times and accuracy, we compared an additive model (movement + naturalness + subject ID) to a model without each variable in turn (for movement, naturalness + subject ID). A larger Bayes Factor would indicate that the inclusion of that variable makes a model that is more likely given the data (Rouder et al., 2012). This can be interpreted similarly to the main effect in a traditional ANOVA.

For decoding analyses, we used a series of t-tests using the `ttestBF` function (Morey et al., 2018) from the BayesFactor package with the parameters described above. The alternate hypothesis is that the decoding is above chance (50%), and the null-interval was effect sizes from negative infinity up to 0.5, as effect sizes during baseline periods prior to stimulus onset from previous work have shown this to be most appropriate (Teichmann et al., 2021). This formed a one-sided hypothesis that the effect size for alternate hypothesis should be positive. For linear modelling, in which both negative and positive results are meaningful, we used the same procedure with the alternative hypothesis that the betas are different to zero, with a two-sided prior from -0.5 to 0.5.

Bayes Factors are interpreted according to Jeffreys (1961/1998), where Bayes Factors larger than 30 are very strong evidence for the alternate hypothesis, Bayes Factors larger than 10 are strong evidence for the alternate hypothesis, Bayes Factors larger than three provide some evidence for the alternate hypothesis, and Bayes Factors smaller than 1/3 provide evidence for the null hypothesis.

Results

We used behavioural and neural measures to investigate how aliveness and movement are processed by the brain. In two experiments, participants rapidly classified images according to aliveness (Experiment 1) or capacity for movement (Experiment 2) while we measured neural responses with millisecond precision.

Behavioural: Passive viewing

In the passive viewing task, participants performed an orthogonal fixation change task. Behavioural performance on the passive viewing blocks of both EEG experiments indicated that participants were engaged with the task. Participants correctly identified the target colour change within 600ms on 93.77% of occurrences for Experiment 1 (SE = 0.93, range 79.07% - 100%) and on 95.76% of occurrences for Experiment 2 (SE = 0.54, range 88.04% - 98.89%).

Behavioural: Categorisation task

To examine the relationship between movement and aliveness in categorisation of naturalistic image stimuli, we used behavioural metrics (reaction time, classification accuracy) and multivariate pattern analysis of neural data. The median reaction time for Experiment 1 was 457ms (SE = 10.7ms, range of participant means 322ms – 561ms), and for Experiment 2 was 456ms (SE = 11.53ms, range of participant means 373ms – 588ms)([Figure 3.3](#)). Participants showed high accuracy in classifying the stimuli, with few trials (on average, ~16 of 1600 trials per participant) that timed out without a response (misses). In Experiment 1, the mean percentage of correct responses was 87.42% (SE = 1.4152%, range 69.75% - 97.5%), with an average of 1.10% misses (SE = 0.26, range 0.13% - 5.94%). For Experiment 2, there were 82.97% (SE = 1.64%, range 61.67% - 94.42%) correct responses, on average, with 0.97% misses (SE = 0.18, range 0.19% - 3.00%). Though some participants had low ‘accuracy’ scores, these always arose from consistent classification in the opposite direction from what was predicted (e.g., consistently responding that plants were not alive

in Experiment 1, or consistently responding that moving natural stimuli did not move in Experiment 2).

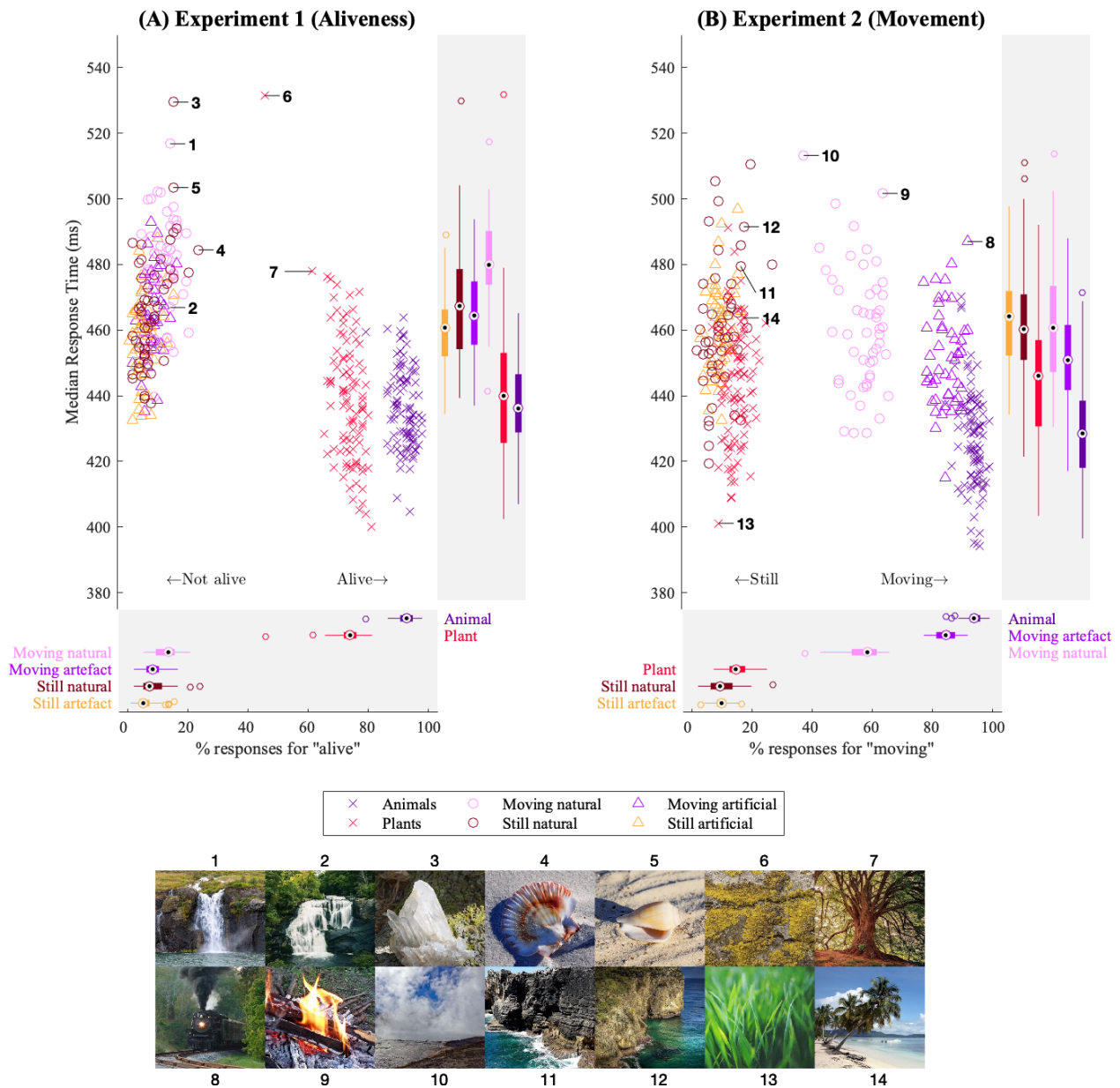


Figure 3.3

Median response times and classifications of stimuli from EEG Experiments 1 and 2. Data from participants considering whether the stimulus was alive or not is shown in (A) and data from classifying images by capacity for movement are shown in (B). Sample images below correspond to the labelled data points, showing a selection of responses.

Behavioural: Experiment 1

We were interested in how image category influenced how participants categorised images according to whether they were alive or not in Experiment 1. First, we assessed performance for the alive images, which consisted of animals and plants, as previous work has shown that animals are considered ‘more alive’ than plants (Yorek et al., 2009). Bayesian t-tests were used to evaluate whether there were differences in reaction time and classification between plants and animals. There was very weak evidence for differences in reaction time between plants and animals in the aliveness task of Experiment 1 ($BF = 1.09$) and some evidence that responses to animals were faster than plants in the movement task of Experiment 2 ($BF = 3.17$). However, there was strong evidence that plants were classified as “not alive” more often than animals ($BF = 16.66$), suggesting that plants are considered ‘less alive’ than animals, as predicted by behavioural models of aliveness (Yorek & Narli, 2009).

For the stimuli that are not alive, we used Bayesian linear modelling to investigate how moving and natural stimuli influenced aliveness judgements compared with still and artificial stimuli. Natural stimuli were mistakenly classified as alive more often ($BF = 184.70$) and more quickly ($BF = 3757.79$) than artificial stimuli. This is somewhat expected, given that all of the stimuli that are alive are also natural. Capacity for movement also influenced judgements of aliveness, with non-living moving stimuli classified as alive more often ($BF = 132.28$) and more slowly ($BF = 667.90$) compared to still stimuli. These results are in line with use of intuitive biological knowledge under time pressure (Goldberg & Thompson-Schill, 2009), mistaking moving and natural stimuli for being alive.

Behavioural: Experiment 2

We were also interested in how image category influenced movement classification in Experiment 2. There was weak evidence for no difference in reaction time ($BF = 0.68$) in classifying plants and animals as moving or non-moving. There was also weak evidence that animals were

classified as moving more often than plants were classified as still ($BF = 3.17$). For non-living stimuli, we investigated the impact of capacity for movement and naturalness on movement classification using the Bayesian equivalent of an ANOVA. We found that natural stimuli were classified less accurately than artificial stimuli ($BF = 66.50$), and moving stimuli were also classified less accurately than still stimuli ($BF = 1815.09$). There was weak evidence for the null hypotheses that naturalness did not affect reaction times ($BF = 0.92$), and weak evidence for the null hypothesis that movement did not affect reaction times ($BF = 0.29$). Crucially, there was a significant interaction effect ($BF = 168.7$) for accuracy, suggesting that stimuli that are both moving and natural were responded to less accurately. This difference is clear in [Figure 3.3B](#) (pale pink circles), showing the low agreement across participants on whether these natural moving stimuli are moving or not.

Decoding image category

We were interested in the temporal dynamics of visual information processing in the brain, from low-level image identity to category level representations. To test if individual images (e.g., tree1, cat1) and categories (e.g., plant, animal) were distinguishable from the EEG recording, we used a linear discriminant classifier to classify stimuli at these two levels. Neural responses contained information about image identity (e.g., dog1) and category (e.g., animal) from 90-120 milliseconds after stimulus onset, characteristic of early-stage visual processing (Carlson et al., 2013; Cichy et al., 2014). Both when participants were passively viewing images ([Figure 3.4A, C](#)) and when they were classifying them ([Figure 3.4B, D](#)), information about stimulus identity remained present for more than 400ms after stimulus offset. This is in line with prior work demonstrating enduring neural representation after stimulus offset in rapid serial visual presentation sequences (Grootswagers, Robinson, & Carlson, 2019; Mohsenzadeh et al., 2018; Robinson et al., 2019).

In both EEG experiments, participants completed the same passive viewing task ([Figure 3.4A, C](#)). At both levels of classification, neural data revealed similar information was present over

time for the passive trials in both experiments. This similarity indicates that there are unlikely to be major differences in data quality between the two experiments.

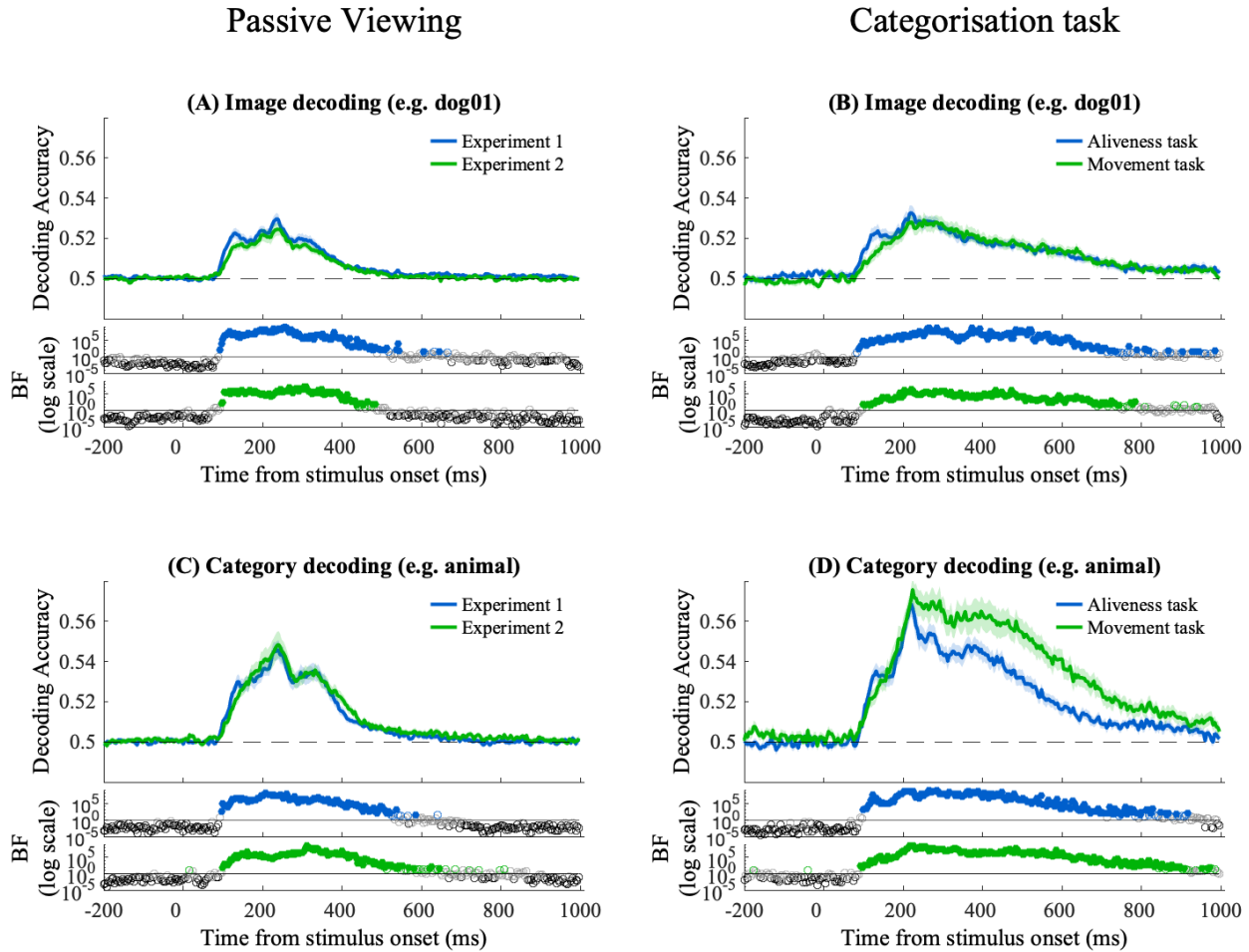


Figure 3.4

Decoding stimulus identity. Plots show pairwise decoding accuracy from an LDA classifier over time for image-level (A, B), and category-level (C, D) classification. The dashed line at 0.5 indicates chance decoding, with higher values indicating more discriminability between classes of stimuli. Blue lines show data from Experiment 1 (aliveness task) and green lines show data from Experiment 2 (movement task). Shaded areas indicate standard error across subjects (N=24 for each experiment). Bayes Factors (BF) above 30 (very strong evidence) are shown in the filled coloured dots, BF between 10 and 30 (strong evidence) are shown as unfilled coloured dots, BF between 1/3 and 10 are shown in grey, and BF below 1/3 (evidence for the null) are shown in black. For passive viewing blocks (A, C) the task was the same across both experiments. For categorisation trials (B, D) participants classified stimuli by aliveness in Experiment 1 (blue) and by capacity for movement in Experiment 2 (green).

EEG: Linear modelling

To investigate how much the conceptual categories of movement and aliveness explained brain activity, we used linear modelling to see which theoretical models best explained patterns of brain activity over time ([Figure 3.5](#)), in both the passive and categorisation tasks. These linear models allowed us to assess how movement and aliveness account for the neural data both during task-related classification and passive viewing, once accounting for stimulus naturalness, animacy, low-level features such as colour and rectilinearity.

We also ran a model to predict the passive viewing neural data, to examine whether the same information about movement and aliveness was present without a relevant semantic task. For passive viewing, aliveness explained patterns of neural activity 120ms after stimulus presentation ([Figure 3.5A](#)), for a brief period of approximately 50ms. In contrast, information about movement was present slightly later, from 200ms for both experiments, and for a longer period of time ([Figure 3.5C](#)).

During the categorisation task, aliveness explained patterns of neural activity for a very brief period from 120ms to 150ms after stimulus onset in Experiment 1 and 130ms to 160ms after stimulus onset in Experiment 2 ([Figure 3.5B](#)). In contrast, movement explained variance in patterns of neural recordings from 180ms in Experiment 1 and 200ms in Experiment 2, with a peak at around 230ms - 240ms for both experiments, until approximately 320ms after stimulus onset for Experiment 1 and 500ms after stimulus onset for Experiment 2 ([Figure 3.5B](#)). Though both aliveness and movement had a similar time course in both tasks, aliveness seems to have an earlier and less prolonged peak than movement.

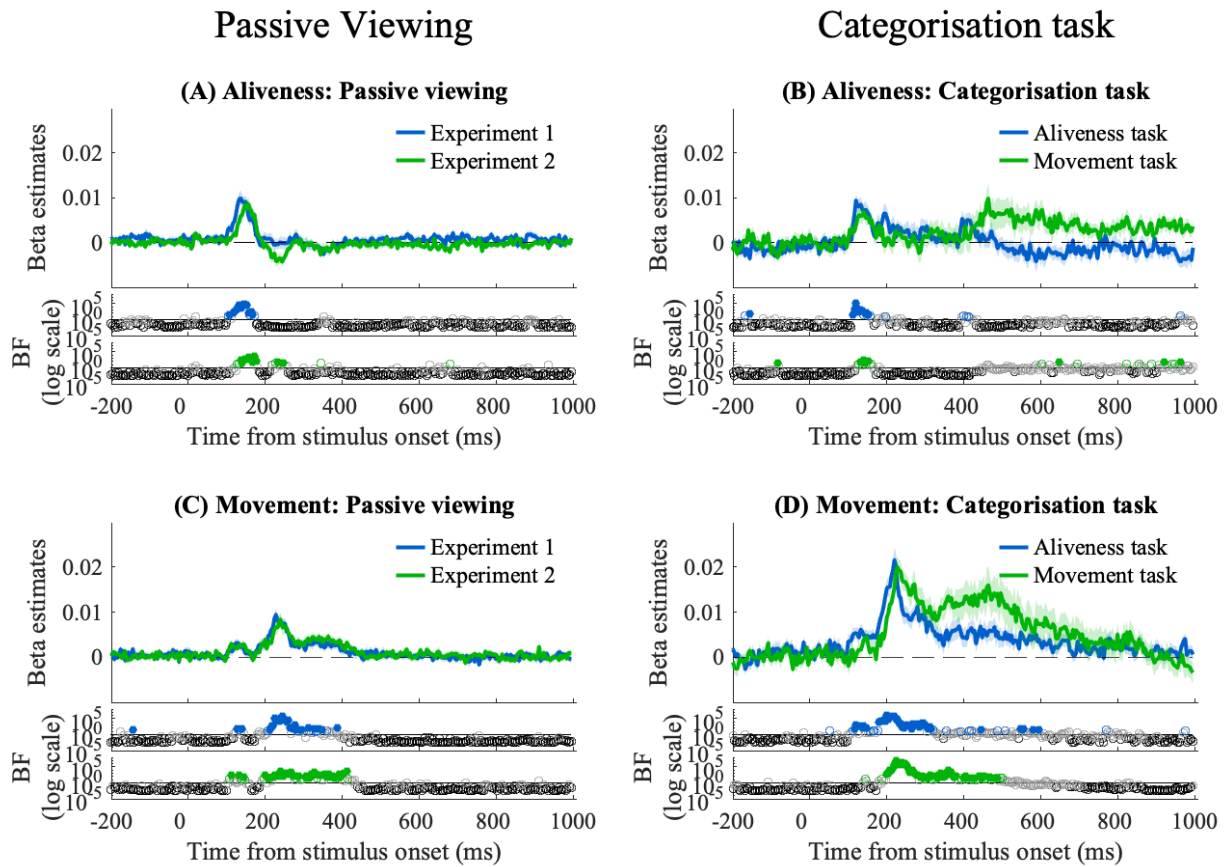


Figure 3.5

Aliveness and movement explained a significant proportion of brain activity during categorisation and passive viewing tasks. Plots show beta estimates for aliveness (A, B) and movement (C, D) from linear modelling, which included behavioural (aliveness, movement, naturalness) and image-level (colour, greyscale, rectilinearity) models, as well as a model of animacy. For the categorisation task (right column), the passive viewing RDM from the corresponding time point was also included. Blue lines show data from Experiment 1 (aliveness task) and green lines show data from Experiment 2 (movement task). Shaded regions show standard error across subjects (N=24 for each experiment). Bayes Factors (BF) above 30 (very strong evidence) are shown in the filled coloured dots, BF between 10 and 30 (strong evidence) are shown as unfilled coloured dots, BF between 1/3 and 10 are shown in grey, and BF below 1/3 (evidence for the null) are shown in black.

Neural Network

To further investigate whether the neural signal more closely resembled higher-order processing or lower-level visual processing, we examined the correlation between neural activity and layers of a neural network modelling the visual system, CORnet (Kubilius et al., 2018, 2019). CORnet includes layers that resemble processing in four visual areas: V1, V2, V4 and Inferotemporal cortex (IT). In both experiments, all four layers were correlated with neural activity

from approximately 100-120ms after stimulus presentation to approximately 180ms after onset, with a peak at approximately 120-130ms (Figure 3.6). Notably, only the layer resembling IT is significantly correlated with neural activity after approximately 300ms post-stimulus onset. This extended correlation with the IT layer suggests that the neural activity from around 300ms is related to higher-order classification, and that the later significance of movement in the linear modelling may be attributed to higher-order categorisation processes.

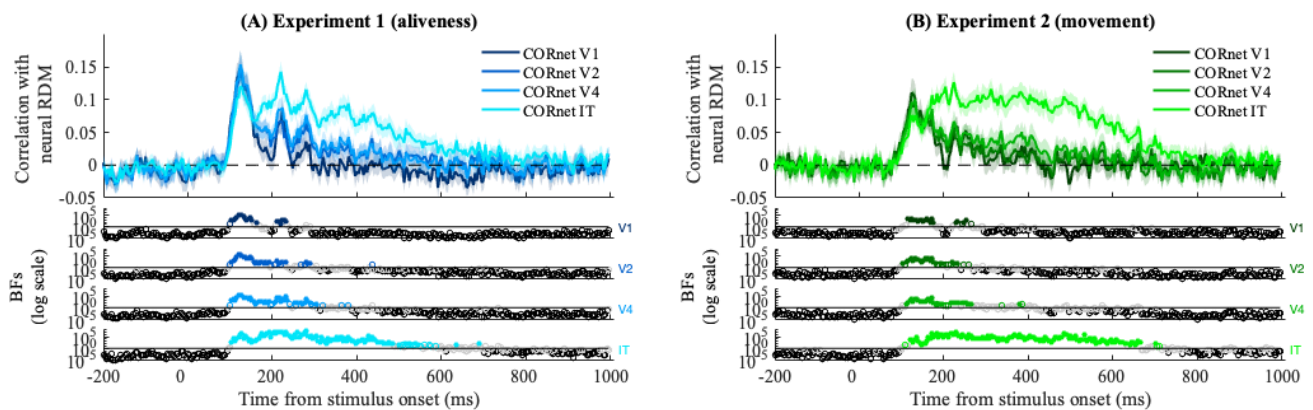


Figure 3.6

Correlation between neural activity and layers of CORnet (Kubilius et al., 2018, 2019) representing areas of the visual system, for Experiment 1 (A) and Experiment 2 (B) during the categorisation task. Shaded regions show standard error across subjects (N=24 for each experiment). Bayes Factors (BF) above 30 (very strong evidence) are shown in the filled coloured dots, BF between 10 and 30 (strong evidence) are shown as unfilled coloured dots, BF between 1/3 and 10 are shown in grey, and BF below 1/3 (evidence for the null) are shown in black.

Discussion

In this study, we used EEG to investigate the contribution of movement and aliveness in categorisation. Previous work has focused on animacy as a major dimension in visual object processing, but animacy tends to co-occur with movement, raising the question of how much these object features contribute to categorical object processing in the brain. Here, we show that movement is an important organisational principle in the brain. We use naturalistic image stimuli including moving elements of the natural landscape (e.g., waterfall, fire) to show that the brain processes movement associated with non-living kinds as well as movement from living things. EEG data

revealed that information about capacity for movement was present in neural signals both during active classification as well as passive viewing of stimuli, after accounting for categorical similarities in colour, shape, naturalness, animacy, and aliveness. The results show that capacity for movement is an important dimension in human visual object perception.

Behavioural results from the categorisation task showed that moving things (waterfalls, clouds, etc.) were more likely to be judged as alive under time pressure, and that elements of the natural landscape tend to be perceived as still. These trends are in line with prior work showing that under time pressure, adults may rely on intuitions about the world (Goldberg & Thompson-Schill, 2009; Kelemen et al., 2013; Shtulman & Harrington, 2016; Shtulman & Valcarcel, 2012; Young & Shtulman, 2018). Our behavioural results build on these prior findings to show that application of scientific intuition in adulthood is not limited to judgements about the accuracy of complex statements about physics and chemistry, or judgement of words that are used in prior work, but also extends to basic judgements of aliveness and to naturalistic pictorial visual stimuli. The presence of these behavioural classification biases under time pressure may reflect that they are adaptive in most situations in both modern times and for our ancestors (New et al., 2007). For example, assuming that moving things are alive allows for rapid reactions even when these assumptions are wrong, such as moving away from an oncoming car. The behavioural results, therefore, suggest that natural movement is uniquely positioned in a spectrum of movement because of its ambiguous causal relationships.

Though here we consider all kinds of movement together, it is clear that moving natural things like fire and waterfalls move in different ways to animals and vehicles. Animate movement differs from inanimate movement, in terms of having a goal-directed trajectory (Gergely et al., 1995), predictability of movement (Pratt et al., 2010), and the speed and angle of directional changes (Tremoulet & Feldman, 2000), among other things. Given the evidence of neural processing of goal-directed movement and agency (Thorat et al., 2019) it is possible that difficulties and inconsistencies in classifying movement in the natural landscape (e.g., see pink dots in [Figure 3.3](#)) occur because

there is no obvious agent causing natural movement. This is in contrast to all the other moving stimuli, which can generate spontaneous goal-directed movement (animals) or move with the intervention of humans (all the moving man-made stimuli were vehicles). Future studies may evaluate whether moving artificial stimuli that move without clear human intervention (e.g., clocks, fireworks) show similar response patterns.

Alternately, these difficulties in classifying the moving natural objects may be due to colloquial implications of the language we used in the instructions. For example, there were four participants in Experiment 1 who consistently responded that plants were not alive. The term ‘alive’ can colloquially be interpreted to mean ‘animate’ (Leddin et al., 2009) particularly in childhood, so it is possible that these participants interpreted the instructions as such. Similarly, in Experiment 2, some participants consistently classed the moving natural things as still, potentially because they interpreted ‘can move’ to refer only to self-generated movement, animate movement, or as movement of an item relative to the environment it is in. However, these same participants also reliably classified vehicles as moving, so it is unclear whether this is a semantic or lexical distinction that is important. Further research is required to fully understand the impact of lexical factors on classification behaviour in the current context.

Our behavioural results suggest movement and aliveness are related in making judgements about stimuli, yet our linear modelling showed that they are processed differently in the brain. Information about movement was present in neural activity around 180-200ms after stimulus onset, regardless of the task ([Figure 3.5C, D](#)). Even after accounting for visual controls, the movement model still explained a large portion of variance in brain activity, indicating that capacity for movement is an inherent feature of object representations. After an initial peak at approximately 230-240ms, there was an extended period where movement explained a proportion of the variance in neural activity until around 500ms after stimulus onset. The combination of an early peak and an enduring significance suggests that this ‘movement’ factor is capturing some elements of automatic early visual processing, as well as some higher-order cognitive influences in the later period while

participants are making a decision on how to classify the stimuli. Similar temporal dynamics are present in the first 300 milliseconds of linear modelling of neural processing during passive viewing ([Figure 3.5A, C](#)), indicating that visual representations are inherently organised in terms of capacity for movement, even when it is not the focus of the task. It is also possible that these movement representations are driven by animacy differences within the living stimuli. However, when only considering the non-living images (moving and non-moving artefacts and natural things), movement remains decodable within both the passive viewing and the categorisation task, albeit more strongly in the categorisation task ([Supplementary Figure 3.1](#)). Thus, visual representations appear to be organised in terms of capacity for movement, and these representations of movement may be enhanced when they are task relevant.

To investigate whether the later periods of significance represent processing in brain areas associated with higher-order abstract object perception (Carlson et al., 2013), we compared the brain data to a neural network. The correlations between brain activity and CORnet (Kubilius et al., 2018, 2019), a neural network designed to model the visual system, revealed that early neural activity correlated well with all layers (V1, V2, V4 and IT) with a peak at approximately 120 - 130ms ([Figure 3.6](#)). The earlier layers remain significant for a short period of time. In both experiments from approximately 300ms onwards while participants were classifying the stimuli, patterns of brain activity were most similar to the IT layer, indicating that neural representations in this later time period were likely to be more abstract, higher-order classifications (Carlson et al., 2013). In particular, the movement task of Experiment 2 may engage more higher-order processing than the aliveness task in Experiment 1. The correlation between the IT layer of CORnet and neural activity appears to be sustained longer in the movement task ([Figure 3.6B](#)) compared to the aliveness task ([Figure 3.6A](#)), and it seems that movement may explain more variance in neural activity in Experiment 2 compared to Experiment 1 ([Figure 3.5D](#)). Similarly, object category (e.g., animal, plant) was more separable in the neural responses during the movement task than the aliveness task ([Figure 3.4D](#)), further suggesting that judgements about movement might inherently involve some

higher-level category responses. The combination of these analyses suggests that the ‘movement’ factor in the current experiment represents some combination of more abstract features at later time points, in addition to some visual similarity at earlier time points between all things that move, such as blurred edges.

It is notable that even when participants were classifying the images by aliveness, movement still explained variance in neural activity (blue lines in [Figure 3.5D](#)). This suggests that when judging if something is alive, we may be using the quality and type of the movement to provide clues about aliveness. This would fit with an evolutionary explanation of the current effects; threats to our ancestors were primarily moving animate things, and thus detection and distinction of animals rapidly in the environment may have been advantageous for survival (New et al., 2007). As noted above, it is also the case that the quality and type of movement associated with animates differs from movement in the natural environment. It is possible that these differences in movement contribute to the decision-making about whether something is alive or not. This higher-order processing would fit with the hierarchy proposed in some behavioural and philosophical models of aliveness, which claim that we understand whether something is living based on similarity to a human prototype, from humans, to moving things and plants, and to non-living things (Yorek & Narli, 2009).

A particularly interesting finding was that aliveness only explained patterns of brain activity in a very brief period shortly after stimulus onset. Attention to particular features of a stimulus based on the task can affect neural representations (Harel et al., 2014), and thus we were surprised that aliveness did not account for more variance in brain activity in Experiment 1 when it was the focus of the task. There is little consensus about the degree to which aliveness explains patterns of brain activity in object representations, with some work showing that aliveness is a better correlate of brain activity than animacy (Contini et al., 2020), and others showing that it is important for behaviour but does not explain variance in brain representations (Jozwik et al., 2021). The fit of aliveness models may depend on the choice of stimuli; in Contini and colleagues’ (2020) study, robots and toys appeared more animate than inanimate, reducing the fit of the animacy model compared to the

aliveness model. In the current study, aliveness may have poor explanatory power in our linear models because the differences between living and non-living stimuli are captured by other variables in the linear models, particularly naturalness which is not evenly distributed across alive and non-alive stimuli, and the low-level visual correlates of aliveness such as rectilinearity (Nasr et al., 2014).

Converging evidence from neuroscience and behaviour has shown that animacy and aliveness are best described as represented on a continuum according to capacity for goal-directed movement (Connolly et al., 2012; Contini et al., 2020; Sha et al., 2014; Thorat et al., 2019; Yorek et al., 2009). In the current study, we show that capacity for movement is an important dimension in human visual object perception, not only for animate movement, but also for inanimate movement in the natural world. Our results support previous work showing that animacy processing in the brain is closely related to the capacity for self-initiated movement and extend this to show that natural movement may be a part of this spectrum. Overall, our results show that capacity for movement is an important dimension in the representation of visual objects in humans.

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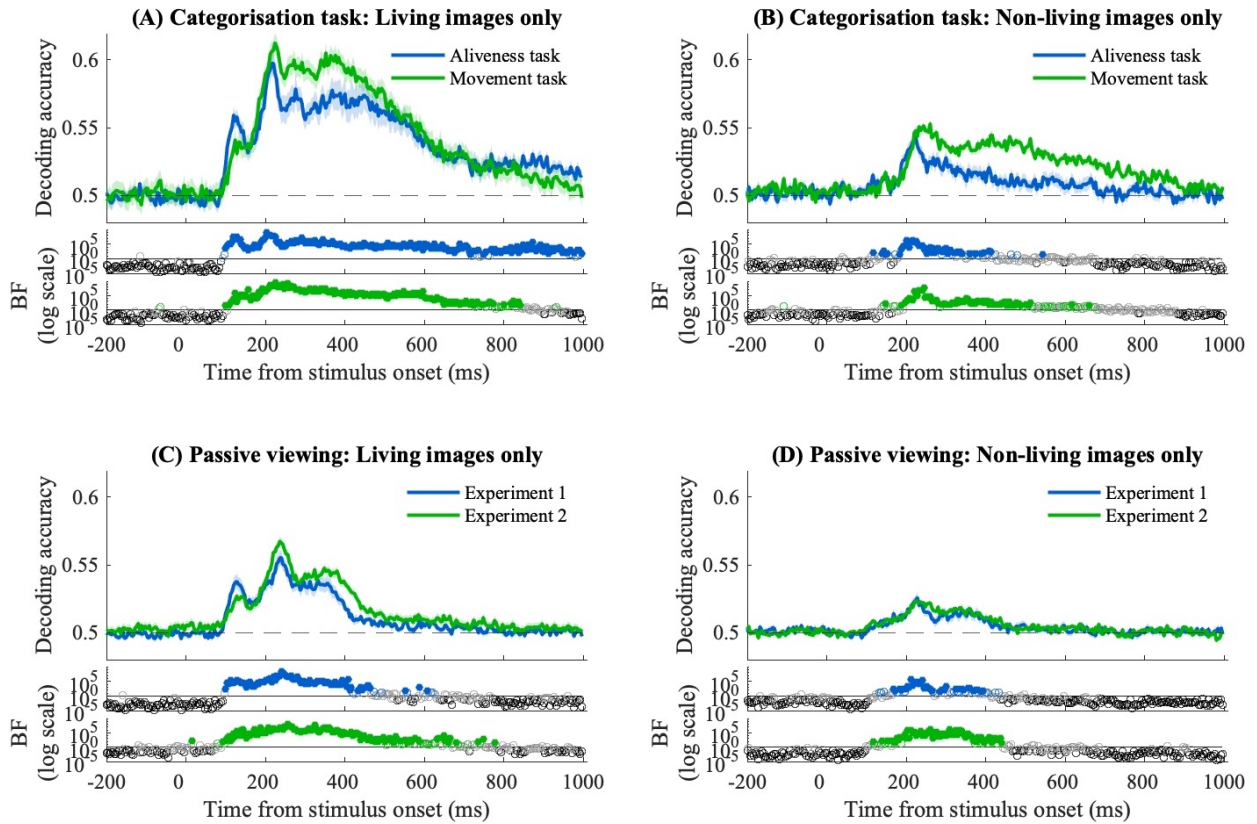
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Supplementary Materials

Supplementary Figure 3.1

Movement representations are present in both living and non-living objects

To assess whether movement decoding could be coming exclusively from images of living things, we performed decoding separately for living and non-living things. The results show clear movement related responses in both living and non-living stimuli. Decoding appeared stronger in living, but note that this analysis was comparing two different categories (animals versus plants) compared to the nonliving analyses, which included 2 categories per class (moving artefacts and moving natural things compared to still artefacts and still natural things). Together, these results suggest that movement representations for combined analyses (paper [Figure 3.5](#)) are not driven by one category type, and that similar representational separation exist for moving and non-moving items, regardless of aliveness.



Decoding movement from living and non-living images separately. For both passive viewing and categorisation task epochs independently, an LDA classifier was trained to distinguish movement within only the images depicting living things (plants/animals) and tested with a leave-one-block out partitioning structure. Then, separately, the same process was repeated for the non-living things (non-moving artefacts, non-moving natural things, moving artefacts and moving natural things), for both passive viewing and categorisation task epochs. Blue lines show data from Experiment 1, where participants were classifying by aliveness, and green lines show data from Experiment 2, where participants were classifying by capacity for movement. Shaded areas indicate standard error across subjects (N=24 for each experiment). Bayes Factors (BF) above 30 (very strong evidence) are shown in the filled coloured dots, BF between 10 and 30 (strong evidence) are shown as unfilled coloured dots, BF between 1/3 and 10 are shown in grey, and BF below 1/3 (evidence for the null) are shown in black.

Chapter 4: Capacity for movement provides cues for categorisation in the brain and in behaviour

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Abstract

The human visual system is tuned to process movement and can do so even from still images that imply motion (e.g., Kourtzi & Kanwisher, 2000). However, the role of movement in object recognition remains unclear. In the current study, we investigate whether movement is relevant for categorisation behaviour, and which characteristics of movement are relevant for both categorisation behaviour and neural processing. Results from an unconstrained ‘odd-one-out’ judgement task show that movement, as well as naturalness and animacy, are important factors in judgements of similarity. In a second experiment, we investigated how ratings of these same stimuli on various aspects of movement (e.g., how quickly they change position, how manipulable they are, how much they can move without changing position) correlated with patterns of neural activity from electroencephalography (EEG) data in Shatek et al. (2022; [Chapter 3](#)). We found that moving natural things like waterfalls and fires were perceived to move independently, replicating findings from [Chapter 2](#). Correlations with EEG data revealed that neural representations of capacity for movement are initially related to the speed at which an object typically moves, then later processing is related to whether this movement is independent or animate. Overall, our results reveal that movement is a behaviourally and neurally relevant characteristic in object categorisation.

Capacity for movement provides cues for categorisation in the brain and in behaviour

One of the most fundamental tasks of the human visual system is to identify items in the world so we know how to appropriately interact with them. Certain characteristics of objects, such as animacy, seem to be automatically and rapidly processed by the brain (Carlson et al., 2013; Konkle & Caramazza, 2013; Kriegeskorte et al., 2008). Recent research has suggested that animacy processing is better represented as a spectrum (Sha et al., 2014), according to related attributes such as similarity to humans (Contini et al., 2020; Ritchie et al., 2021), or capacity for agency (Proklova & Goodale, 2022; Thorat et al., 2019). As animates are defined by their capacity for agentic movement, another important dimension captured by many of these studies is capacity for movement. Yet, it remains difficult to separate animacy from elements like agency or goal-directed movement, because typically animate things (animals, humans) are natural, living, and moving, and inanimate things (vehicles, tools, etc.) are man-made, non-living, and still. Thus, it remains difficult to determine what role an object's capacity for movement plays in object processing.

Movement is important for behavioural categorisation of objects, particularly in development. Children use movement as the key factor in determining whether something is alive (Richards & Siegler, 1986), and typically have difficulty identifying plants as moving because they do not recognise that they can perform goal-directed movement (Opfer & Siegler, 2004). These childhood associations between movement and aliveness persist into adulthood. When adults classify things by aliveness under time pressure, they tend to make mistakes on items that violate the association between moving and being alive – plants which are alive but do not move, and moving natural things (e.g., fire, rivers) which are not alive but do move ([Chapter 2](#); Goldberg & Thompson-Schill, 2009)

In addition to behavioural classification, movement seems to also be important for neural object representations. The visual system has a distributed functional architecture to ensure rapid perception of movement (Tootell et al., 1995), which is active when any kind of motion is perceived, even if it is not reflected in the visual input, such as from an optical illusion (Zeki et al., 1997), or from an image where the motion is implied, such as a still frame of a person running (Kourtzi &

Kanwisher, 2000; Senior et al., 2000). Though visual processing is often thought of as separating into two separate streams ('what' and 'where'/'how') (Goodale & Milner, 1992; Kravitz et al., 2011; Ungerleider & Haxby, 1994), these two streams may interact when motion is relevant for object identification (Farivar, 2009; Kellenbach et al., 2003; Kourtzi et al., 2002; Lu et al., 2015; Proklova & Goodale, 2022; Robert et al., 2023). Patient studies show clear double dissociations between knowledge of an object's function and how it is manipulated or grasped (Goodale et al., 1991, 1994; Jakobson et al., 1991; Perenin & Vighetto, 1988), suggesting that motor-relevant objects are encoded with reference to how they should be interacted with (Buxbaum et al., 2000). This seems to only be the case for man-made objects (Magri et al., 2021), which are more defined by their function than natural things (Ahn, 1998; Gelman, 2013; Kalenine & Bonthoux, 2006). Man-made objects also appear to be represented in the brain according to their real-world size (Konkle & Caramazza, 2013), potentially because larger objects tend to remain in a single position and are functionally useful for navigation (Julian et al., 2017; Troiani et al., 2014). Thus, the brain seems to process information about movement in the context of manipulability, which is also fundamentally related to whether an object is man-made or natural, how quickly or frequently it typically moves, and how large it is.

By definition, movement and animacy are closely related, and it is difficult to disentangle their impacts in studies on animacy. Most studies of animacy contain no examples of moving natural stimuli so it is difficult to separate naturalness from movement. One study that including 'forces of nature' showed that they were rated as being highly unpredictable, and this unpredictability was reflected in both lower- and higher-level areas of visual cortex (Jozwik et al., 2022). Shatek et al. (2022; [Chapter 3](#)) also showed that movement is represented in patterns of brain activity, for both living and non-living stimuli. Participants were shown images that were either living or non-living, natural, or man-made, and moving or still. An object's capacity for movement was represented in patterns of neural activity, after controlling for aliveness, naturalness, and low-level visual characteristics. fMRI studies have also shown that the brain distinguishes what kind of movement an

object typically performs (e.g., in a circular motion, as a pendulum), independent of the context, even for still images (Borghesani et al., 2019).

It is clear that the brain processes objects in terms of their movement, and this informs how we interact with them. Yet it remains unclear what characteristics of this movement, if any, are important for object identification, whether this differs across man-made and natural items, and how these are distinguished in the brain. For example, is it necessary that the movement is agentive or goal-directed? Are natural things processed differently to man-made things? In the current study, we investigate different characteristics of movement, and how they relate to both behavioural judgements and neural processing. Using the stimulus set from Shatek et al. (2022; [Chapter 3](#)), we first considered whether movement is a behaviourally relevant dimension for object categorisation by using an ‘odd-one-out’ task to identify how participants judge similarity. In a second experiment, we investigated how ratings of these same stimuli on various aspects of movement (e.g., how quickly they change position, how manipulable they are, how much they could move locally without changing position) correlated with patterns of neural activity from electroencephalography (EEG) data in Shatek et al. (2022; [Chapter 3](#)). The results show that movement is a behaviourally relevant dimension in object categorisation, though less so than naturalness. The brain also appears to initially process overall movement speed, and then later process the agency of this movement. These findings are discussed in the context of real-world size, manipulability, and other factors relevant to neural processing of movement.

Methods

To investigate how capacity for movement is important for behavioural categorisation we used two tasks, an ‘odd-one-out’ judgement task, and a questionnaire on the characteristics of object movement. We related these two tasks to EEG data collected by Shatek et al. (2022; [Chapter 3](#)), which can be accessed at <https://doi.org/10.18112/openneuro.ds003885.v1.0.7> (Experiment 1) and

<https://doi.org/10.18112/openneuro.ds003887.v1.2.2> (Experiment 2). Stimuli were identical across the previous EEG study and these new data.

Stimuli

Stimuli were 400 realistic colour images used by Shatek et al. (2022; [Chapter 3](#)), gathered from online sources with Creative Commons 0 licenses and modified to remove text. Images fall into six superordinate categories based on those in Goldberg and Thompson-Schill (2009): animals, plants, still artificial things, still natural things, moving artificial things, and moving natural things ([Figure 4.1A](#)). Each superordinate category was also divided into objects. There were 10 objects for animals (bee, cat, dog, dolphin, eagle, horse, lemur, pigeon, tiger, whale) and plants (cactus, clover, fern, flower, grass, lemon tree, moss, palm tree, tree, vine). There were 5 objects for the remaining superordinate categories, still artificial things (bench, clothes peg, headphones, lock, mug), still natural things (cliff, crystal, rock, sand, shell), moving artificial things (boat, bus, car, helicopter, train), and moving natural things (fire, hot spring, river, waterfall, waves). For each of these objects there were 10 different images (e.g., dog1, dog2, ... dog10). If the object was able to move (animals, moving natural things, and moving artificial things), the image depicted it in motion rather than still. For example, birds and helicopters were shown in flight ([Figure 4.1A](#)).

EEG data

Though behavioural ratings are typically closely aligned to patterns of brain activity, similarity judgements typically identify more fine-grained distinctions between objects than are present in the brain (King et al., 2019; Mur et al., 2013). To investigate how closely our behavioural ratings of similarity and movement characteristics were reflected in neural activity, we used neural Representational Dissimilarity Matrices (RDMs) and behavioural data from Shatek et al. (2022; [Chapter 3](#)). In this study, the same images were presented to participants in two formats: (1) passive viewing of Rapid Serial Visual Presentation (RSVP) streams, where each image was presented on

the screen for 100ms, with a 50ms inter-stimulus interval; and (2) as part of a categorisation task where each image was displayed for 100ms and participants had to classify it by whether it was alive (Experiment 1) or whether it could move (Experiment 2). For every time point in a trial, the correlation between the neural data and the behavioural model generated from the ‘odd-one-out’ task was calculated. Pre-processing and analysis are detailed in Shatek et al. (2022; [Chapter 3](#)). In brief, data were filtered between 0.1 and 100Hz, re-referenced to an average reference, down-sampled to 250Hz, and epoched between 300ms before stimulus onset and 1000ms after stimulus onset.

Models from Shatek et al. (2022)

We also used conceptual models from Shatek et al. (2022; [Chapter 3](#)), including behavioural models, veridical models, visual models, and CORnet models (Kubilius et al., 2018). These models are visualised in [Supplementary Figure 4.1](#). Similarity between all models is shown visually in [Figure 4.1B](#) and correlations between all models are shown in [Supplementary Figure 4.2](#). Creation of these models is summarised below, and full details are contained in Shatek et al (2022; [Chapter 3](#)).

Judged (behavioural) models

Behavioural models of aliveness, movement, and naturalness were generated based on classification by online participants. Each participant completed a single task (e.g., aliveness), and classified all 400 images according to this task (e.g., alive or not alive). There was no time limit to these judgements, and RDMs were created based on the percentage of positive responses (i.e., the percentage who classified a given image as alive/ moving/ natural).

Visual models

Models of luminance (greyscale intensity), colour, and rectilinearity were generated to investigate whether movement representations were better captured by low-level features.

CORnet models

CORnet is a deep neural network designed such that each layer mimics the computations in visual areas of the brain (Kubilius et al., 2018). Feature activations from V1, V2, V4, and IT layers were used to create an RDM for each layer.

New models

In addition to the models used in Shatek et al. (2022; [Chapter 3](#)), we created additional models based on classifications in the EEG experiment, and the expected/ veridical classifications.

EEG models

In Experiment 1 of Shatek et al. (2022; [Chapter 3](#)), participants classified stimuli by aliveness. We created a model of aliveness in the same way as the other models of classification behaviour, by calculating the Euclidean distance between the percentage of times each pair of stimuli was classified as alive across all participants. This matrix was then averaged over each category to form a 40x40 RDM comparable to the behavioural similarity model. The same process was completed for the data from Experiment 2, where participants classified the stimuli by capacity for movement.

Veridical models

Veridical models of aliveness, movement, naturalness, and animacy were created based on the ‘expected’ classification for each item by the design of the stimulus set (e.g., vehicles were non-living, moving, artificial, and inanimate; plants were living, still, artificial, and inanimate).

Statistical inference

For statistical inference with EEG data we used Bayes Factors, run through the R package BayesFactor (Morey et al., 2018). For all analyses, we used a two-sided medium width prior and a default scale of 0.707, as these serve as minimally informative defaults (Rouder et al., 2009; Teichmann et al., 2022). Bayes Factors can be interpreted similarly to an odds ratio; a Bayes Factor

of 3 suggests that there is 3 times more evidence for the alternate hypothesis than the null hypothesis (Rouder et al., 2009). For correlations with time-series EEG data, analyses were guided by recommendations in Teichmann et al. (2022). A Bayesian t-test was conducted at each time point, indicating the likelihood that the correlations at that point were significantly different to zero.

For behavioural work, we ran analyses within both frequentist and Bayesian frameworks to ensure our conclusions were independent of the analysis method chosen, and to increase interpretability. To compare movement ratings across categories, we used statistics similar to Goldberg and Thompson-Schill (2009) who created the structure of the stimulus set. Living things (animals and plants) were compared using t-tests and the Bayesian equivalent of a t-test implemented by the `ttest` function in the `BayesFactor` package. For the non-living things, we used a 2-way ANOVA (and the Bayesian equivalent) to investigate movement and naturalness. Under a Bayesian framework, we can run a series of linear models and look at the difference between a combined model (e.g., movement + naturalness) and the model with the single factor (e.g., naturalness) to look at the unique effect of any given factor, similar to a main effect in an ANOVA (Rouder et al., 2012). To compare between categories directly, a Tukey Honestly Significant Difference (HSD) test, controlling for the family-wise error rate at .05, and a series of Bayesian t-tests were used. Only differences that were significant using both methods are interpreted.

Behavioural similarity (triplet) ratings

Participants

Participants in the ‘odd-one-out’ task were 430 undergraduates (134 male, 280 female, 7 non-binary and 9 who preferred not to disclose their gender), recruited from the University of Sydney, Australia, in exchange for course credit. Their mean age was 20.56 (range 17-48), and the median age was 20. Participants gave informed consent before participating, and protocols were approved by the University of Sydney ethics committee.

Procedure and materials

The experiment was conducted online through a web browser on the participants' personal computer, hosted on Pavlovia (Peirce et al., 2019, <https://www.pavlovia.org/>). It was coded using plugins from the JSPsych library (de Leeuw, 2015), and a minor modification of one of the JSPsych plugins. After giving consent via an online form, participants were told that they would see three images on the screen and their task was to click the “odd one out, or the image that is most different compared to the other two” ([Figure 4.1C](#)). Each participant was presented with 500 sets of randomly selected triplets. The triplets were constructed based on all combinations of the 40 categories (e.g., cat-dog-lock, dog-lock-wave, etc.), using a random image from within each selected category.

Each set of triplets was displayed in a triangle formation with two rows (one row with one image, and one row with two images). For each presentation, the display formation was randomly chosen so that sometimes the single image was on the top row, and sometimes the single image was on the bottom row ([Figure 4.1C](#)). Participants were encouraged to respond rapidly, and to go with their intuition. The task took participants approximately half an hour. On average, each triplet was rated by 21 participants (range 8-41).

Analysis

Triplet matrix. To form a representational dissimilarity matrix, the triplet data was used to calculate how similar each pair of images was. If an object was chosen as the odd one out, we can infer that the two remaining images are more similar than either of the two remaining images are to the odd one out. Hence, to calculate how similar two objects were, we calculated the ratio between the number of times a given pair of objects were not chosen as the odd one out (i.e., they were more similar) to the number of times they appeared together. This can be interpreted as the proportion of times that a given pair of stimuli were picked as the most similar pair in a set of three. A lower number indicates that the images were left together more often and are thus more dissimilar, and a higher number indicates that the images were not the odd one out and are thus more similar. This

ratio was calculated for every pair of objects (e.g., cat-dog, cat-lock, cat-wave...), pooled across all participants. These ratios were then compiled into a Representational Dissimilarity Matrix (RDM) by subtracting each ratio (measure of similarity) from one.

Multi-dimensional scaling. Multi-dimensional scaling (MDS) was used to visualise the similarity between different objects, and between different dimensions. As the interpretation of MDS is qualitative, we used multiple methods of visualising the data to ensure interpretation was not unique to the chosen parameters. We ran both traditional MDS and t-SNE, both initialised at two different random seeds (which were chosen pre-analysis as 1234 and 5678).

Comments. After completing all triplets, each participant was asked “Was there any strategy that you were using to make decisions?” and provided a blank text box to type an answer. To investigate commonalities across participants, a Word Cloud was created to represent the most common words using the WordCloud library in python. A full list of observations is also included in the OSF repository.

Partial correlations. To investigate what factors individuals use to judge ‘similarity’, we calculated partial Spearman rank correlations with each of the models used in Shatek et al. (2022; [Chapter 3](#)), using all other models as covariates. As some models are highly correlated (e.g., there are three models of aliveness: from the online ratings, veridical model, and EEG categorisation task), we removed the other models of the same concept when calculating the partial correlation for aliveness, movement, and naturalness. For example, the partial correlation for veridical aliveness was calculated using all variables shown in [Figure 4.2A](#) as covariates, except other models of aliveness (online aliveness and EEG aliveness). Bayes Factors larger than 10 were taken as evidence for the alternate hypothesis that correlations were significantly different to zero.

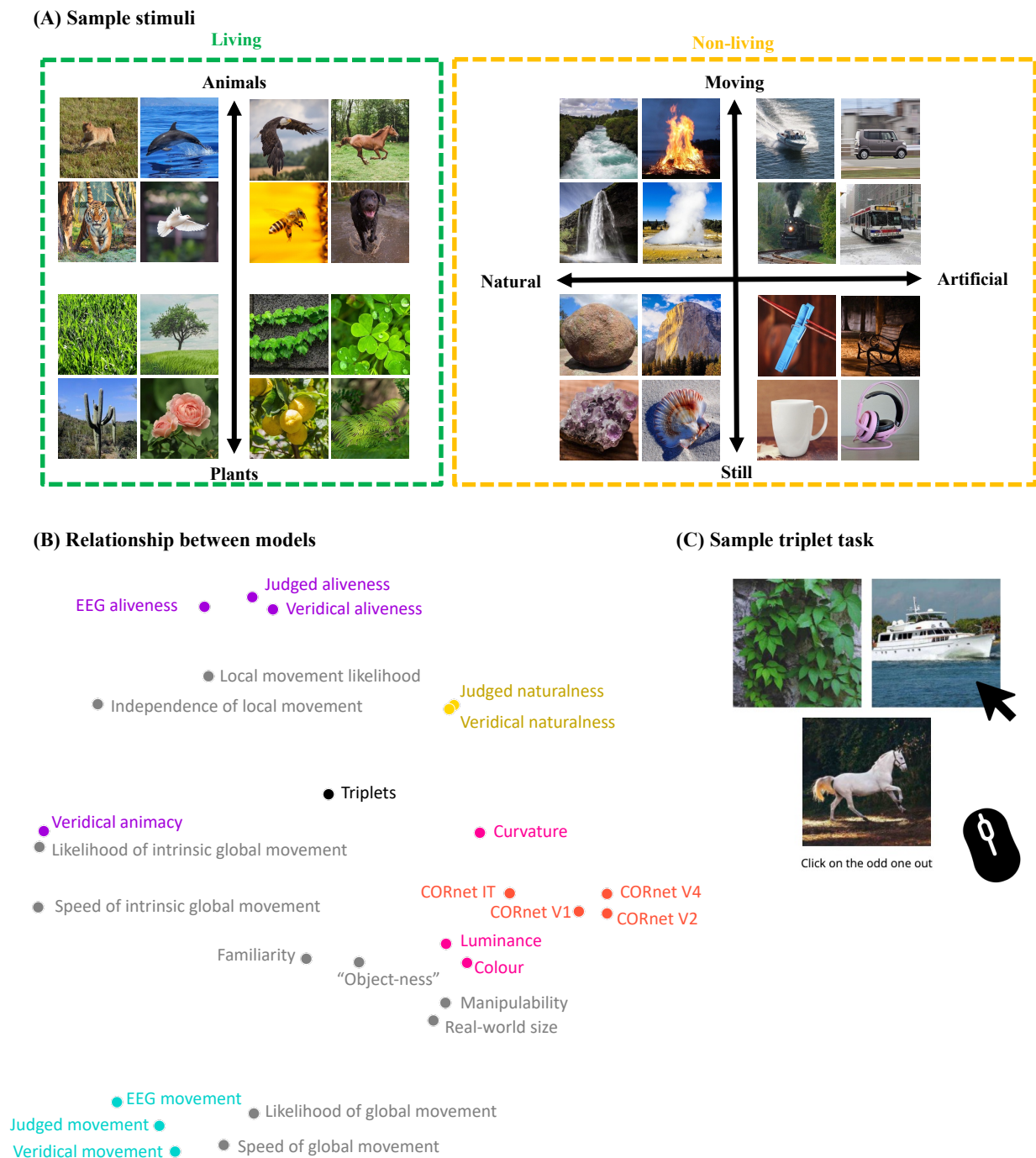


Figure 4.1

(A) Stimuli were taken from Shatek et al. (2022; [Chapter 3](#)), covering three dimensions: living/ non-living, moving/ still, and natural/ artificial. (B) Multi-dimensional scaling of all models. (C) To make a model of behavioural similarity, participants chose the ‘odd one out’.

Questionnaire

Participants

Participants in the questionnaire study were 48 undergraduate psychology students (34 women, 14 men), who participated in exchange for course credits. The mean age was 20.3 years (range 17-34). Participants gave informed consent, and protocols were approved by the University of Sydney ethics committee. All participants reported that English was the first language they learned to read and speak. Of the 48 participants, 19 (40%) had taken high school biology and 33 (69%) had taken at least one university biology course.

Procedure

As in the previous study, the experiment was conducted online via Pavlovia (Peirce et al., 2019, <https://www.pavlovia.org/>) using modifications of JSPsych plugins (de Leeuw, 2015). Methods were similar to those in Chapter 2. Participants were first taken through an extensive set of instructions describing the difference between global and local movement, and what it meant for movement to be independent. The instructions explained the difference between local and global movement with an example of a dog wagging its tail or changing location on the screen. The distinction between global movement and *intrinsic* global movement was also explained with examples of external intervention: gifts of leaves blowing off a tree, and two men throwing leaves in the air. Participants were explicitly told to consider gravity and other forces as a source of external intervention. Participants could move through the instructions at their own pace. On average, participants spent 1 minute and 42 seconds reading the instructions, but times were variable (range 15 seconds – 8 minutes). The full instructions can be found in the deactivated version of the experiment in the OSF repository.

Each participant answered 11 questions ([Table 4.1](#)) for 40 images, one random image from each of the 40 object categories. Each screen displayed all 11 questions with the image presented at the top, and participants needed to move the slider on every question from its initial starting location

at 50 to advance to the next image. After completing all 40 images, participants were asked whether they had noticed any categories of objects from the words they rated. Two attention check questions were also included, at around 1/3 and 2/3 through the 40 images, where participants were shown a scene with these instructions superimposed: ‘This is a test of whether you are paying attention. Please move the slider to the left for all the questions and ignore the content of this image.’ We planned to remove any participant with an average score of more than 25 on these trials, but no participants failed.

Table 4.1

Questions on movement characteristics

		Question	Scale labels
Naming	0	Type a single word that best names this object	Open text box
Familiarity	1	How familiar are you with this thing?	0: Very UNfamiliar 100: Very familiar
Global movement	2a	How likely is this thing to change position in daily life (including influence of external forces e.g., gravity, wind, a human)?	0: Does not change position 100: Highly likely to change position
	2b	How much does this thing typically change position in one minute, on average (including influence of external forces e.g., gravity, wind, a human)?	0: <1mm 25: 1cm 50: 1m 75: 1km 100: > 100km
Intrinsic global movement	3a	How likely is this thing to change position in daily life, WITHOUT external intervention (i.e., by itself)?	0: Does not change position by itself 100: Highly likely to change position by itself
	3b	How much does this thing typically change position in one minute, on average, WITHOUT external intervention (i.e., by itself)?	0: <1mm 25: 1cm 50: 1m 75: 1km 100: > 100km
Local movement	4a	Without changing position, how likely is this thing to move in daily life? (e.g., grow, change shape, have moving parts)	0: Does NOT move without changing position 100: Definitely moves without changing position

	4b	Without changing position, how much external intervention is required for this object to move? (e.g., grow, change shape, have moving parts)	0: Always requires external intervention to move 100: Can always move without external intervention
Manipulability	5	How easy is it for you to pick up and move this thing?	0: Immobile or difficult to move 100: Easily moveable
Scene-ness	6	Is the image representing something that is more like an object, or more like a scene?	0: More like an object 100: More like a scene
Real-world size	7	How big is this thing in real life?	0: <1cm 33: 1m 66: 100m 100: >1km

Analysis

Making RDMs and EEG correlations. To examine the relationship between each of the movement questions and neural activity, we created Representational Dissimilarity Matrices (RDMs) for each question. For each question, ratings for each of the 40 objects were collated, and the Euclidean distance between each pairwise combination of objects was computed. With these RDMs, we calculated the spearman rank correlation coefficient (ρ) between each question model and neural RDMs from Shatek et al. (2022; [Chapter 3](#)). To determine if the correlations were significantly different to zero, a Bayesian t-test was run at each time point. Bayes Factors larger than 10 were considered strong evidence for the alternate hypothesis that the correlation was significantly different from zero.

Word cloud. To qualitatively explore what categories of objects participants identified in the stimulus set, we used the WordCloud package for python (Mueller, 2022) to compile a word cloud based on the text participants typed into a box at the end of the experiment, asking them whether they recognised any categories of objects. Larger words reflect more frequent use.

Decoding object characteristics from movement characteristics. To investigate how important each of these movement characteristics is for object categorisation, we used the mean ratings for each image as features to train a linear discriminant classifier to object identity and

category identity. The classifier was trained on 80% of the data and tested on the remaining 20%. This process was repeated 100 times and the mean accuracy for each characteristic was obtained by averaging across repeats. To investigate whether categorisation accuracy was significantly higher than chance, we compared all 100 iterations to chance using a Bayesian t-test.

Results

To examine what dimensions individuals use to judge similarity, we used three different methods. Firstly, relationships between items and categories in 2-dimensional space were visualised using dimensionality reduction strategies t-SNE and multi-dimensional scaling. Secondly, participants' descriptions of their strategies in completing the odd-one-out task were examined. Thirdly, partial correlations were used to explore the unique variance in the similarity ratings explained by each model.

Participants mostly use naturalness to judge similarity

Partial Spearman rank correlations with each of the models used in Shatek et al. (2022; [Chapter 3](#)) revealed which factors best explained similarity judgements. Variation in the triplet behavioural model was best explained by the veridical and online ratings of naturalness with partial correlations of 0.73 and 0.59 respectively ([Figure 4.2A](#)). All three models of movement explained a significant portion of the variation in the behavioural similarity model, from the online study ($\rho = 0.41$), from the EEG classifications ($\rho = 0.40$) and from the veridical model ($\rho = 0.32$). Though still significant, models of aliveness and animacy represented a smaller portion of the variance in the behavioural similarity model. Out of all the CORnet layers, only the model of IT explained a significant portion of variance in the triplet task, suggesting the participants rely more on conceptual or abstract features than lower-level visual features like colour.

Multi-dimensional scaling of behavioural similarity reveals clear animacy and naturalness effects

MDS and t-SNE were used to visualise relationships between categories based on similarity ratings ([Figure 4.2C](#)). In both methods of visualisation, there is a clear separation between natural and artificial, suggesting that naturalness is the main dimension on which participants make similarity judgements, reaffirming model rankings above. In both plots, animals (red) form a distinct cluster separate to plants, which are more closely grouped to the other natural things. Notably, despite the correlation between the movement model and the behavioural data, there is not a visible distinction between the moving and non-moving things in the t-SNE or MDS for the natural things (green), though there is some distinction in the MDS for the artificial things (blue).

Comments suggest participants were mostly relying on animacy and colour

As another way to investigate what elements of the image set were useful for similarity, participants commented on whether they were using a particular strategy to select the odd one out. The most common words used in these comments are shown in [Figure 4.2B](#). Many participants reported differentiating animals from other categories, particularly from plants. Several participants also identified that they distinguished between man-made and natural items. Other themes included mentions of colour, and relatedness (things that are typically found together in the same location). A full list of participant comments on strategy can be found in the OSF repository. The ranking of models by correlation ([Figure 4.2A](#)) is also reflected in participants' descriptions of their own strategies. When asked what kinds of strategies they used, participants frequently provided a list of several characteristics, including naturalness, and often movement (e.g., *"First see if it's alive, then see if it's natural or man-made, then see if it's animal or plant, and see if it's still or moving."*) Participants also often mentioned movement, (e.g., *"... compare birds and helicopters as they can fly as compared to a peg"*), though this was frequently mentioned after naturalness, and often used

specifically to differentiate between animals (e.g., “*I divide them as animals, land animals, animals that swim or fly*”).

Behavioural similarity is a good correlate of neural activity

The temporal dynamics of the correlation between brain and behavioural similarity provided insight into how behavioural similarity ratings relate to patterns of neural similarity. As expected, the behavioural model is significantly correlated with brain activity in both experiments and in both tasks ([Figure 4.2D-G](#)). For the passive viewing, there are two peaks at around 210ms and 320ms, which could reflect a weighted combination of the other models, some of which have similar time courses.

Movement from natural kinds is perceived to be agentic

To compare ratings of movement across different categories, we tested all combinations of categories for each question. A subset of comparisons is reported in the text for brevity, as many of the results are similar across questions (e.g., showing that moving things move more frequently quickly than still things). All statistics can be found in the supplementary information ([Supplementary Table 4.1](#) and [4.2](#)). Significant comparisons, where both the Bayes Factors and frequentist statistics indicate very strong evidence for the alternate hypothesis ($BF > 30$) and significant p-values after correction for multiple comparison, are also shown visually in [Supplementary Figure 4.4](#).

We investigated movement along several dimensions, including overall changing position (global movement), independently changing position (intrinsic global movement), and movement that doesn't involve changing position (local movement) ([Figure 4.3](#)). First, we looked at any kind of overall movement that involves changing position. We found that animals were more likely to change position, and change position more quickly than plants, but were equally likely to move as the non-living moving things (moving artefacts and moving natural things).

When only considering movement that was possible without external intervention, animals were more likely to change position, and do so more quickly compared to all other categories. Curiously, moving natural things were also more likely to change position independently, and do so more quickly than all other categories except animals.

We also investigated movement that does not involve changing position, such as growing, changing shape, or having moving parts. Animals and plants were similarly likely to move locally, and moving natural things were more likely than all other non-living things to have local movement. As in the previous questions about intrinsic global movement, the local movement in moving natural things was also perceived to be agentive, on a similar level to plants.

Questions about how easy an object was to pick up and move (manipulate) revealed that non-living moving items (both natural and artificial) were harder to manipulate, and that these same items also tended to have a larger real-world size. The moving natural things were also perceived to be more like ‘scenes’ than objects, compared to all other categories.

In sum, we find that moving natural things are perceived to move independently, both globally and locally, and are less object-like. Moving things also tend to be larger in real life, and are less manipulable than non-moving things, plants, and animals.

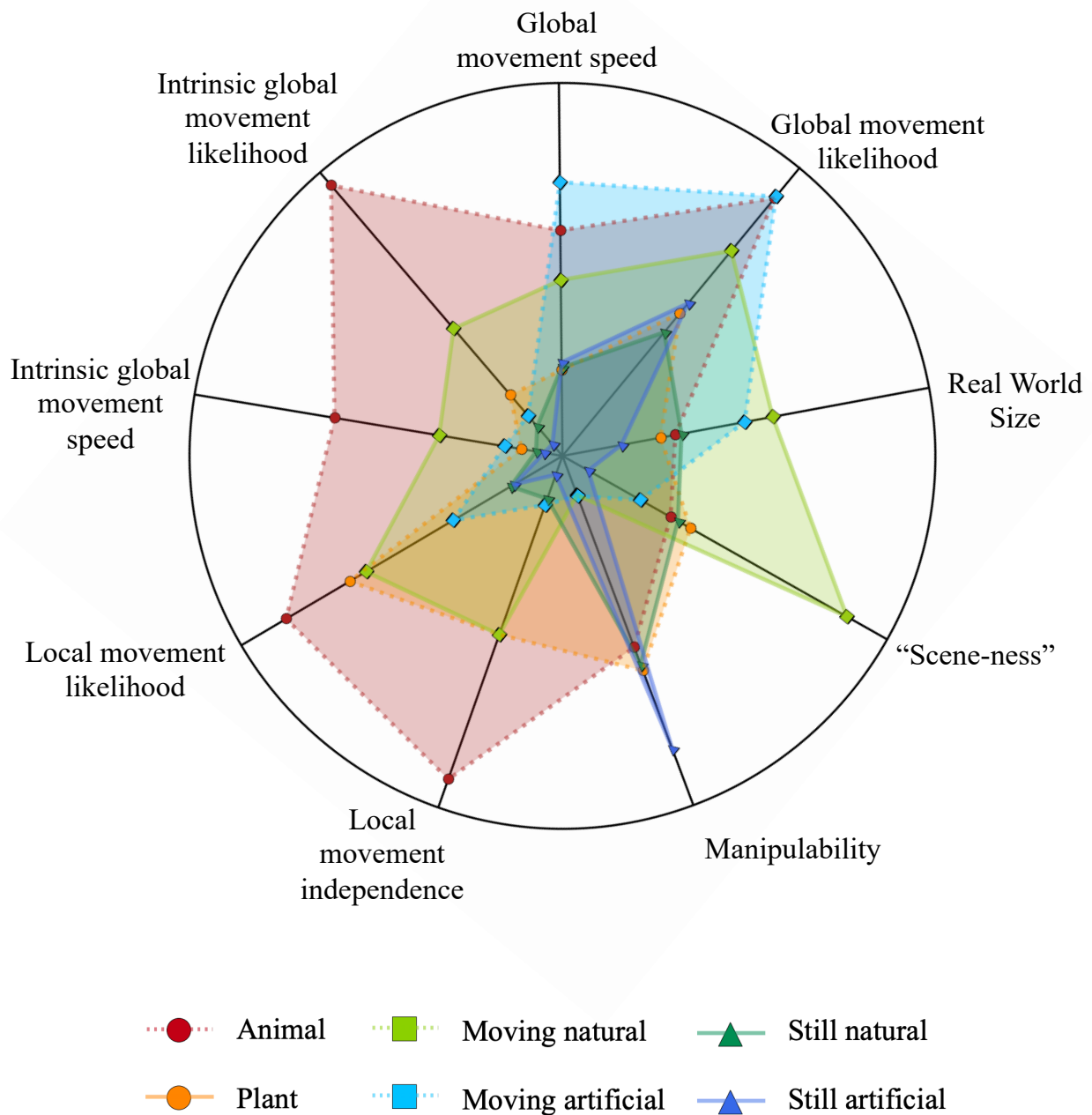


Figure 4.3

Mean rating on each movement characteristic for each category. Dashed lines indicate items that can move, solid lines show items that are still. Natural items are shown in green and artificial in blue, animals in red and plants in orange.

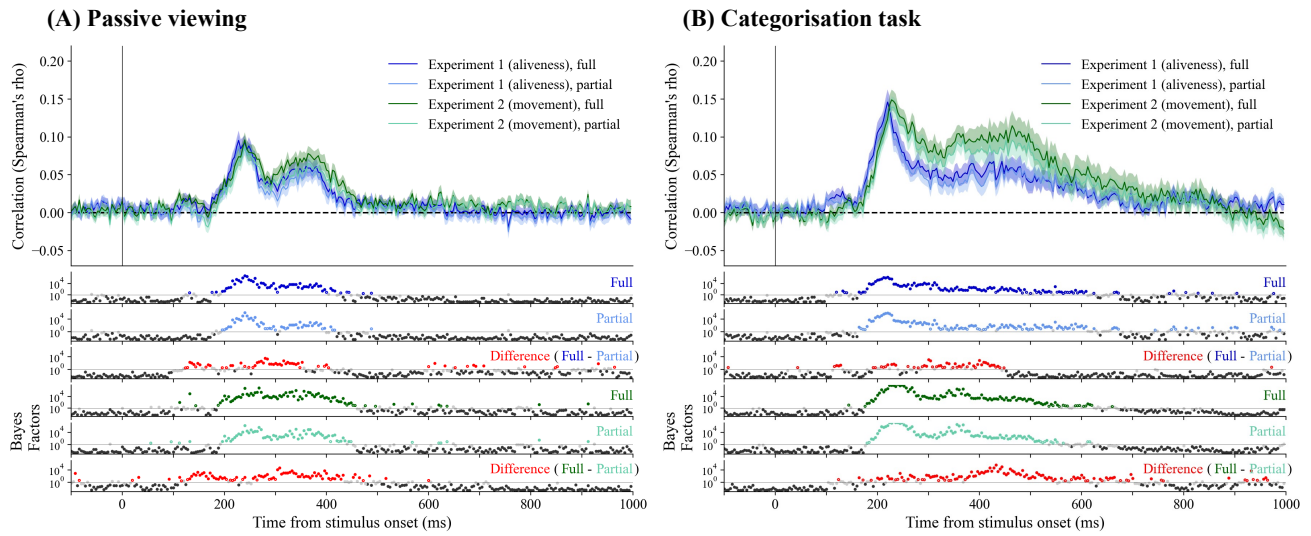


Figure 4.4

Full and partial correlations with the movement models from Shatek et al. (2022) for the passive viewing (A) and categorisation task (B). Full correlations are shown with darker lines for both experiments, with Experiment 1 in blue and Experiment 2 in green. Partial correlations were calculated including colour, luminance, rectilinearity, aliveness, naturalness, real-world size and 'scene-ness' as covariates. Shaded regions show the standard error (N=24 in each experiment). Time points with significant differences between the partial and full correlations are shown in red. Bayes Factors with evidence for the null hypothesis that the correlation is at chance ($BF < 1/3$) are black, BFs indicating a lack of evidence are in grey ($1/3 < BF < 3$), unfilled coloured dots indicate some evidence for correlations different from zero ($3 < BF < 10$), and filled coloured dots indicate strong evidence for significant correlations ($BF < 10$).

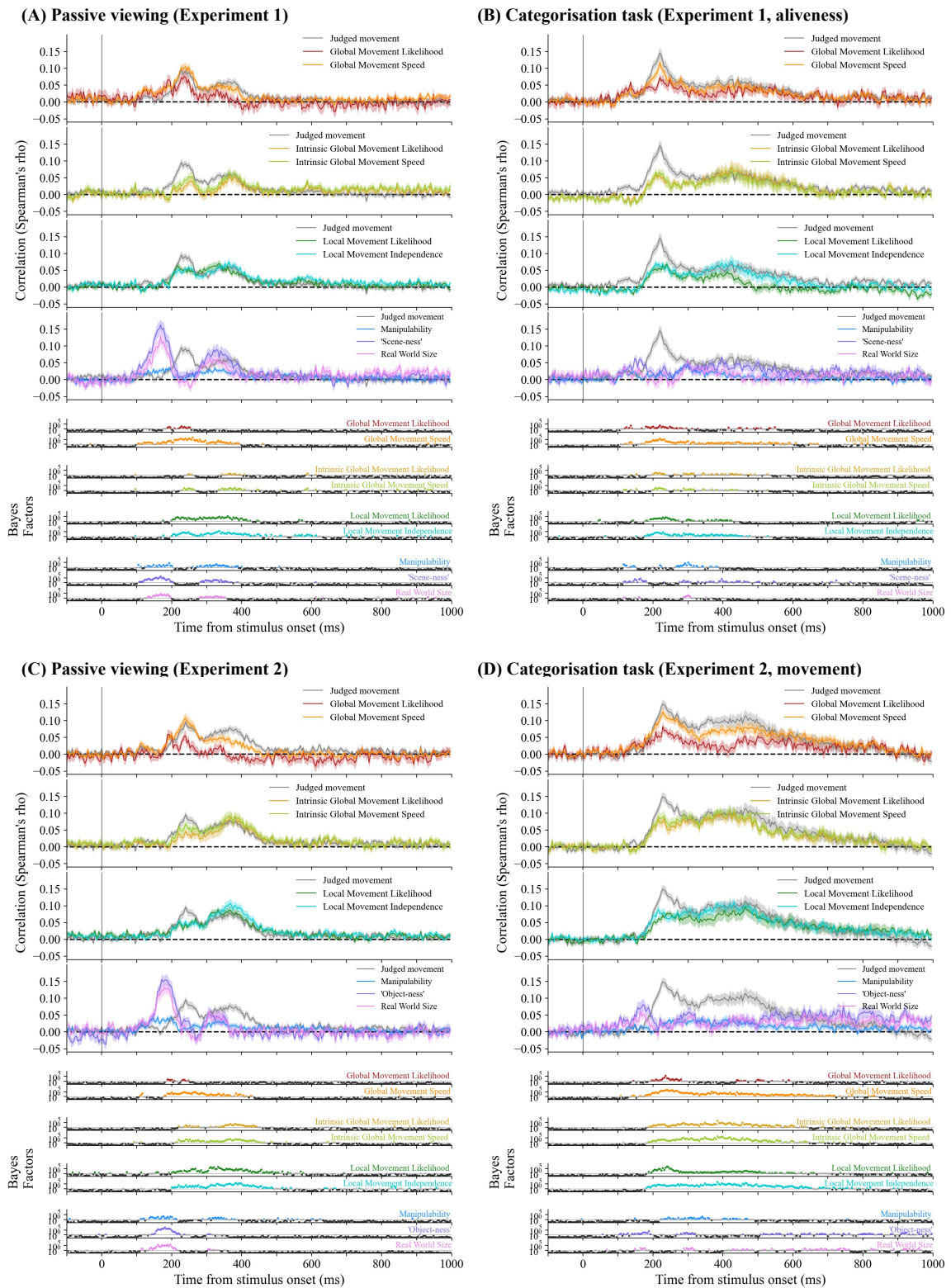


Figure 4.5

Correlations between each movement characteristic and brain activity for both tasks and both experiments in Shatek et al. (2022; [Chapter 3](#)), passive viewing (A, C) and the categorisation task (B, D). Grey lines are identical within the four plots of each panel, showing the correlation with the movement model used in Shatek et al. (2022; [Chapter 3](#)). Shaded regions show the standard error. Bayes Factors with evidence for the null ($BF < 1/3$) are black, BFs indicating a lack of evidence are in grey ($1/3 < BF < 3$), unfilled coloured circles indicate some evidence for correlations different from zero ($3 < BF < 10$), and filled coloured circles indicate strong evidence for significant correlations ($BF < 10$).

Real-world size doesn't diminish the movement correlations when included as a covariate in partial correlations

Previous findings suggest that real-world size is an important organising principle in the ventral visual stream (Blumenthal et al., 2018; Coutanche & Koch, 2018; Coutanche & Thompson-Schill, 2019; Huang et al., 2022; Khaligh-Razavi et al., 2018; Konkle & Oliva, 2010, 2011, 2012; Magri et al., 2021), and thus the finding that moving things tend to be larger (have a bigger real-world size) could explain movement effects in neural data. To investigate whether movement representations in Shatek et al. (2022; [Chapter 3](#)) can be attributed to differences in real-world size, we ran a partial correlation between our movement model (based on binary classifications of 'moves' or 'doesn't move') and neural data, with real-world size included as a covariate. If the brain is only representing real-world size and not movement, the partial correlation with real-world size included as a covariate should be substantially lower. However, this is not the case ([Figure 4.4](#)). Though there are differences between the full and the partial correlation (red in [Figure 4.4](#)), this reduction could be attributed to any of the other covariates, including visual models of colour, luminance, and rectilinearity, in addition to naturalness, aliveness, real-world size and 'scene-ness'. The time-course of the partial correlation remains similar to the full correlation, suggesting that while these factors may explain some variance in the movement model, the movement factor still remains a significant correlate of neural activity.

The double peak structure of movement correlations in Shatek et al. (2022) may reflect early speed judgements and later appraisals of agency

To investigate how these different aspects of movement are represented in the brain, we first looked at the correlations between each of the models of movement from the questionnaire and neural activity ([Figure 4.5](#)). For global movement, speed of movement seems to be a better model of neural activity than overall likelihood of movement, particularly for the passive viewing where likelihood of global movement shows only brief periods of significance around 200ms. In contrast,

when only considering intrinsic movement, likelihood and speed show similar temporal dynamics, and seem to map closely to the second peak in the movement model from Shatek et al. (2022; [Chapter 3](#)) based on binary classification of movement. Similarly, both the likelihood and independence of local movement seem to align with the second peak of the overall movement model in both the passive viewing and classification task. Though the peak in the classification task is flatter and longer, similar trends seem to be emerging with later differences accounted for by models that capture agency. Overall, these correlations suggest that the double peak structure of the correlation between the judged movement model and the neural activity may be composed of elements of global movement speed at the first peak, and some measure of local or intrinsic movement in the second peak. The brain may be processing objects initially by how quickly they can move, and then later appraising whether this movement is agentic and unpredictable.

Reaffirming earlier results suggesting that our movement signal does not purely reflect real-world size or ‘scene-ness’, both these models are correlated with neural activity early in the time course (around 150 – 200ms), but do not capture as much of the later neural activity. There is a second peak of the real-world size model at around 300ms, but the timing of this peak does not clearly align with the overall model or any of the other movement models and is therefore harder to interpret. Curiously, the real-world size and ‘scene-ness’ models have a significant early correlation (120-220ms) with neural activity in the passive viewing, but this is substantially reduced in the classification task. Manipulability also differs between the passive viewing and movement classification task, with a flat early peak at a similar time to ‘scene-ness’ and real-world size in the passive viewing and a short period from 300-350ms, but for the classification task, there is no early peak and only small period of spotty significance between 250 and 300ms.

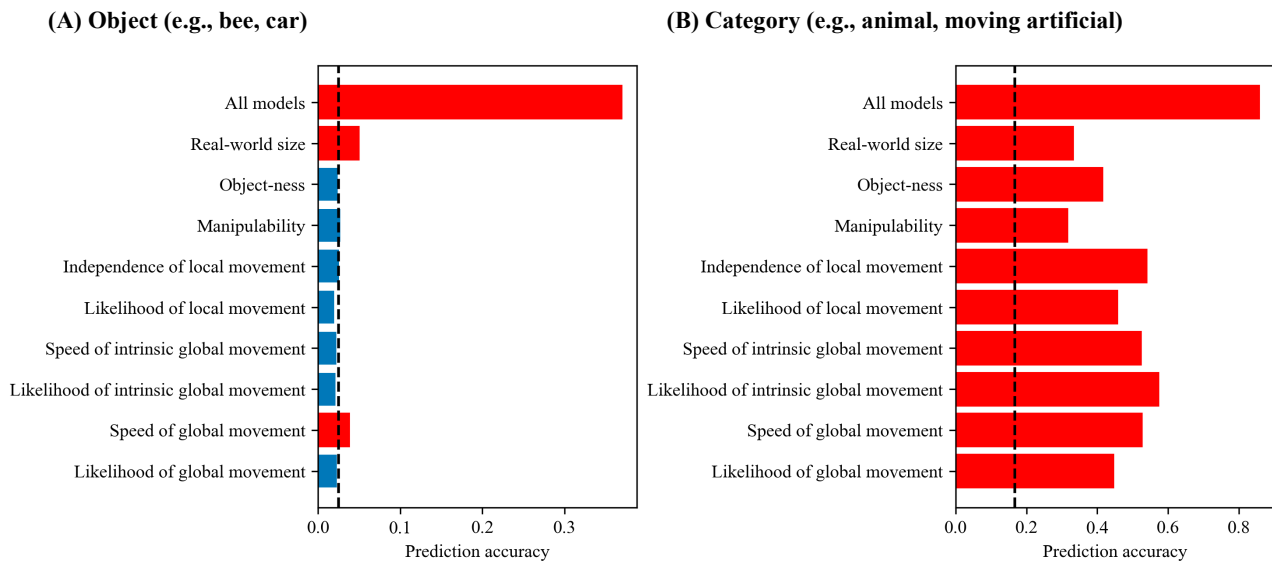


Figure 4.6

Predicting the object and category based solely on ratings of movement characteristics. A classifier was trained using the ratings for each object (A) or category (B). Chance accuracy is marked as a vertical dotted line, and accuracies that are significantly above chance ($BFs > 30$) are shown in red. “All models” refers to a classifier trained using all movement characteristic as features.

Movement characteristics can predict object identity

To look at how informative these movement characteristics were for classification, we trained a linear discriminant classifier on the ratings for each movement characteristic to see how well it could predict the category and object identity for each image ([Figure 4.6](#)). A higher prediction accuracy indicates there is sufficient information in those ratings to distinguish between objects or categories. We found there was sufficient information in each individual movement characteristic to distinguish the category (animal/ plant/ moving natural etc.) of an object. At the object level (e.g., cat, boat, tree), only real-world size and global movement speed achieved above-chance classification. However, when all the movement features were included together, the prediction accuracy increased dramatically from 5% to around 35% (chance guessing would be 2.5%). This suggests that though a few of the features are sufficient to predict category identity, the constellation of features describing an object’s movement are related to its identity. As the data violated the

assumption of normality in LDA, we reran the analyses with a logistic regression, and found virtually identical results, though manipulability was also a significant predictor of object identity.

Discussion

This study explored how movement influences categorisation behaviour, and which properties of movement are most important in neural processing and behaviour. Results from an unconstrained triplet ‘odd-one-out’ task showed that movement is used in behavioural classification, in addition to naturalness. Ratings of different characteristics of movement, such as speed and likelihood of global and local movement, revealed that objects which violate the typical association between movement and aliveness, moving natural things (which move but are not alive) and plants (which are alive but do not obviously change position), stand out on several movement dimensions. For example, people intuitively believe that moving natural things move by themselves. Correlations between movement characteristics and brain activity suggest that neural processing of movement capacity may involve an initial processing of how fast an object typically moves, and then later processing of agency. While these findings are largely exploratory and are by no means an exhaustive questionnaire on movement characteristics, they highlight an important role for movement in object concepts and paths for future study.

Data from the triplet ‘odd-one-out’ task revealed two key findings; that movement is an important dimension in behavioural similarity judgements, and that behavioural similarity is a good correlate of patterns of neural similarity. Despite having no prior knowledge of the structure of the stimulus set, participants were able to identify the three main dimensions (movement, aliveness, and naturalness; [Figure 4.1](#)) and use them to make similarity judgements. We can see these dimensions in the correlations between the behavioural similarity model and conceptual models, and participants’ descriptions of their own strategies. This provides further evidence for the utility of the ‘odd-one-out’ triplet task in elucidating latent dimensions of any given stimulus set (Hebart et al., 2020).

Naturalness is the primary feature participants are using to judge similarity, which is reflected in participants' strategy descriptions, partial correlations, and 2D visualisation of the behavioural similarity model ([Figure 4.2A, 4.2B, 4.2C](#)). This may be because it is an important attribute for classification, as in other naturalistic image sets (King et al., 2019), but also may be because naturalness is not balanced across the dataset and is therefore a more noticeable feature to distinguish objects by. After naturalness, movement explained the most variance in behavioural similarity judgements. Movement was also mentioned in several strategy descriptions by participants, particularly in the context of animals and vehicles. However, it was not an obvious dimension in the multi-dimensional scaling in [Figure 4.2C](#). While there is a clear divide between natural and non-natural stimuli, they appear to be primarily clustered by category with no differentiation between moving and non-moving. One potential explanation for the absence of movement in the MDS is that object category is more important than any of the conceptual models in similarity judgements, and that features like movement or naturalness contribute to defining these differences between classes.

In support of the hypothesis that capacity for movement is important for object categorisation because it can help define object categories, we find that together the movement characteristics (including real-world size, manipulability and 'scene-ness') are sufficient to differentiate individual objects (bee, car, tree) substantially better than chance. The studies in Chapter 2 used similar questions and stimulus structure, but using different exemplars, and words rather than images. The results across both are remarkably similar, suggesting that these attributes are common to the category itself rather than unique to a particular set of objects. As previous work has shown that movement characteristics and object identity interact, particularly for animate forms (Lu et al., 2015), our findings suggest that information about the quality of movement may be stored to help identify an object. Together, the robustness of ratings across modalities and the predictability of object identity from movement characteristics suggest that quality of movement in an object is an integral cue to its identity.

The behavioural similarity model was significantly correlated with patterns of brain activity from around 100ms after stimulus onset to 500ms in the categorisation task and 600ms in the passive viewing task. As in previous studies using open-ended methods of gathering similarity ratings (such as the ‘odd-one-out’ task here (Grootswagers et al., 2023), multi-arrangement (Bankson et al., 2018; Jozwik et al., 2022), or explicit similarity judgements (Wardle et al., 2016)), behavioural similarity was a good correlate of brain activity from approximately 100ms after stimulus onset in both the RSVP passive viewing and categorisation task. As many of the conceptual models explain significant portions of the variance in the behavioural model, it is likely that the similarity model is a weighted combination of these features and thus a better model of neural activity. Though it seems unsurprising that behavioural judgements best reflect what is going on in the brain, this is not always the case and seems to depend on the instructions or task given to participants (Connolly et al., 2016; Jozwik et al., 2022).

Despite many participants mentioning using colour in their descriptions of their strategy ([Figure 4.2B](#)), models of lower-level visual characteristics did not explain a substantial proportion of unique variance. This suggests that participants’ triplet strategies are more conceptual, which is also reflected in the significant variance accounted for by the IT layer of CORnet but none of the lower CORnet layers. It is possible that these lower-level visual models are accounted for by another conceptual model. For example, the ‘colour’ variable may be captured by ‘naturalness’, as many of the plant/natural images are greener.

One particularly interesting finding from the ratings of movement quality was that participants rated moving natural things, such as waterfalls and fires, to have higher likelihood of independent global movement than other non-living moving things (e.g., vehicles) and plants. This finding replicates and explains earlier work suggesting the difficulty childhood understanding that moving natural things are not living persists into adulthood (Goldberg & Thompson-Schill, 2009; [Chapter 2](#)). Developmental researchers suggest that children find these moving natural things challenging because there is no clear intervening agent, making them appear to move on their own

(Gelman & Gottfried, 1996). Adults may also draw upon ‘intuitive physics’. The forces that cause movement in the moving natural things (e.g., gravity) are relatively constant in our environment and are non-observable, and thus we may have integrated them into our understanding of the object concepts themselves (Freyd, 1992; Hubbard, 1996). Even physics professors who are explicitly aware of Newtonian principles rely on intuitions in some tasks (Kozhevnikov & Hegarty, 2001).

After accounting for low-level visual models, real-world size, and ‘scene-ness’, correlations with the model of capacity for movement still explained significant variance in neural activity from 200ms for the passive viewing task and from 180ms for the categorisation task in both experiments. This reinforces the conclusions from Shatek et al. (2022; [Chapter 3](#)) that movement is automatically processed as part of object recognition, and suggests that what is being captured in the brain correlations is primarily a more abstract concept. Despite the moving natural things being perceived more as scenes than objects and having a larger real-world size ([Figure 4.3](#)), including ‘scene-ness’ and real-world size as covariates did not eliminate the correlations with movement models, suggesting movement remains important even beyond these factors. This is particularly notable because all categories were significantly different from each other in the real-world size ratings ([Supplementary Figure 4.4](#)), so in a way, this also suggests that the movement variable is not accounted for by categorical differences.

When comparing the temporal dynamics of the correlations between brain activity and each of the movement characteristics, the timing of different models appear temporally aligned with the two peaks of the judged movement model from Shatek et al. (2022; [Chapter 3](#)). The first peak of the movement correlation seems to reflect overall global movement speed (including external intervention; top graph in each panel of [Figure 4.5](#)), and the later peak seems to reflect a mixture of the other attributes, though primarily those associated with agency (which were more similar to the animacy model in [Figure 4.1B](#)). These findings suggest that we first process whether an object has any kind of movement, and then more characteristics of this movement. From an evolutionary perspective, these patterns are logical; the more quickly moving item poses an immediate threat. This

kind of processing might be action relevant, and therefore processed automatically by the brain.

Future work might consider these variables in a more realistic setting where action is possible, such as in a virtual or augmented reality setting.

It is possible that the early correlation with global movement speed could also reflect visual similarities in the objects that move more quickly (e.g., the background could be more blurred). There is at least some evidence that the blur associated with implied motion causes differential pupil dilation (Castellotti et al., 2021). Yet, correlations in Shatek et al. (2022; [Chapter 3](#)) with early layers of CORnet are from approximately 150-200ms, which suggests that potentially whatever aspect of ‘movement’ captured here from around 200-250ms may be more abstract. Future studies should explicitly explore whether the same effects are shown for stimuli that are not shown in motion.

Though real-world size model is closely related to ‘scene-ness’ and manipulability ([Supplementary Figure 4.2](#)), the temporal dynamics of correlations between each of these individual models and neural activity suggests they may be capturing something different to the other movement variables. In contrast to the movement models (global and local movement) which correlate with neural activity from 200ms after stimulus onset, real-world size, ‘scene-ness’ and manipulability have an early peak from 100ms (real-world size, ‘scene-ness’) or 120ms (manipulability) to 220ms ([Figure 4.5](#)). Curiously, the models of real-world size, ‘scene-ness’, and manipulability show a similar time course for both tasks, but the impact is more pronounced in the categorisation task. The relationship between these variables is complex; neural representations of man-made objects (compared to natural objects) seem to be more sensitive to variations in both motor-relevance (Magri et al., 2021) and real-world size (Konkle & Caramazza, 2013; though see also Coutanche & Thompson-Schill, 2019), and larger objects are less manipulable and serve more as landmarks. Recent work has shown that perceptions of real-world depth (size in a scene) are separable from perceptions of real-world size, with real-world depth being processed first, then real-world size with a later peak closer to 200ms (Lu & Golomb, 2023). These findings suggest that our model of real-world size is picking up on some visual features associated with a larger size, such as

the amount of space the object takes up in the image. Future work may consider using an approach similar to Jozwik et al. (2022) to create a stimulus set that maximally differentiates these variables, so their effects can be considered as independently as possible.

In sum, we have shown that movement is relevant for object categorisation in both the brain and behaviour. Our findings demonstrate that ratings of movement properties within broad categories are robust across exemplars and modalities. Movement is also important for judgements of similarity, and movement characteristics alone can predict object identity, suggesting that movement is an important part of our conceptual understanding of objects. Building on previous findings showing that movement may be an organisational principle in the brain (Shatek et al., 2022; [Chapter 3](#)), we show that this movement processing may be attributed to an initial processing of how fast that object typically moves (regardless of whether this is agentive movement), and then a later more extended processing of something more closely associated with agency.

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Supplementary Materials

Supplementary Table 4.1

Summary of ANOVAs and t-tests for each movement characteristic

Question	Animals vs plants	ANOVA naturalness	ANOVA movement	ANOVA interaction
Familiarity	$t(48) = -0.33$, $p = 0.745768$, $BF_{10} = 1.6754e-04$	$F(1,188) = 22.57$, $p < .00001$, $BF_{10} = 2.0810e+11$	$F(1,188) = 4.50$, $p = 0.03516$, $BF_{10} = 9.3964e+01$	$F(1,188) = 1.00$, $p = 0.31901$, $BF_{10} = 1.9005e+00$
Likelihood of global movement	$t(48) = 8.64$, $p < .00001$, $BF_{10} = 5.5309e+08$	$F(1,188) = 30.42$, $p < .00001$, $BF_{10} = 1.3334e+06$	$F(1,188) = 157.80$, $p < .00001$, $BF_{10} = 3.2764e+26$	$F(1,188) = 3.84$, $p = 0.051432$, $BF_{10} = 3.8729e+00$
Speed of global movement	$t(48) = 17.35$, $p < .00001$, $BF_{10} = 1.4906e+19$	$F(1,188) = 64.77$, $p < .00001$, $BF_{10} = 4.3095e+09$	$F(1,188) = 464.83$, $p < .00001$, $BF_{10} = 1.5947e+45$	$F(1,188) = 58.86$, $p < .00001$, $BF_{10} = 5.2284e+12$
Likelihood of intrinsic global movement	$t(48) = 20.70$, $p < .00001$, $BF_{10} = 1.9171e+22$	$F(1,188) = 49.96$, $p < .00001$, $BF_{10} = 4.8615e+09$	$F(1,188) = 64.95$, $p < .00001$, $BF_{10} = 2.2189e+12$	$F(1,188) = 20.51$, $p = 1.1e-05$, $BF_{10} = 8.4001e+04$
Speed of intrinsic global movement	$t(48) = 26.91$, $p < .00001$, $BF_{10} = 1.2798e+27$	$F(1,188) = 21.46$, $p < .00001$, $BF_{10} = 3.8291e+05$	$F(1,188) = 62.58$, $p < .00001$, $BF_{10} = 1.8416e+15$	$F(1,188) = 13.29$, $p = 0.000345$, $BF_{10} = 1.7336e+04$
Likelihood of local movement	$t(48) = 6.91$, $p < .00001$, $BF_{10} = 1.8844e+06$	$F(1,188) = 19.23$, $p = 1.9e-05$, $BF_{10} = 1.8709e+03$	$F(1,188) = 95.01$, $p < .00001$, $BF_{10} = 2.2728e+16$	$F(1,188) = 15.05$, $p = 0.000145$, $BF_{10} = 1.2088e+03$
Independence of local movement	$t(48) = 11.83$, $p < .00001$, $BF_{10} = 9.9973e+12$	$F(1,188) = 76.71$, $p < .00001$, $BF_{10} = 2.2725e+12$	$F(1,188) = 88.13$, $p < .00001$, $BF_{10} = 1.0034e+14$	$F(1,188) = 35.82$, $p < .00001$, $BF_{10} = 4.8701e+07$
Manipulability	$t(48) = -3.27$, $p = 0.00204$, $BF_{10} = 9.0062e+00$	$F(1,188) = 51.85$, $p < .00001$, $BF_{10} = 2.4338e+07$	$F(1,188) = 1120.98$, $p < .00001$, $BF_{10} = 5.2139e+71$	$F(1,188) = 49.32$, $p < .00001$, $BF_{10} = 2.0412e+09$
“Scene-ness”	$t(48) = -0.97$, $p = 0.335287$, $BF_{10} = 1.8157e-03$	$F(1,188) = 314.78$, $p < .00001$, $BF_{10} = 3.3117e+35$	$F(1,188) = 176.02$, $p < .00001$, $BF_{10} = 1.7596e+23$	$F(1,188) = 49.75$, $p < .00001$, $BF_{10} = 2.0065e+10$
Real-world size	$t(48) = 5.14$, $p < .00001$, $BF_{10} = 5.4867e+03$	$F(1,188) = 63.13$, $p < .00001$, $BF_{10} = 9.5657e+14$	$F(1,188) = 402.60$, $p < .00001$, $BF_{10} = 2.5474e+53$	$F(1,188) = 13.16$, $p = 0.000369$, $BF_{10} = 1.1292e+04$

Supplementary Table 4.2

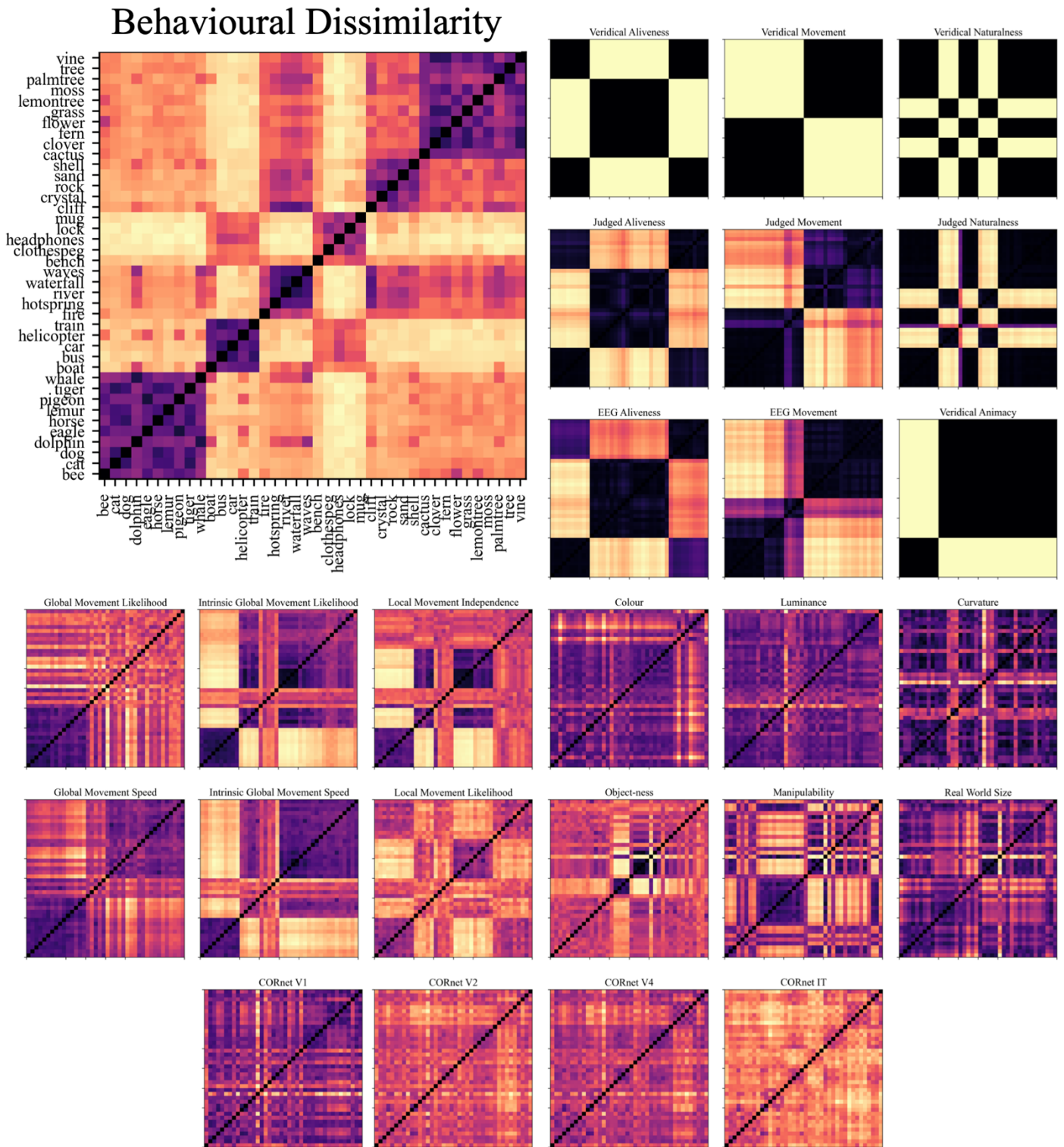
Statistics comparing movement characteristics across all categories

		Familiarity	Likelihood of global movement	Speed of global movement	Likelihood of intrinsic global movement	Speed of intrinsic global movement	Likelihood of local movement	Independence of local movement	Manipulability	“Scene-ness”	Real-world size
Animal	Plant	p = 1.0000, BF10 = 1.6754e-04	p<0.00001*, BF10 = 5.5309e+08**	p<0.00001*, BF10 = 1.4906e+19**	p<0.00001*, BF10 = 1.9171e+22**	p<0.00001*, BF10 = 1.2798e+27**	p = 0.0002**, BF10 = 1.8844e+06**	p<0.00001*, BF10 = 9.9973e+12**	p = 0.0198*, BF10 = 9.0062e+00	p = 0.9419, BF10 = 1.8157e-03	p = 0.0669, BF10 = 5.4867e+03**
Animal	Moving artificial	p = 0.5385, BF10 = 4.6508e+01**	p = 0.9994, BF10 = 3.3122e-04	p<0.00001*, BF10 = 2.3054e+08**	p<0.00001*, BF10 = 2.5245e+24**	p<0.00001*, BF10 = 4.9985e+17**	p<0.00001*, BF10 = 1.3159e+11**	p<0.00001*, BF10 = 5.2611e+22**	p<0.00001*, BF10 = 1.7189e+20**	p = 0.2634, BF10 = 1.2371e+00	p<0.00001*, BF10 = 1.3177e+21**
Animal	Moving natural	p = 0.9328, BF10 = 1.3799e-02	p = 0.0001**, BF10 = 5.2502e+02**	p<0.00001*, BF10 = 3.7997e+03**	p<0.00001*, BF10 = 1.5474e+12**	p<0.00001*, BF10 = 4.0809e+11**	p<0.00001*, BF10 = 9.2566e+06**	p<0.00001*, BF10 = 8.2708e+09**	p<0.00001*, BF10 = 4.3188e+19**	p<0.00001*, BF10 = 6.7799e+11**	p<0.00001*, BF10 = 1.4703e+18**
Animal	Still artificial	p = 0.0017*, BF10 = 2.3501e+07**	p<0.00001*, BF10 = 6.3021e+08**	p<0.00001*, BF10 = 7.3672e+19**	p<0.00001*, BF10 = 8.9533e+35**	p<0.00001*, BF10 = 5.3592e+32**	p<0.00001*, BF10 = 7.7969e+19**	p<0.00001*, BF10 = 7.1221e+29**	p<0.00001*, BF10 = 7.6566e+12**	p<0.00001*, BF10 = 2.1784e+04**	p<0.00001*, BF10 = 5.8163e+24**
Animal	Still natural	p = 1.0000, BF10 = 1.5675e-04	p<0.00001*, BF10 = 1.4142e+13**	p<0.00001*, BF10 = 8.7856e+17**	p<0.00001*, BF10 = 1.0600e+25**	p<0.00001*, BF10 = 1.8756e+29**	p<0.00001*, BF10 = 1.5183e+18**	p<0.00001*, BF10 = 7.5928e+24**	p = 0.5655, BF10 = 3.0398e-02	p = 0.9988, BF10 = 1.9407e-04	p = 0.9520, BF10 = 3.9789e-03
Plant	Moving artificial	p = 0.6484, BF10 = 6.4821e+00	p<0.00001*, BF10 = 1.5308e+10**	p<0.00001*, BF10 = 2.9566e+25**	p = 0.4099, BF10 = 2.4734e-01	p = 0.8429, BF10 = 1.9257e-02	p<0.00001*, BF10 = 4.6017e+04**	p<0.00001*, BF10 = 1.9616e+07**	p<0.00001*, BF10 = 6.7562e+20**	p = 0.0281*, BF10 = 1.2945e+01*	p<0.00001*, BF10 = 1.2972e+18**
Plant	Moving natural	p = 0.8740, BF10 = 1.7914e-02	p<0.00001*, BF10 = 6.4672e+05**	p<0.00001*, BF10 = 1.0783e+13**	p<0.00001*, BF10 = 4.5674e+05**	p<0.00001*, BF10 = 8.8430e+09**	p = 0.8743, BF10 = 1.3816e-02	p = 0.9906, BF10 = 2.6550e-04	p<0.00001*, BF10 = 6.9070e+21**	p<0.00001*, BF10 = 4.3470e+15**	p<0.00001*, BF10 = 9.5988e+19**

Plant	Still artificial	p = 0.0032*, BF10 = 7.2616e+06 **	p = 0.9502, BF10 = 2.5724e-03	p = 0.9362, BF10 = 7.9882e-03	p = 0.0001**, BF10 = 9.8287e+04 **	p = 0.2367, BF10 = 1.9073e+06 **	p<0.00001*, *, BF10 = 5.4379e+13 **	p<0.00001*, *, BF10 = 7.5204e+11 **	p<0.00001*, *, BF10 = 5.5180e+09 **	p<0.00001*, *, BF10 = 1.7125e+09 **	p<0.00001*, *, BF10 = 3.1705e+10 **
Plant	Still natural	p = 0.9995, BF10 = 7.9586e-04	p = 0.6815, BF10 = 2.4630e-01	p = 0.9844, BF10 = 7.9968e-03	p = 0.0928, BF10 = 3.7284e+01 **	p = 0.7126, BF10 = 1.3602e+02 **	p<0.00001*, *, BF10 = 1.1771e+13 **	p<0.00001*, *, BF10 = 3.1452e+08 **	p = 0.6419, BF10 = 2.2214e-01	p = 0.9952, BF10 = 1.1216e-03	p = 0.0044*, BF10 = 1.2410e+04 **
Moving artificial	Moving natural	p = 0.0907, BF10 = 9.2209e+02 **	p<0.00001*, *, BF10 = 4.2559e+03 **	p<0.00001*, *, BF10 = 1.9879e+11 **	p<0.00001*, *, BF10 = 7.2923e+06 **	p<0.00001*, *, BF10 = 6.5938e+04 **	p<0.00001*, *, BF10 = 1.9502e+03 **	p<0.00001*, *, BF10 = 2.4269e+08 **	p = 1.0000, BF10 = 1.0765e-04	p<0.00001*, *, BF10 = 1.7730e+16 **	p = 0.0130*, BF10 = 1.3850e+02 **
Moving artificial	Still artificial	p = 0.2419, BF10 = 1.0654e+04 **	p<0.00001*, *, BF10 = 4.2123e+12 **	p<0.00001*, *, BF10 = 1.0748e+31 **	p = 0.0903, BF10 = 8.6941e+01 **	p = 0.0101*, BF10 = 2.2218e+02 **	p = 0.0004**, BF10 = 2.1308e+03 **	p = 0.1990, BF10 = 2.2373e+02 **	p<0.00001*, *, BF10 = 3.4348e+24 **	p = 0.0062*, BF10 = 1.3973e+03 **	p<0.00001*, *, BF10 = 2.0919e+30 **
Moving artificial	Still natural	p = 0.4344, BF10 = 6.0945e+01 **	p<0.00001*, *, BF10 = 2.5963e+16 **	p<0.00001*, *, BF10 = 6.7124e+24 **	p = 0.9765, BF10 = 1.7943e-03	p = 0.0980, BF10 = 6.4057e+00	p = 0.0017*, BF10 = 4.0535e+01 **	p = 0.9982, BF10 = 6.4837e-04	p<0.00001*, *, BF10 = 7.2474e+19 **	p = 0.1141, BF10 = 1.6394e+00	p<0.00001*, *, BF10 = 2.1414e+10 **
Moving natural	Still artificial	p<0.00001*, *, BF10 = 4.9576e+06 **	p = 0.0001**, BF10 = 9.7419e+03 **	p<0.00001*, *, BF10 = 2.5674e+10 **	p<0.00001*, *, BF10 = 5.2546e+11 **	p<0.00001*, *, BF10 = 1.0589e+13 **	p<0.00001*, *, BF10 = 8.7973e+12 **	p<0.00001*, *, BF10 = 3.4359e+13 **	p<0.00001*, *, BF10 = 8.8783e+25 **	p<0.00001*, *, BF10 = 4.9548e+30 **	p<0.00001*, *, BF10 = 2.5274e+27 **
Moving natural	Still natural	p = 0.9690, BF10 = 5.0602e-03	p<0.00001*, *, BF10 = 3.3762e+07 **	p<0.00001*, *, BF10 = 9.6291e+10 **	p<0.00001*, *, BF10 = 3.4753e+09 **	p<0.00001*, *, BF10 = 3.0786e+12 **	p<0.00001*, *, BF10 = 6.1121e+11 **	p<0.00001*, *, BF10 = 8.0709e+09 **	p<0.00001*, *, BF10 = 2.8635e+22 **	p<0.00001*, *, BF10 = 3.6150e+21 **	p<0.00001*, *, BF10 = 4.9798e+14 **
Still artificial	Still natural	p = 0.0009**, BF10 = 1.0210e+08 **	p = 0.1752, BF10 = 3.3851e+01 **	p = 0.9998, BF10 = 2.2782e-04	p = 0.4030, BF10 = 7.4906e+01 **	p = 0.9698, BF10 = 6.5220e-01	p = 0.9991, BF10 = 3.5982e-04	p = 0.4220, BF10 = 2.9670e+02 **	p<0.00001*, *, BF10 = 3.9989e+12 **	p<0.00001*, *, BF10 = 9.0151e+12 **	p<0.00001*, *, BF10 = 5.6412e+14 **

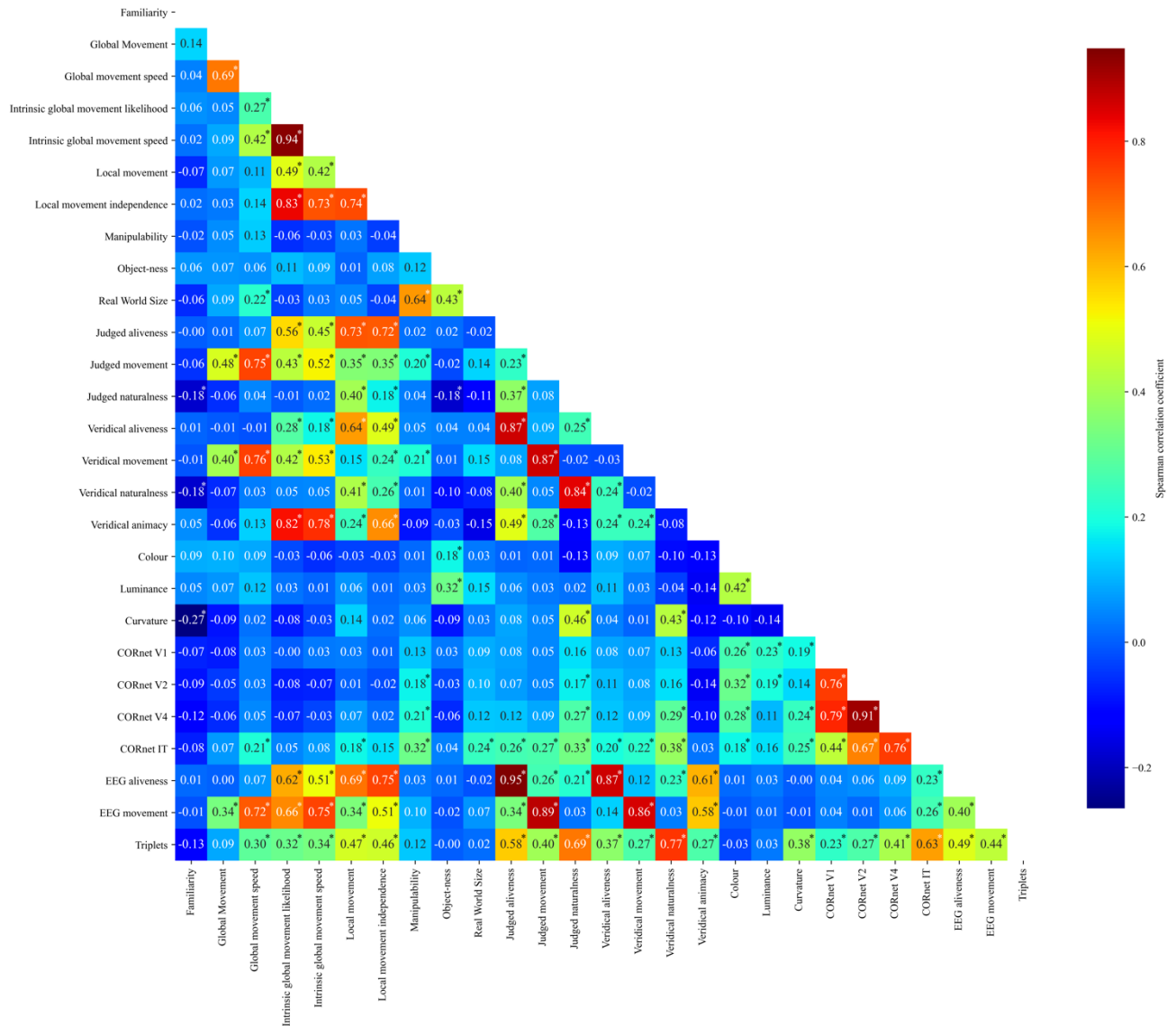
Supplementary Figure 4.1

Representational Dissimilarity Matrices for the model based on the ‘odd-one-out’ similarity task, compared to all other models used in the study. Stimuli are clustered by category, from the bottom left corner, by alphabetical order (animals, moving artificial, moving natural, still artificial, still natural).



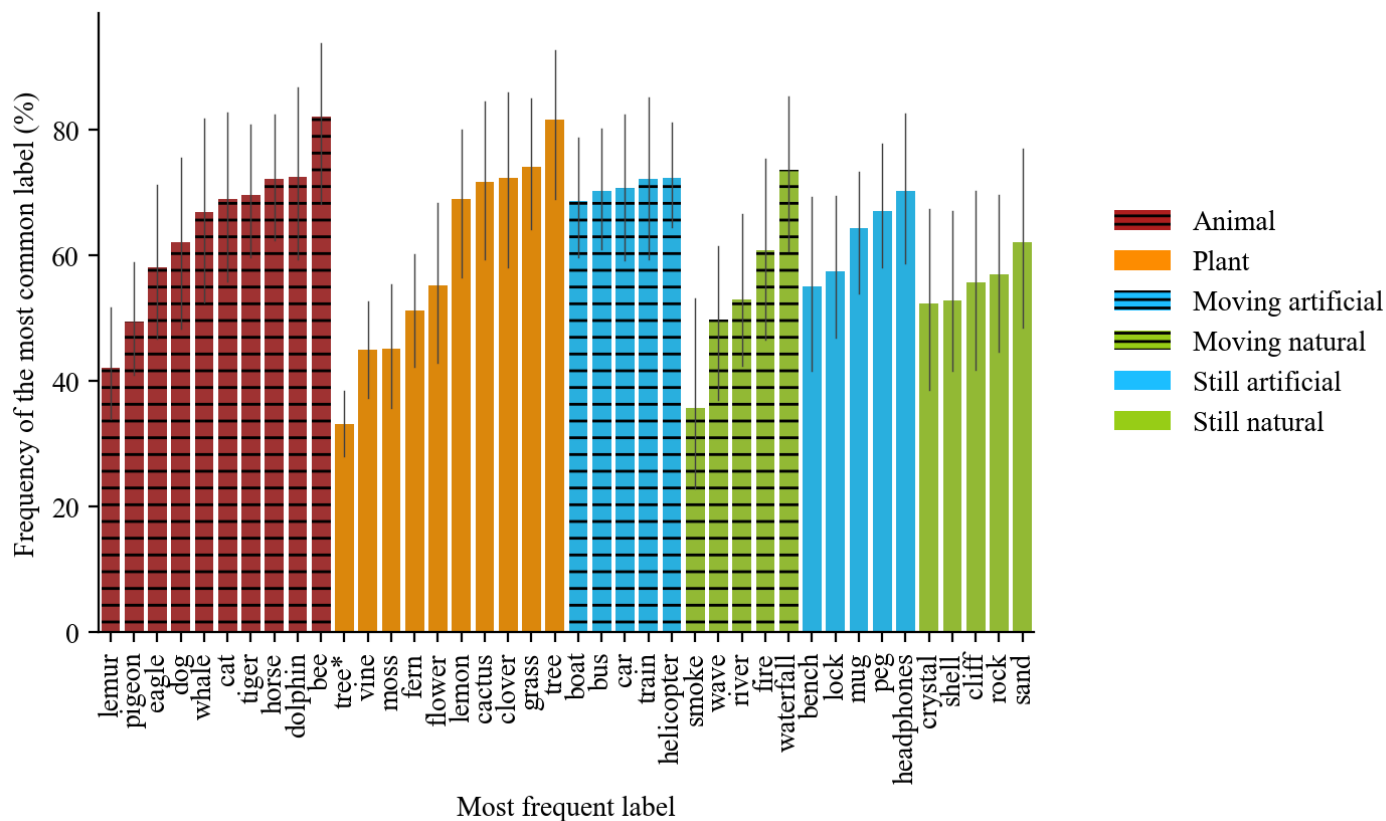
Supplementary Figure 4.2

Spearman rank correlations between all models in the experiment. Warmer colours indicate more positive correlations, and cooler indicate stronger negative correlations. Stars indicate correlations that were significant after a Bonferroni correction for multiple comparisons at $p < .001$.



Supplementary Figure 4.3

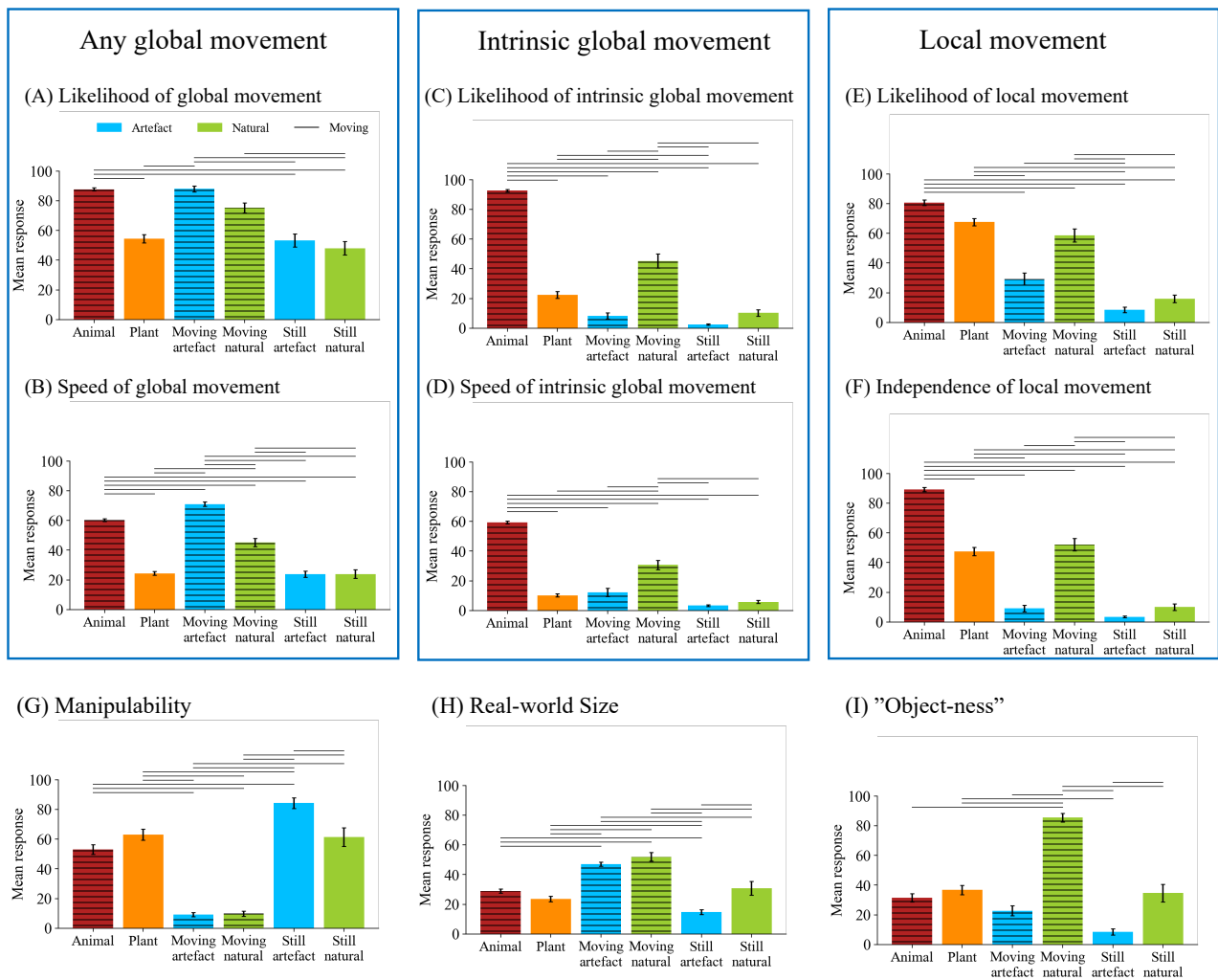
Consistency across participants in naming data. For each object, the most common label was identified, and the percentage of responses that were the most common label was calculated. Higher values, therefore, indicate that the object was more consistently named across participants. Note that each object consists of multiple images, so naming consistency also depends on the consistency of the images within each category.



Two separate objects were most commonly labelled ‘tree’, the first one here indicated “tree” was palm trees, which many of the participants noted but the mixed format (two words/ one word) meant ‘tree’ was the most common label.

Supplementary Figure 4.4

The same data as in [Figure 4.3](#), visualised in an alternate way so that comparisons across categories are shown.



Chapter 5: Animal, plant, or mineral: disentangling object concepts from visual features

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CRedit:

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Thomas A. Carlson: Methodology, Writing – Review and Editing, Supervision, Funding acquisition

Abstract

Recent studies have attempted to disentangle neural processing of visual features from semantic knowledge. Many of these approaches employ some form of visual scrambling that renders objects unrecognisable. Here, we use images of real but unfamiliar animals, plants, and minerals from Schmidt et al. (2017) to investigate how perception of objects occurs in the absence of knowledge about their true category. We recorded brain activity with electroencephalography (EEG) while participants classified the ambiguous stimuli as animals, plants, and minerals, and during a fixation monitoring task. Our results indicate that mid-level visual features such as aspect ratio and symmetry are crucial for object perception in the absence of top-down stimulus knowledge. Participants were largely naive of the objects' true identities, and liberally classified objects as minerals but rarely labelled them as animals or plants. Despite this poor classification performance, both the true class and the perceived class of the stimulus were distinguishable from multivariate patterns of neural activity in both tasks. When judging similarity, participants use a similar set of visual features to those used to predict object class and those that best correlate with brain activity. Our findings suggest that the same set of mid-level features are crucial for object perception in the absence of categorical knowledge, for neural processing, for similarity judgements, and for categorisation.

Animal, Plant or Mineral: Disentangling Object Concepts from Visual Features

The human brain can identify objects remarkably rapidly, from individual object identity to increasingly abstract categorical identity (Carlson et al., 2013; Potter et al., 2014; VanRullen & Thorpe, 2001). However, it is possible that this category-selectivity in the ventral visual stream represents tuning to particular visual features associated with each category of objects, rather than the more abstract conceptual category (Andrews et al., 2015). Mid-level visual features alone (e.g., how curved an object is) explain a considerable proportion of both behavioural judgements of animacy (Schmidt et al., 2017), and neural activity (Nasr et al., 2014; Papale et al., 2020; Yue et al., 2020) beyond object class. This relationship between visual features and object class is complex and necessarily interrelated because categorical distinctions are, in part, defined by shared visual features. For example, animate things tend to be more curved (Zachariou et al., 2018), and more visually similar to each other than other categories such as tools (Humphreys et al., 1988). Therefore, both theoretically and practically, it remains difficult to separate perceptual from semantic or conceptual processing, as they are often closely related.

One method of differentiating visual features from object category is to construct a stimulus set where visual features are matched across classes (Bracci et al., 2017). Constructing such a stimulus set with shape-matched stimuli allows control over the global shape (e.g., a coil of rope and a coiled snake, a cow-shaped mug and a cow, a glove and a hand), but leaves local features, textures, and identity intact. Generally, studies using functional Magnetic Resonance Imaging (fMRI) have revealed that semantic features play a role in object processing beyond carefully controlled visual similarity, particularly in more anterior regions of the ventral visual system (Bracci et al., 2019; Bracci & Op De Beeck, 2016; Kaiser et al., 2016; Proklova et al., 2016). However, studies using time-sensitive methods like magnetoencephalography (MEG) and electroencephalography (EEG) have shown more mixed findings, with some finding that animates cannot be distinguished from inanimates when shape is matched (Proklova et al., 2019), and others showing animacy representations for shape-matched hands/gloves and torsos/shirts (Kaiser et al., 2016). Overall, these

findings with tightly controlled stimulus sets suggest semantic knowledge influences object perception beyond overall shape, though this may depend on the stimuli and the measurement techniques used. However, objects in these studies are recognisable and it is unclear what impact the top-down feedback of object identification might have on the processing of lower-level visual attributes without closer examination of time-sensitive data.

Another method of separating semantic processing is to scramble images so objects are no longer recognisable, but the visual features are retained. Typically, scrambled images show some overlap with early visual processing of intact images, suggesting that visual features are coded for early in the visual processing hierarchy in the absence of semantic information (Coggan et al., 2016; Levinson et al., 2021; Tiurina & Markov, 2022; Zachariou et al., 2018). However, scrambled stimuli remove all identifiable visual features, including lower and mid-level features (e.g., textures, curvature). To maintain mid-level features, Long et al. (2018) created texforms, which maintain the texture and other mid-level image statistics but still render the objects unrecognisable. Experiments with texforms have shown that information about both animacy and real-world size is present in the brain even when the stimuli are unidentifiable (Long et al., 2017, 2018; Wang et al., 2022). However, Grootswagers et al. (2019) failed to find representations of animacy or real-world size for texforms in rapid presentations (20, 30, or 60Hz), suggesting these attributes may only be present with sufficient processing time. Though texforms and scrambled images are no longer identifiable, they are also no longer bounded objects, and it is thus difficult to compare processing to processing of more naturalistic, bounded objects.

To disentangle semantic influences from perception, we can also use unfamiliar, disguised, or unidentifiable objects. Schmidt et al. (2017) collected images of animals, plants, and minerals that were camouflaged and/or disguised to look like another category. Participants rated these images on several mid-level features, as well as how much they looked like an animal, plant, and mineral. Schmidt et al. (2017) found that mid-level shape features, like how curvy or elongated the item was, were used to distinguish object classes in the absence of semantic knowledge. For example, more

plant-like items were more symmetrical, systematic, and repetitive. Individual features explained little of the variance in ratings of how animal-, plant-, or mineral-like items were, but a combination of mid-level shape features was sufficient to differentiate items that were perceived as animals, plants, and minerals. Other recent work using texforms and scrambled images has shown that participants can accurately estimate which stimuli are derived from animate images (Tiurina & Markov, 2022), suggesting that mid-level features are sufficient to convey animacy.

In the current study, we explore the relationship between mid-level features and object categorisation in the brain using unfamiliar images from Schmidt et al. (2017) and temporally-precise EEG. The use of these ambiguous images allows us to separate the influence of top-down processing from mid-level feature processing, while still displaying stimuli that are real, bounded objects. To foreshadow results, we find that shape is an important element of object processing in the absence of clear category information. Moreover, the set of visual features that are used for judging the class of an object are similar to those used in similarity judgements, and in patterns of brain activity.

Methods

Participants

Participants were 36 undergraduate students from the University of Sydney who participated in exchange for course credit. The mean age was 20.27 (range 18-31), and there were 21 women, 14 men and one non-binary person. All participants had normal or corrected-to-normal vision and were not colourblind. All participants gave both written and oral consent, and this study was approved by the University of Sydney Ethics Committee.

Stimuli/ Design

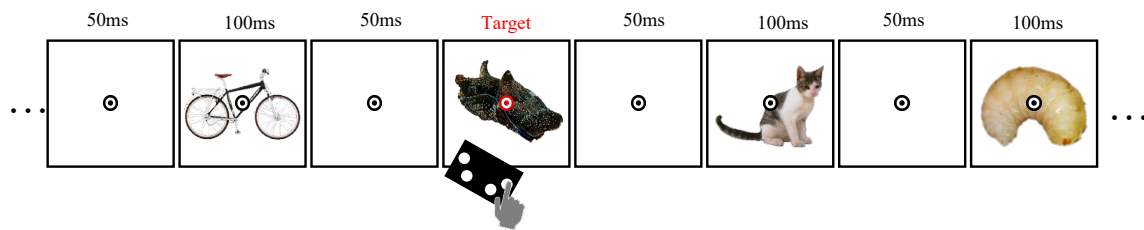
Stimuli were 75 unfamiliar objects, including ambiguous animals (25 images), plants (25) and minerals (25) obtained from Schmidt et al. (2017). To ensure participants were completing the

classification task properly, 15 prototypical identifiable animal (5), plant (5), and mineral (5) images were also included. These 15 images were downloaded from pngimg.com under a CC0 license. Participants completed two tasks: a fixation monitoring task ([Figure 5.1A](#)), and a categorisation task ([Figure 5.1B](#)). Tasks were interleaved, such that participants completed a block of fixation monitoring trials, then a block of categorisation trials.

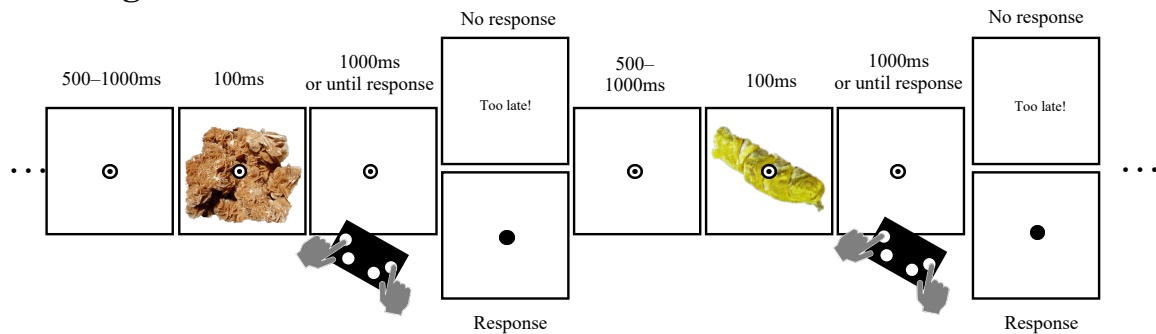
Fixation monitoring task

In the fixation monitoring task, participants viewed a Rapid Serial Visual Presentation (RSVP) stream of images and responded to a colour change at fixation ([Figure 5.1A](#)). Images were shown for 100ms, followed by a 50ms fixation cross. Previous work has shown that object information can still be identified even from rapid presentations (Grootswagers, Robinson, & Carlson, 2019; Mohsenzadeh et al., 2018; Robinson et al., 2019). To enable comparison between the ambiguous objects and identifiable objects, we also included 120 identifiable objects from Contini et al. (2020) from 12 different categories (humans, primates, domestic animals, birds, fish, invertebrates, plants, robots, machines, tools, toys, and stationary objects). Each sequence contained all 75 ambiguous images from Schmidt et al (2017), as well as the 15 prototypical images, and the 120 identifiable objects from Contini et al. (2020). Three sequences were shown together between categorisation tasks, so each stimulus was viewed 27 times in the fixation monitoring task (three repeats for each of nine blocks of categorisation tasks).

A. Fixation detection



B. Categorisation task



C. Model similarity

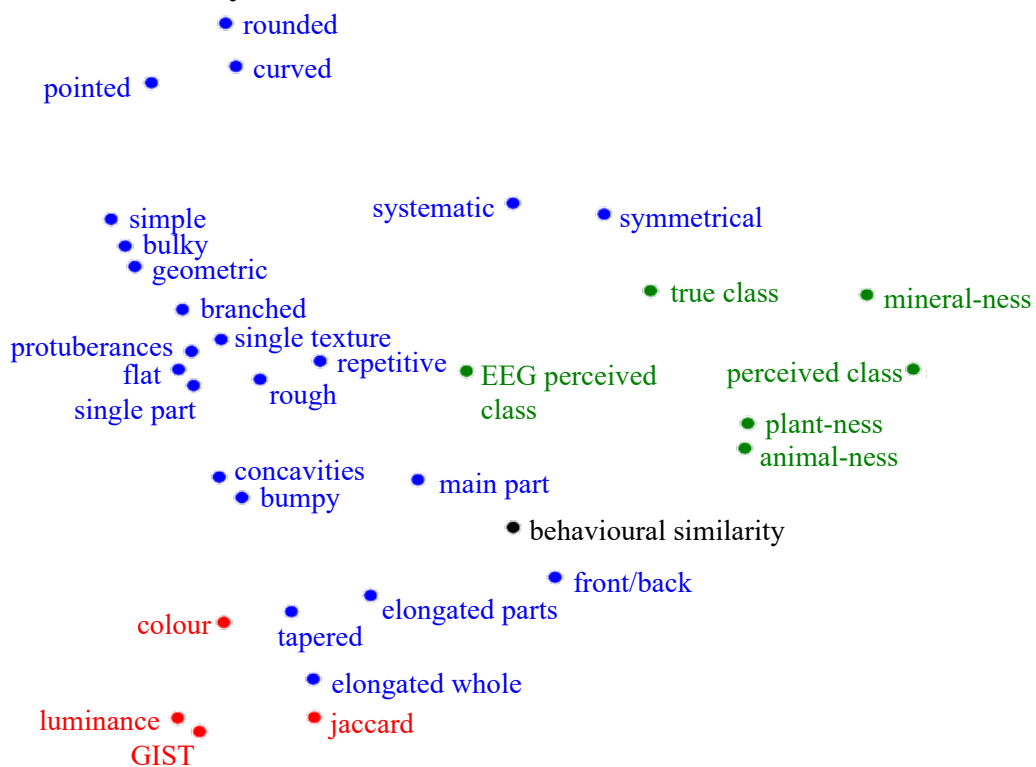


Figure 5.1

Participants in the EEG experiment (N=36) completed two interleaved tasks. For fixation detection (A), participants pressed a button whenever the fixation dot changed colour. For the categorisation task (B), participants viewed images and classified them according to whether it was an animal or not, mineral or not, or plant or not. In (C), all models from Schmidt et al. (2017) are shown with more similar models shown closer together (using PCA for dimensionality reduction). All images in the experiment are subject to copyright, so images here are visually similar CC0 replacements crudely edited by the authors.

Categorisation task

In the categorisation task, participants alternated between three tasks. Participants classified each image according to either (1) animal or not an animal, (2) plant or not a plant, and (3) mineral or not a mineral. Participants pressed one of the two outer buttons on a four-button box to indicate their response (as shown in [Figure 5.1B](#)). Each participant completed all three of these tasks, repeated three times (nine classification blocks in total). Task order and button-mapping were fully counterbalanced across participants. Each block contained all 75 ambiguous stimuli, as well as the 15 prototypical/identifiable images. Timing of the presentation is shown in [Figure 5.1B](#). Each image was preceded by a fixation cross, displayed for a random duration between 500 and 1000ms. The image was shown for 100ms (as in the fixation monitoring task) and was replaced with a fixation spot for 1000ms or until the participant responded by pressing a button. If the participant responded within 1000ms, the fixation spot turned black, and the next trial began with the 500-1000ms fixation cross. If participants did not respond, a message appeared on the screen reading “Too late!” for 2000ms. Participants were verbally instructed prior to completing the task that some of the images might be difficult to classify, and they should make their best attempt to make a guess even if they were not sure.

EEG data collection

Raw EEG data were collected using a 64-channel BrainProducts ActiCAP system, with an online reference of FCz, at 1000Hz. Electrodes were placed according to the 10-20 system (Oostenveld & Praamstra, 2001). Stimuli were displayed centrally, at approximately 5 degrees of visual angle, on a white background on a 1920 x 1080 Asus gaming monitor with a refresh rate of 60Hz.

EEG data pre-processing

Data were minimally pre-processed (Delorme, 2023), as in previous work (Grootswagers, Robinson, & Carlson, 2019; Shatek et al., 2022). Data were high pass-filtered at 0.1Hz, low-pass filtered at 100Hz, re-referenced to an average reference, and down-sampled to 250Hz. Epochs were generated from 300ms before stimulus onset to 1000ms after stimulus onset.

EEG behavioural analysis

In the classification blocks of the EEG study, participants completed three different classification tasks: whether the stimulus was an animal or not, a mineral or not, and a plant or not. To analyse classification performance (including misclassifications) and confirm if the true class of the image was largely unknown, we calculated the number of times within each task that a participant responded with the affirmative choice (e.g., “yes, it is an animal/ plant/ mineral”) for each stimulus category separately. This allows us to look at both correct classifications as a function of task, but also at how liberally participants apply the inclusion criteria for each category (how many times they press the ‘yes’/ affirmative button).

EEG decoding

To examine whether the true class of the image was represented in the brain, we used a linear discriminant machine learning classifier to distinguish brain activity when participants were viewing true animals, true plants, and true minerals (3-way classification). For both classification and fixation monitoring trials, a leave-one-block-out cross-validation was used, such that the classifier was trained on all blocks except one (eight blocks), and then tested on the left-out (ninth) block. This procedure was repeated so each block was used as the testing set, then averaged over all cross-validation folds. A similar method was used to decode each category compared to the other two (e.g., animals compared to plants and minerals).

EEG Representational Similarity Analysis (RSA)

To explore how different characteristics of the stimuli related to each other and to neural activity, we used Representational Similarity Analysis (RSA; Kriegeskorte et al., 2008). Creation of Representational Dissimilarity Matrices (RDMs) is described below.

Feature ratings from Schmidt et al. (2017)

The stimuli in the current experiment were taken from Schmidt et al. (2017), who also collected behavioural data on these images over two experiments. In experiment 1 of Schmidt et al. (2017), participants rated how much each image looked like an animal, like a plant, or like a mineral (here referred to as ‘animal-ness’, ‘plant-ness’, and ‘mineral-ness’). In a second experiment, different participants rated each of the stimuli on a number of visual features. Half of these features were framed as opposites (e.g., whether it was rounded or not, rated on a scale labelled “rounded” at one end and “angular” at the other), and half were framed as statements for which participants had to rate their agreement (e.g., whether it was branched, “has a branched structure”, with true at one end and false at the other). Features measured as opposites (and the corresponding scale labels) included: rounded (rounded, angular), symmetrical (symmetrical, asymmetrical), rough (rough/spiky, smooth), simple (simple, complex), systematic (regular/systematic/orderly, random/chaotic/disorganised), repetitive (consists of reoccurring parts, consists of unique parts), curved (bent/curvy parts, straight/linear parts), pointed (pointed part, rounded off parts), single part (consists of one part, consists of multiple parts), single texture (homogenous texture, has multiple textures), bulky (fat/bulky shape or parts, thin/wispy shape or parts). Features measured as statements included: front/back (front and back orientation noticeable), branched (has a branched structure), concavities (has concavities/ holes/ lumps), geometric (similarity to simple geometric shapes), elongated whole (appears elongated), tapered (tapered towards one or both ends), elongated parts (has elongated parts), main part (has one obvious main part), flat (is flat), protuberances (has eversions), bumpy (has bumps).

To look at how these features might explain neural activity associated with each class, we used the raw behavioural ratings from all participants in Schmidt et al. (2017) as features, and calculated the Euclidean distance between each pair of images to create an RDM for each visual feature. A visualisation of how these models are related is shown in [Figure 5.1C](#).

Perceived class ratings from Schmidt et al. (2017)

We also created a model of the ‘perceived class’ by calculating the Euclidean distance between each pair of stimuli, using the ratings of animal-ness, plant-ness, and mineral-ness from Schmidt et al. (2017) as features for each stimulus.

Visual models

In addition to the models from Schmidt et al. (2017), we also created models of pixel-wise colour, rectilinearity, GIST (Oliva & Torralba, 2006), and luminance. The colour model was created by computing the Euclidean distance between CIELab colours for corresponding pixels in each pair of images. The rectilinearity model was computed using code from Nasr et al. (2014) retrievable from https://github.com/cechava/Rectilinearity_Toolbox. The GIST model, which aims to capture perceptual dimensions such as naturalness and roughness by analysing the spatial structure of the image, was calculated using code from Oliva and Torralba (2006) at <https://people.csail.mit.edu/torralba/code/spatialenvelope/>. The luminance model was computed by converting each pixel RGB values to greyscale and calculating the Euclidean distance between corresponding pixels in each pair of images.

Correlations between features and true/perceived class

To investigate which features were used for judging predicted and true class, we ran a Spearman rank correlation with the lower triangle of each of the visual feature RDMs (e.g., symmetrical, systematic, etc.) and the true and perceived class models separately.

Full and partial correlations between EEG and true/perceived class

As the decoding analysis showed that true class was distinguishable from neural activity, we wanted to investigate the degree to which this decoding was explained by visual features. In a conceptual replication of the decoding, we first examined the temporal dynamics of the correlation between the neural RDMs and with the RDM model of true class. Then, a partial correlation between the neural RDM and the true class RDM was run, including all visual feature models as covariates. Any remaining correlation would indicate that the brain had patterns of activity associated with true class that were not attributable to the specific mid-level features included here. This full and partial correlation was also repeated for the perceived class models, to investigate whether neural representations more closely resembled the perceived or the true class, and the degree to which the visual features contributed to these correlations.

Partial correlations between features and brain activity

To investigate the correlation between models and neural activity, a partial Spearman rank correlation was calculated between the lower half of the visual feature model RDMs and neural RDMs for each time point, for each task type (fixation monitoring, classification task). True class was included as a covariate, so the partial correlations reflect the influence of that feature on perception after accounting for the variance from true identity. Though only a few are shown for brevity ([Figure 5.4](#)), correlations with all features are contained in [Supplementary Figure 5.2](#).

To examine which features seem to best capture brain activity, we used two different metrics: the peak correlation, and the sum of the area under the correlation at all time points. The peak correlation was calculated by taking the maximum correlation across all time points for each model, and the area under the curve was calculated by summing the absolute value of the correlations across all time points. Each model was ranked on both metrics for both tasks.

Behavioural similarity ratings

To explore how behavioural similarity related to neural similarity, we also gathered data online from a separate group of participants. Participants in this behavioural experiment were 260 undergraduate students at the University of Sydney, who participated in exchange for course credit. There were 61 men, 146 women, 4 non-binary people, and one person who preferred not to disclose their gender, with a mean age 20.33 (range 16-39). All participants gave consent to participate, and procedures were approved by the University of Sydney ethics committee.

Participants completed an ‘odd-one-out’ task (Hebart et al., 2020). Three images were displayed on the screen ([Figure 5.5A](#)), and participants were instructed to click the odd one out. The method by which participants choose the odd one out on each trial is unconstrained, and the only instructions they were given were to “... click on the ‘odd one out’, or the image that is most different from the other two. Just go with your intuition, don’t spend too long thinking about each one.” Each participant rated a random set of 400 triplets. The task was coded using a modification of a plugin from JSPsych (de Leeuw, 2015) and hosted on Pavlovia (Peirce et al., 2019, <https://www.pavlovia.org/>).

Creating a perceptual similarity RDM

To derive a model of similarity from the triplet data, data was pooled across all participants. We assume that the two stimuli that are not chosen as the ‘odd one out’ are more similar than any other pair of stimuli (Hebart et al., 2020). For example, if a participant is presented with A, B, and C, and chooses A as the odd one out, we assume that B and C are more similar than A and C, or A and B. For each pair of stimuli, the ratio of the number of times they were left together (i.e., they were not chosen as the odd one out when presented together), compared to the number of times they were presented together was calculated. A higher ratio would mean that the stimuli left out together more often (and thus are more similar), and a lower ratio would mean the stimuli were not left out together very often (and thus are more dissimilar). These pairwise similarity scores can then be formed into a

Representational Dissimilarity Matrix (RDM; Kriegeskorte et al., 2008) by subtracting the similarity matrix from 1 to invert the scores (high similarity scores become low dissimilarity scores).

Participants' descriptions of strategy

Participants in the 'odd-one-out' experiment were also asked to describe their strategy once they had completed the task. Given the task instructions are very broad, and the stimuli have no clearly categorical dimensions on which the stimuli can be rated, these descriptions provided qualitative insight into participant strategy. To visualise the strategies, we created a word cloud ([Figure 5.5B](#)) using the WordCloud library for python (Mueller, 2022). Larger words indicate that participants mentioned them more frequently.

Correlations of perceptual similarity with neural activity and visual features

To investigate how well neural activity was captured by the model of perceptual similarity, we ran a Spearman rank correlation between the perceptual similarity RDM and the neural RDMs for both tasks, then averaged over participants. As with the true and perceived class models, we also ran a partial correlation with all the visual features as covariates, to inspect whether there were patterns of neural activity explained by the perceptual similarity model that were not captured by these mid-level feature models. To investigate which features participants might be using to complete the 'odd-one-out' task, we also looked at the correlations between the perceptual similarity RDM and each of the visual features.

Neural network

To look at how the stimuli might be represented in different brain areas, at different levels of abstraction, the stimuli were passed through CORnet (Kubilius et al., 2018). CORnet is a deep convolutional neural network designed such that 4 of the layers mimic computations in different areas of the ventral visual stream: V1, V2, V4, and Inferotemporal cortex (IT). Feature weights for

these layers were extracted and used to compute the distance between each pair of stimuli as an RDM, such that pairs of stimuli with more similar feature weights in each layer were closer together. The RDM for each layer was then correlated with neural activity, to explore when patterns of features from each layer of the neural network (each brain area) were similar to patterns of representation in the brain. If the true class of the image was unknown, there would be very little relevant information in IT, which is typically associated with higher-order object recognition. If this is the case, we would expect V4, which integrates more coarse patterns and visual features such as curvature and colour (Roe et al., 2012), to better capture patterns of neural activity.

Statistical inference

A Bayesian statistical framework, guided by Teichmann et al. (2022), was used to for statistical inference. All analyses were implemented through the `ttestBF` function in the `BayesFactor` package for R (Morey et al., 2018), called through custom Python code. A JZS prior was used, with the default scale factor of 0.707, which makes minimal assumptions about the expected effect size (Rouder et al., 2009). Bayes Factors can be interpreted as odds ratios in favour of the alternate hypothesis, such that a Bayes Factor of 3 suggests there is three times more evidence for the alternate hypothesis than the null hypothesis. According to Jeffreys (1961/1998), Bayes Factors above 3 can be interpreted as evidence for the alternate hypothesis, Bayes Factors above 10 can be interpreted as ‘strong evidence’ and Bayes Factors above 30 can be interpreted as ‘very strong evidence’ for the alternate hypothesis. Bayes Factors less than 1/3 are interpreted as evidence for the null hypothesis. For decoding analyses, a one-sided prior was used to evaluate evidence that decoding was above chance. A two-sided prior was used for correlation analyses, as negative correlations are meaningful and interpretable.

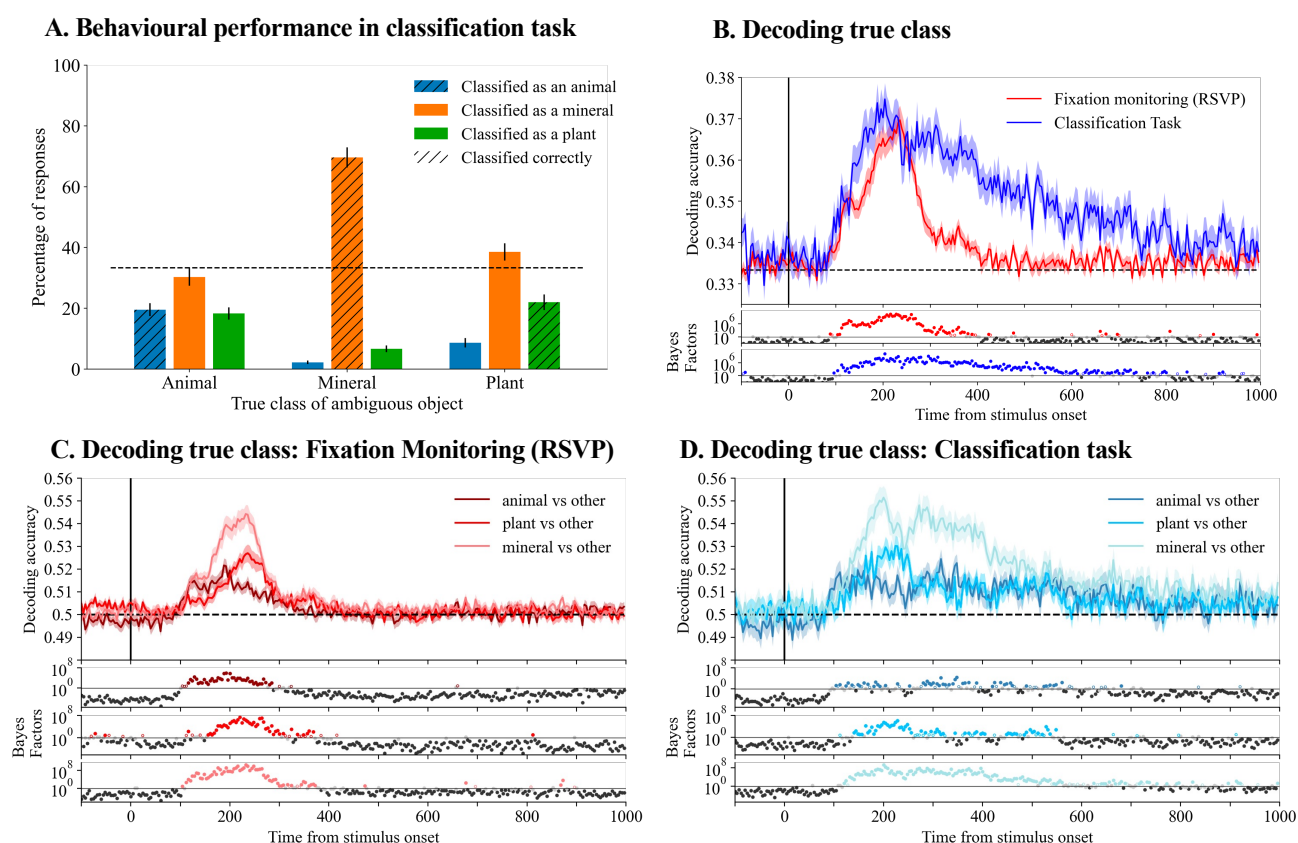


Figure 5.2

(A) During the classification task of the EEG experiment, in separate blocks, participants decided whether each item was an animal or not, plant or not, and mineral or not. (B) The true class of the object was decodable from patterns of neural activity for both the classification task (blue) and the fixation monitoring task (red). (C,D) This appears to be driven by the differences between true minerals and true plants/animals in both the fixation monitoring task (C), and the classification task (D). Under each plot, Bayes Factors are filled and coloured if $BF > 10$, outlined if $3 < BF < 10$, grey if $3 < BF < 1/3$, and black if $BF < 1/3$. Coloured dots show evidence for the alternate hypothesis of significant difference from chance.

Results

Classification criteria for minerals are more liberal than for animals or plants

To examine how participants classified the ambiguous stimuli, we calculated the number of times participants responded in the affirmative (e.g., “yes, it is an animal/ plant/ mineral”) for each task, and for each category ([Figure 5.2A](#)). Overall, we found that participants were more willing to label objects as minerals than plants or animals. On average, participants claimed the object was a

mineral on 46% of mineral-task trials. In contrast, in the animal task, only 10% of stimuli were classified as animals, and in the plant task only 15% of stimuli were classified as plants.

The true category of stimuli was distinguishable from brain activity, mostly driven by true minerals

As behavioural results revealed that the true class of many objects was unknown to most participants, we wanted to see if the true class was distinguishable from patterns of brain activity. [Figure 5.2B](#) shows that the true class of the ambiguous items was decodable from neural recordings from approximately 100ms after stimulus onset, for both the classification task and fixation monitoring task. This decoding appears to be primarily driven by the difference between minerals and the other two categories (plants and animals together) ([Figure 5.2C, 5.2D](#)).

Features that are most related to perceived class are also correlated with true class

To investigate whether there were visual features that differed between each of the true classes that could be driving the decoding, we investigated the correlations of each visual feature model and the models of true and perceived class. These correlations are shown in [Figure 5.3A](#) and [5.3C](#), with the colour-scheme based on the ordering of features for the perceived class. Schmidt et al (2017) found an array of features were associated with being ‘animal-like’, ‘plant-like’ and ‘mineral-like’. For animals, for example, these characteristics were having a front/back, being symmetrical, being systematic and having a main part. Three of these characteristics (except having a main part) were the only features that were informative for differentiating all three categories in Schmidt et al. (2017). These features were also correlated with the perceived class, as well as the true class models. Some of the true class decoding shown in [Figure 5.2B](#) may be explained by visual features that are associated with both true class and perceived class. The correlation among some of these features is also high – for example, the correlation between the ratings for ‘systematic’ and ‘symmetrical’ is .60.

Notably, the lower-level models differ in their ranking between perceived and true class. Models of luminance, pixel-wise colour, and GIST, for example, seem to be more closely related to perceived than true class, suggesting that these features may be used to judge the perceived class.

True class representations are almost entirely accounted for by mid- and low-level features

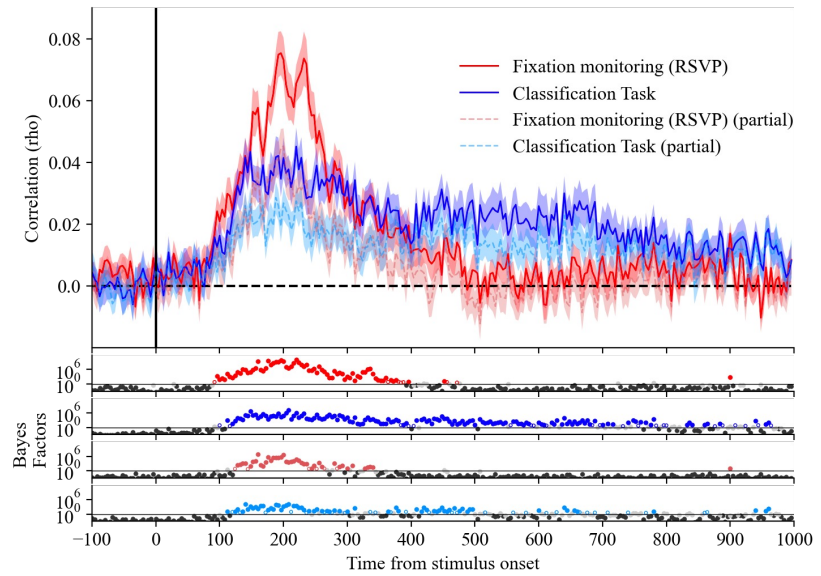
To test the degree to which these features explained representation of true class in the brain, we looked at the correlation between the neural activity and a model of true class. This is a conceptual replication of the decoding analysis ([Figure 5.2B](#)) and allows us to compare directly to a partial correlation between brain activity and true and perceived class, including all the visual feature models as covariates. Accounting for the influence of the visual features in the partial correlation substantially reduces the correlation between the true class model and brain activity, though some significant points of correlation remain between 150-250ms for the classification task and from 180-250ms for the fixation monitoring task ([Figure 5.3D](#)). This suggests that the neural representations of true class are primarily driven by a set of visual features that are common to both the perceived class and true class of the object.

Correlations with the perceived class appear much larger than those with true class ([Figure 5.3B](#)). Though the partial correlation is reduced, significant points remain from approximately 120ms to 250ms after stimulus onset. These periods of significant correlation, particularly compared to the correlations in [Figure 5.3D](#), suggest that the perceived class is somewhat driven by visual features, but less so than the true class model.

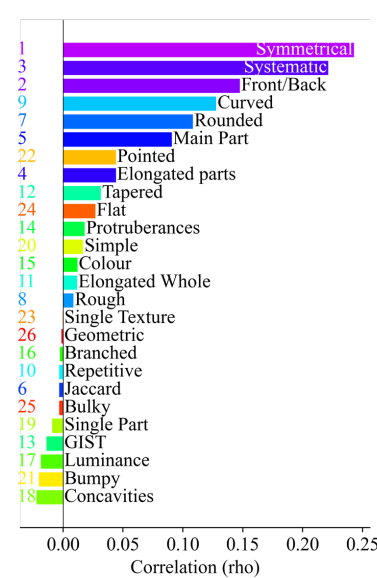
A. Correlation between perceived class and visual features



B. Correlation between perceived class and EEG



C. Correlation between true class and visual features



D. Correlation between true class and EEG

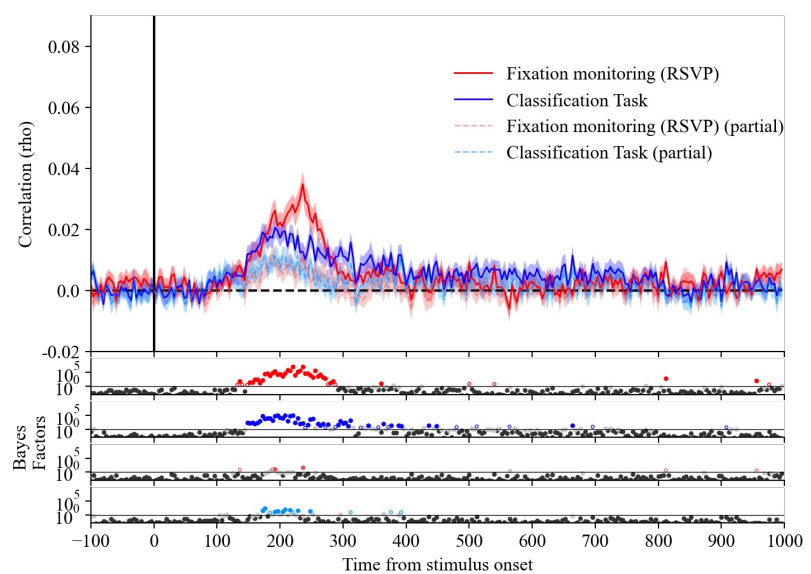


Figure 5.3

Correlations with the perceived object class and the true object class. Features that are correlated with the model of perceived class (A) and true class (C) overlap to some degree, with the top 3 features shared. The correlations between the predicted and true class and brain activity are shown for both fixation monitoring (solid red lines, B/D) and the classification task (solid blue lines, B/D). Pale dashed lines in B/D show partial correlations with all visual features shown in A/C included as covariates. Colours and left-aligned numbers in C correspond to those in A. Under panels B and D, Bayes Factors are filled and coloured if $BF > 10$, outlined if $3 < BF < 10$, grey if $3 < BF < 1/3$, and black if $BF < 1/3$. Coloured dots show evidence for the alternate hypothesis of significant difference from chance.

Visual features that most inform category judgements also correlate with brain activity

To investigate whether the same visual features are being used by the brain as those used to behaviourally judge similarity, we looked at the correlation between all the visual features and brain activity. Though many features showed almost no correlation with neural activity, several features were significantly correlated with neural activity in both tasks. Some sample correlations are shown in [Figure 5.4](#) (all features are shown in [Supplementary Figure 5.2](#)), for the three mid-level feature models from Schmidt et al. (2017) with the highest maximum correlation (being symmetrical, being systematic, and having a clear front/back), plus the Jaccard model, which was one of the top correlates of brain activity by all metrics described below. These models were also the top three correlates of perceived class.

To examine whether the same features used in decision-making were also used by the brain, we looked at the rankings of each of the model correlations with brain activity using two different metrics ([Figure 5.4E-H](#)). For both EEG tasks, a single value for correlation that could be compared across visual attributes was calculated based on both the peak correlation between the visual model and brain activity, and the total summed area under the correlation. Using the colour scheme from [Figure 5.3A](#), it is evident that regardless of the task, regardless of the metric, many of the same features are informative and the correlations between these different metrics are high ([Supplementary Figure 5.1](#)).

Judgements of perceptual similarity rely on similar mid-level features to the brain

To investigate which features were most salient for perceptual experience, we created a model of perceptual dissimilarity based on judgements in an ‘odd-one-out’ task ([Figure 5.5A](#)). In the absence of characteristic features for classification, participants claim that they are using mostly shape and colour to choose the odd one out ([Figure 5.5B](#)). Model correlations indicate that participants are primarily using the shape of the object; the top correlates with the similarity model are models of the silhouette shape (Jaccard) and having elongated whole and parts ([Figure 5.5C](#)).

The similarity model was significantly correlated with brain activity from around 100ms after stimulus onset for fixation monitoring and 120ms for the classification task, for both EEG tasks. However, when mid-level features are added as covariates, the correlation between the similarity judgements and brain activity substantially decreased (pale lines in [Figure 5.5D](#)). This suggests that the same features that are being used by the brain are also being used to judge similarity, particularly in the absence of other informative information about the category of the object.

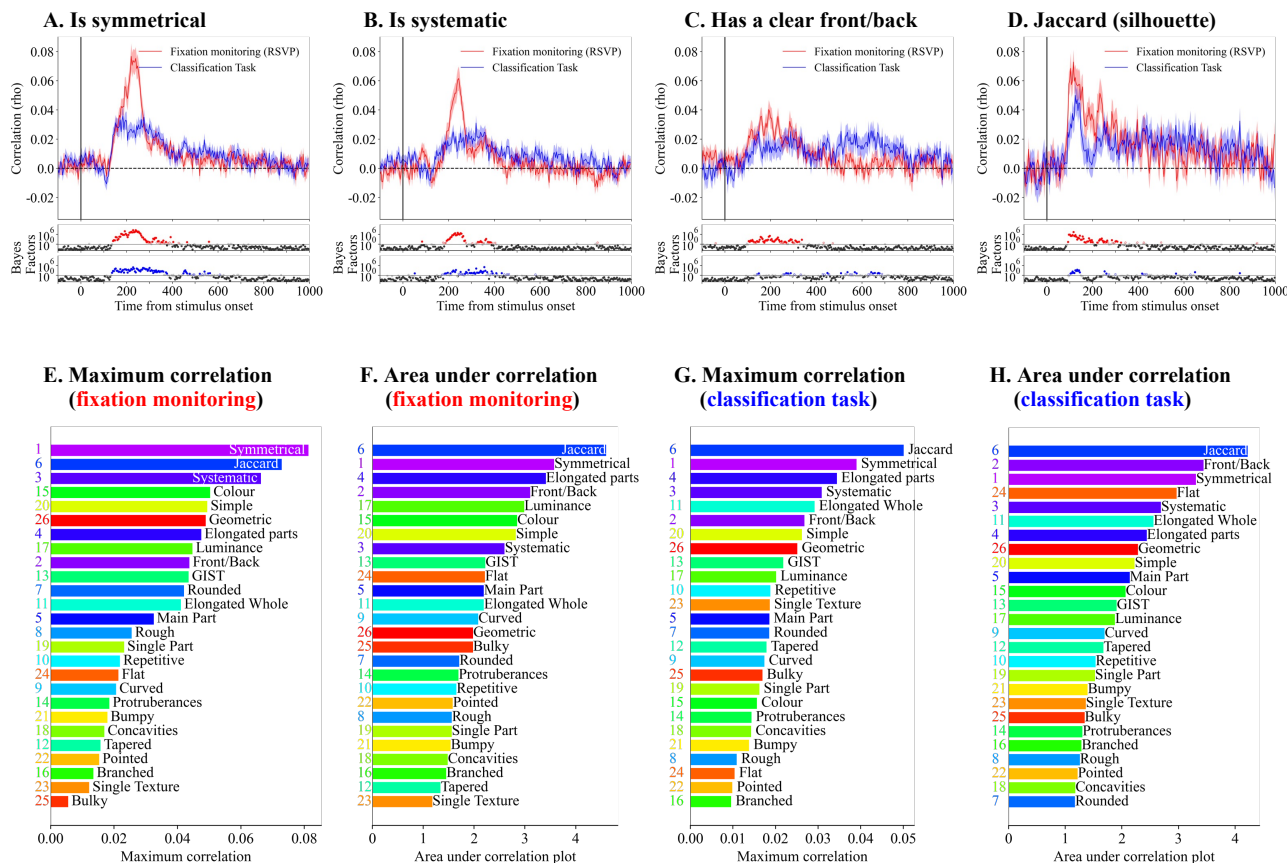


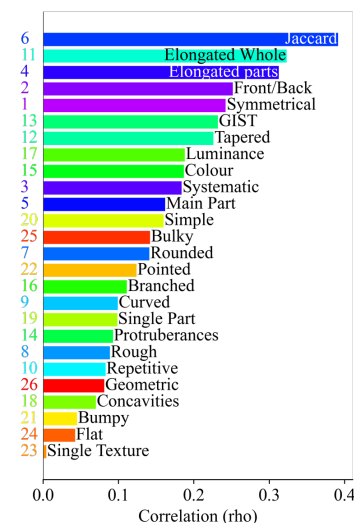
Figure 5.4

Correlations between the top 3 models of true/predicted class have some of the best correlations with brain activity. Lines show partial correlations with ratings of whether the item is symmetrical (A), systematic (B), has a clear front/back (C) and its overall silhouette shape (D), with true class as a covariate. Models are ranked by their maximum correlation (peak) with neural activity (E, G), and the area under the curve for all time points (F, H) for both tasks. Colours in E and F correspond with colours in [Figure 5.3A](#), and numbers indicate the rank order from predicted class. Under panels A-D, Bayes Factors are filled and coloured if $BF > 10$, outlined if $3 < BF < 10$, grey if $3 < BF < 1/3$, and black if $BF < 1/3$. Coloured dots show evidence for the alternate hypothesis of significant difference from zero.

B. Participant strategy descriptors



C. Correlation with features



D. Correlation of behavioural model with brain activity

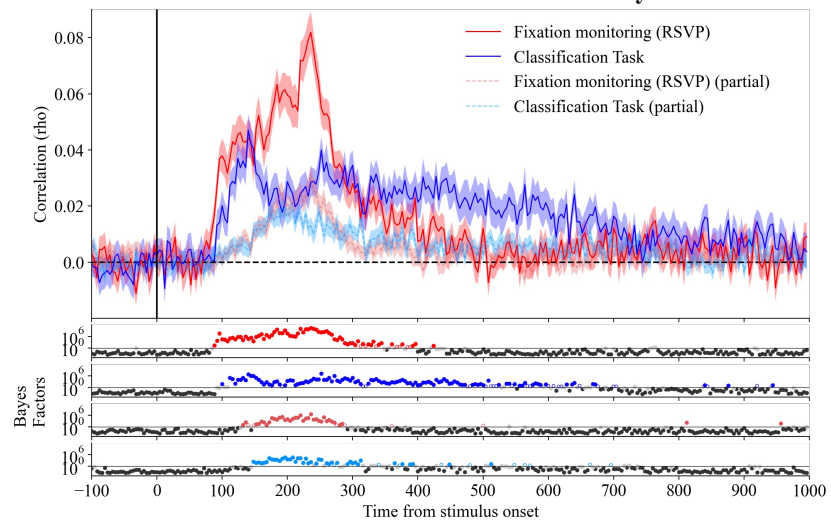


Figure 5.5

(A) Ratings of behavioural similarity were gathered using a triplet task, where participants chose the ‘odd-one-out’ from each set. (B) Participants described their strategy for the odd one out task. Larger words indicate more frequent usage. (C) Correlations between the behavioural similarity model and the visual features are shown using the same colour scheme as in [Figure 5.3A](#). Numbers indicate ranks from correlations with perceived class. (D) Behavioural similarity is correlated with brain activity, with full correlations for both tasks (dark lines). Partial correlations included visual models as covariates, and reduce the correlation substantially but not completely (pale lines). Bayes Factors are filled and coloured if $BF > 10$, outlined if $3 < BF < 10$, grey if $3 < BF < 1/3$, and black if $BF < 1/3$. Filled, coloured dots show evidence for the alternate hypothesis of significant difference from chance.

A neural network model of V4, not IT, best correlates with brain activity

Behavioural results from the classification in the EEG experiment ([Figure 5.2A](#)), as well as the prominence of the visual features in explaining participants' descriptions of their perceptual similarity judgements ([Figure 5.5C](#)), suggest that participants do not know the true class of the stimuli. If this is the case, areas of the ventral visual stream that process higher-order associations

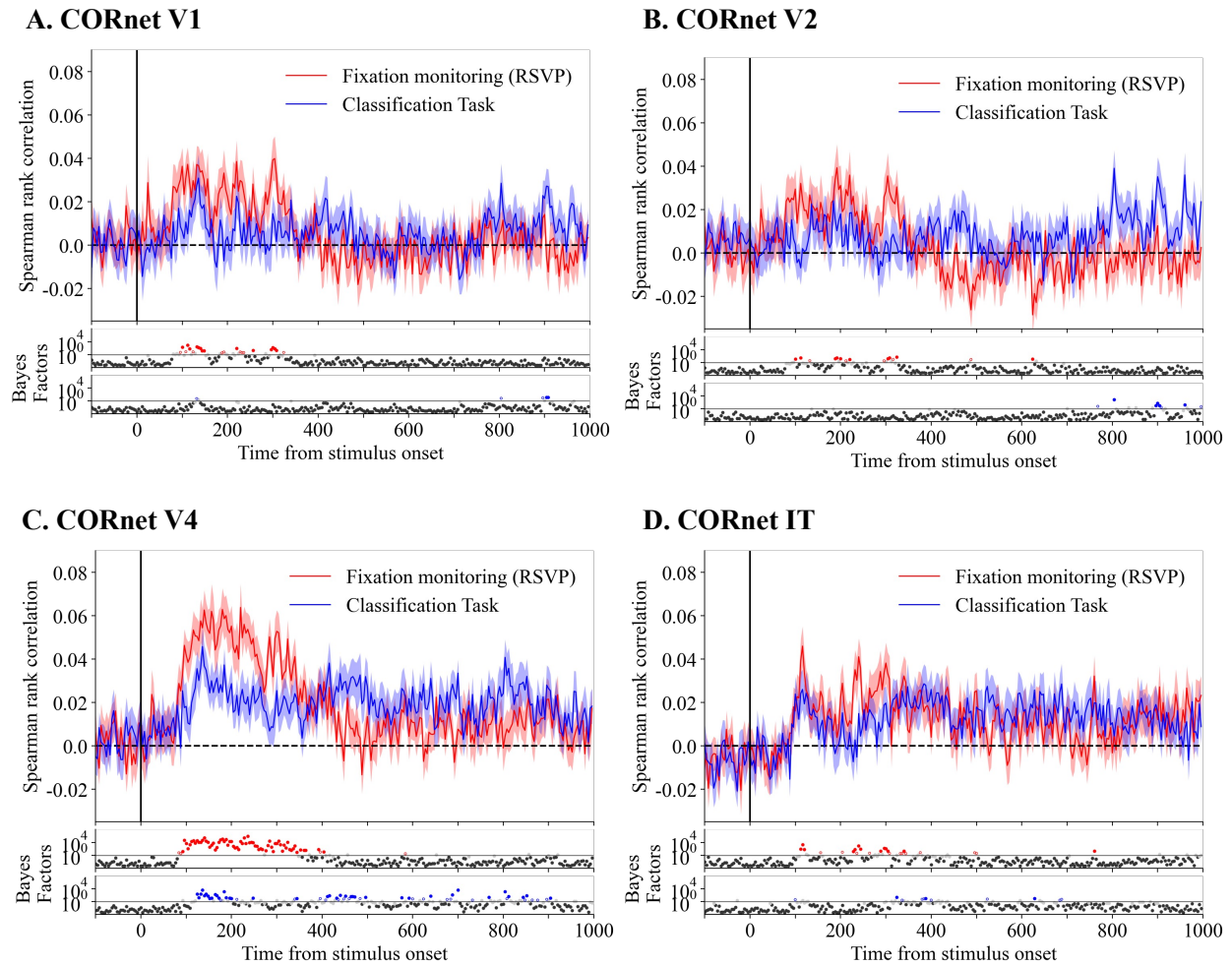


Figure 5.6

Correlations between brain activity and features from different layers of CORnet: V1 (A), V2 (B), V4 (C) and IT (D), for both the classification task (blue) and fixation monitoring (red). Under each plot, Bayes Factors are filled and coloured if $BF > 10$, outlined if $3 < BF < 10$, grey if $3 < BF < 1/3$, and black if $BF < 1/3$. Coloured dots show evidence for the alternate hypothesis of significant difference from chance.

should have a lower correlation with brain activity compared to areas that integrate visual features (e.g., V4). To explore this possibility, we used a neural network model, CORnet (Kubilius et al., 2018). As shown in [Figure 5.6](#), brain activity correlates with the CORnet model of V4 from approximately 100ms after stimulus onset, until around 350ms for the fixation monitoring task, and around 200ms for the classification task, with an additional period of correlation from 400-500ms for the classification task. In contrast, there are few extended periods of significant correlation for the CORnet model of IT, V1, or V2. This suggests that participants, as they report in the perceptual

similarity task, are primarily processing the stimuli for their ‘mid-level’ visual features such as the ones modelled by Schmidt et al. (2017), rather than higher-level object or identity information.

Discussion

In the current study, we investigated how visual object processing occurs in the absence of knowledge about an object’s identity by using ambiguous or disguised animals, plants, and minerals (e.g., flowers with animal-like shapes). Despite poor classification performance, the true class of the object was distinguishable from patterns of neural activity. The same features that are used for judging class membership are also used by the brain and in other, less explicit, behavioural similarity judgements such as the ‘odd-one-out’ triplet task. Overall, the results suggest that a combination of shape-related features are crucial for decoding object identity in both brain and behaviour, and that for ambiguous objects, these features are often overlapping.

One of the key findings of Schmidt et al. (2017) was a separation between animals/ plants and minerals, which we replicate and extend here, showing that criteria for judging minerals is more liberal than for plants and animals, and that minerals are most distinct in patterns of neural activity ([Figure 5.2A](#)). In the rapid classification task, participants were more hesitant to classify images as animals and plants compared to minerals. Schmidt et al. (2017) offer several reasons for this distinction of minerals from plants and animals, including that minerals may have a weaker set of defining characteristics than animals/ plants, that the defining features of animals/plants (e.g., eyes/ green colour) are absent in these ambiguous stimuli, or that minerals are perceived more like a ‘material’, texture, or substance than a distinct entity. EEG decoding shows that this separation is reflected in neural activity as well, with decoding of true minerals compared to plants/animals showing very similar temporal dynamics to decoding of true class in both tasks but especially in the fixation monitoring task.

The distinctiveness of minerals in both brain and behaviour seems to favour a model of ‘aliveness’ as opposed to animacy. Though typically animacy is strongly represented in the brain,

findings on aliveness have been more mixed. Some studies suggest that aliveness is a stronger correlate of brain activity than animacy (Contini et al., 2020), while others indicate its importance in behaviour but not in explaining brain representation differences (Jozwik et al., 2021). The applicability of an animacy model compared to a ‘living’ model may be dependent on the stimulus set, as Contini et al. (2020) also included toys and robots which may decrease the accuracy of the animacy models. Here, many of the images were unidentifiable because they are camouflaged. As this kind of disguise is typically for either self-preservation or hunting, it may involve hiding any features associated with being alive. For example, many camouflaging animals resemble plants so they can appear as part of the surroundings to predators, and thus do not have visible animal-like features such as a face. This may be another explanation for why minerals are the dominant response for behavioural classification; the plants and animals are often disguised as minerals, and this thus becomes the most obvious category in the stimulus set which participants can use to inform their decisions. As Schmidt et al. (2017) highlight, it is also possible that the minerals simply have looser ‘defining’ features compared to plants and animals and are therefore the default classification.

Correlations with the perceived class remained after partialling out the variance explained by the mid-level feature models ([Figure 5.3B](#)). Studies that have used inanimate and animate stimuli matched for shape have generally found that category is still decodable from neural activity, and suggested that the remainder can be attributed to categorical information (Proklova et al., 2016). Here, we can decode the perceived object category, suggesting that there is some factor beyond each of the features individually. This could be some integration of the visual features but could also be use of conceptual knowledge to parse the visual information available. Partial correlations also remained significant for the fixation monitoring task, suggesting this integration occurs even when it is not task relevant.

As Schmidt et al. (2017) found for behavioural classifications, we also found that no single feature was superior in terms of correlation with brain activity or with behavioural similarity judgements. Instead, a cluster of features related to global silhouette shape seem to be the most

relevant for both the brain and behaviour. Though the model based on only the silhouette shape (Jaccard) is not informative for the true class of the object, it is one of the top two correlates of both similarity judgements and brain activity. This dominance of shape in object perception fits with recent primate work showing that primate cortex is organised according to spikiness and stubbiness, or differences in the aspect ratio of an object (e.g., a trombone or toothbrush is more spiky and a digital camera or jam jar is more stubby) (Bao et al., 2020). The ambiguous stimuli here seem to also be processed by the characteristics that are most helpful in discerning animals and plants from minerals in Schmidt et al. (2017), suggesting object shape is an important factor in both behavioural and neural processing of objects. This emphasis on shape may have been increased in the current study by using images of objects without backgrounds or context, and future work should investigate whether it is still as prominent a factor in images with backgrounds, in natural environments.

The similarity model from the ‘odd-one-out’ task was a good model of brain activity, particularly for the classification task ([Figure 5.5D](#)). More importantly, when visual features were included as covariates in the correlation, the partial correlation remained significant for a short period of time between 150ms and 300ms after stimulus onset. This remaining significance suggests that there is some factor beyond those accounted for by the mid-level visual features used here that participants are using to make their similarity judgements, similar to, but slightly later than, the perceived class model. This could be the same integration of knowledge, as discussed above, but used to make similarity judgements based on perceived category.

The correlations between neural activity and CORnet suggest that most processing is occurring at the level of visual features rather than abstract concepts or categories. Though there are only scattered points of significant correlations for the IT layer, there are significant correlations with the V4 layer from approximately 100ms after stimulus onset, until around 350ms for the fixation monitoring task, and around 200ms for the classification task. This suggests that, unlike recognisable stimuli (e.g., in Chapter 3, [Figure 3.6](#)), which have strong correlations with IT, the ambiguous stimuli are primarily being processed at the level of the visual features.

While our findings suggest that visual features are important for perception in the absence of categorical information, we present them with a few important caveats. Firstly, the features we have used here from Schmidt et al. (2017) are by no means an exhaustive list. Rather than identifying which individual features are important, our findings seem to show that it is consistently *a similar* set of features that are used in both behavioural judgements of similarity and in neural processing, and these features are those that are most informative for both the predicted class of the object. Further, there is no individual feature that seems to be the single best across any of the domains, but rather, as Schmidt et al. (2017) showed, a collection of these features is necessary for classification.

Secondly, we note that the tasks here are specifically designed to bias processing towards a reliance on visual features. Participants viewed each stimulus for only 100ms, and classification decisions were time pressured. Both these factors may have increased the bias towards relying on overall shape to judge category. However, the behavioural classifications largely replicate findings by Schmidt et al. (2017), so it is also possible that the timing had little impact. Future studies should investigate neural representations with increased viewing time to clarify the importance of these design choices.

Overall, our findings suggest that mid-level features are crucial for classification in the absence of identifiable semantic features, and these same features also influence perception of similarity in the brain and unconstrained behavioural tasks. When the stimuli are disguised and the visual attributes that would normally be helpful in discerning class boundaries are misleading, a set of mid-level visual features is used to identify the predicted class, determine how similar that image is to others, and by the brain to process that image. Our findings suggest that the same set of features are used in both the brain and behaviour to distinguish between perceived classes of objects.

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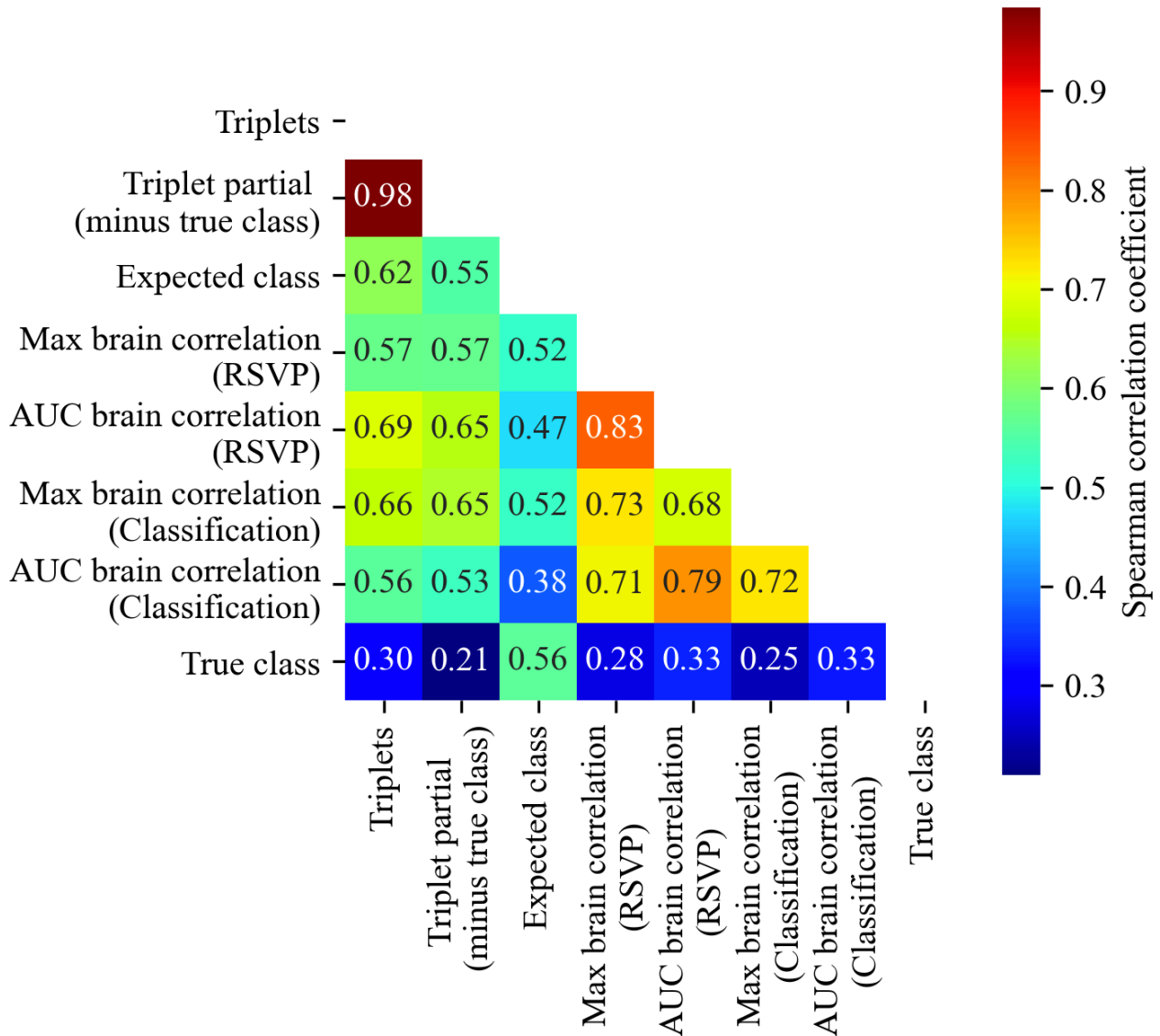
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Supplementary Materials

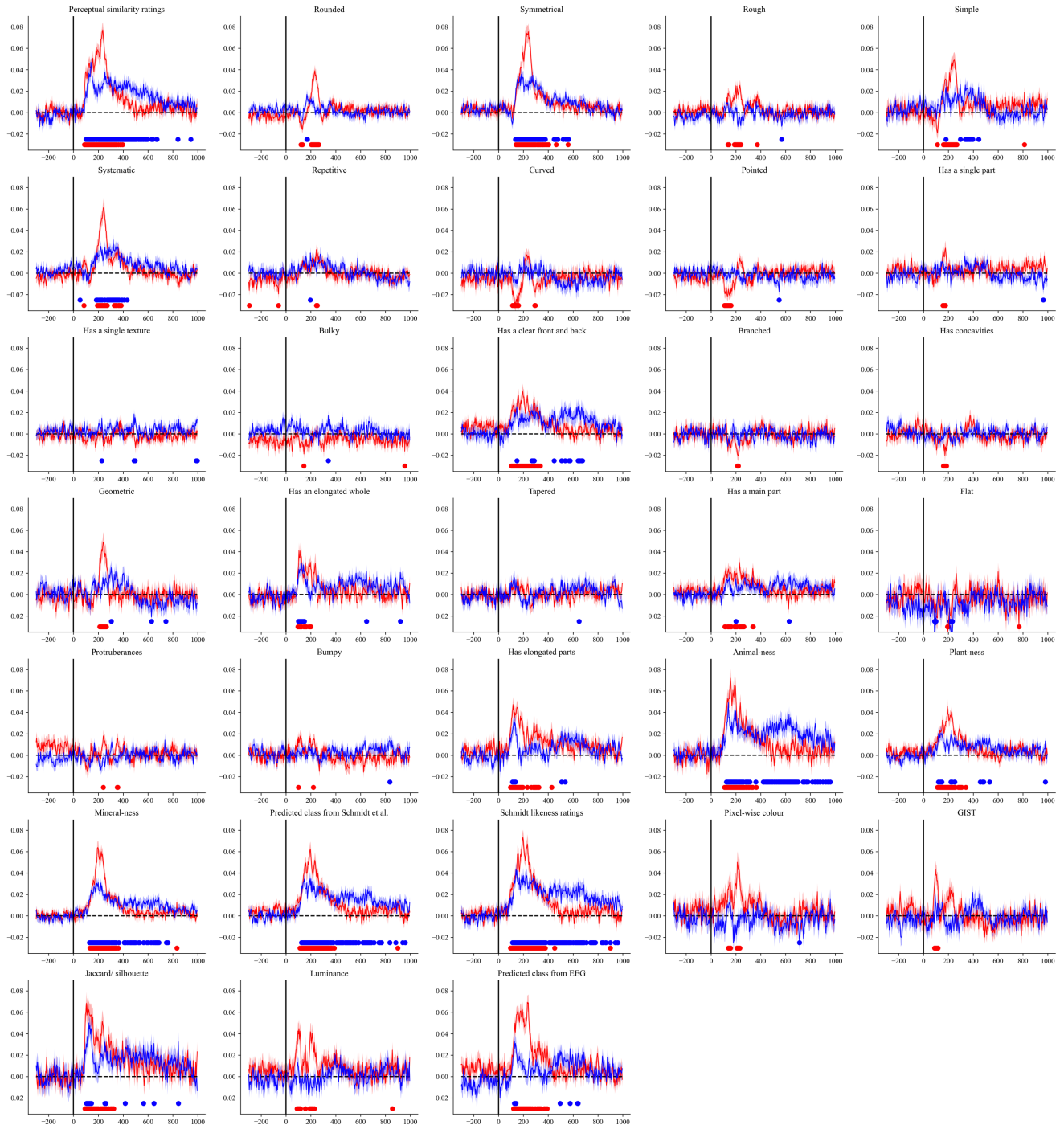
Supplementary Figure 5.1

Correlations between the different models of classification. Partial correlations labelled “Triplet partial (minus true class)” are a partial spearman correlation between the triplet model with the true class model included as a covariate. Two different indicators of the correlation between each model and brain activity are used, the peak correlation (“Max brain correlation”) and the total area under the correlation trace (“AUC brain correlation”), for both the RSVP task and the Classification task.



Supplementary Figure 5.2

All partial correlations between visual feature models and brain activity, with true class included as a covariate. RSVP streams are shown in red, and the classification task in blue. Bayes Factors larger than 10 are shown as filled dots.



Chapter 6: Object representations in the developing brain

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Abstract

Neuroimaging studies have shown that the adult human brain encodes objects according to higher-order dimensions such as animacy and similarity to humans. Much of our understanding of the neural basis of object recognition comes from studies in adults, yet children interact differently with the world. Preschool-age children tend to attribute characteristics of animate things, like thinking and feeling, to non-living things like robots. Despite these differences, there is limited information about how the developing brain encodes objects. To investigate how objects are represented in the developing brain, electroencephalography (EEG) was recorded in children aged 4 to 5 years old, as well as in young adults performing the same task. Both age groups were shown Rapid Serial Visual Presentation (RSVP) streams containing images of objects, including ordinary objects, such as animals, plants, and tools, as well as more ambiguous categories including robots or animal-shaped toys. To investigate how classification behaviour develops, both children and young adults completed an identical ‘odd-one-out’ task. Our findings suggest that category representations in preschool-aged children resemble those in adults, but there are subtle differences in categorisation of some more ambiguous categories like plants. Overall, using identical tasks in adults and children to facilitate direct comparison, the results provide an initial demonstration that object conceptions in preschool age children are already similar to adults in both behaviour and in the brain. .

Object representations in the developing brain

One of the defining characteristics of childhood is imaginary play, or interacting with toys and dolls as if they were alive (Mottweiler & Taylor, 2014; Taylor et al., 2004). Despite treating inanimate objects as if they were alive, children seem to be aware that these toys do not share characteristics with humans, such as being able to breathe or grow. This creates a kind of paradox: though conceptually children seem to understand the difference between animals and non-living objects, they interact with the world in a different way. The current study explored children's categorical understanding of the world by looking representations of different objects in the brain and in behaviour of children, and compare these representations to adults.

Though children seem to be able to differentiate between animates and inanimates very early in infancy (Rostad et al., 2012), they do not seem to form a 'living' category that is inclusive of plants until around age 6 or 7. Children rarely name or judge plants as alive (Carey, 1985; Hatano et al., 1993; Meunier & Cordier, 2004; Richards & Siegler, 1986), and often fail to attribute them properties of life, such as reproduction (Stavy & Wax, 1989). The acquisition of the concept of 'aliveness' seems to be associated with formal education. Recognition that plants are living substantially increases upon starting formal schooling between ages five and six (Martínez-Losada et al., 2014), and children are more likely to group plants with animals after being explicitly taught that plants can change trajectory to grow towards the light (Opfer & Siegler, 2004).

Despite poor performance on explicit categorisation tasks for plants, children's understanding of 'aliveness' may depend on how it is queried. Many studies have now shown that children have a remarkably good grasp of what makes inanimates different from humans, particularly in terms of biological and visual similarities. For example, children do not attribute animal properties to objects that resemble people, like dolls (Gelman et al., 1983), or mechanically moving toys (Carey, 1985). Specific properties of plants are also often understood correctly even when children don't classify them as alive. For example, many preschool age children understand that plants grow (Inagaki & Hatano, 1996), can heal themselves after being damaged (Backscheider et al., 1993), require

nourishment (Hatano & Inagaki, 2002; Inagaki & Hatano, 1996) and can die (Nguyen & Gelman, 2002; Waxman, 2005).

What children understand about aliveness, therefore, seems to depend on how they are asked. Some of the issues with plants, for example, may arise from a mis-understanding of the word ‘alive’ (Leddon et al., 2009). Anggoro et al. (2008) found that most children could correctly sort objects by whether they can grow or die, but children as old as 9-10 years old often claimed plants were not alive when they were asked explicitly. Children’s interpretation of the term ‘alive’ is also much broader than what an adult might typically consider. When Carey (1985) asked children to list things that were not alive, they commonly responded with things that are dead or extinct (e.g., dinosaurs), things that are imaginary (e.g., fairies), or with things that are representations of reality (e.g., people on television). The phrasing of determining whether something is ‘alive’ may also confuse adults, with 16% of undergraduates performing a speeded classification task based on aliveness reliably classifying plants as non-living (Shatek et al., 2022; [Chapter 3](#)). Thus, by around preschool age children may not explicitly correctly classify whether something is ‘alive’, but they attribute appropriate properties to them to show that they have some understanding of what it means, biologically, to be alive.

However, evidence on attribution of psychological characteristics is more varied. As children often use self-generated motion as a cue to animacy (Richards & Siegler, 1986), human or animal-shaped robots are an interesting edge case. Robots share many physical features with humans and animals, such as eyes, which children use as a cue for animacy (Jones et al., 1991; Martínez-Losada et al., 2014). While children rarely attribute biological properties (needing to eat, grow) to humanoid robots, they often attribute them psychological capacities like having thoughts and emotions (Jipson & Gelman, 2007), especially when the robot is seen to interact contingently with a human (Kim et al., 2019). Even when they judged robots as non-living, 6-year-old children claimed a robot had emotions (Nigam & Klahr, 2000), and older children aged 7-15 claimed that a robot dog could ‘feel happy’ (Melson et al., 2009).

In sum, while children have a reasonably good grasp of the biological attributes that link plants and animals, they do not seem to group plants with animals without further formal biological education, typically occurring between ages 5 and 8 (Slaughter, 2005). At this age, they are still developing an understanding of more abstract psychological attributes, particularly for edge cases like robots. One proposal to account for children's categorical structure is that children use similarity to humans to determine whether something is alive (Carey, 1985). When children make predictions about the biological behaviour of animals and plants, 5- and 6-year-old children often refer to how humans would react to a particular situation as a reference for making their decisions (Inagaki & Hatano, 1991). However, this 'similarity to humans' model is not particularly fine grained. Children do not group humans with primates, or even other animals. Instead, children often choose the human as the 'odd-one-out' when presented with images of a person, a chimpanzee and another animal (e.g., a centipede; Coley, 2007; Johnson et al., 1992)). There is also evidence that similarity to humans also guides adult perception and behavioural classification. Yorek et al. (2009) found that teenagers primarily associated the concept of life with humans, then animals, and then plants. For adults, the reliance on intuitive science increases when they are placed under time pressure, or the concepts are unfamiliar (Arenson & Coley, 2018).

This anthropocentric, or human-centric, thinking is also mirrored in the brain. Objects seem to be processed in the brain according to their degree of animacy (Connolly et al., 2012; Sha et al., 2014), or their similarity to humans (Contini et al., 2020; Thorat et al., 2019), Contini and colleagues (2020) examined the temporal dynamics of perception in adults using magnetoencephalography (MEG). Their stimulus set included recognisable common objects and animals, but also robots and toys as edge cases (which have attributes of animate features such as faces and limbs, but are not living). At later time points, the best correlates of neural activity were models of psychological similarity to humans, such as how much each item was conscious, could feel fear, desire, or pleasure, could think, and how similar it was to humans overall.

Both children and adults seem to use a human-centric model for understanding aliveness, and this is reflected in adult brain activity. Is it also reflected in the neural activity of children? Due to methodological difficulties associated with collecting neuroimaging data from preschool age children, very few studies to date have examined whether the same animacy/humanness spectrum that is present in the adult brain is also present in the developing brain. Though some work has been done with infants (Bayet et al., 2020; Xie et al., 2022), comparison to adults remains challenging because both age groups complete a different task. In the current study, 4- and 5-year-olds are compared to young adults using the exact same tasks and EEG recording equipment, increasing the validity of comparisons across age groups. In Australia, this is just before most children start structured education in primary school. Formal education may impact categorical structures, for example, in understanding which attributes of life plants share with humans (Martínez-Losada et al., 2014; Opfer & Siegler, 2004), so children were tested before this age. At this same age, an understanding of biological causal mechanisms are just starting to develop (Hickling & Gelman, 1995).

As we were particularly interested in children's responses to border cases, including plants, robots, and toys, we used stimuli from Contini et al.'s (2020) adult MEG study. To foreshadow, the 'odd-one-out' similarity task revealed that children have largely similar object categories to adults, though the EEG data showed no significant correlations between children's brain activity and higher-order psychological attributes associated with humanness. These results may suggest that representations of more abstract psychological attributes are more variable in children who are still developing an understanding of what it means to be alive.

Methods

Participants

To examine developmental object processing, both children and young adults completed an identical EEG experiment and a behavioural task. Each task was run with a separate group of participants.

EEG participants

The developmental EEG sample consisted of 19 children (12 males, 7 females) with a mean age of 4 years and 7 months (range 4 years and 1 month – 5 years 0 months). Children were recruited from the general public through the existing database of the developmental research group (Seedling Lab) at the University of Sydney, through Facebook advertising, and through flyers at local preschools. Parents filled in a pre-screening questionnaire and children were excluded if they had a history of seizures, head injury, or developmental delays. Parents gave consent for their children to participate, and children were asked for their assent at multiple stages of the study. Children were given a small toy or t-shirt upon completion of the study, and parents were reimbursed for travel costs with a fuel voucher.

The adult EEG participants were 28 undergraduate students, who participated in exchange for course credit. There were 11 men, 15 women, and two non-binary people, with a mean age of 20.89 (range = 18-32). In all analyses and plots forthwith, only the first 19 of these subjects are included to match the number of children. This sub-sample contains 11 men, seven women and one non-binary person, with a mean age of 20.57 (range 18-32). As the experiment only lasted 15 minutes when completed by an adult, participants completed the task in the same session as another unrelated EEG experiment which lasted approximately 30 minutes. All participants had normal or corrected-to-normal vision. Both verbal and written consent were obtained, and the protocol was approved by the ethics committee at the University of Sydney.

Behavioural participants

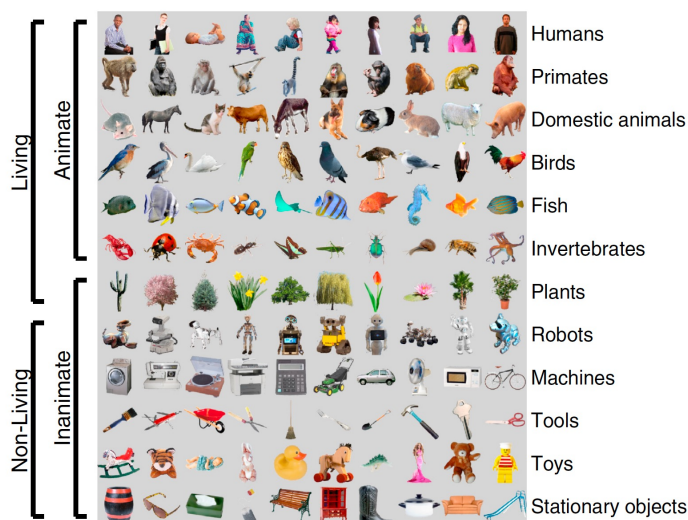
Children were recruited to complete the behavioural task on an iPad from public playgrounds in Sydney, Australia. Researchers supervised children to complete the task on an iPad. Written parental consent was obtained before starting, and children were asked for their assent and verbally explained the format of the task before participating. The task took approximately 5-10 minutes but this varied widely depending on the child's age. There were 100 boys and 103 girls, with an average age of 6 years and 10 months (range 3 years and 3 months to 12 years 9 months). Data from any child who completed more than 20 triplets was included, but most were able to complete all 100 triplets. Age distributions are shown in [Supplementary Figure 6.1](#).

Adult participants in the behavioural study were 77 undergraduate students at the University of Sydney, who participated in exchange for course credit. There were 14 males, 61 females, one non-binary person, and one who preferred not to disclose their gender, with a mean age of 20.9 (range 17-49). All participants indicated their consent online by choosing to advance past the information statement. Each participant completed 400 trials, and the task took approximately 20 minutes.

Design: stimuli

Stimuli were taken from Contini and colleagues (2020), who investigated how humanness was represented in the brain. This set was chosen because it contains an array of object categories in addition to some more ambiguous ones like robots and toys that might be confusing to children. The stimulus set contains 120 images, from 12 categories (humans, primates, domestic animals, birds, fish, invertebrates, plants, robots, machines, tools, toys, and stationary objects), with 10 objects in each category ([Figure 6.1A](#)).

(A) Stimuli from Contini et al. (2021)



(B) Similarity “odd-one-out” task



(C) EEG

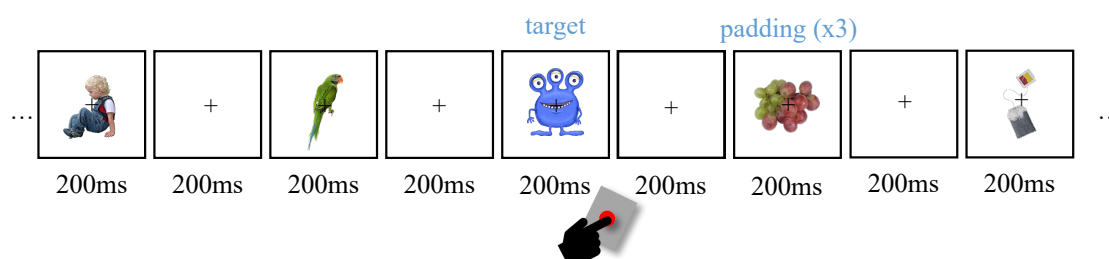


Figure 6.1

(A) Stimuli were 120 images from Contini et al. (2020), with 10 images in 12 categories. We collected data from both adults and children – similarity data and EEG recordings. (B) The similarity ‘odd-one-out’ task required participants to choose the item that did not belong within the set of 3. (C) In the EEG task, participants viewed an RSVP stream of images and pressed a button whenever they saw an alien. Each alien was followed with three padding images, which were excluded from the final analysis. Panel A is from Contini et al. (2020).

Design: EEG Experiment

The experiment was designed to be a ‘space adventure’, where participants travel through the solar system and catch aliens at each planet ([Figure 6.1C](#)). At each of eight planets, an RSVP stream containing all 120 objects was displayed, with between 8 and 13 aliens interspersed. Whenever participants saw the alien, they pressed a button. Pilot testing suggested that children often looked at the experimenter for affirmation after successfully catching aliens. As a result, three padding images were shown after each target alien, that were removed from all further analyses. Each image was

displayed on the screen for 200ms followed by a 200ms fixation cross. The whole task took approximately 15-20 minutes, which for some children was the absolute limit of attention and for others was not an issue. Children tracked their progress through the planets by placing a sticker on a sticker chart of the solar system at the end of each planet. Procedures during recording adults and children were matched as closely as possible. Adult participants were presented with an identical task but were able to advance at their own pace, with no sticker chart. Most adult participants completed the task in approximately 15 minutes.

Apparatus

Adults and children participated in different rooms with appropriately sized furniture, but with identical EEG recording set ups. EEG data were recorded using a gel-based 64-channel BrainProducts ActiCAP system (Brain Products GmbH), with active electrodes arranged according the 10-20 placement system (Oostenveld & Praamstra, 2001). Raw EEG data were recorded at 1000Hz, with an online reference of FCz. Stimuli were displayed at approximately 60cm on the 1920 x 1080 pixel Asus gaming monitor with a refresh rate of 60Hz.

EEG pre-processing

We used a minimal EEG pre-processing pipeline (Delorme, 2022), as in previous adult work. All EEG processing was completed using EEGLab (Delorme & Makeig, 2004) for MATLAB (2020a). Data were low-pass filtered at 100Hz and high-pass filtered at 0.1Hz, re-referenced to an average reference and down-sampled to 200Hz. Epochs were generated from 300ms prior to stimulus onset to 1000ms after stimulus onset.

Developmental data was noisier than adult data due to children's attentional constraints when applying electrolyte gel to reduce impedances. As performed in previous developmental EEG work, further pre-processing steps were also tested, such as removing or interpolating bad channels,

baseline correction, and removing bad epochs. However, none of these methods revealed substantial changes to the decoding, so the minimal pipeline was used.

Decoding

To explore how the temporal dynamics of the developing brain differ from the adult brain, we used a linear discriminant classifier to decode the category (e.g., human, toy) of images presented to participants. Pairwise analyses, with a leave-one-block-out partitioning structure, were conducted at the image and category level, as well as for animacy (plants grouped with inanimates) and aliveness (plants grouped with animals and humans). These results were used to create Representational Dissimilarity Matrices (RDMs) (Kriegeskorte et al., 2008) for each time point.

Correlations between brain activity and RDMs from Contini et al. (2020)

For their MEG study, Contini et al. (2020) created a number of visual and behavioural models. These models included visual models (Jaccard/ silhouette, HMAX, and shape), models based on the contemporary object recognition literature (animacy continuum, animal vs other, faces/bodies, object category, and variations on these models), and models based on ratings of characteristics associated with humanness (self-control, emotion recognition, desire, thought, shape, and overall humanness). To examine how these models relate to brain activity over time, we ran a Spearman rank correlation comparing each of these models with the neural dissimilarity RDMs at each time point. These analyses were all conducted at the image level, for which there were only 8 repeats of each image, so results were somewhat noisy. Analyses were repeated at the category level by averaging the visual and behavioural models down to the category level (12 x 12) and computing the neural RDMs using category-level decoding to ensure that the temporal signature was similar with increased power but less detail, with largely similar results.

Design: Behavioural similarity ratings (triplet task)

Procedure

To examine whether children had a similar object category structure behaviourally, compared to adults, both completed an ‘odd-one-out’ task (Hebart et al., 2020). Three images were presented on the screen, randomly arranged as either two on the top and one on the bottom, or two on the bottom and one above ([Figure 6.1B](#)). Adult participants were instructed to choose the ‘odd one out’, and prompted, as the children were verbally, to choose the one that ‘doesn’t belong’ on every trial, as piloting suggested this phrasing was easier for children to understand. Under each triplet was the prompt, “Which one doesn’t belong?” Children completed three practice trials, consisting of two identical or same category images and a different third image (e.g., two donkeys and a car), to ensure they understood the task before commencing. Researchers emphasised to children that there was no correct answer, but occasionally asked the children how they were making their decisions (e.g., “Why do you think that one doesn’t belong?”) if they seemed distracted or were moving very quickly. Adults were also asked at the end of the experiment if there were any particular strategies they were using to make their decisions.

The tasks were nearly identical for adults and children, with four minor exceptions: (1) adults completed 400 triplets each and children completed 100, (2) adults did not complete any practice trials and children completed three, (3) adults completed the task on a computer and children completed the task using an iPad, and (4) adults read instructions on the screen, and the task was verbally explained to children.

Calculating the similarity model

To explore which items were more ‘similar’ to each other, it is assumed that for each triplet, the pair of stimuli that are not the ‘odd-one-out’ are more similar than all the other combinations of pairs (Hebart et al., 2020). For example, if the participant was presented with images A, B, and C and chose A, then B and C are more similar than A and B, or A and C. For every pair of stimuli, we

calculated ratio of the number of times it was not chosen as the odd one out (i.e., left together, and therefore more similar) to the number of times it was presented. This generates ratings of similarity for each pair of images, where pairs that are more similar have a higher ratio than pairs that were more different. These similarity matrices are converted into a dissimilarity matrix by subtracting all values from 1 so higher numbers correspond to more dissimilar images and low numbers correspond to more similar images. Separate RDMs were created for adults and children.

Comparing the behavioural similarity model to other models

To compare the behavioural model to brain activity, we ran Spearman rank correlations with the behavioural similarity model and the neural RDMs at each time point, separately for each participant, and then averaged over all adults and children to get an estimate of how closely the behavioural ratings of similarity related to patterns of similarity in the brain. To investigate how participants were completing the task, correlations between each of the models from Contini et al. (2020) and our behavioural similarity model were run.

Statistical Testing

To test for statistical significance, we used Bayes Factors guided by Teichmann et al. (2022), implemented using the BayesFactor package for R (Morey et al., 2018) called from MATLAB (v2019a). For decoding analyses, decoding accuracy at each time point was compared to chance (for pairwise analyses, 0.5) using a one-tailed JZS prior (as only above-chance decoding is meaningful) with a scale factor of 0.707. These are the default prior and scaling in the BayesFactor package and “ttestBF” function, and serve as a “non-informative default” (Rouder et al., 2009, p. 232). For correlations with RDMs, we used similar calculations, but with a two-sided prior as both negative and positive correlations are meaningful. Bayes Factors can be interpreted as odds ratios. A Bayes Factor of 10 indicates that there is 10 times as much evidence for the alternate hypothesis that correlations are significantly different to the null hypothesis of zero correlation at that time point.

Bayes Factors above 3 are considered evidence for the alternate hypothesis, and Bayes Factors above 10 are considered strong evidence for the alternate hypothesis. Bayes Factors less than 1/3 are considered evidence for the null hypothesis (Jeffreys, 1961/1998). Onset of decoding is reported as the first time point with $BF > 10$ where the subsequent two time points also have $BF > 10$ (i.e., three consecutive time points).

Results

Good behavioural performance in alien detection task

Both adults and children performed relatively well the alien task in the EEG session, which was designed to maintain attention on the screen for the children. On average, children correctly identified 89.63% of the aliens (range 67.42% - 97.53%) and adults correctly pressed for 98.49% (range 91.14% - 100%) of the aliens.

Image, category, animacy, and aliveness are decodable from brain activity

To investigate the temporal dynamics of hierarchical processing in the brain, we looked at whether the image (e.g., dog, cactus), category (e.g., domestic animals, plants), animacy, and aliveness (plants included with animates) were distinguishable from neural activity over time. Despite the rapid presentation rate, image and category identity were distinguishable from 90ms in children and adults, with significant decoding extending to approximately 600ms for adults, and approximately 820ms for children ([Figure 6.2A, B](#)). Onset of category decoding was slightly delayed for children (105ms) compared to adults (85ms), with extended decoding and no clear peak.

Despite child data producing lower decoding accuracies in the image and category decoding, animacy decoding in children is of a similar magnitude to adults ([Figure 6.2C](#)). Animacy was distinguishable from neural activity from around 290ms in children, compared to 135ms in adults. Though aliveness was a good model of adult neural activity, with significant decoding from 115ms

after stimulus onset, for children there are only points of scattered significance later, around 500ms (Figure 6.2D).

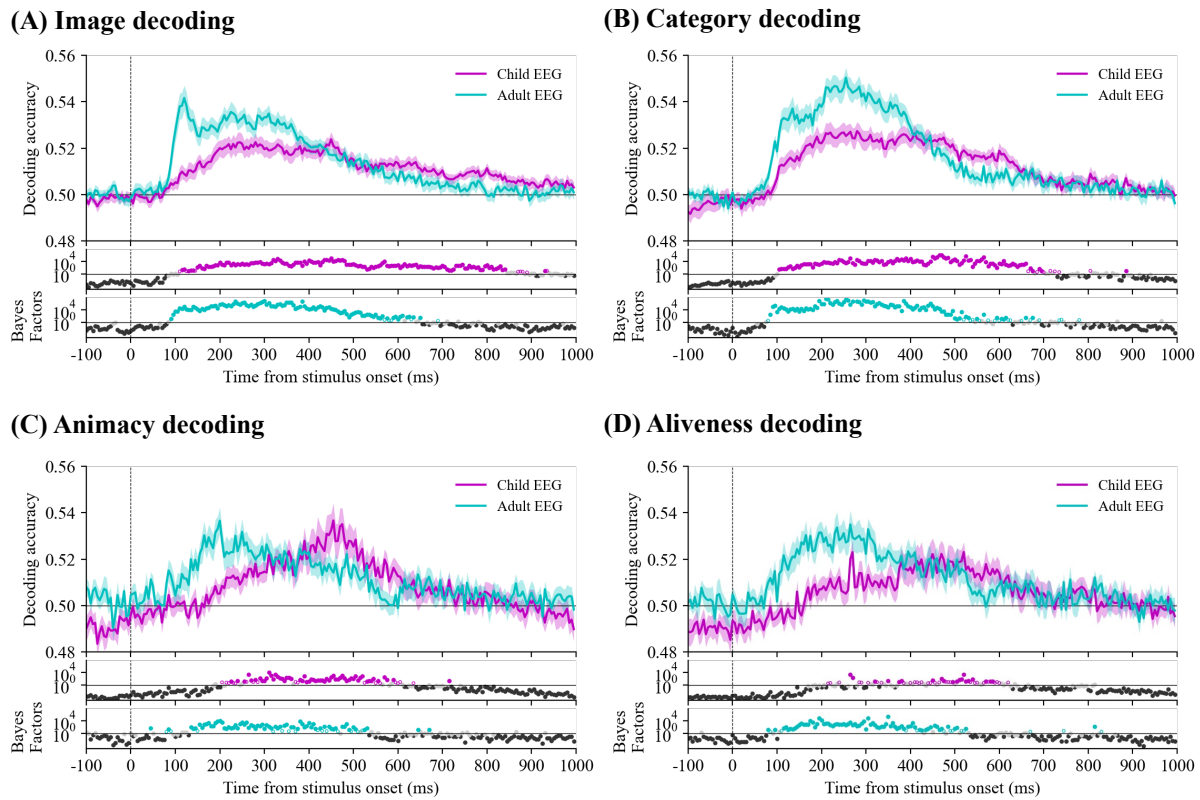


Figure 6.2

Decoding accuracy at different hierarchical levels of object classification for adults (turquoise) and children (magenta). Analyses were conducted at the image level (A; e.g., robot 1, human 2), the category level (B; e.g., robots, humans), for animacy (C) and aliveness (D; same as animacy, but plants are included with animals/humans). Shaded areas show the standard error. Bayes Factors shown under the plot are filled for $BF > 10$, outlined for $3 < BF < 10$, grey for $3 < BF < 1/3$ and black for $BF < 1/3$.

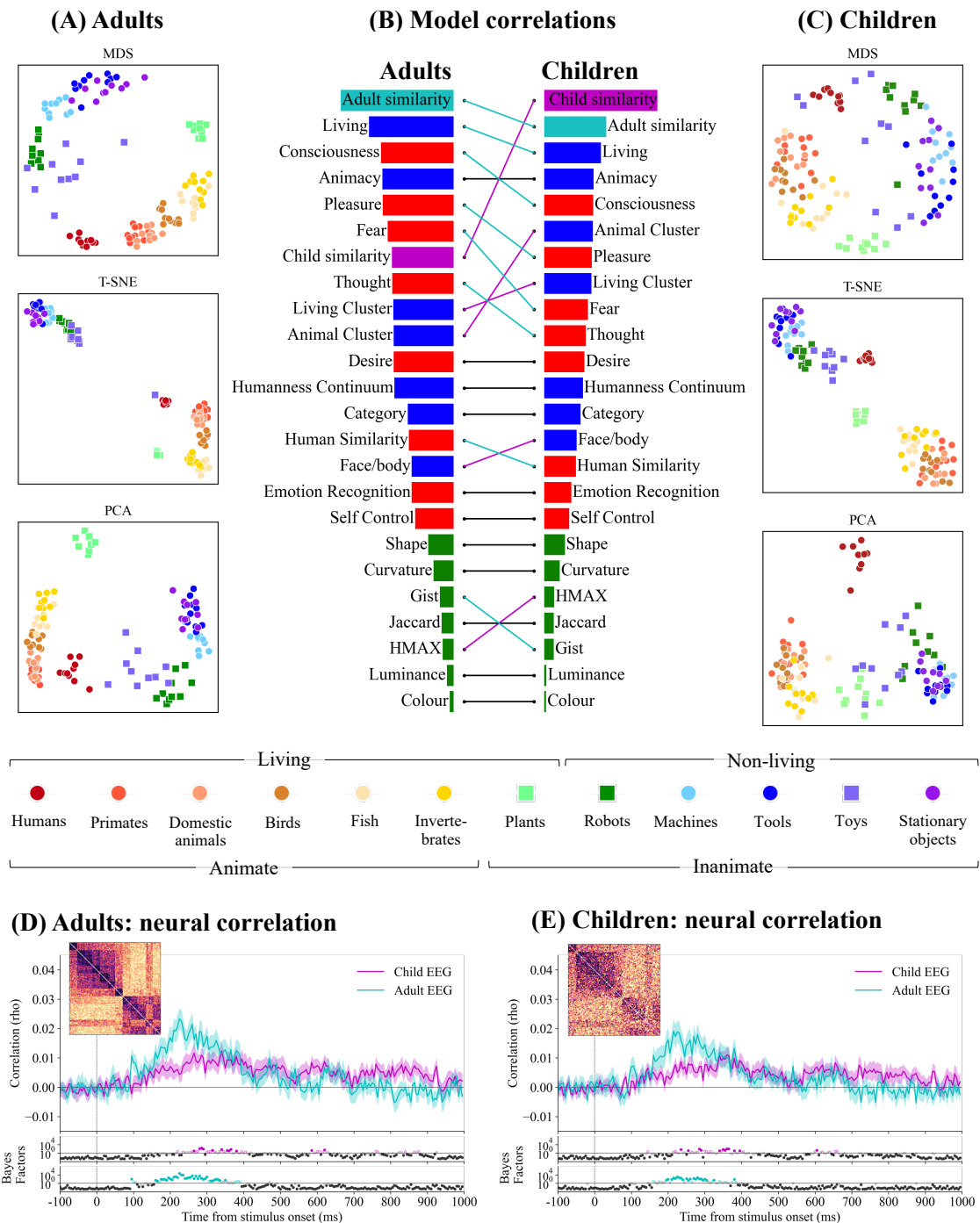


Figure 6.3

Categorical structure in adults and children was compared using the ‘odd-one-out’ task. This structure is visualised using three methods (MDS, t-SNE, and PCA) for adults (A) and children (C). Categories of theoretical interest (robots, toys, and plants) are shown as squares. The correlation between the similarity model and all other models is shown in (B), for adults on the left and children on the right. Visual models are in green, categorical models in blue, and humanness models in red. Correlations between the similarity model and neural activity are shown for adults (D) and children (E). Shading indicates the standard error. Bayes Factors shown under the plot are filled for $BF > 10$, outlined for $3 < BF < 10$, grey for $3 < BF < 1/3$ and black for $BF < 1/3$.

Both children and adults use a spectrum of animacy in similarity judgements

To qualitatively explore the relationship of different categories in the similarity judgements, the dissimilarity data was plotted in 2D using three different techniques, multi-dimensional scaling (MDS, [Figure 6.3A, C](#), top panel), t-distributed stochastic neighbour embedding (T-SNE, [Figure 6.3A, C](#), middle panel), and principal components analysis (PCA, [Figure 6.3A, C](#), lower panel). Though categories appear more clearly clustered for adults, this may be a function of the child data being noisier. In both adults and children, the toys (pale purple squares) appear closer to the humans (dark red circles) than all other inanimate/ non-living items. For the adults, the barbie doll (8th item in the toy row of [Figure 6.1A](#)) is very similar to the humans. A spectrum of animacy (Sha et al., 2014; Thorat et al., 2019) is also clearly shown in all three visualisations for adults, as well as children to some degree, from primates – domestic animals – birds – fish – invertebrates. Humans appear clustered separately from the other animates for the children, reflecting previous findings that children tend to separate humans from other animals (Johnson et al., 1992).

Different models explain the similarity judgements for adults and children

To explore the dimensions both age groups might have been using to complete the odd-one-out triplet task, we looked at correlation between the similarity judgements model and the models of visual, categorical, and humanness ratings ([Figure 6.3B](#)). For adults, the living model had the highest correlation to similarity judgements. For children, after the adult triplet model, the best four models were the categorical models, living, animal cluster (animals similar to each other, everything else dissimilar), living cluster, and animacy. Broadly, children seem to use the higher order attributes of humanness (red in [Figure 6.3B](#)) less than the adults.

Similarity judgements are a good model of adult brain activity

The correlation between behavioural similarity judgements and patterns of neural similarity revealed that the similarity judgements from both adults and children were a good model for adult

neural activity, from around 160ms for the adult behavioural similarity model and 210ms for the child behavioural similarity model ([Figure 6.3D, E](#)). However, neither behavioural similarity model had more than scattered points of significance with the child brain data, with a small cluster of significant points around 350-365ms for both behavioural models.

Children show no significant correlation with humanness models

Using the model RDMs from Contini et al. (2020), we examined the temporal dynamics of correlations between each of the models and brain activity for both children and adults. Given the relatively low sample sizes, these results are largely exploratory. For the visual models ([Figure 6.4A, B](#)), the luminance, colour and curvature models had very few points of significant correlation. For both adults and children, outline shape is a good correlate from around 110ms for adults and 165ms for kids. For children, but not adults, lower-level visual models GIST and HMAX also showed significant correlations at some time points between 200ms and 400ms.

Categorical models were also somewhat similar between adults and children in terms of timing ([Figure 6.4C, D](#)). The category model seemed to be the best for both adults and children, with significant correlations from 95ms for adults and 200ms for children. Though there were very few significant time points for the living model for children, adults showed a brief period of significant correlations between 200 and 350ms.

Compared to the relatively similar time course in the visual and categorical models, the humanness models were dramatically different between children and adults ([Figure 6.4E, F](#)). While the models generally showed some correlation between 200 and 450ms with the adult brain data, there were almost no significant time points for the child brain data. Possible explanations for this lack of correlation between the child brain activity and the humanness models are explored in the discussion.

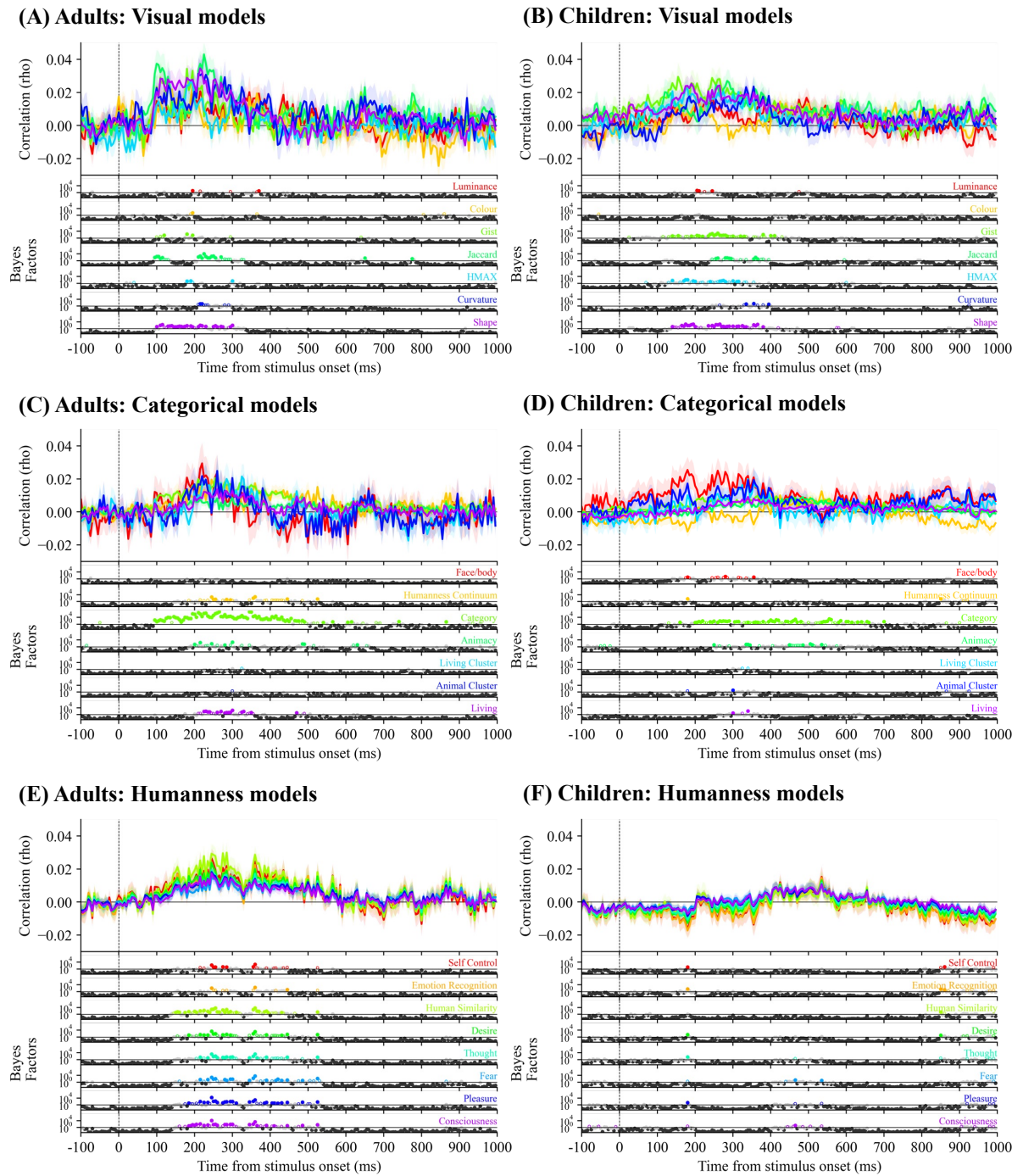


Figure 6.4

Correlations between representational dissimilarity matrices (RDMs) and brain activity are shown in the top panel of each plot, for both adults (left) and children (right), for visual models (A, B), categorical models (C, D), and humanness models (E, F). Shading indicates the standard error. Bayes Factors shown under the plot are filled for $BF > 10$, outlined for $3 < BF < 10$, grey for $3 < BF < 1/3$ and black for $BF < 1/3$.

Discussion

In the current study we aimed to explore object categorisation in the brain and in behaviour of both young adults and preschool aged children. Using two tasks that were common across both age groups, similarity judgements and the temporal dynamics of neural representations could be directly compared. Results revealed that children's categorisation behaviour largely resembles that of adults, but with some differences for toys, robots, and plants. Image identity, object category, and animacy were decodable from patterns of neural activity in both adults and children. Though visual and categorical models showed somewhat similar temporal dynamics in adults and children, there were differences for models of psychological humanness. Correlations with the psychological humanness models in adult EEG resembled those in Contini et al.'s (2020) adult MEG study, but there were no significant correlations with child EEG. This result is difficult to interpret given the low sample size and large variability in children. However, it may suggest that children lack higher-order representations of psychological attributes associated with animacy, or that these representations are highly variable and still developing in preschool age children.

Children and adults showed similar categorical organisation in the odd-one-out task, though category boundaries were less clearly defined in children. For animate stimuli, there is a very clear spectrum of humanness (Connolly et al., 2012; Sha et al., 2014; Thorat et al., 2019), particularly in adult behavioural judgements ([Figure 6.3A](#)) but also in children's behavioural judgements ([Figure 6.3C](#)). Curiously, primates appear more similar to the rest of the animals than the humans, for both children and adults (compare orange and red dots in [Figure 6.3A, C](#)). This separation of primates from humans has been demonstrated behaviourally in children using a similar triplet task. When children are told to pick the odd one out from a chimpanzee, human, and centipede, they rarely group the human and the chimpanzee together, no matter how dissimilar the other animal is (Johnson et al., 1992). In the current study, we replicated this finding: when children were presented with a human, a primate, and another animal, children chose the human as the odd one out in 67% of trials, the animal on 18% of trials, and the primate on 15% of trials. Adults pick the primate less frequently,

choosing the humans 64% of trials, animals on 32% of trials and primates on 5% of trials. Though less frequent than in the children, the fact that adults still chose the human as the odd one out around two-thirds of the suggests that some kind of intuitive biology is still present in adults. This provides further support for the idea of a humanness model in brain and behaviour, where humans are distinct from animals.

The models that explain variance in similarity judgements differed between adults and children. While children's classifications were better explained by categorical models describing life status and animacy, the life status model was the best for adults, followed by several of the humanness characteristics ([Figure 6.3B](#)). All models that were ranked higher for children than adults were categorical, and almost all models ranked higher for adults than children were humanness-related (except animacy and the humanness continuum). This is an initial indication that children's object concepts were primarily based on categorical and visual cues rather than the psychological attributes associated with being human. As expected, neither adults nor children were reliably using low-level visual features to determine similarity.

For the first time, as far as we are aware, we found that image, category, and animacy could all be decoded from patterns of brain activity in children, as well as from adults. However, the dynamics of the developmental data were slightly different between the adults and the children. Developmental decoding at the image and category level does not have a clear peak, and the onset is gradual ([Figure 6.2A, B](#)). Similarly, the onset of animacy decoding is gradual, and peaks later than the adult decoding. This more gradual onset and later peak may correspond to developmental changes in ERP components. Up until late adolescence, components thought to reflect sensory and cognitive processes have later peaks than their assumed adult equivalents (Thomas & Casey, 2003). The later peak for animacy decoding may also reflect increased variation within the child data, as individual decoding traces vary across children ([Supplementary Figure 6.2](#)), where the smoother curve reflects averaging over more varied timing. Increased individual variation could be a result of

lower signal to noise ratio in the child data resulting from limited set up time, or could originate from children's patterns of neural activity being more varied than adults as they are still developing.

One area where children did differ from adults was the correlations for models of psychological humanness from Contini et al. (2020). Children showed no significant correlations with models of psychological similarity to humans (e.g., capacity for pain, fear, thought). There are several possible explanations for the lack of significant correlation between the humanness models and child EEG data. The first, and in our view, the most likely explanation, is that the signal to noise ratio from a low sample size is insufficient to observe any regular patterns across children. One possible explanation is that children have not yet developed sufficient understanding of abstract concepts like the ability to feel and regulate emotions, and therefore these do not manifest in patterns of brain activity. More simply, it may be that children's brains are not processing objects at this more abstract level and primarily using physical or biological similarities between objects. Model correlations with behaviour ([Figure 6.3B](#)) also suggest that children rely more on these categorical similarities than adults. While children have a reasonable understanding of biological similarities between humans and animals or plants, they are often more confused by psychological attributes, particularly in robots (Kim et al., 2019; Severson & Carlson, 2010). Children often infer animacy based on typical animate features like eyes (Jones et al., 1991), suggesting a reliance on surface features as the basis for generalisation of more abstract features. In contrast to the absence of significant correlations with the psychological humanness models, correlations with some of the visual models that are composite summaries of low-level visual characteristics, GIST and HMAX, seem to be better models of the child EEG data than the adult data. Thus, it is possible that the neural architecture for object processing in the developing brain relies more on visual features, and that the abstract processing for more psychological properties is still developing. This may reflect an ongoing shift from reliance on perceptual features to more conceptual knowledge through development (e.g., Eimas, 1994). Correlations with neural network models of the visual system (CORnet; Kubilius et al., 2018, 2019) seem to support this notion, with models of V1 showing some correlation with

children's brain activity, and less to adults ([Supplementary Figure 6.3](#)). However, these should be interpreted with caution, as the correlations for both adults and children across all brain areas are low and noisy.

Alternatively, the human-like characteristics of toys and robots might be perceived differently by the children, decreasing the validity of the adult ratings as a model of brain activity, and/or increasing the noise in the correlations with these models. The stimulus set is specifically designed to include edge cases that share visual attributes with animate things (robots and toys), which might be understood differently by children. The toys and robots are a unique case because they have animate features but are not alive, and children seem to still be developing an understanding of their capacities (Nigam & Klahr, 2000). Across both age groups, robots are grouped with the inanimates/non-living things, but toys seem to be less of a coherent category and instead are more distributed according to the real-life object they represent ([Figure 6.3C](#)). For example, the female doll is similar to humans for both children and adults, and the animal-shaped toys are closer to other animals for children. It is also possible that the adult conceptions of which items are able to feel fear, pleasure, etc. differ from children, and therefore these models may not be a good fit for brain activity.

Finally, it is possible that the children do have abstract representations of the humanness characteristics, but that these are highly varied across children at different developmental stages during a period of substantial change. For both the decoding and RDM correlations, there was considerable variation between participants. Given the variation between participants ([Supplementary Figure 6.2](#)), this seems a likely explanation. Participants in the child EEG experiment ranged from 4 years and 1 month to 5 years 0 months, which is a crucial time in which understanding of many biological concepts. Previous work has shown that biological concepts such as what it means to be alive are developing at this age (Hickling & Gelman, 1995). Nguyen and Gelman (2002) found substantial differences between 4-year-old and 6-year-old children's understanding of whether plants can die. Similarly, Kim et al (2019) found that 3-year-olds and 4-year-olds were significantly more likely to claim that a humanoid robot was alive, compared to 5-

year-olds. This evidence suggests that significant changes in understanding of biological processes and life status occur around this 4- to 5-year-old range, which is why we chose this age to study. However, these changes may occur at different rates for different children, and thus representations of psychological humanness may be present but more variable in children. As the EEG data themselves are noisier due to the practical constraints of setting up children, it is also possible that the signal to noise ratio in representations of higher order concepts are more affected by noisy EEG data because they are less tightly constrained than some of the lower-level visual features. Future work with an increased sample size may be able to explore more individual differences.

As in previous work, there is mixed evidence on the merit of an ‘aliveness’ model compared to an ‘animacy’ model from decoding ([Figure 6.2](#)), from the RSA correlations ([Figure 6.4](#)), and from the visualisation of the behavioural similarity data. Though both animacy and aliveness had significant evidence for above chance decoding in adults, in children only the animacy model had a substantial period of above-chance correlations. As the difference between the living and animate models is the plants, this may be because children’s perception of plants as living things has not yet developed at age 5 (Stavy & Wax, 1989). Behaviourally, children seem to consider the plants further from living things than adults (compare the pale green squares in [Figure 6.3A and C](#)), placing them somewhere in between the animates and inanimates. This is particularly interesting, given our ‘odd-one-out’ task was unconstrained in terms of how they made the similarity ratings, so it is not subject to some of the potential linguistic or interpretation issues of asking children directly about whether things are alive (Leddon et al., 2009). Animacy, where plants are grouped with inanimates, seems to be a better fit for developing brain activity than aliveness, where plants are grouped with humans and animals.

Very few studies to date have looked at object representations in children, particularly using the exact same task to compare to adults. Here we demonstrate that both RSVP methods and the ‘odd-one-out’ triplet task are promising methods of gathering data among special populations with short attention spans like children. Recent work has shown that reliable decoding accuracies can be

obtained with just six repetitions (Grootswagers, 2023), and here we demonstrate that with eight repeats we are able to obtain reliable decoding for image, category, and animacy from adults in just a 15 minute session. Attention in children was highly variable, but most children could focus long enough to complete the task in around 20 minutes.

Overall, our results show that though children's categorical behaviour largely resembles adults by school age, there are marked differences in how children group plants, toys, and robots. Image, category, and animacy were decodable from patterns of neural activity in both adults and children. Though we replicated the correlations between more abstract models of psychological similarity to humans and neural activity in adults (Contini et al., 2020), there were no such correlations for children. Together, these findings suggest that behaviourally, children's processing of similarity between conceptual categories is comparable to adults. Further work is required to discern potential causes for the lack of correlation between children's brain activity and models of psychological humanness , with increased sample sizes.

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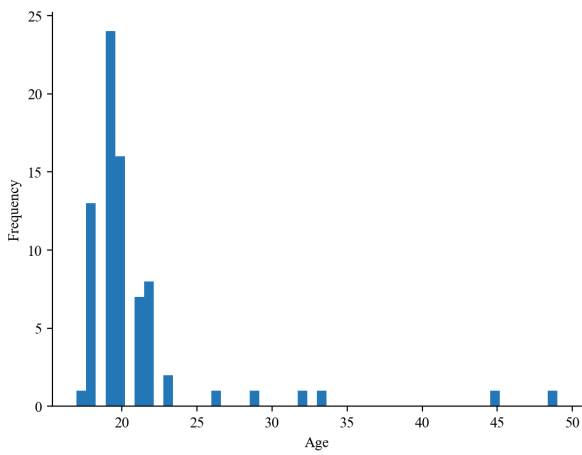
Yorek, N., Sahin, M., & Aydin, H. (2009). Are Animals 'More Alive' than Plants? Animistic-Anthropocentric Construction of Life Concept. *Eurasia Journal of Mathematics, Science & Technology Education*, 10.

Supplementary Materials

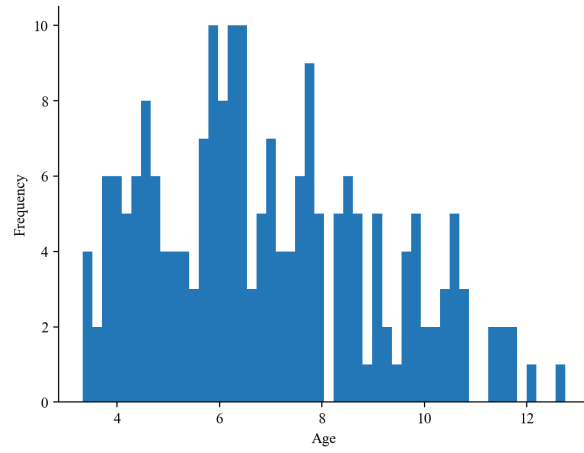
Supplementary Figure 6.1

Age distributions for the children and adult participants in the behavioural studies.

(A) Adults: Age distribution

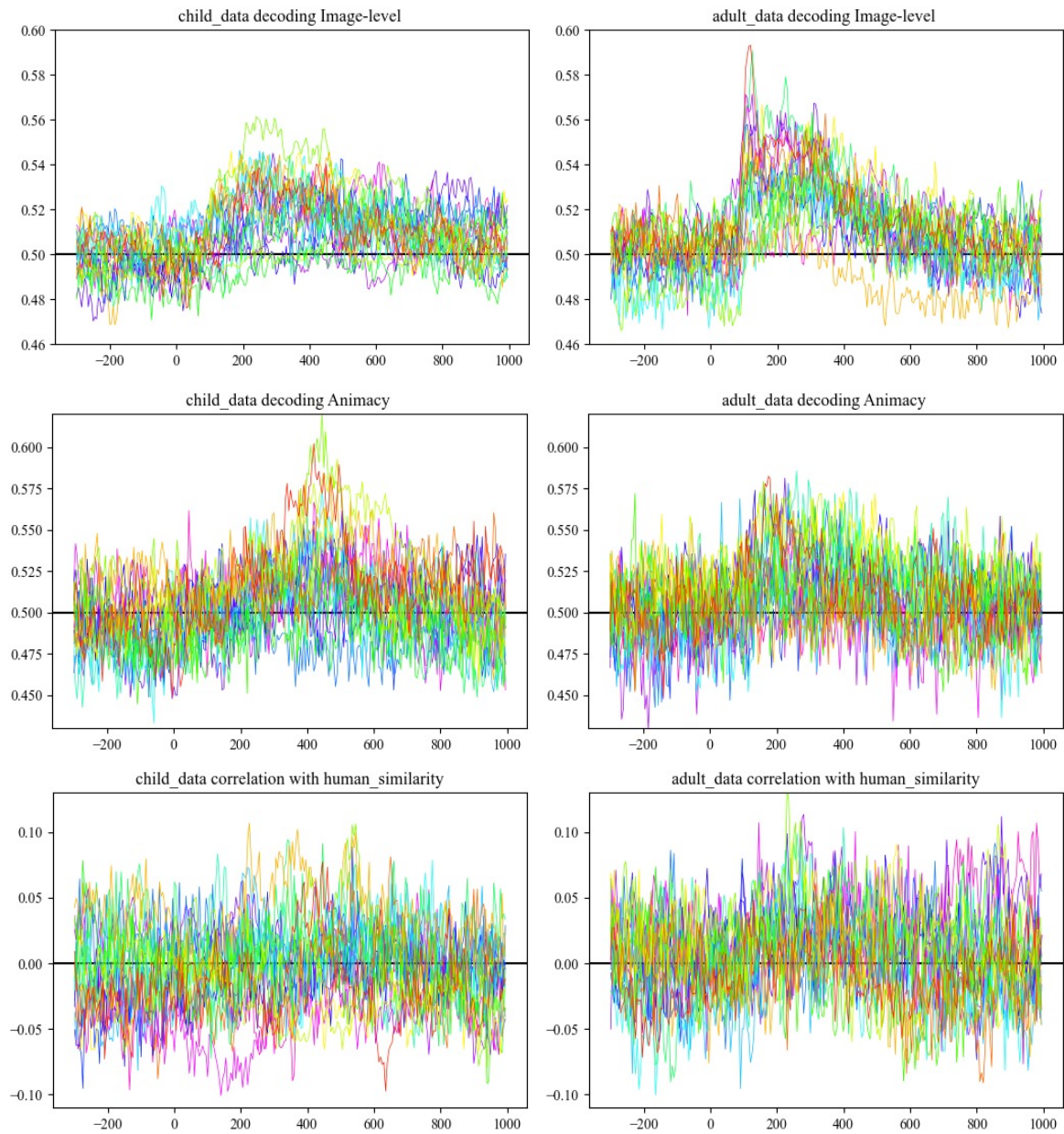


(B) Children: Age distribution



Supplementary Figure 6.2

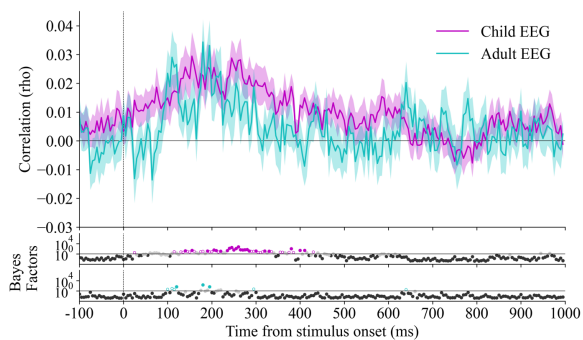
Individual subject decoding traces and correlations.



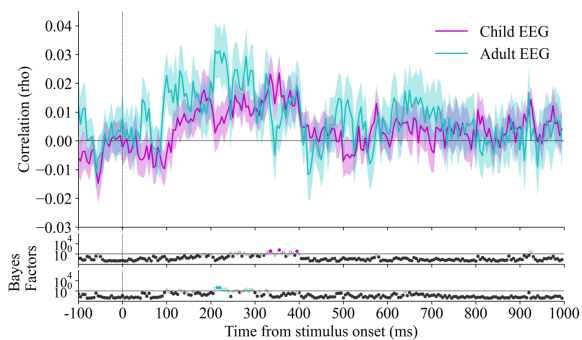
Supplementary Figure 6.3

CORnet activations for layers V1, V2, V4 and IT, correlated with both child (pink) and adult (turquoise) neural activity.

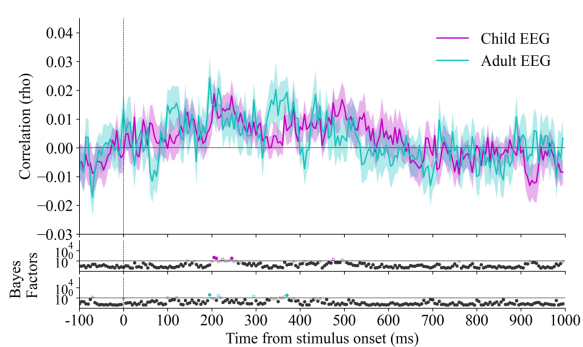
A) Cornet V1



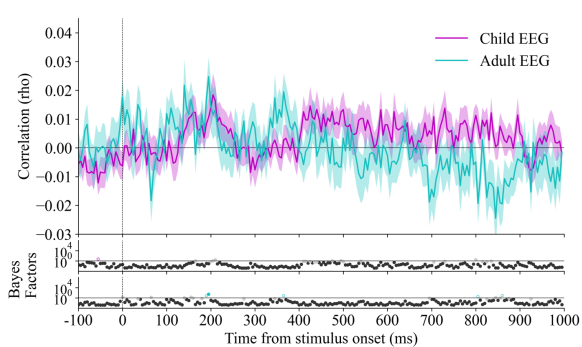
B) Cornet V2



C) Cornet V4



D) Cornet IT



Chapter 7: Overall discussion and conclusions

Understanding object categorisation through development: the influence of movement and other developmental heuristics on adult cognition

Over five empirical chapters, this thesis combined methods and ideas from cognitive neuroscience and developmental psychology to explore how development of categorical processing is reflected in the brain and behaviour of adults and children. We first addressed this question by looking at how developmental trends are reflected in adults. Across Chapters 2, 3, and 4, we collected EEG data from time-pressured aliveness classification, ratings of movement characteristics and ‘odd-one-out’ similarity judgements. Using both images and words, we showed that undergraduates make mistakes in classifying objects that violate the typical association between movement and aliveness: plants (which are alive but do not move) and moving natural things (which are not alive but move). These movement cues also seem to be encoded by the brain, both when they are relevant to the task and when they are not (Chapter 3). These neural representations of movement appear to correspond to an initial processing of overall movement speed, followed by more abstract attributes like whether the movement is independent (Chapter 4). These results suggest that processing an object’s capacity for movement may be an automatic part of object processing.

To investigate how object recognition in the brain changes through development, we directly compared adults and children by collecting EEG data and ‘odd-one-out’ similarity judgements from both ages, as well as using ambiguous objects to mimic the absence of conceptual knowledge in development. By using ambiguous objects in Chapter 5, we show that perceptual features, such as aspect ratio and symmetry, are sufficient to identify the true class of an object from brain activity, even when participants are unable to report which category it belongs to. Though patterns of behaviour and brain activity were very similar between adults and children, we found no correlation between children’s brain activity and abstract psychological properties at preschool age (Chapter 6). Development, therefore, may involve a process of optimising the integration of perceptual features and conceptual knowledge, so these features are appropriately and flexibly weighted depending on the information that is available (Madole & Oakes, 1999).

The findings of this thesis have a number of important theoretical and practical implications. The developmental EEG study (Chapter 6) is one of few to directly compare adults and children who are completing the exact same task, and to include neural and behavioural measures. It is common in developmental research to make the task for adults more complex or longer (e.g., Bayet et al., 2020), which introduces more variables that differ between groups. The matched methods for both age groups allow us to make more valid comparisons between age groups. The ease of comparison points to the strengths of using RSVP and the ‘odd-one-out’ task for gathering data from populations with limited attentions spans. By using methods of cognitive neuroscience in a developmental context, and considering how development might inform adult cognition, we provide important insights for both our understanding of development and the processes of object recognition in the brain.

Our findings also have important implications for researchers creating stimulus sets to investigate object processing in the brain. Very few studies on object recognition even include plants, much less moving natural things. For example, the stimuli from the commonly used fMRI and MEG data from Kriegeskorte et al. (2008) and Cichy et al. (2014) contain all animate things that can move, and all inanimate things that do not move. Given that movement seems to be processed in the brain, and that our ratings of movement characteristics were sufficient to predict object class, future stimulus sets should consider including at least inanimate moving things, if not inanimate *natural* moving things to avoid confounding animacy with movement and naturalness. Recent trends towards studying objects within scenes, such as the Natural Scenes Dataset (Allen et al., 2022), may also improve the breadth of stimuli we are able to study in a more naturalistic manner, particularly for studying movement in the natural environment.

These findings can be summarised in two key theoretical takeaways. Firstly, our results support characterisation of development as a continuous process, which is reflected in both patterns of brain activity and in behavioural judgements. This process may involve a gradual transition from childhood to adulthood informed by increasing conceptual knowledge and attention to informative perceptual features. Secondly, an object’s capacity for movement may be an important feature for

judging aliveness and differentiating between categories of objects because it is adaptive, or because our concepts and judgements of aliveness are built upon a foundation of similarity to humans based on goal-directed movement.

Robust results across words and images

Results across all chapters provide evidence for an influence of childhood learning on behaviour. In Chapters 2 and 3 we found that adults responded more slowly and less accurately when classifying plants and moving natural things as living or non-living under time pressure. We also found that moving natural things are perceived to move independently. These pervasive difficulties

for plants and moving natural things were replicable using the same design and stimuli as Goldberg and Thompson-Schill (2009). More importantly, they were also replicable using images rather than words, and a different set of objects. The remarkably similar patterns of results across words and images for both aliveness classification and ratings of movement characteristics are shown in [Figure 7.1](#) and [Figure 7.2](#). Both stimulus sets in themselves have limitations; the words in Chapter 2 contain a large proportion of less frequent flower words, and the images in Chapter 3 show the moving objects in motion. Yet, the results are similar across both, suggesting that the results are attributable to some aspect of the categories themselves rather than any unique attribute of the stimuli or objects chosen within each category.

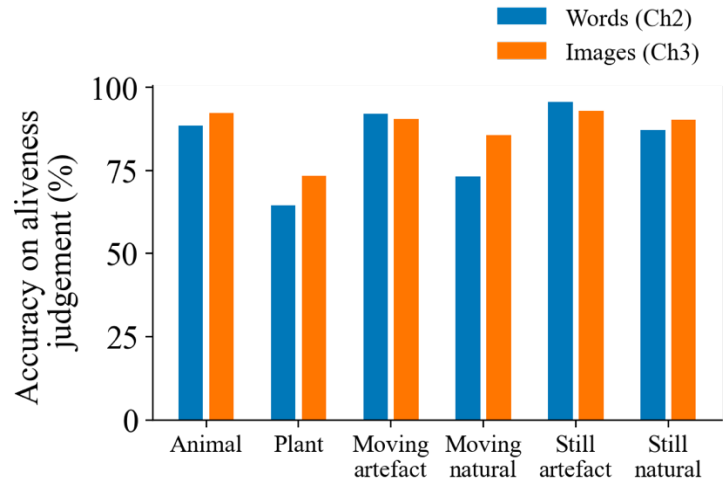


Figure 7.1
Comparing accuracy on the same aliveness classification task for the word stimuli in Chapter 2 (blue) and the image stimuli in Chapter 3 (orange)

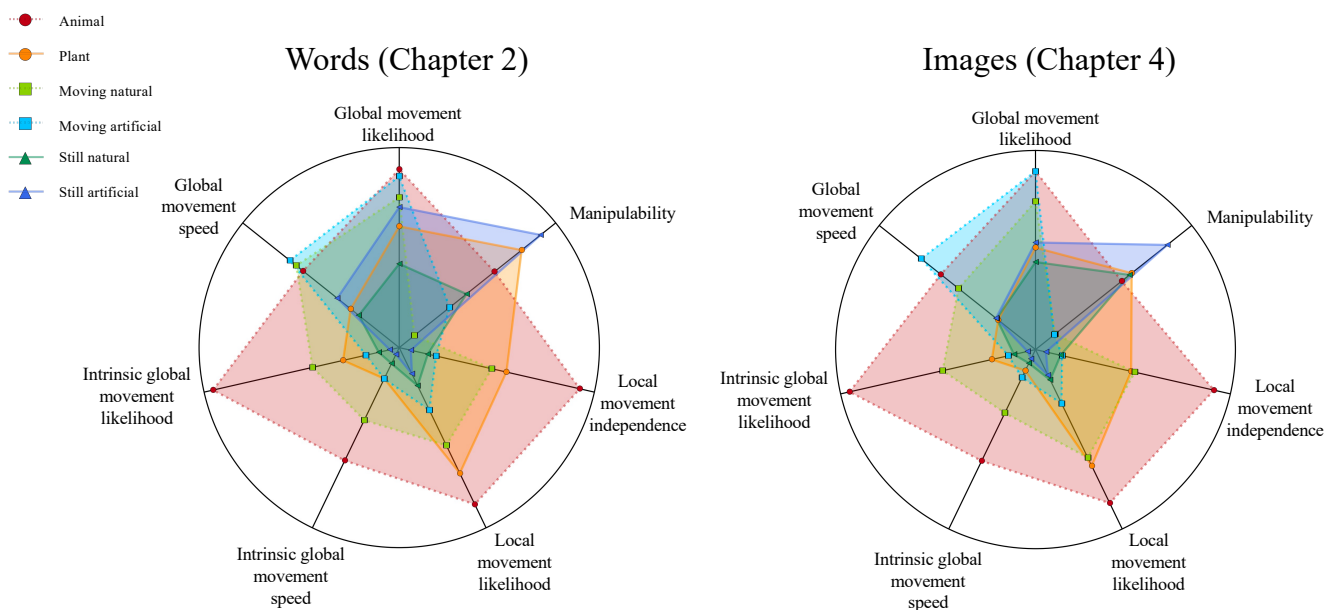


Figure 7.2

Comparing responses on the same questions about movement characteristics for word stimuli in Chapter 2 (left) and the image stimuli in Chapter 4 (right). Moving things are shown with dashed lines and still things with solid lines. Round markers are for living things, square markers indicate non-living moving things, and triangle markers indicate non-living, still things. Artificial things are in blue and natural in green.

Naïve biology influences adult cognition, even without time pressure

Most previous work showing teleological (assuming everything has a cause) and essentialist thinking (assuming things in the same category share some kind of underlying ‘essence’ that makes them similar) in adults involves rapid verification of statements for which naïve theories and scientific theories are contradictory, for example, “coats produce heat”, or “pressure produces heat” (Shtulman & Valcarcel, 2012). The fact that we see the same trends for judging aliveness, which is a scientific principle often taught early in formal education (particularly compared to areas like thermodynamics in the example above), suggests that perhaps judging aliveness is a more complex decision than it may seem. Making a scientific judgement on aliveness without a category label could involve integrating factors like movement, reproduction, growth, and energy production, not all of which are immediately visible. Being tuned early in development to a more visually salient attribute like movement could be adaptive, if it permits rapid decisions and appropriate responses in

threatening situations. Scientific naivete is unlikely to explain these errors on plants or natural forces, as many of the students had completed either high school or university biology, and most participants would have completed at least high school science classes to be admitted to the university. Reliance on these shortcuts can therefore be interpreted as evidence for the simplest heuristics, developed in childhood before acquisition of formal scientific knowledge, remaining active into adulthood.

Many previous experiments demonstrating how naïve science from childhood influences adult cognition use time pressure to elicit these errors from adults, and prevent access to scientific knowledge that contradicts these intuitions. However, participants in our studies report that moving natural things (e.g., fire, waterfalls) can move independently, even without time pressure. This is despite participants being explicitly instructed in both tasks to consider forces like gravity in their decisions, with an example of leaves falling off a tree in the wind. Participants in the online stimulus verification tasks of Chapter 3 completed the same aliveness judgement tasks without time pressure, and the results were very similar to those performed under time pressure in the EEG experiment ($p=.95$). Plants are rated as alive more often without time pressure, but they are still consistently rated as alive less often than animals. The use of shortcuts even when scientific knowledge is potentially accessible (without time pressure) suggests that reliance on simple intuitions and heuristics is more widespread than previously thought.

Alternately, it is possible that the reliance on easily and rapidly accessible intuitive scientific beliefs may be a quirk of testing undergraduates, who are awarded a pre-determined amount of credit for completing a study, based on the researcher's estimate of how long the study should take. In this system, students are motivated to complete studies quickly. If this is the case, they may simply not take the time to consider the more abstract or invisible forces that might be at play, effectively creating a form of time pressure or reliance on a mental shortcut. Some students may also have not spent sufficient time reading the instructions to use this information; a couple of students spent less than 20 seconds reading the instructions. Future research should expand the sampling to a wider population, and explore ways of discouraging preference for speed over deeper consideration.

By age 4 children are similar to, but not identical to, adults

Our results provide support for a continuous transition between childhood and adulthood where many of the shortcuts used in childhood continue to influence adult cognition in the absence of formal scientific knowledge. One characterisation of continuous development suggests that conceptual development can be characterised by an increase in conceptual knowledge over time, which refines attention to the most appropriate and informative perceptual features (Madole & Oakes, 1999). Our findings with ambiguous objects show that when objects were disguised and lacking in identifiable features, and there are no clearly category-specific features available (like eyes for animals or leaves for plants), visual features were sufficient to identify the true class of the object from patterns of brain activity (Chapter 5). However, these patterns did not translate into behaviour, as participants classified the majority of stimuli as non-living minerals. It is possible that a machine learning classifier is more sensitive to complex and subtle patterns of visual features than we can assess when under time pressure. Therefore, when the features we have learned are informative for differentiating animals, plants, and minerals (e.g., faces, legs) are absent, our behavioural classification system looks for other obvious patterns based on our experience, even when these are not necessarily correct. This suggests an important role for conceptual knowledge in translating feature correlations into behaviourally relevant information.

The lack of correlation for humanness models in children in Chapter 6 can also be interpreted through this lens, that visual features are sufficient to inform behaviour and correctly categorise stimuli, but the less observable features that are reliant on knowledge or experience are still being acquired. However, these interpretations should be considered in the context of the low sample size and low signal to noise ratio. Similarity judgements between adults and children were very similar, suggesting that by around age 6, conceptual knowledge is beginning to resemble that of young adults. However, patterns of neural activity were more difficult to interpret, as there was no correlation between brain activity in preschool age children and abstract features associated with

being human, such as capacity for fear. Similarities in brain and behaviour indicate that already by age 4 there are several similarities in conceptual structure, but that these are still not identical to adults, and that development continues into the early school years as more scientific knowledge is acquired.

Capacity for movement may be an important feature for categorisation

We found that capacity for movement is reflected in patterns of brain activity both when movement is task-relevant and when it is not. Why might movement be represented in the brain, and why might our decisions about aliveness be influenced by movement? One potential explanation is that processing capacity for movement is adaptive and may have promoted survival in our ancestors. It is also possible that our conceptual structure, particularly in judging what is alive or animate, is based on similarity to humans and includes consideration of goal-directed movement.

Associating particular categories of objects with their movement characteristics may be adaptive, as it allows for rapid calculation of how to appropriately interact with a given object. Some evidence suggests our attention is particularly tuned to detecting animals, but not other moving things like vehicles (New et al., 2007). However, these experiments are commonly confounded by naturalness, where moving things were either animate and natural (animals), or inanimate and not natural (vehicles). We found that participants see moving natural, but not artificial, things as having agentic movement, which may have helped promote survival of early humans in learning how to respond appropriately to unpredictable movement in the natural environment (Lowder & Gordon, 2015). It is possible that this unpredictable, agentic movement in both animals and moving natural things is the important signal for determining the appropriate actions. Neural representations of movement seem to correspond to this action-orientation; first the speed of the object is processed, then whether it is able to move independently. Future work should consider the degree to which predictability and perception of agency are similar concepts, and whether perception of predictability could explain why moving natural things are often perceived as living.

Movement might inform judgements of human similarity in behaviour

Movement may be important for object recognition because it provides information to help judge how similar a given object is to a human. Findings across several chapters support this human-centric concept of aliveness, like those proposed by Carey (1985) and Yorek (2009). Both children and adults perceive humans as their own separate category, and other living things are represented in terms of their similarity to humans. Moving natural things were perceived to have agentive movement like humans do and thus may be closer to the human prototype, so making decisions about aliveness is harder. This view of aliveness, which relies on movement as a key factor in judging similarity to the human prototype, can also explain findings on plant blindness, as plants are visibly dissimilar to humans, including in how they move and demonstrate agency (Schussler & Olzak, 2008; Wandersee, 1986; Wandersee & Schussler, 1999). Adults are less familiar with plant terms than other categories (Chapter 2), take longer to associate them with aliveness (Chapters 2 and 3), and often mistake them for not being alive (including the four undergraduates in Chapter 3 who claimed that plants were not alive). The fact that plants do not have global movement (Chapters 2 and 4) is one possible explanation for this neglect, as this places them further away from conceptions of aliveness based on similarity to humans, such as those proposed in the animistic-anthropocentric model (Yorek et al., 2009)

Movement might also inform neural processing of similarity to humans

Human-centric processing is also reflected in patterns of brain activity. As animacy can be characterised as a spectrum of agency or goal-directed movement (Connolly et al., 2012; Sha et al., 2014; Thorat et al., 2019), our results suggest that plants and moving natural things may fall somewhere in the middle of this spectrum. There is some evidence from linguistics that inanimate objects also “lie on a continuum of force creation” (Lowder & Gordon, 2015, p. 86), from natural forces which seem to be capable of creating their own energy, to tools which are dependent on an

animate agent to create force. This attribution of agency to natural forces is reflected in language, in the way that we describe forces of nature using animate adjectives (e.g., describing the seas as ‘calm’). Perhaps this spectrum of ‘inanimacy’ joins onto the commonly described animacy spectrum to encompass all objects according to their similarity to humans. This spectrum of animacy or humanness is shown clearly in similarity judgements of both adults and children in Chapter 6, from invertebrates to fish to birds to domestic animals and primates. For both adults and children, humans are perceived as separate to all other animals, even the primates, reinforcing the ideas of a human-centric understanding of living things.

In the brain, patterns of activity are often better explained by animacy than aliveness, though this does seem to depend somewhat on the stimulus set (Contini et al., 2020; Jozwik et al., 2022). The dominance of animacy-based models in the cognitive neuroscience object recognition literature suggests that while aliveness may seem like a simple distinction, it is not a natural one to form. Children do not typically spontaneously group animals with plants until formal education around ages 6 and 7 (Anggoro et al., 2005, 2008; Looft, 1974; Nguyen & Gelman, 2002; Stavy & Wax, 1989; Villarroel et al., 2017) and for both adults and children, plants are clustered separately to both humans and inanimate things ([Figure 6.3B](#)). Humans are also clustered separately to all the other animals and living things, suggesting that humans might be separate from animals and the basis for all the other judgements, as in Yorek et al.’s (2009) animistic-anthropocentric model.

Limitations

These conclusions must be considered in the context of several caveats. Firstly, the results are likely to be somewhat culturally and situationally specific. Conceptual structures, particularly in terms of understanding of the natural world, vary according to the environment a child grows up in, and individual experiences and expertise in adulthood. Children who grow up in more rural environments tend to show less anthropocentric (human-centred) reasoning than children in urban environments (Medin et al., 2010; Ross et al., 2003). For all studies in this thesis, participants were

primarily Western, educated, and English-speaking. All adult participants were undergraduate students at an inner-city university in Sydney, and though we did not collect comprehensive demographics on parents, most children were from the area close to the university campus and likely from upper middle-class backgrounds. It is possible that ignorance of plants for example, might be greater among our inner-city participants, as adults may have less regular exposure to plants. Indeed, we attempted to measure exposure to plants in piloting for Chapter 1, as a potential moderator in the aliveness task, but found that most undergraduates spent less than 1 hour a week tending to plants. Therefore, our work has limited applicability outside of this context. Future work should address how these results are similar across different language groups, environments, and cultures.

Though we attempted to cover several of the dimensions of movement used in previous literature, the characteristics included here are by no means an exhaustive list. Many other aspects of how we interact with objects, and more fine-grained distinctions are missing here. Though movement seems to influence judgements of aliveness and can help us to distinguish between categories, capacity for movement is merely *one* aspect that is relevant for behaviour and that is processed by the brain.

Though studying movement via still images and words can control for some of the visual confounds, these methods also have limited ecological validity, as objects in the real world are not 2-dimensional stills on a screen. Children perform differently on categorisation tasks with images compared to when they are able to interact with the physical toy (Oakes & Madole, 2003), suggesting that categorisation might be influenced by perceptual input beyond visual features (e.g., weight distribution). Future work can address more realistic vision contexts in more complex 3D environments, potentially using augmented or virtual reality.

Finally, the lack of correlations between psychological attributes of humanness and children's patterns of brain activity should be interpreted with caution. These exploratory results provide a clear demonstration of the benefits of study design where adults and children are able to perform the

almost identical tasks, but in the current state lack the power to generate clear conclusions. Future work should look to replicate these results with an increased sample size.

Conclusion

This thesis investigated how concepts develop from childhood into adulthood, and how this is reflected in both the brain and behaviour. It has explored how developmental trends affect adult cognition, and how perceptual and conceptual features interact to facilitate developments in object recognition from childhood into adulthood. The findings indicate that childhood cognition continues to influence the adult conceptual system, particularly in the seemingly simple task of determining whether something is alive. Items violating the association between movement and aliveness, plants and moving natural things, are more difficult to classify as alive. Capacity for movement is processed in the brain, and this may be characterised by first identifying the speed at which each object might move, followed by more abstract characteristics like how predictable or independent the motion is.

Despite sharing many characteristics of life with humans, plants do not share characteristics of global movement, and are thus further from a human-centric conception of what it means to be alive. While this human-centred understanding may be characterised in the brain by some visual statistical regularities like faces or legs, there is at least some abstract element of psychological similarity to humans that is still developing in children. Perception may be sufficient for classification in certain circumstances, particularly where there are no clear identifying features, but conceptual knowledge may also play a role in translating these patterns to inform behaviour. Future work is needed to address these results in a broader cultural context, and in a more naturalistic manner. Nevertheless, these results collectively point to a human-centric conception of our visual world based on agentic global movement, and clearly demonstrate the need for interaction between different areas of research in psychology.

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