NEURAL MECHANISMS OF VISUAL CATEGORIZATION

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‘Categorization is not a matter to be taken lightly. There is nothing more basic than categorization to our thought, perception, action, and speech. Every time we see something as a kind of thing, for example, a tree, we are categorizing’

(Lakoff, 1987, p. 5).

Remarks

Chapter 3.1 is published as “Do categorical representations modulate early automatic visual processing? A visual mismatch-negativity study.” by Ann-Kathrin Beck, Stefan Berti, Daniela Czernochowski, and Thomas Lachmann (2021, in Biological Psychology). Since the first experiment was part of the thesis (M.Sc.) of Ann-Kathrin Beck it is labeled *pilot study* in the following text.

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ABBREVIATIONS

“game” = category game

[game] = concept game

italics = important words

‘some’ = quotes

ACC	accuracy
ANOVA	repeated measure Analysis of Variances
AS	Asperger’s Syndrome
ASD	autism spectrum disorder
ASDS	Asperger’s Syndrome Diagnostic Scale
B	Bayes Factor
Bayesian 95 % CI	Bayesian 95 % credibility interval
cloglog	complementary log-log
CMS	Common Mode Sense
d’	d prime
DRL	driven right leg
DTI	Diffusion Tensor Imaging
EEG	electroencephalogram
EHA	(discrete-time) event history analysis
ER	error rate
ERP	event-related potential
ES	equivalence set
ESS	equivalence set size
FFA	fusiform face area
FG	fusiform gyrus
fMRI	functional Magnetic Resonance Imaging
HF-ASD	high functioning ASD
HR	hazard ratio
ICA	independent component analysis
IT	inferior-temporal
ITC	inferior-temporal cortex
ITI	intertrial-interval
IQ	Intelligence Quotient

LF-ASD	low functioning ASD
LORETA	Low-Resolution Electromagnetic Tomography Analysis
LPFC	lateral prefrontal cortex
M	sample mean
MMN	mismatch negativity
NT	neurotypical
OR	odds ratio
OTC	occipito-temporal cortex
PD	presentation duration
PFC	prefrontal cortex
PPA	parahippocampal place area
ROI	region of interest
RSVP	rapid serial visual presentation
RT	reaction time
SD	standard deviation
SE	standard error
TF-IDF	Term Frequency Inverse Document Frequency approach
V1	primary visual cortex
V2	secondary visual cortex
V4	visual area 4
V5	visual area 5
vMMN	visual mismatch negativity
VTC	ventral occipito-temporal cortex
WCC	Weak Central Coherence
WEIRD	Western, Educated, Industrialized, Rich, and Democratic

CHAPTER 1: INTRODUCTION

The ability to categorize is a fundamental cognitive skill for animals, including human beings (Murphy, 2002). Our lives would be utterly confusing without categories. We would feel overwhelmed or miss out on important aspects of our environment if we would perceive every single entity as one-of-a-kind. Additionally, we would need a unique name for each unique entity, making our language and communication incredibly complex (Smith & Mervin, 2013). For instance, to speak and understand languages, children need to stop differentiating among all experienced morphemes but continue only to differentiate among the ones that are relevant for their native language (Brown & Bebko, 2012). Therefore, categorization is of great importance for perception, learning, remembering, decision making, performing an action, certain aspects of social interaction, and reasoning (Foroni & Rumiati, 2017). The seemingly effortless and instantaneous ability to transform sensory information into meaningful categories determines the success for interacting with our environment (Hanson & Hanson, 2017). However, the apparent ease with which we use categorization and categories conceals the complexity of the underlying brain processing that makes categorization and categorical representations possible (Hanson & Hanson, 2017). Therefore, the question arises: how are categorical information encoded and represented in the brain?

Investigating different types of categorization is one method to contribute to our understanding of the brain processing that underpins categorization and categories. A detailed review about the existing literature on categorization and categories will be described in Chapter 2. Among others, categorization can be further understood by looking at research on cognitive divergence. More specifically, neurodevelopmental disorders in which divergences in categorization can be observed (i.e., autism spectrum disorder; Chapter 2.3). At the end of the literature review, the two sets of investigations as well as their research question and research objectives will be described (Chapter 2.4.3). The first set of empirical investigations aim to examine categorical representations of perceptual categorization in visual processing (Chapter 3). More specifically, these investigations examine whether perceptual categorical information can be encoded in early visual processes. In contrast, the second set of empirical investigations examine categorical representations of semantic categorization in visual processing (Chapter 4). More specifically, the investigations aim to inspect when and where more detailed information for semantic categorization is implicitly encoded. Following the two sets of investigations, the results of both will be discussed in a more general way and future directions will be described in Chapter 5. Lastly, the findings will be summarized in the conclusion (Chapter 6).

CHAPTER 2: LITERATURE REVIEW

2.1 CATEGORIZATION IN COGNITIVE SCIENCE

‘Categorization is the mental operation to sort any one element, object, or event into subsets’ (categories; Beck, Berti, Czernochowski & Lachmann, 2021, p. 1). This mental operation is vital in the construction of our knowledge of the world (Cohen & Lefebvre, 2017). Therefore, it is one of the most basic phenomena in cognition and it’s understanding a fundamental predicament in cognitive science (Cohen & Lefebvre, 2017). Cognitive science is concerned with human cognition, the underlying processes, and the modelling of these processes (Cohen & Lefebvre, 2017). To achieve a better understanding of human cognition, cognitive science comprises different disciplines. The founding disciplines of cognitive science are philosophy, cognitive anthropology, linguistics, cognitive computer science, psychology, and neuroscience (Miller, 2003). As categorization is one of the most fundamental phenomena and is studied across all founding disciplines of cognitive science, an abundance of definitions, theories, and models have been proposed by many authors.

First, I will describe the definitions of categories and categorization in the founding disciplines (Chapter 2.1.1), followed by some common topics shared by all founding disciplines: the types of categorization (Chapter 2.1.2) and the structures of categories (Chapter 2.1.3).

2.1.1 Notion of category and categorization in founding disciplines

Both the notion of *category* and *categorization* are investigated in the founding disciplines of cognitive science. Each discipline investigates this fundamental phenomenon in a different way with a focus on concepts, structural arrangements, grammatical categories, artificial system categories, cognitive processes, or the question of how the brain represents categorical knowledge (Cohen & Lefebvre, 2017).

Philosophy

Philosophy is the discipline that has discussed categories and categorization the longest. Both terms are closely intertwined with the term *concept*. A concept, in the classical view (Aristotle’s book ‘Metaphysics’ in Taylor, 1995), can be defined by (1) common properties that are necessary and sufficient for each instance of a concept (Smith & Medin, 2013). Note that the smaller units are interchangeably referred to as properties, features, properties, or attributes (Taylor, Devereux, & Tyler, 2011). Additionally, there are three more basic assumptions in this definition: (2) properties are binary, (3) concepts have clear boundaries, and (4) all instances of a concept have equal status. Euclid used this view to define arithmetic and geometric concepts (Rey, 2017). For example, Euclid's definition of a [circle] would have the properties of a 'plane figure bounded by one continued line […]; and having a certain point within it, from which all straight lines drawn to its circumference are equal.' (The Elements of Euclid, Book 1, Definition 15 in Byrne, 1847).

This classical view has been challenged and criticized, since not all concepts can be handled in this way, and new views have emerged (for a review see Goldstone, Kersten, & Carvalho, 2018). One of these views is expressed by Wittgenstein (1953). He observed that instances of the category [game] did not share common properties (e.g., can be played alone or with many; can be on a board, with cards, with a ball, etc.) but rather that all instances share some similarities. Wittgenstein used the metaphor of *family resemblance*, in which each instance shares common properties (i.e., characteristics) with some but not all other instances (Wittgenstein, 1953). Thus, instead of the conjunction of properties, instances can be based on the similarities of an exemplar instance of a particular concept. Not quite independent of these views is the notion of categorization (i.e., concepts do not coincide with categories). Despite of the diversity of views regarding categorization, one could say that concepts have multiple functions and categorization is one of them (e.g., as well as communication; Solomon, Medin, & Lynch, 1999). Categorization can be defined as the function involved in determining that a specific instance belongs to a concept (e.g., a creature as a [sparrow]) or that one concept is a subset of another (e.g., a [sparrow] as a [bird]; Medin & Smith, 1981). To put it differently, a category refers to a set of entities that are grouped together, whereas a concept refers to a 'mentally possessed idea or notion' (Goldstone et al., 2018, p.276). Thus, the category "bird" would consist of all entities in the real world that are appropriately categorized as birds, whereas the concept [bird] would signify the mental idea of birds. The question whether concepts determine categories or vice versa is an ongoing debate (Goldstone et al., 2018).

Cognitive Anthropology

Cognitive anthropologists contribute to the debate of determination related to categories and concepts since they investigate different human societies, implying a relation between society and human mind. Investigating cultural differences is of great importance for cognitive science, considering that most studies are conducted in western, educated, industrialized, rich, and democratic (WEIRD; Henrich, Heine Norenzayan, 2010) cultures. ‘A society’s culture consists of whatever it is, one has to know or believe to operate in a manner acceptable to its members […]; it does not consist of things, people, behavior, or emotions’ (Goodenough, 1957; 1965, p.36). Since this first definition by Goodenough, other anthropologists defined culture in any way they deemed useful, as long as the definition roughly corresponded to the original one (Boster, 2017). In the beginning, cognitive anthropologists limited their research to investigate the cognitive organization of linguistic responses, i.e., terms of the lexicon (Boster, 2017; Frake, 1962). To explore the semantic organization of lexicons, cognitive anthropologists use the method of componential analysis, and later also, for instance, the method of taxonomy, open-ended semantic networks, and methods from psychology (Boster, 2017). The most investigated topics are kinship, emotions, colors, and ethnobiological categories (Boster, 2017). For example, ethnobiology is the study of folk categorization of plants and animals (Boster, 2017). A folk-specific category might be defined as a category that does not include any other categories (Berlin, Breedlove, & Raven, 1966). With this definition, Berlin and colleagues (1966) observed in a study that 41% of folk categories consisted of more than one scientific species, 34% of folk categories were in correspondence with one scientific species, and 25% of folk categories were over-differentiated (e.g., “sweet corn”, “popcorn”, and “dent corn” all belong to the same scientific species “Zea Mays”). They concluded that there is no clear correspondence between folk categories and botanical species. Regardless of the topic of investigation, clear cultural differences in categorization were observed (Medin, Ross, Atran, Burnett, & Blok, 2002; Medin, Ross, & Cox, 2006). Overall, one could say that categories in cognitive anthropology are structural arrangements of the lexicon investigated and compared across cultures (Cohen & Lefebvre, 2017).

Linguistics

Rather than looking only at lexical subsets, in linguistics, categories are additionally defined as phonetic, phonological, syntactic, and semantic subsets of a language (Muysken, 2017). Language can be defined as a symbolic system (Taylor, 1995). The categories encoded in a language are motivated by entities in the real world, human interaction with the real world (in a particular culture), and by (the formation of) mental entities, i.e., concepts (Taylor, 1995). One way to investigate these subsets is by studying "phonemes", "nouns", "verbs", and "grammatical sentences". In doing this, 'linguists are undertaking acts of categorization' (Taylor, 1995, p. ix). Another way is to study the meaning of linguistic forms and which information these meanings entail for the categorization of the world (Taylor, 1995). Either way, in accordance with the classical approach of philosophy, a category can be described in terms of feature bundles (Taylor, 1995). Feature bundles are defined by a combination of properties (features; Cohen & Lefebvre, 2017). In addition to the basic assumptions of the classical approach in philosophy, phonologists added four additional assumptions: (5) features are primitive, (6) features are universal, (7) features are abstract, and (8) features are innate (Taylor, 1995). For example, according to Chomsky, there are four major lexical categories (Universal Grammar; Chomsky, 1970): "nouns", "verbs", "adjectives", and "pre-/postpositions". Each category can be defined by the combination of having (+) or not having (-) features of a "noun" or of a "verb" (+/- verb). With this definition, the categories "nouns" or "verbs" only consists of features of a "noun" (+ noun, - verb) or of a "verb" (- noun, + verb). However, the category "adjectives" consists of features of both a "noun" and a "verb" (+ noun, + verb), whereas the category "pre-/postpositions" consists of features neither of a "noun" nor a "verb" (- noun, - verb).

Computer Science

In computer science, the terms categories and categorization are used in data mining. Data mining is the process of retrieving, organizing, and summarizing information from large data sets (Sadiq & Abdullah, 2012). The most important – and challenging part – is the categorization of information or the process of assigning a given input to one or more categories (Sadiq & Abdullah, 2012), for instance, in object image categories (e.g., Babenko, Branson, & Belongie, 2009). A category is an artificial system which can either be constructed dynamically for a data set or prior (i.e., by a human or an algorithm) for a number of datasets. There are two main techniques to construct categories: information retrieval systems for dynamic categories and machine learning for categories set a priori (Basu, Walters, & Shepherd, 2003). Information retrieval systems use algorithms to cluster information (i.e., feature bundles). For instance, when categorizing text, this can be achieved by inspecting and weighting word occurrences. One popular way to weight words is via the Term Frequency Inverse Document Frequency approach (TF-IDF; Salton, 1987), proposing two assumptions to weight words in a text: multiple occurrences of a word in a text are more important than single occurrences and rare words are more important than frequent words. Thus, categories are constructed dynamically for each data set. A disadvantage of this system is that the constructed categories cannot be used for novel data sets.

On the other hand, machine learning systems use algorithms in which the information (i.e., feature bundles) defining a category is learned in a training data set. Learning in a training data set can either be supervised or unsupervised (Basu et al., 2003). When learning is supervised, the training data set consists of already categorized instances, whereas when learning is unsupervised, the algorithm determines the category of each instance (Basu et al., 2003). Thus, a category is defined a priori either by a human (i.e., supervised learning) or an algorithm (i.e., unsupervised learning). Since algorithms use examples and their similarities to construct categories, it can also be used for novel data sets. As both systems have advantages and disadvantages, different combinations of both systems have been suggested. For example, Babenko and colleagues (2009) proposed a two-step procedure for object categorization in which information retrieval algorithms cluster some simple categories and uses machine learning algorithms and training data to learn similarities. Nonetheless, Edelman (2009) emphasized that the fundamental problem of categorization in data mining lies in the assumption that any input is fully interpretable in terms of a finite set of discrete categories.

Psychology

Whereas computer science, linguistics, and cognitive anthropology focus on the content of a category, psychology focuses on the process of categorization. Like the philosophical view, in psychological studies, the term category is closely intertwined with the term concept. The concept constitutes tools for categorization (Cohen & Lefebvre, 2017) and establishes order in the environment through mental categories (Goldstone et al., 2018). Mental categories allow us to make sense of the world and predict how worldly entities can be used or will behave (Goldstone et al., 2018). Hence, categories might be based on perception (for instance, see Wertheimer, 1912) or might be defined as different sets of situations that emerge from interactions between an agent and the environment (for instance, see Gibson, 1979). One example of categories based on perception can be observed in Gestalt psychology (beginning with Wertheimer, 1912). 'Gestalt' is the primary unit of life and will be perceived before its subsets. The most general principle in Gestalt psychology (Wertheimer, 1923) is the *law of conciseness* (in German: Prägnanz), positing that objects within the visual field will be associated with the simplest structure (in each condition). Additionally, there are specific principles (like proximity, similarity, closure, common fate, continuity, and symmetry) that contribute to the mental representation of the Gestalt, e.g., of an object (for a review of empirical work on each principle see Vezzani, Marino, & Giora, 2012).

Criticism has been expressed regarding the original methodical and conceptual investigation of the principles (Wagemans et al., 2012). These shortcomings have been addressed (and partially solved) over the last decades (see Table 4 in Wagemans et al., 2012). However, one alternative approach which includes not only the perception of a human but also its environment, was proposed by Gibson (1979). In Gibson's account, the focus is shifted from mental representations of Gestalts to the examination of the environment in which something is perceived, i.e., adding the relation of a person-environment interaction (Heft, 1997). For example, in Gestalt psychology, the mental representation of a "chair" would be based on the perception and the associated principles, e.g., uniform density. In the ecological account of Gibson, a "chair" is an object of the environment with specific properties (e.g., can be used to sit on) in relation to an individual (e.g., must support the weight of an adult or child). Overall, categories can be considered as abstract forms of experience and therefore continue to evolve rather than being fixed (Cohen & Lefebvre, 2017).

Neuroscience

In neuroscience, researchers are interested in the nervous system and its mechanisms. Before the middle of the twentieth century, neuroscientists categorized brain structures and their different functions with an emphasis on localization (Finger, 2001). The Localization Theory is based on the biological assumption that structures which look different have different functions. One taxonomy still used today was proposed by Brodmann (1909), which dissociated different areas of the cortex (i.e., Brodmann's area) based on the structure of specific nerve cells. The research about categorizing different looking structures began with postmortem studies of the human brain in, for instance, ancient Egypt, Mesopotamian, ancient India, or ancient Greek (Finger, 2001).

2.1.2 Types of categorization

Across all founding disciplines of cognitive science, different types of categorization can be distinguished. Types of categorization refer to categorization based on recognizing category members due to encoded internal representations (for instance, Malt, Sloman, Gennari, Shi, & Wung, 1999), based on connecting category members due to meaning or words (for instance, Malt et al., 1999; Gillon, 2017), or based on inferring category membership due to knowledge structures (for instance, Quinn, Eimas, & Tarr, 2001). Each of these types of categorization will be discussed successively.

Perceptual categorization

Perceptual categorization refers to the processing and recognition of instances based on perceptual similarities with other instances or an internal category representation (Quinn et al., 2001). Perceptual similarities refer to shared perceptive properties that are deemed equivalent for a set of instances (Reznick, 2000). Perceptive properties can be based on one or multiple sensory experiences, like auditory, visual, tactile, olfactory, or/and gustatory experiences. The internal representation could also be called *categorical representation* (Quinn et al., 2001; Edelman, 1987). As a consequence of categorical representation, the similarities of an instance with category members as well as differences of an instance with category non-members are particularly salient (Cohen & Lefebvre, 2017). Perceptual categorization is observed as early as the first year of life (for a review see Haith & Benson, 1998), in many non-human species (for a review see Zentall, Wasserman, Lazareva, Thompson, & Rattermann, 2008), and in artificial systems (Nolfi & Marocco, 2002; Poirier, Hardy-Vallée, & DePasquale, 2017; Caplette, McCabe, Blais, & Gosselin, 2017). For example, the perceptual categorization of an instance to the category "kiwi fruit" is based on perceptual properties, like it's ovoid shaped, specific size, brown and hairy outside, green inside and so on.

Semantic categorization

Semantic categorization refers to categorical representations that are based on meaning (or usage) (Gillon, 2017) or words (Quinn et al., 2001). The latter refers to the connection of instances of both the production of a name for an instance and the understanding of a name used by someone else (Malt et al., 1999). Either way, the semantic(-lexical) categorization is culture-bound and varies over time (Clark, 2017). For example, a traditional English *"teacup"* 'has a handle' whereas a traditional Chinese *"teacup"* (in Chinese: 茶杯 / Chábēi) 'has no handle'. Semantic categorization diverges from perceptual categorization, since many perceptual features might be overlapping (Malt et al., 1999). To put it differently, perceptual experience does not provide all categories that are represented semantically (Clark, 2017). For example, the semantic categorization of the instance 'container that holds liquid' might be based on the usage, e.g., 'containing coffee' (i.e., "coffee cup") instead of 'containing tea' (i.e., "teacup"). Hence, even though both containers might have the same perceptive properties, they have different semantic representations. Semantic categorization seems to be only observable in humans and infants with linguistic abilities (Sloutsky, 2010; Quinn, Eimas, & Rosenkrantz, 1993).

Conceptual categorization

Conceptual categorization refers to categorical representations that are based on knowledge structures (i.e., concepts; Quinn et al., 2001). These knowledge structures are important components of thought for inductive inference, communication, and cognitive economy (Goldstone et al., 2018). Inductive inference not only refers to the abstraction of information (e.g., "cat" as "living being") but also to the creation of categories that were not yet established (e.g., "living on mars") or to the engagement in abstract category-based inductive reasoning (Sloutsky & Fisher, 2011). The term cognitive economy is used to describe the economic advantage of encoding and storing categories rather than all information about specific instances (e.g., “blue” instead of all spectral wavelengths between 450 and 500 nm; Goldstone et al., 2018). Note that knowledge structures do not need real-world counterparts (e.g., “unicorn”; Medin, 1989). Consequently, the similarities of instances in conceptual categorization are based on abstract properties, which do not share obvious perceptual or semantic features (Reznick, 2000). However, the definition of conceptual knowledge structures is not agreed upon in the literature (Sloutsky & Fisher, 2011). Neither is there an agreement on the influence of perceptual categorization on conceptual categorization (vice versa, or none). For instance, some approaches suggest conceptual categorization might emerge from perceptual categorization (i.e., Knowledge-based approach), whereas others suggest that both types of categorization are independent (i.e., Coherence-based approach; Sloutsky & Fisher, 2011). In addition, semantic categorical representations do not seem to be mapped onto conceptual representations (Clark, 2017). In more detail, the conceptual categorical representation of the category “cat” includes properties that must be inferred (e.g., ‘vision of a cat’, Sloutsky, 2010). However, the lexicalization of abstract properties allows nontrivial generalizations (e.g., ‘plants and animals are alive’, Sloutsky, 2010).

Conceptual categorization of prelinguistic infants is a matter of debate (Sloutsky, 2010) with two contrary opinions. On the one hand, some researchers suggest that prelinguistic infants have a rich inventory of conceptual categories that are innate and universal (e.g., space, quantity, causality, agency, and animacy; Clark, 2017) and these are not thought to change throughout human development (Papafragou, 2017). On the other hand, some researchers posit that prelinguistic infants do not have conceptual categorization representations but are rather able to discover the presence of similar and dissimilar events, without any higher order cognition involved (e.g., “kitchen utensils” as ‘everything that is in a kitchen’, Reznick, 2000). However, changes during development due to language acquisition or changes of mental states are observed, hence conceptual categorical representations undergo changes (Papafragou, 2017) and, for instance, knowledge structures become more abstract (e.g., instances in the category “happiness” might be more abstract for an adult than for a child; Madole & Oakes, 1999).

Taken together, the categorization of instances can be context dependent (Clark, 2017). For example, an instance can be perceptually categorized as ‘made of white ceramic, has a handle that can be grasped with one or all fingers, and has a decorated pattern imprinted’, can be semantically categorized as “teacup” or can be conceptually categorized as “a container that holds tea”. Thus, categorical information might rely on multiple representations (Gentner & Goldin-Meadow, 2003; for more information see Chapter 2.2.1)

2.1.3 Structure of categories

As may have become obvious in the definitions of categories and categorization across the different founding principles of cognitive science, there seems to be a distinction between categories with discrete, well-defined or vague, ill-defined structures. Both structures will be discussed successively.

Well-defined structure

Members of a category with a discrete, well-defined structure are categorized based on all critical features that are singularly necessary and jointly sufficient (Nakamura, 1985). Hence, whether an instance is a member or not is well-defined (Bourne, 1966) by clear boundaries, which separate category members from non-members (McCloskey & Glucksberg, 1978). All category members should be equally representative for a category (Nakamura, 1985). For example, a well-defined category is the biological taxonomy of “dolphins”, with a critical feature ‘being part of the parvorder Odontoceti’ (also called toothed whales). The categorization of an animal as a dolphin is therefore well-defined and based on explicit rules (e.g., ‘being an aquatic mammal’ and ‘possessing teeth’). Note that this category structure corresponds to the basic assumptions of the philosophical ‘classical view’ on concepts (Aristotle’s book ‘Metaphysics’ in Taylor, 1995). Accordingly, this mostly corresponds (1) to the notion of category and categorization in cognitive anthropology and linguistics (e.g., feature bundles), (2) to the information retrieval algorithms in computer science, Gestalt psychology (principles of perceptual categorization), and (3) to the categorization of brain structures based on biological differences in neuroscience. Overall, most studies on discrete or well-defined categories seem to be laboratory studies with artificial categories

(Bourne, 1982). These categories are simple since only a few features are varied on a limited number of separable dimensions (Garner, 1978).

Ill-defined structure

However, most natural categories have an overlapping, ill-defined structure (Neisser, 1967). Natural categories consist, for example, of man-made objects or events (Larochelle, Richard, & Soulières, 2000). Members of a category with an ill-defined structure are not categorized based on a discrete set of critical features (Martin & Caramazza, 1980), but rather on a continuous set of infinitely variable features (Bourne, 1982; Homa & Little, 1985). Hence, whether an instance is a member or not is a probabilistic or graded judgment rather than an all-or-none certainty (Larochelle et al., 2000). Therefore, categories with an ill-defined structure have vague category boundaries (McCloskey & Glucksberg, 1978). Vagueness implies that there are only weak probabilities for an instance to belong to any category (Molden & Higgins, 2004). The question can be asked: *Which, if any*, of the weak alternative categories should an instance be sorted into? For example, the instance ‘good’ can be categorized as “fine” (as in ‘good weather’), “hard-working” (as in ‘good student’), or “caring” (as in ’good people’; Zhang, 1998).

Consequently, vagueness captures the idea of typicality (Cohen & Lefebvre, 2017), implying that some members of a category have a high probability of category membership (i.e., highly typical), whereas other category members have a low probability of membership (i.e., less typical), while non-members have near-zero probability of membership (McCloskey & Glucksberg, 1978). Typicality of an instance reflects the number of variable features that one member shares with other category members (i.e., family resemblance; Wittgenstein, 1953). For example, some members of the category “violet” are more typical (e.g., ‘color of lavender’) or less typical (e.g., ‘color of eggplant’). This corresponds to the notion of category and categorization in computer science using machine learning algorithms and to Gibson’s view on perception in psychology. Note, however, that vagueness should not be confused with ambiguity. Ambiguity implies that there is more than one strong probability of category membership. This means which of the strong alternative categories should an instance be *not* sorted in (Molden & Higgins, 2004). For example, the instance ‘not giving up’ strongly relates to the category “persistent” or “stubborn”

(Molden & Higgins, 2004). However, since both conflicting categories are highly accurate, the categorization process would be ambiguous.

2.1.4 Conclusion

In sum, I described the different notions of category and categorization in the founding disciplines of cognitive science (i.e., philosophy, anthropology, linguistics, computer science, psychology, and neuroscience), discussing that some disciplines focus on categories whereas others highlight the processes underlying categorization. Parallelism of the classical view in philosophy (i.e., individually necessary and jointly sufficient properties; Aristotle's book 'Metaphysics' in Taylor, 1995) as well as the view by Wittgenstein on categories (1953; i.e., family resemblance) can be observed between all founding disciplines. This can be also observed when looking at the structures of categories. A category can have either a well-defined or an ill-defined structure. Membership of instances in well-defined categories are based on explicit rules (Cohen & Lefebvre, 2017) enclosing all critical properties (Nakamura, 1985), whereas ill-defined categories are based on the probability of a set of infinite variable features (Bourne, 1982; Homa & Little, 1985; Larochelle et al., 2000). An ill-defined structure results in vague category boundaries (Keefe, 2000) in which category membership can be graded, with some instances being more probable, typical for a category as other, less typical instances (McCloskey & Glucksberg, 1978). In addition, the categorization process can be divided into perceptual, semantic, and conceptual categorization. Perceptual categorization refers to the process based on perceptual similarities to other instances or an internal representation, whereas semantic categorization refers to the process based on meaning or words (Quinn et al., 2001). Overall, it seems that the type of categorization can be context dependent (Clark, 2017) and categorical information might rely on multiple representations (Gentner & Goldin-Meadow, 2003).

2.2 OBJECT CATEGORIZATION IN COGNITIVE NEUROSCIENCE

Each founding discipline applies a particular way of looking at categories (and categorization) and each progressed far enough to recognize that the answer to some questions can only be found in cooperation with other disciplines (Miller, 2003). The cooperation between different disciplines, theoretically and by linking their tools together, resulted in a marvelous change in the understanding of categories and categorization (Cohen & Lefebvre, 2017). For example, the cooperation between psychology and neuroscience made it possible to observe cognitive and perceptual mechanisms in the brain (Baars & Gage, 2010) by relying on overt behavior complemented by neuroscientific techniques (Cohen & Lefebvre, 2017). With some additional contributions in medicine, biochemistry, biology, physics, and computer science, cognitive neuroscience contributed immensely to the understanding of categories and categorization (Baars & Gage, 2010; Cohen & Lefebvre, 2017).

Gall (1835) was the first in cognitive neuroscience to investigate functional differences based on over 300 skulls from individuals and their known mental characteristics. One of the first widely accepted associations between a brain structure and function was proposed by Broca (1861). He linked a structure in the frontal cortex (later termed Broca's area) to fluent, articulated speech. Shortly after, the association between movement and the motor cortex was discovered by Fritsch and Hitzig (1870), followed by observations of functional specificity in other areas (for instance, Harlow, 1868, with the patient Phineas Gage). Since then, many researchers contributed to the association of brain structures to specific functions. The mechanisms and localizations of categories and categorization are discussed during this chapter (Chapter 2.1.2). In the context of cognitive neuroscience, as in psychology, the content of categories is not of primary interest (Cohen & Lefebvre, 2017).

In cognitive neuroscience, research focuses on the mental representation of events (e.g., "walking a dog") and objects (e.g., "dog"; Hanson & Hanson, 2017). The investigation of event categories is derived either from how people segment events (in social psychology), the organization of event knowledge in data (in cognitive computer science), or from everyday events (Majid, Staden, Boster, & Bowerman, 2004). However, the majority of research focuses on mental representations of object categorization (Hanson & Hanson, 2017; Majid et al., 2004). In the following, I will describe object categorization in cognitive neuroscience by summarizing theories about categorical representation in the brain as well as models of the acquisition of categorical knowledge.

In the following chapters, theories and models of object categorization in cognitive neuroscience will be reviewed. More specifically, theories of object representation in the brain (Chapter 2.2.1) and models of the categorical judgment (Chapter 2.2.2).

2.2.1 Categorial representations in the brain

During visual presentation of object categories, the occipito-temporal cortex (OTC) is the most active (Harel, 2016). The activation was observed in functional Magnetic Resonance Imaging (fMRI; for instance, Grill-Spector & Malach, 2004), in intracranial (for instance, Liu, Agam, Madsen, & Kreiman, 2009) and scalp recordings (for instance, Kiefer, 2001), and in patients' studies with lesions in the OTC (for instance, Gainotti, 2000). More specifically, the activation of the ventral occipito-temporal cortex (VTC) seems to play an important role. The VTC is most active during object recognition (Goodale and Milner, 1992). However, the question of how object categories and their categorical representations are represented in the brain is an open debate. There are three main theories: (1) category-selective representation, (2) feature-specific representation, and (3) process-specific representation (Hanson & Hanson, 2017). Each theory of categorical representation of objects in the brain will be discussed in turn.

Category-selective representation

In the theory of category-selective representation, researchers assume that a specific category is associated with selective brain structures (Hanson & Hanson, 2017). These structures are active while presenting images from one category (e.g., "animals") but not for another (e.g., "tools"), while not being active vice versa (for "tools" but not for "animals"; Hanson & Hanson, 2017). Research shows the involvement of distinct structures of the VTC as a response to different object categories (Martin & Chao, 2001). For example, the fusiform face area (FFA) for "faces" (Kanwisher, McDermott, & Chun, 1997; Puce, Allison, Gore, & McCarthy, 1995; Kanwisher & Yovel, 2006), the extrastriate body area for "bodies" (Chao, Haxby, & Martin, 1999; Peelen & Downing, 2007), or the parahippocampal place area (PPA) for "buildings" (Aguirre, Zarahn, & D'Esposito, 1998). Individuals diagnosed with, among others, anoxia, stroke, head injury, or dementia caused by Alzheimer's disease, have deficits in the categorization of specific categories, thus also referred to as category-specific disorders (Capitani, Laiacona, Mahon, & Caramazza, 2003).

There are three general critiques to the account of category-selective representation: equipotentiality hypothesis and cognitive economy. Equipotentiality hypothesis is the ability of some brain areas to take over the function of a damaged brain area (Lashley, 1929). Cognitive economy refers to the assumption that there is not enough space in the cortex to encode every single category separately, especially considering that most natural categories are ill-defined (Gauthier, 2000). In addition to the general criticisms, many researchers observed results which cannot be explained with this theory. For example, Chao and colleagues (1999) observed that the lateral fusiform gyrus and the right posterior superior temporal sulcus are active when presenting images of animals, faceless animals, and human faces. This suggests that object categories are distributed and overlapping in the brain (Martin & Chao, 2001).

Feature-specific representation

Martin and Chao (2001) proposed the cortex may be a ‘lumpy feature-space’ (p. 196), in which a specific feature is associated with specific brain structures. A feature-specific representation is in line with results from studies with nonhuman primates (for instance, Tanaka, 1996) and with computational models of object recognition (for instance, McClelland & Rumelhart, 1985). The association based on features can either be interpreted as feature maps (i.e., ‘feature-map model’; Gauthier, 2000) or as object forms (i.e., ‘object-form typology’; Haxby, Ishai, Chao, Ungerleider, & Martin, 2000). Gauthiers (2000) proposed feature-maps like, for example, in the visual cortex, where the activity of the V1 area is associated with orientation and direction (DeAngelis, Ohzawa, & Freeman, 1995), the V2 area with color, spatial frequency, and orientation (Anzai, Peng, & Van Essen, 2007), and V3 with motion (Braddick et al., 2001). In line with this, the PPA might reflect cardinal orientation and right angles, which are typical features of buildings (Nasr, Echavarria, & Tootell, 2014). Thus, the VTC would transform low-level visual input with the goal to arrive at high-level descriptions that can be compared with stored representations (Kravitz, Saleem, Baker, Ungerleider, & Mishkin, 2013). However, this account did not explain some of the observed results. For example, Epstein and Kanwisher (1998) observed that the brain's response to two objects with similar features was not identical. The hypothesis of object-from typology can account for these observations (Haxby et al., 2000). This hypothesis suggests that the encoded features are not visual features of the object itself but are influenced by the mental representation of objects. Two main findings support this assumption: (1) the VTC is strongly modulated by attention (O'Craven, Downing, & Kanwisher, 1999) and (2) mental imagery or the mere reading of an object's name can elicit the same activation as perceiving an object (Haxby et al., 2000).

Process-specific representation

Based on the assumption that the brain's activation for a perceived object is influenced by its mental representation, activation might either encode subtle differences or similarities (Gauthier, 2000). In the process-specific representation account, the activation would reflect (1) the processing goal and (2) experience with an exemplar (Gauthier, 2000). A processing goal can be defined by how information is used, for instance, by the level of categorization (Rosch, 1987). The levels of categories can be described as different levels of object categorization varying in abstraction (Poulin-Dubois & Pauen, 2017). At the top level of the hierarchy is the superordinate level (e.g., "animal"), followed by the basic (e.g., "dog"), and the subordinate (e.g., "poodle") level of categorization (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). The basic level categorization is the most inclusive level and the most referred to in spoken language. At this level, the properties of members are considered as equivalent among all or most members of a category (Rosch, 1987). Hence, at this level, the similarities between members are the highest while the similarities between a member and non-members are the lowest (Poulin-Dubois & Pauen, 2017). One example for this is the observation that the FFA is not only active when categorizing faces. This could be explained by the association of the FFA with a more fine-grained, subordinate level (Gauthier, Tarr, Anderson, Skudlarski, & Gore, 1999) in comparison to a basic level of categorization (Ishai, Ungerleider, Martin, Schouten, & Haxby, 1999; Gauthier, 2000). Consequently, a subordinate level of categorization of pictures elicits activation in the FFA (Gauthier & Tarr, 1997; Gauthier et al., 1999).

On the other hand, experience in this account associates with expertise in the distinction of visual information to object categories (Harel, 2016). Thus, the mere repetitive exposure to an object category is not equivalent to expertise in the object category (e.g., just because one has seen many cars does not make one an expert in “cars”; Gauthier, James, Curby, & Tarr, 2003; Rossion & Curran, 2010). The influence of expertise on the structure of the OTC was observed with different categories (Harel, 2016). The influence of expertise on FFA (for example) can be observed by less activation in individuals with autism spectrum disorder (ASD) in comparison to individuals without ASD (Schultz et al., 2003). This can be explained by the fact that individuals with ASD pay less attention to faces and are therefore less of an expert than individuals without ASD.

To summarize, there is no clear consensus about the representation of categorical information in the brain. There are three main theories, (1) the category-selective representation, in which a specific *category* is associated with specific brain structures, (2) the feature-specific representation, in which a specific *feature* is associated with specific brain structures, and (3) the process-specific representation, in which a specific *process* is associated with specific brain structures (Hanson & Hanson, 2017). Even so, they are not mutually exclusive. For example, object representation may differ across hemispheres (Deacon et al., 2004; left: category-selective; right: feature-specific representation) or a specific structure may be responsible for face categorization due to their sociobiological relevance (Gauthier, 2000).

2.2.2 Models for categorical judgments

The process of categorization and categorical judgment has been described in different models: the classical model (i.e., rule-based model; Bruner, Goodnow, & Austin, 1956), similarity-based models (i.e., prototype or exemplar models; Brooks, 1978; Mervis & Rosch, 1981), and other models (category boundary or theory model; Ashby, 1992; Murphy & Medin, 1985), which will be described in turn.

Rule-based model

The rule-based model (by Bruner, Goodnow, & Austin, 1956), also called the ‘classical’ model, describes the process of categorization as an active mechanism of forming and testing rules. The rule encompasses all shared properties of all instances of a category in necessary and sufficient conditions. The number of conditions seems to be restricted by our short-term memory (i.e., between 4 (Cowan, 2016) and 7 (Miller, 1956) chunks of information; Harnad, 2017). An example would be the category “dog” and one of its lexical entries: ‘any carnivore of the dog family Canidae, having prominent canine teeth and, in the wild state, a long and slender muzzle, a deep-chest muscular body, a bushy tail, and large, erect ears’ (Dictionary.com, n.d.). Activity in the basal ganglia is associated with the rule-based model (Ell, Marchant, & Ivry, 2006; Lieberman, Chang, Chiao, Bookheimer, & Knowlton, 2004) as well as the anterior cingulate and dorsolateral prefrontal cortices (Elliott, Rees, & Dolan, 1999; Rao et al., 1997; Savage et al., 2001). Three main critiques emerged over time: (1) for some categories, the rule specification can be complex or even impossible (Wittgenstein, 1953; see above for the example of the concept [game]), (2) category membership is not clear and might vary between and within people (McCloskey & Glucksberg, 1978; for example, the category “happiness”), and finally (3) not all members are equally representative for a category (Rosch and Mervis, 1975). The latter is observed in typicality ratings, in which some instances are rated to be more representative, typical (e.g., chair as a “furniture”) compared to less representative, atypical (e.g., hammock as a “furniture”) instances of a category. One approach to address these issues is an adaption of the model that proposes probabilistic rather than deterministic rules (Piantadosi & Jacobs, 2016; Tenenbaum, Kemp, Griffiths, & Goodman, 2011). Hence, a few of conditions, each imperfect on their own, are integrated in a flexible and weighted condition bundle.

Similarity-based model

Another approach to address the criticism on the rule-based model was the proposal of similarity-based models. In both similarity-based models, the exemplar model (Brooks, 1978; Medin & Schaffer, 1978) and the prototype model (Mervis & Rosch, 1981), an instance is either categorized based on its similarity to all exemplar instances or based on one prototype instance (respectively) of a category. In the exemplar model (Brooks, 1978; Medin & Schaffer, 1978), the categorical representation consists of all actual individual instances (i.e., exemplars) one has observed belonging to the category. This way of categorization is associated with activity in parietal as well as frontal striatal brain regions (Aizenstein et al., 2000; Poldrack & Gabrieli, 2001; Milton, Bealing, Carpenter, Bennattayallah, & Wills, 2017). However, the storage of each individual experienced exemplar might be economically questionable (i.e., cognitive economy; Harnad, 2017). Hence, only some exemplars (Aha, 1992) or only one exemplar (Lassaline & Logan, 1993) might be stored.

Taking into consideration the typicality effect (Rosch and Mervis, 1975), the prototype model proposes the storage of one prototypical exemplar (Mervis & Rosch, 1981). A prototype consists of the most common features extracted from all instances of the category. In other words, it is based on similarities, i.e., *family resemblance*, across all instances (Mervis & Rosch, 1981), with explicit extraction, storage in memory, and usage of a prototype to categorize a novel instance. For example, if we would observe four members of the category "cat" with a tail length of 28, 28, 28, and 20 cm, the prototype models' value would be 28 cm. This way of categorization is associated with activity in the extrastriata cortex (Tracy et al., 2003). Many natural categories seem to be organized by the graded typicality of a categorical prototype (Goldstone et al., 2018). Studies observed that, for example, typicality ratings are correlated with ratings of how good an example an instance is of its category (Rosch & Mervis, 1975), participants' reaction time to verify a statement like 'An [instance] is a [category name]' (Smith, Shoben & Rips, 1974), and the frequency and speed of listing instances of a category (Mervis & Rosch, 1981). However, variation in typicality should result in unclear category boundaries (Goldstone et al., 2018), which is not observed in the literature. For instance, Davis and Love (2010), observed that an image of a face at the category boundary is categorized more accurate compared to the prototype.

Category boundary and theory model

The issue of clear category boundaries is addressed in the category boundary model (associated with the work of Ashby, 1992; for instance, Goldstone, 1996). In the category boundary model, a category is described by its boundaries to the surrounding categories. In other words, a category is defined by its periphery (e.g., like a caricature) rather than its center (as in the similarity-based models). One difficulty with this model is that the location of the boundary between the two categories depends on several contextual factors (e.g., Repp & Liberman, 1987). For example, the boundary between “flowers” and “weeds” depends on the desirability of the plants’ growth. Contextual factors and prior knowledge (e.g., expertise in gardening) and their modulation on the process of categorization are addressed in the theory model (for instance, Murphy & Medin, 1985). Theory model assumes that categorization is depended on the theories people have about the world. One confirmation of the modulation by prior knowledge can be found in a study by Pazzani (1991). He observed that learning of novel categories is faster when the learner has appropriate prior knowledge (Pazzani, 1991). Therefore, prior knowledge can connect the properties of a category and learning is facilitated. However, the theory model does not exclude similarity-based (e.g., prototype or exemplar) models or rule-based models of categorization (Goldstone et al., 2018).

All the above-mentioned models do not specify the content of the category (Goldstone et al., 2018). Thus, to investigate the process of categorization, researchers are flexible in choosing any category or concept. To investigate the rule-based model, categories whose instances can be sorted based on simple rules are mostly used (Bruner, Goodnow, & Austin, 1956). Investigations of the exemplar model are mostly concerned with categories whose instances include an exceptional instance that must be individually memorized (Nosofsky, Palmeri, & McKinley, 1994). Experiments studying the prototype model use categories whose instances are made up of distortions around one prototype (Posner & Keele, 1968). Lastly, to investigate the theory model, participants are given categories they already know something about (Murphy & Kaplan, 2000). Conclusively, it seems like the researcher’s choice to investigate a specific representation determines the experiment rather than the experiment having an influence on the choice of representation (Goldstone et al., 2018). More recently, researchers proposed multiple representational models, which are flexible based on the category that must be learned (Weiskopf, 2009). Evidence also indicates that similarity-based and rule-based judgments are engaged in parallel in (Wirebring, Stillesjö, Eriksson, Juslin, & Nyberg, 2018). Additionally, reliable individual differences in the preference of using rule-based or similarity-based models were observed (McDaniel, Cahill, Robbins, & Wiener, 2014).

2.2.3 Conclusion

In sum, I described multiple theories regarding the representation of categorical information in the brain. One of them is the process-specific theory, in which specific processing goals or experiences regarding a category are encoded (Gauthier, 2000).). A specific processing goal could be associated with the level of categorization (i.e., subordinate, basic, superordinate level), whereas experiences could be associated with expertise regarding a specific category (Harel, 2016). Additionally, I described different models regarding the acquisition of categorical knowledge. Rule-based models suggest that categorical knowledge is acquired by rules (Bruner, Goodnow, & Austin, 1956), whereas similarity-based models suggest that categorical knowledge is acquired by similarity comparison with either exemplars (Brooks, 1978) or prototypical instances (Mervis & Rosch, 1981). Although some theories and models seem to be conflicting, they are not mutually exclusive (Hanson & Hanson, 2017; Goldstone et al., 2018).

2.3 OBJECT CATEGORIZATION IN AUTISM SPECTRUM DISORDER

One way to further understand object categorization is by looking at research on neurodevelopmental and cognitive divergences. Neurodevelopmental disorders include all disorders that result in changes in cognitive function (American Psychiatric Association, 2013). As categorization is one of the most basic phenomena in cognition, inferences about the encoding of categorical information in the brain as well as categorical judgments can be drawn from research of neurodivergent individuals. One well-known neurodevelopmental disorder with observed divergences in categorization is ASD (Hill, 2004).

In the following chapters, I will introduce autism spectrum disorder (ASD) by giving some information about its prevalence rate, core features, and subtypes of ASD (Chapter 2.3.1). Next, the neuroscience of ASD (Chapter 2.3.2), more specifically neuroanatomical and functional changes, is described, followed by an outline of cognitive theories (Chapter 2.3.3) of ASD, with a more detailed focus on the weak central coherence theory and the perceptual hypothesis and their implications on object categorization (Chapter 2.3.4).

2.3.1 Introduction to autism spectrum disorder (ASD)

ASD is a neurodevelopmental disorder (American Psychiatric Association, 2013; first documented by Kanner, 1943). The diagnosis of ASD is not influenced by geographic or ethnic/cultural factors (French, Bertone, Hyde, & Fombonne, 2013). In 2016, about 1 in 54 children aged 8 years was diagnosed with ASD, with a 4.3 times higher rate for boys than for girls (Maenner et al., 2020). Since the year 2000, this prevalence rate increased by 175% (2.8 times; Maenner et al., 2020). The increase in prevalence rate cannot be directly mapped to an increase of incidence due to changes to broader diagnostic criteria, policies for special education, and an increase in the availability of health services (French et al., 2013). All these changes presumably result in better identification and a more reliable diagnosis at a young age (Kolevzon & Buxbaum, 2013). For example, due to the availability of health services, a higher prevalence rate was observed in higher socioeconomic groups (French et al., 2013). However, the possibility of an increase in incidence rates is still under debate since the observed changes cannot account for the world-wide increase (French et al., 2013; Kolevzon & Buxbaum, 2013). Growing evidence suggests that maternal lifestyle, preconceive or prenatal maternal nutrition, maternal infections and medications, and exposure to environmental chemicals (e.g., air pollution) might influence the occurrence of ASD (French et al., 2013).

ASD is diagnosed by considering two core features (American Psychiatric Association, 2013): impairment in communication skills and reciprocal social interaction as well as restricted, repetitive, and stereotyped patterns of behavior. Deficits in communication skills can be observed in severe developmental delays in expressive language and in speech quality issues (e.g., unusual prosody or rhythm; Kim & Lord, 2013). The impairment in reciprocal social interaction can be observed in the insufficient ability to use facial expressions and gestures in social interactions, the inability to establish relationships with peers, as well as the lack of sharing interests and activities with other people (American Psychiatric Association, 2013). The second core feature, engagement in restricted, repetitive, and stereotyped patterns of behavior, can be differentiated into insistence on sameness, repetitive sensory-motor behaviors, and circumscribed interest (Kim & Lord, 2013). The insistence of sameness can be observed in an excessive adherence to (specific, nonfunctional) routines and in an inflexibility to and discomfort with changes (American Psychiatric Association, 2013). Repetitive sensory-motor behaviors can be observed in unusual reactions to sensory stimuli (either extremely strong or weak) and in repetitive motion sequences (American Psychiatric Association, 2013). Circumscribed interest refers to a limited range of interests, yet intense for particular topics and to unusually strong attachments to certain objects (American Psychiatric Association, 2013). Although the criteria to diagnose individuals with ASD are clearly described in the Version 5 of the Diagnostic and Statistical Manual of Mental Disorders (DSM-V; American Psychiatric Association, 2013), the term ‘spectrum’ suggests a heterogeneous manifestation of the disorder. Even though the core symptoms are observable in most diagnosed individuals, the severity of those symptoms constitutes a spectrum (Kim & Lord, 2013). Thus, behavioral manifestations vary widely between individuals (Kim & Lord, 2013). For example, researchers observed that twins with a diagnosis of ASD do not have identical symptoms (Folstein & Rutter, 1978). In addition, multiple comorbid features can be observed (Matson & Goldin, 2013; for details see, Appendix I).

In addition to the widely varying behavioral manifestations, the term ASD encompasses individuals with low functioning ASD (LF-ASD), high functioning ASD (HF-ASD), and Asperger’s Syndrome (AS). In all subtypes, impairments in communication skills and reciprocal social interaction as well as restricted, repetitive, and stereotyped patterns of behavior can be observed (Andrews, Pine, Hobbs, Anderson, & Sunderland, 2010). The diagnosis of LF-ASD and HF-ASD is not defined in the DSM-V (American Psychiatric Association, 2013), but it is used to differentiate between individuals based on their intellectual abilities. LF-ASD is defined as being accompanied by an intellectual disability (IQ under 70), whereas high functioning individuals with ASD have no or only a mild intellectual disability (average or above average IQ; de Giambattista et al., 2019). However, developmental language and cognitive delay are observed in both. The diagnosis of AS is defined as a subgroup of ASD since DSM-V (American Psychiatric Association, 2013); individuals diagnosed with AS (first described by Asperger, 1944) have no clinically significant delay in language development and in cognitive abilities (Andrews et al., 2010). However, due to normal cognitive functioning, there is an ongoing debate whether the same etiological factors can explain the difference between HF-ASD and AS (Kim & Lord, 2013; de Giambattista et al., 2019).

2.3.2 Neuroscience of ASD

Kanner (1944) documented not only the core features of ASD but also an enlarged head size in 5 out of 11 children with ASD aged 2 to 8. Kanner (1944) used the heads circumference as an indication for the size of the brain. In recent years, the neuroanatomy of the brain of individuals with ASD was investigated using postmortem analysis and experimental techniques, like structural MRI and Diffusion Tensor Imaging (DTI). Structural MRI is used to investigate the static anatomical information of the brain (Symms, Jäger, Schmierer, & Yousry, 2004) such as measuring the brains' volume, the volume of subregions, or by looking at the distribution of white and gray matter. White matter contains mostly long-range myelinated axons, while gray matter contains mostly cell bodies (e.g., glial cells and synapses; Fields, 2008). DTI is a variant of MRI assessing the microstructures of white (mostly) and gray matter. More specifically, neural circuits can be investigated by visualizing nerve tracts (tractography; Fields, 2008). A meta-analysis of studies using head circumference, postmortem, and structural MRI analysis suggests an increased brain growth during early childhood in ASD, followed by a plateau, resulting in a brain size within the normal range by adulthood (Redcay & Courchesne, 2005). Even though absolute brain size is no longer enlarged in adults with ASD, differences in white and grey matter volume (for review see Cauda et al., 2011 and Yang et al., 2016; for details see Appendix II) as well as overall structural and functional abnormalities can be found throughout the brain (Stigler & McDougle, 2013). All studies mentioned in this chapter investigate adults with ASD. In the following, neuroanatomical differences between individuals with and without ASD in specific brain regions with relevance for categorization in cognitive neuroscience, as well as connectivity (structural and functional) within the brain will be reviewed.

Specific brain regions with relevance for categorization in cognitive neuroscience

Neuroanatomical differences can be observed in many brain regions. Exemplarily, differences in (a) the fusiform gyrus and (b) the basal ganglia will be discussed due to their relevance for categorization in cognitive neuroscience (for review see Stigler & McDougle, 2013 or Jumah, Ghannam, Jaber, Adeeb, & Tubbs, 2016). (a) The fusiform gyrus (FG) is involved in the processing of faces (Haxby, Hoffman, & Gobbini, 2002) or in the subordinate level of categorization (Gauthier & Tarr, 1997). With respect to its volume, results were inconsistent reporting no changes (Pierce, Müller, Ambrose, Allen, & Courchesne, 2001), an increase (Waiter et al., 2004), and a decrease (Toal et al., 2010; Sato et al., 2017) in FG volume for individuals with ASD. (b) The basal ganglia are associated with rule-based categorization. (Ell, Marchant, & Ivry, 2006; Lieberman et al., 2004) Multiple studies observed an increase in the volume of the caudate nucleus in individuals with ASD in contrast to NT adults (for instance, Sears et al., 1999; Langen, Durston, Staal, Palmen, & van Engeland, 2007), which is a part of the basal ganglia. Interestingly, a correlation between increased volume and restricted, repetitive, and stereotyped behavioral patterns was observed (positive correlation: Hollander et al., 2005; Rojas et al., 2006; negative correlation: Sears et al., 1999).

Structural Connectivity

In recent years, in addition to the research about neuroanatomical changes in matter and specific brain regions in ASD, both structural and functional connectivity within the brain has been investigated. Structural connectivity reflects the brain’s neuron-to-neuron connections (Rane et al., 2015). Studies using DTI to investigate white matter connectivity in individuals with ASD observed an overall decrease in axonal density and a decrease in myelination compared to neurotypicals (NT; Travers et al., 2012). The decrease of axonal density was observed, for instance, in the corpus collosum, the ventral temporal lobe, and the superior temporal gyrus (for review see Travers et al., 2012 or Stigler & McDougle, 2013), and was often accompanied by a decreased myelination (Travers et al., 2012).

Functional Connectivity

Functional connectivity reflects the brain’s common patterns of neuronal activity across circuits (Rane et al., 2015). Common activation patterns can either be differentiated in long- or short-distance connectivity (Maximo, Cadena, & Kana, 2014). Long-distance, or long-range, connectivity is the interaction between distant brain regions, commonly across different brain lobes or both hemispheres

(Maximo et al., 2014) and can be associated with top-down integration of information (Von Stein, Chiang & König, 2000; O'Reilly, Lewis, & Elsabbagh, 2017). Top-down integration of information describes the process of integrating prior knowledge of the world (i.e., internal representation) with the incoming sensory information (O'Reilly et al., 2017). Short-distance, or short-range/local, connectivity is the interaction between spatially close units (Rane et al., 2015). Spatial closeness can vary from microns to millimeter to centimeter (Rane et al., 2015). Short-range connectivity can be associated with local, bottom-up propagation of information (Von Stein et al., 2000; O'Reilly et al., 2017). The bottom-up propagation of information is a process that modifies internal representation to minimize the mismatch between the internal representation and sensory information (O'Reilly et al., 2017).

Courchesne and Pierce (2005) proposed that both long-range underconnectivity and local overconnectivity, were related to the behavioral features of ASD. A recent review suggests a more mixed pattern of under- and overconnectivity (Anagnostou & Taylor, 2011). In long-range connectivity decreases (for instance, Just, Cherkassky, Keller, & Minshew, 2004; Kleinhans et al., 2008; Catarino et al., 2013; Peiker et al., 2015) and increases (for instance, Noonan, Haist, & Müller, 2009; Buard, Rogers, Hepburn, Kronberg, & Rojas, 2013) in ASD adults compared to NT adults is reported. The similar pattern of findings can be observed in short-range connectivity, with results indicating decreases (for instance, Villalobos, Mizuno, Dahl, Kemmotsu, & Müller, 2005; Turner, Frost, Linsenbardt, McIlroy, & Müller, 2006; Khan et al., 2013; Coskun et al., 2013) and increases (for instance, Shen et al., 2012; Welchew et al., 2005; Mizuno, Villalobos, Davies, Dahl, & Müller, 2006; Barttfeld et al., 2011). Note that the studies of both long- and short-range connectivity vary widely conceptually (e.g., definition of the path length association with the terms 'short' and 'long'; Rane et al., 2015), methodologically (e.g., paradigms or participant characteristics), or analytically (e.g., processing of data; O'Reilly et al., 2017). Therefore, the isolation of a specific pattern or even the replication of the results is challenging (Maximo et al., 2014). Overall, a trend for long-range underconnectivity can be observed (O'Reilly et al., 2017), with studies suggesting a relation to autistic traits (for instance, Catarino et al., 2013).

2.3.3 Cognitive theories on the processing of sensory information in ASD

Cognitive theories of ASD are concerned with explaining the core features of ASD: impairments in social interaction, repetitive motions, and the processing of sensory information. The Theory of Mind hypothesis addresses mainly the impairment in reciprocal social interaction and communication skills (for instance, Shamsi, Hosseini, Tahamtan, Bayat, 2017) whereas the Executive Dysfunction hypothesis addresses mainly repetitive motion sequences, adhering excessively to routines, and reacting inflexible to changes (for instance, Turner, 1997). Finally, the Weak Central Coherence (WCC) theory (Happé, 2005) and the Perceptual hypothesis (Plaisted, 2001) address the processing of sensory information. Due to the necessity of processing sensory information for categorization and because both the Theory of Mind hypothesis and the Executive Dysfunction hypothesis rely on the interpretation of sensory information, only the Weak Central Coherence theory and the Perceptual hypothesis are reviewed in the following paragraphs. A short description on the Theory of Mind hypothesis and the Executive Dysfunction hypothesis can be found in Appendix III and IV.

Central coherence

Central coherence describes the everyday tendency to process information as one coherent, global whole rather than as multiple local, separate parts (Happé, 2005). To put it differently, information is combined to an abstract meaning at the cost of details (Frith, 1989). For example, individuals perceive a car rather than the individual shapes and pieces of a car (e.g., tires, mirror, and bumper; Brown & Bebko, 2012). An advantage of global processing in comparison to local processing was first investigated by Navon (1977), who constructed a global form of a letter by using local letters (e.g., large S consisting of small Hs). Participants responded faster to the global whole than to the local parts (Navon, 1977). The global precedence effect has been replicated in multiple modified studies showing, for instance, a larger advantage for sparse than dense elements (Martin, 1979), for foveal than peripheral presentation (Pomerantz, 1983), for spatial certainty than uncertainty (Lamb & Robertson, 1988), for long than short presentation time (Luna, 1993), and for few larger than many smaller elements (Yovel, Yovel, & Levy, 2001). This global precedence effect was observed even in infants (age: 6 months; Bhatt, Rovee-Collier, & Shyi, 1994).

The term ‘central’ can be referred to different information types, which range from conception to perception (Johnson-Laird, 1983), resulting in two different levels of central coherence: conceptual and perceptual coherence (Plaisted, 2001). Conceptual coherence is referred to as higher-level central coherence. Conceptual coherence is the process of assimilating the meaning of information depending on the context or mental representation (i.e., concept; Plaisted, 2001). One way to investigate this is to look at verbal-semantic coherence (Plaisted, 2001). Verbal-semantic coherence describes the process of verbal information being interpreted in grammatical or semantic relations to each other (Happé, 2005). For example, a word sequence can be either completely random or highly coherent with verbal meaning and contextual structure (i.e., language). Memory (i.e., the recall of words) are better for coherent sequences than for random sequences (Hermelin & O’Conner, 1967). Perceptual coherence also is referred to as lower-level central coherence (Plaisted, 2001). Perceptual coherence is the process of extracting perceptual meaning from an input depending on, for instance, the spatial relation between information (i.e., visuo-spatial coherence; Happé, 2005). One way to investigate the visuo-spatial coherence is by using the Embedded Figures Test (Witkin, 1950). The Embedded Figures Test reflects the ability to locate targets in a potentially confusing background (Witkin, Oltman, Raskin, & Karp, 1971). Thus, it was assumed to investigate the ability to see a local item independent of the global context in which it is presented (Witkin et al., 1971). Better performance was consistently linked to higher general intelligence (Goodenough & Karp, 1961; Richardson & Turner, 2000).

Neuroscience of central coherence

The ability to perceive the global whole rather than local parts was first associated with activation in the right hemisphere. In more detail, the ability to perceive the global whole is associated with *right* posterior superior temporal parietal region, whereas the ability to perceive local parts is associated with *left* posterior superior temporal parietal region (for review see Robertson & Lamb, 1991). In a study using a Rey-Osterrieth complex figure (developed by Rey in 1941 and standardized by Osterrieth in 1944), patients with a lesion in the right hemisphere were observed to recall rather the global shape than the local parts. However, patients with a lesion in the left hemisphere were observed rather to recall the local parts than the global shape of the figure (Kaplan, 1976). Recent studies using neuroimaging techniques support the notion of hemispheric specification for global and local processing (for instance, for an fMRI study see Fink et al., 1997; for an electroencephalogram study see Heinze, Hinrichs, Scholz, Burchert, & Mangun, 1998). These studies observed an activation during global processing in the right lingula gyrus, whereas in local processing an activation of the left inferior occipital cortex was observed (Fink et al., 1997). More recently, studies with clinical populations suggest that central coherence might be additionally associated with changes in functional connectivity (for instance, for Alzheimer's disease see Sankari, Adeli, & Adeli, 2010; for anorexia nervosa disorder see Favaro et al., 2012; for ASD see Kéïta, Mottron, Dawson, & Bertone, 2011).

Central coherence in ASD

In ASD the 'inability of experiencing wholes without full attention to the consistent parts' was observed with the first diagnosis (Kanner, 1943, p. 246). In the DSM-V (American Psychiatric Association, 2013), this core characteristic is described as intense interest in limited information and the interest in unusual environmental stimuli (American Psychiatric Association, 2013). Frith (1989) proposed that differences in central coherence in individuals with ASD might explain this core characteristic. This theory of differences in central coherence is named Weak Central Coherence (WCC) theory (Happé, 2005). WCC refers to the inability to recognize the global meaning (Happé, 2005). Thus, individuals with ASD perceive, due to WCC, each local part separately and have difficulty perceiving the global whole (Happé, 2005).

Over the last decades, the WCC theory proposed by Frith (1989) was extended and revised multiple times (Brown & Bebko, 2012). For instance, WCC is considered being a cognitive style rather than a cognitive deficit. Thus, the cognitive style of WCC would be normally distributed in the population (Happé, 1999). The extent of WCC as a cognitive style has been associated with resistance to change and specialized interest in neurotypical individuals (Briskman, Happé, Frith, 2001; Happé, Briskman, & Frith, 2001). Additionally, studies showed that individuals with WCC do not have an impairment in global processing but rather a local bias (Brown & Bebko, 2012). A study observed no impairment in global processing in individuals with WCC (i.e., children with ASD) when the attention was directed to the global whole (Plaisted, Swettenham, & Rees, 1999; Plaisted, Saksida, Alcantara, & Weisblatt, 2003). Plaisted and colleagues (1999) used the Navon task (e.g., large S consisting of small Hs; Navon, 1977) and compared the performance of children with and without ASD in two conditions: divided and selective attention task. In the divided attention task, no information was given regarding the level (i.e., global or local) at which a target letter (i.e., A) would be presented, whereas in the selective attention task, children were instructed to attend to either the local or the global letter. They observed that in the divided attention task children without ASD made less errors when the target appeared at the global level (than at the local level), while children with ASD made less errors when the target appeared at the local level (than at the global level). In contrast, in the selective attention task no difference was observed between both groups. Hence, when attention was not directed to the global whole, individuals with WCC preferred local processing (Plaisted et al., 1999). Studies investigated the effect of WCC on conceptual and perceptual processing in ASD. For instance, for conceptual processing, the WCC theory predicts that individuals with ASD have a weak verbal-semantic coherence. In line with the prediction, the results showed no memory (i.e., recall) benefit for words with semantical or grammatical relations (Hermelin & O'Conner, 1967). However, conceptual WCC has been investigated relatively little and further research is needed (Brown & Bebko, 2012). For perceptual processing, the WCC theory predicts an improvement performance in the Embedded Figure Test, which was observed in multiple studies (for instance, Shah & Frith, 1983; 1993).

While WCC theory describes the effect of preferred local processing in individuals with ASD accurately, it does not provide an explanation for this preference (Plaisted, 2001). Additionally, other studies looking at perceptual WCC observed non-significant differences between individuals with and without ASD (Mottron & Belleville, 1993; Ozonoff, Strayer, McMahon, & Filloux, 1994; Plaisted et al., 1999) or even observed results contrary to the predictions based on the WCC theory (Plaisted, O'Riordan, & Baron-Cohen, 1998a). For instance, in a study by Plaisted and colleagues, participants were asked to detect a target that shares features with two or more simultaneously presented sets of distractors, such as a grey X target among grey T and black X distracters. Thus, the color and shape features must be considered. In line with the WCC theory, one would predict that individuals with ASD would perform worse compared to neurotypical individuals. However, they observed that individuals with ASD were faster in solving the task than individuals without ASD. Due to this and other studies observing superior performance in perceptual tasks (Shah & Frith, 1983; Shah and Frith, 1993; Jolliffe & Baron-Cohen, 1997), an alternative perceptual hypothesis was proposed by Plaisted (2001).

The perceptual hypothesis

The alternative perceptual hypothesis focuses on the assets of cognitive processing of individuals with ASD rather than deficits. Therefore, this hypothesis might also explain the special and savant abilities observed in ASD (Plaisted, 2001). The underlying phenomenon of the alternative hypothesis is discrimination. Discrimination describes that if most or all features of two instances are opposing, they are regarded as different and will be responded to differently (Stokes & Baer, 1977). The perceptual hypothesis states that individuals with ASD have, on a perceptual level, enhanced discrimination abilities (Plaisted, 2001). These abilities result in perceiving stimuli as highly dissimilar. They perceive seemingly irrelevant local parts of a complex global stimulus as important (Plaisted, 2001). To put it differently, individuals with ASD notice features about a situation, event, or object that might be small or insignificant for neurotypical individuals (Plaisted, 2001). The enhanced discrimination abilities in individuals with ASD have been observed, for instance, in auditory (Mottron, Peretz, & Ménard, 2000; O'Riordan & Passetti, 2006) and visual (Litrownik, McInnis, Wetzel-Pritchard, & Filipelli, 1978) stimuli. For example, they might perceive every flower as unique due to small changes in the shape of the blossom and leaves. Yet, color (Franklin, Sowden, Burley, Notman, & Alder, 2008) and tactile (O'Riordan & Passetti, 2006) discrimination seems to be an exception.

Even so, the perceptual hypothesis can explain the results of studies predicted by the WCC theory; even the ones contradictory to the WCC theory (Plaisted, 2001). For instance, in the Embedded Figure Test, an embedded figure is defined by unique features but shares features with the overall figure. To solve the test, both the unique and shared features must be identified. Hence, there would be an improvement in performance if all features are processed in detail and perceived as dissimilar. Thus, the enhanced discrimination abilities proposed by the perceptual hypothesis can explain the observed advantage of individuals with ASD in the Embedded Figure Test (Plaisted, 2001). The same line of argument can be used to explain the superior performance in the visual search task (Plaisted, O'Riordan, & Baron-Cohen, 1998a). In the visual search task, the target (grey T) is defined by unique features and shares features with the distractors (grey X and black T). To solve the task, both features must be identified. Hence, the performance would improve if all features of the stimuli would be perceived as dissimilar (i.e., the target would "pop out"; see also (O'Riordan & Plaisted, 2001; O'Riordan, Plaisted, Driver, & Baron-Cohen, 2001; O'Riordan, 2004). Thus, enhanced discrimination ability can explain the superior performance (Plaisted, 2001). One explanation might be excessive lateral inhibition between neurons (Plaisted, 2001). Lateral inhibition describes the phenomenon of an excitatory neuron reducing the activity of its neighboring neurons (Mach, 1865). This phenomenon increases the sharpness of sensory input (von Békésy, 1968). Excessive lateral inhibition would result in a greater differentiation of inputs, resulting in the perception of small and seemingly irrelevant features as important and salient (Plaisted, 2001).

2.3.4 Implications of processing differences for categorization in ASD

Both theories, by Frith (1989) and Plaisted (2001), point out differences in the processing of information in ASD. Both describe a unique processing style of individuals with ASD preferring local parts of a stimulus. To put it differently, specific aspects of a stimulus attract more attention or are preferably attended to in ASD. This unique processing style consequently leads to reduced generalization, overselectivity, and poor categorization (Brown & Bebko, 2012). Each consequence will be discussed successively.

Generalization

Generalization describes that one stimulus will be responded to in a similar way as to another, if both share sufficient common features (e.g., Pearce, 1987; Thompson, 1965). Consequently, if two stimuli have most or all features in common, both are regarded as similar and will be responded to similarly. For instance, this refers to the ability to transfer learned behavior from one situation to another, similar situation, with relevant behavior occurring also in nontrained situations (Stokes & Baer, 1997). For example, the experience a child has with one dog (e.g., being scared) leads a child to have a generalized behavior towards all dogs or dog-like animals. Multiple studies observed reduced generalization abilities in children with ASD (e.g., Swettenham, 1996; Ozonoff & Miller, 1995) as well as in adults with HF-ASD (e.g., Plaisted, O'Riordan, & Baron-Cohen, 1998b). For instance, in the latter, adults with and without HF-ASD were asked to discriminate between familiar and novel stimuli (Plaisted et al., 1998b). They observed that both groups completed the training trials at the same rate. However, in the test phase, the NT adults responded more correctly to familiar than to novel stimuli, while the HF-ASD adults responded similarly to the familiar and novel stimuli. Thus, individuals with HF-ASD regarded the familiar stimuli in the test phase like novel stimuli, suggesting no generalization of prior learned knowledge (Plaisted et al., 1998b). One neuroscientific explanation for this might lie in a reduced associative excitation of neurons between stimuli (Plaisted, 2001). To put it differently, the neuronal activities associative with features in two (or more) stimuli are less similar in individuals with ASD.

Selectivity

Stimulus selectivity describes the ability to select relevant features to generalize across or discriminate between stimuli. Consequently, if the correct relevant feature is selected, generalization and discrimination is possible (based on the definition of overselectivity, Lovaas, Koegel, & Schreibman, 1979). For instance, relevant features to generalize across or discriminate between different dogs could be the shape of the ears, the color of the fur, the length of the tail, and the overall heights. Overselectivity refers to the response to only a part of all relevant features or even to irrelevant features (Lovaas, Koegel, & Schreibman, 1979). In NT adults, overselectivity correlates positively with mental age (e.g., Wilhelm & Lovaas, 1976) and with chronical age (e.g., McHugh & Reed, 2007). In individuals with ASD, overselectivity was observed for visual (e.g., Koegel & Wilhelm, 1973), auditory (e.g., Reynolds, Newsom, & Lovaas, 1974), and tactile (e.g., Ploog & Kim, 2007) features (first by Lovaas & Schreibman, 1971; for review see Ploog, 2010). A study investigating overselectivity in adults with AS asked participants to respond to a relevant target while ignoring irrelevant distractors (Remington, Swettenham, Campbell, & Coleman, 2009). The results showed that adults with AS require a higher perceptual load to ignore irrelevant distracters in comparison to NT adults. This means adults with AS used more potentially task-relevant features to solve the task. Note that the authors did not refer to the term overselectivity even though they referred to the same phenomenon (Ploog, 2010). One neuroscientific explanation for overselectivity in individuals with HF-ASD was investigated by Cohen (1998), suggesting the link to an abnormal degree of neuronal connectivity.

Categorization

A stimulus can be categorized based on similarities between categorical members (i.e., rule-based or similarity-based) or differences between non-members (i.e., category boundaries), based on specific features. Considering the enhanced discrimination, reduced generalization, and overselectivity in ASD, it could be inferred that individuals with ASD show inferior performance in a categorization task. In more detail, enhanced discrimination might make the detection of similarities between stimuli difficult (Soulières, Mottron, Saumier, & Larochelle, 2007); reduced generalization might influence transferring prior learned features of category members to novel stimuli (Goldstein & Bebko, 2005); and overselectivity might result in selecting irrelevant or only some of the relevant features for categorization (Klinger & Dawson, 2001).

The link between enhanced discrimination and categorization was investigated in a study comparing the responses of children in a discrimination and categorization task (Soulières et al., 2007). In the discrimination task, children with and without ASD were asked to discriminate two adjacent ellipses, while in the categorization task participants were asked to classify one ellipse into one of two categories ("thin" and "wide"). Ten ellipse stimuli were created on a continuum from thin to wide. In the discrimination task, NT children were better in discriminating the ellipses in the middle (e.g., 4 vs. 5) than at the end of the continuum (e.g., 8 vs. 9), suggesting an underlying automatic categorization of the stimuli. ASD children discriminated all ellipses on the continuum equally well, suggesting no underlying automatic categorization of stimuli. However, both groups of children achieved identical performance in the categorization task. The authors proposed that for children with ASD categorical representations only emerged in the categorization task (Soulières et al., 2007).

The link between decreased generalization and categorization was investigated by asking children with HF-ASD to generalize a categorization strategy (Goldstein & Bebko, 2005). In the study, children were asked to categorize images and observed no spontaneous categorization. After a rule to categorize the images was proposed to the children, which they all learned quickly, they were able to use this rule to categorize the images. However, when asked to categorize novel images, children with ASD did not generalize the provided rules to these novel images. It seems like individuals with ASD perceive every image as novel unless it is exactly the same (Brown & Bebko, 2012).

Finally, a study by Klinger and Dawson (2001) indicates a link between overselectivity and categorization by investigating categorization based on rule-based or on similarity-based (i.e., prototype) judgments in children with ASD. They observed that children with ASD had no problem categorizing when the rule was given, whereas they had difficulty in categorization when the rule was not provided. More specifically, in the prototype judgment task, the children with ASD did not develop a prototype in comparison to the NT children (Klinger & Dawson, 2001). It seems like enhanced discriminations leads to deficits in similarity-based categorization. Due to the small number of currently published studies, additional research is needed to clarify the categorization abilities in individuals with ASD with different levels of functioning, as well as to establish neuroscientific explanations (Brown & Bebko, 2012).

2.3.5 Conclusion

In sum, I reviewed the core features and the highly heterogenous spectrum of ASD. Of particular relevance for the studies described in the following is the distinction between LF-ASD (accompanied by intellectual disability) and HF-ASD (accompanied by a delay in language development). I summarized neuroanatomical changes in specific brain regions in ASD which are relevant for categorization, such as the fusiform gyrus and basal ganglia (for review see Stigler & McDougle, 2013 or Jumah et al., 2016).

Additionally, functional connectivity differences of the brain in ASD are differentiated between long- and short-range connectivity. The long-range connectivity can be associated with top-down integration of information, whereas the short-range connectivity can be associated with bottom-up propagation of information. Overall, a mixture of over- and underconnectivity was observed (Anagnostou & Taylor, 2011), with a trend for long-range underconnectivity (O'Reilly et al., 2017). The main cognitive theories (Frith, 1989; Plaisted, 2001) concerning the core features of sensory information processing in ASD, indicate a preferential processing of local rather than global features of objects. This can lead to enhanced discrimination, reduced generalization, overselectivity, and poor categorization (Brown & Bebko, 2012). Studies suggest that categorization of stimuli does not emerge spontaneously (Soulières et al., 2007), the creation of prototypes is impaired (Klinger & Dawson, 2001) as well as the generalization of categorical rules (Goldstein & Bebko, 2005) in individuals with ASD. However, additional research is needed to clarify the categorization abilities, especially to establish neuroscientific explanations (Brown & Bebko, 2012).

2.4 CATEGORICAL REPRESENTATION IN VISUAL PROCESSING

The current research project aims to generate insight and knowledge regarding the processing of visual categorical information; more specifically regarding perceptual and semantic categorization. To this purpose, visual processing during categorization will be examined (Chapter 2.4.1), followed by the employed methodology (Chapter 2.4.2). Lastly, the research questions and research objectives in the current project are described (Chapter 2.4.3).

2.4.1 Processing of visual information during categorization

In a model of visual information processing during a categorization task, visual information is processed via pathways that begin in the retina and end in the motor cortex, to elicit an appropriate response (i.e., two-stream hypothesis; first by Milner & Goodale, 1992). First, visual information is processed in the magno-, parvo- and koniocellular cells in the retina, which are sensitive to depth, color and shape, and color, respectively (Tovée, 2008). Information is then passed through the different layers of the lateral geniculate nucleus of the thalamus before reaching the primary visual cortex (V1; Thorpe & Fabre-Thorpe, 2001). After the recombination of information from the retina in V1 and secondary visual cortex (V2), two streams can be distinguished: the dorsal, magnocellular-dominated and the ventral, parvocellular-dominated stream. In the dorsal stream, information processing continues from the visual (i.e., from V1, via V2 & visual area 5; V5) to the parietal cortex and information regarding space, movement, and action of, for instance, an object is processed (Pandya & Seltzer, 1982; Petrides & Pandya, 1984; Barbas & Mesulam, 1985; Lamme & Roelfsema, 2000; i.e., information about 'where' or 'how'; labeled as 'vision for action'). In the ventral visual stream, information processing continues from the visual (i.e., from V1 via V2 & visual area 4, V4) to the temporal cortex, which contains neurons that respond specifically to certain objects (Thorpe & Fabre-Thorpe, 2001; e.g., FFA). The ventral visual stream is associated with object identification and object perception (for review, see Logothetis & Sheinberg, 1996; Petrides & Pandya, 1999; Petrides & Pandya 2002; Ungerleider & Mishkin, 1982; i.e., information about 'what'; labeled as 'vision for perception'). In the early visual areas simple features are represented, such as lines and orientations, whereas in the higher visual areas more complex features are represented (Abe, Fujita, & Kashimori, 2018). The parietal as well as the (inferior-)temporal cortex (ITC) is connected to a variety of areas, including the prefrontal cortex (PFC; Thorpe & Fabre-Thorpe, 2001). Activity in the prefrontal cortex is associated with the generalization and processing of categorical information (for review, see Miller, Freedman & Wallis, 2002 or Pan & Sakagami, 2012), more specifically neurons in the lateral PFC (LPFC) have been reported to encode categorical information (Freedman, Riesenhuber, Poggio, & Miller, 2001). From the PFC, information processing continues to the motor cortex (Goldman & Nauta, 1976; Barbas & Pandya, 1987; Bates & Goldman-Rakic, 1993) to elicit a response via the motor neurons of the spinal cord to reach the muscles in, for instance, the hand (Thorpe & Fabre-Thorpe, 2001).

Even though this model helps to understand visual processing, it is oversimplified. For instance, it does not consider that the parvocellular based information reaches the visual cortex roughly 20 ms after the magnocellular based information (Nowak, Munk, Girard, & Bullier, 1995; Nowak & Bullier, 1997), so that the ventral and dorsal stream interact (for review, see Cloutman, 2013 or Janssen, Verhoef, & Premereur, 2018), or that the processing of visual information is not only defined by feedforward connections (i.e., input from lower levels to higher levels) but also by horizontal (i.e., input from the same level), short-range and long-rang recurrent feedback (i.e., input from higher levels to lower levels) connections (Lamme & Roelfsema, 2000). For example, the feedback connections from V2 seem to shape the information sensitivity in V1 (Shmuel et al., 2005).

Nevertheless, the model gives an insight into the processing of visual information. More specifically, perceptual categorization (i.e., based on perceptual similarities to other instances or internal representation; Quinn et al., 2001) has been associated with both the ITC and the PFC (for example, Roy, Riesenhuber, Poggio, & Miller, 2010). Abe, Fujita, and Kashimori developed a network model consisting of networks of V4, ITC, and PFC to investigate the specificity of and the interaction between ITC and PFC. Regarding the ITC, they showed that the activities of ITC neurons encode critical visual features for categorization (for instance, features of a category prototype). Regarding the PFC, they observed that the PFC neurons have two different firing thresholds, in which low firing threshold neurons are responsible for maintaining information (acting as working memory) and the high firing threshold neurons enhance as a response to a presented stimulus (contributing to decision-making processes). Lastly, regarding the interaction between ITC and PFC, the top-down feedback from PFC to ITC improved the ability of the PFC neurons to categorize images closer to a categorization boundary (Abe, Fujita, & Kashimori, 2018). However, since perceptual categorization is based on shared perceptive properties, the question arises if the representation of categorical information can be observed already in early visual processing (i.e., in the visual cortex; Chapter 3).

In contrast to perceptual categorization, semantic categorization is based on shared properties of word meaning or processing goals and is mostly associated with activity in the PFC (Matsumoto, Soshi, Fujimaki, & Ihara, 2021). The activity over frontal areas is observed even when categorization is mostly based on information from the early stages of visual processing (Fabre-Thorpe, 2011). It was suggested that the encoding of superordinate level categorical information is most likely based on coarse visual representations activated with the first available (magnocellular) visual information (Fabre-Thorpe, 2011). For instance, Thorpe, Fize, and Marlot (1996) presented images for 20 ms and observed that information for superordinate level categorization was encoded over frontal areas (150 ms after stimulus onset). Hence, categorization is possible in impoverished perceptual presentation quality (i.e., short presentation duration). In contrast, for a more detailed encoding of information, for example, for basic level categorization (e.g., “dogs” or “birds” instead of “animals”), more information and longer processing time may be needed (Fabre-Thorpe, 2011) due to top-down feedback constraints on lower-level processes from activated higher-level categorical representations (Gerlach et al., 2002). Hence, the question arises when and where more detailed information for semantic categorization, which is mostly based on information from the early stages of visual processing, is implicitly encoded (Chapter 4).

2.4.2 Behavior and electrophysiological activity as methodology

To investigate the categorization, behavior and electrophysiological activity can be assessed. Behavior can be measured based on counting every occurrence of a behavior, the duration of a behavior (i.e., temporal extent), and timing of a specific behavior (i.e., temporal locus; first by Johnston & Pennypacker, 1993; for more details see Cooper, Heron, & Heward, 2020). For instance, behavioral performance can be measured by calculating correct and incorrect response rates (Cooper et al., 2020). Evaluating when a behavior is initiated is measurable based on the temporal locus, by measuring the elapsed time between the onset of a stimulus and the initiation of a subsequent response (i.e., response latency; Cooper et al., 2020). In contrast, response time (or reaction time; RT) encompasses the initiation, processing, and execution of the subsequent response; it is the total time until a response is given (Kleppmann, 2017). The most common way of analyzing behavioral data is by using a central tendency parameter (e.g., sample mean; *M*) and a dispersion parameter (e.g., standard deviation; *SD*; Whelan, 2008). However, analyzing mean values has multiple limitations specially in response time analysis (Townsend, 1972; Townsend & Ashby, 1983; Townsend, 1990; McElree & Carrasco, 1999), which can be dissolved, for instance, by analyzing the temporal course of behavior (Rousselet, Macé, & Fabre-Thorpe, 2003). One method to study the temporal course of behavior is by using the (discrete-time) event history analysis (EHA; Allison, 1982; Singer & Willett, 1993; Singer & Willett, 2003a; Panis & Wagemans, 2009) in which the distribution of response times can be statistically described and modeled. Note that behavioral data represents the end result of several cognitive processes, including the encoding, categorization, decision-making, and motor response phases of information processing (Massaro & Cowan, 1993).

Distinct phases of information processing can be dissociated by measuring electrophysiological activity (Rugg & Coles, 1995). Electrophysiological activity can be measured in the electroencephalogram (EEG), which measures activity originating in cortical pyramidal neurons from postsynaptic potentials. Postsynaptic potentials arise when neurotransmitters bind to receptors on the membrane of the postsynaptic cell, causing ion channels to open or close and leading to a voltage change at the cell membrane (Luck, 2005). The voltage change on either side of the active tissue has opposite polarities; the specific polarity depends on whether the postsynaptic potential is excitatory or inhibitory (Kappenman & Luck, 2016). When large numbers of neurons (around thousands to millions) are simultaneously active and spatially aligned, their electric fields sum, and the summed voltage can be recorded on the surface of the head with electrodes (Kappenman & Luck, 2016). The voltages recorded on the scalp reflect the neural activity that is occurring at that exact moment, resulting in an excellent temporal resolution (Kappenman & Luck, 2016). In contrast, due to the necessary numbers of simultaneously active and spatially aligned neurons, the voltage recorded at a specific electrode site usually reflects the activity of multiple brain regions, resulting in a bad spatial resolution (Kappenman & Luck, 2016).

One way to analyze EEG data is by using the event-related potential (ERP) technique. This technique is event-related since voltage fluctuations are temporally linked to an event, such as the occurrence of a stimulus or the execution of a response (Luck, 2005). Hence, ERPs have been used for decades to investigate neurocognitive processes in neurotypical and neurodivergent individuals (Kappenman & Luck, 2016). ERPs appear as waveforms unfolding over time, varying in polarity, amplitude, and duration (Kappenman & Luck, 2011). ERP researchers distinguish between peaks (i.e., local voltage maxima) and components (Kappenman & Luck, 2011). ERP components can be defined as a voltage change that reflects a specific neural or psychological process (Kappenman & Luck, 2011) and are usually labeled referring to their polarity (i.e., negative vs. positive) and their temporal position within the waveform (Luck, 2005). For example, N100 (i.e., N1) has a negative polarity and is observed around 100 ms after stimulus onset. Usually, sensory components from different modalities share the same label – due to the same polarity and temporal position in the waveform – but are not functionally related (Luck, 2005). For example, in visual processing the N1 wave can be influenced by spatial attention (for a review see Hillyard, Vogel, & Luck, 1998) and discrimination processing (for instance, Vogel & Luck, 2000), whereas in auditory processing the N1 wave can be influenced by auditory selective attention (for instance, Woldorff et al., 1993).

2.4.3 Research questions and research objectives

To investigate the processing of categorical information, pilot study, Experiment 1, and Experiment 2 aim to determine whether perceptual categorical information can be encoded already in early visual processes (in NT adults), whereas Experiment 3A and Experiment 3B aim to investigate when and where more detailed information for semantic categorization is implicitly encoded (in ASD and NT adults).

Perceptual categorization in visual processing

Hence, the research objectives for the first set of experiments (i.e., pilot study, Experiment 1, and Experiment 2) are to investigate whether categorical information of well-defined perceptual category is encoded automatically in early visual processing. Well-defined categories have clear category boundaries, and all members are equally representative. Additionally, only the same specific features are needed to distinguish between different categories (i.e., rule-based approach). Automatic rather than prompted encoding of categorical information (i.e., categorization is not necessary for the task) changes the processing goal which in turn can influence the encoding of categorical information. In the pilot study and Experiment 1, an oddball paradigm and a Bayesian analysis of ERP results will be employed with the aim to test whether *or not* categorical information is encoded in early visual processing. Due to the recursive nature of the Bayesian approach, i.e., the comparison of empirical data to specific values of the prior which are derived from existing evidence (which can be very specific for a given experimental paradigm), I confirmed and extended these initial results in a second experiment. Based on the results of the pilot study and Experiment 1, Experiment 2 combines an oddball paradigm with a n-back task to determine whether categorical information is encoded in early visual or later cognitive processes of visual processing. Note that for the first set of experiments NT adults were asked to participate.

Semantic categorization in visual processing

The research objectives for the second set of experiments (Experiment 3A and Experiment 3B) are based on behavioral evidences, which indicate that multiple factors can implicitly affect the level of details encoded during semantic information processing. The factors that will be investigated in the second set of experiments are (1) presentation duration, (2) typicality, and (3) the cognitive processing style of participants.

(1) Studies observed that with longer presentation duration, an increasing number of available perceptual features (Rogers & Patterson, 2007) or the information from feedback connections (Carmo et al., 2020) reinforce a more detailed information processing. For instance, Potter and colleagues (2014) observed that neurotypical individuals can identify and extract meaning from pictures in less than 50 ms. Therefore, they suggested that this is the minimum time necessary for feedback connections to influence information processing based on feedforward connections (Potter, Wyble, Hagmann, & McCourt, 2014).

(2) In contrast to typical members of a category, atypical members are more likely to be processed in more detail (Jolicoeur, Gluck, & Kosslyn, 1984; Murphy & Brownell, 1985) and are associated with a larger response in the ventral occipito-temporal cortex (Panis, Wagemans, & Op de Beeck, 2011). The encoding of typicality based on information from the early stages of visual processing, by using an ultra-rapid categorization task, has only been investigated in a behavioral study by Carmo and colleagues (2020). They observed that NT participants were able to categorize atypical images only with longer presentation duration (i.e., at 80 ms) and suggested that a more detailed information processing is needed for atypical in comparison to typical members of a category.

(3) Lastly, according to the literature (as described in Chapter 2.3), individuals with ASD prefer processing information in greater detailed due to a difference in their cognitive processing style. This cognitive processing style results in reduced generalization, overselectivity, and poor categorization (Brown & Bebko, 2012) as well as in hyper-specific and extremely detailed categorical representations (Church et al., 2010).

Hence, the research objectives are to investigate when and where longer presentation duration and atypicality modulate information in an ultra-rapid categorization task using ill-defined semantic categories and whether these modulations differ between for adults with ASD and NT adults. In Experiment 3A and Experiment 3B an ultra-rapid semantic categorization task will be employed. The temporal course of behavior will be analyzed using the EHA in Experiment 3A, with the objective of investigating the effects of presentation duration and typicality on the shapes of reaction time and accuracy distributions in an ultra-rapid superordinate (i.e., “animal”) categorization paradigm. Additionally, the temporal course of the reaction time and the accuracy distribution will be statistically compared between NT and ASD adults. In Experiment 3B, the ERP components related to semantic categorization will be analyzed. In addition, two categories (i.e., “food” and “animal”) will be compared, to observe a modulation of less distinct category boundaries. The aim is to separate discrete phases of semantic categorization in NT and ASD adults and whether these phases are modulated differently by category boundaries, presentation time, and typicality.

CHAPTER 3: CATEGORICAL REPRESENTATIONS OF PERCEPTUAL CATEGORIZATION IN VISUAL PROCESSING

In this chapter, the first set of investigations is described. They are concerned with the investigation about whether perceptual categorical information can be encoded in early visual processing (in NT adults). In Chapter 3.1, the pilot study and Experiment 1 aim to investigate whether *or not* categorical information is encoded in early visual processing, whereas in Chapter 3.2 (based on the results of Chapter 3.1) the Experiment 2 aims to investigate whether categorical information is encoded in (early visual or) later cognitive processes of visual processing.

3.1 DO CATEGORICAL REPRESENTATIONS MODULATE EARLY AUTOMATIC VISUAL PROCESSING? A VISUAL MISMATCH-NEGATIVITY STUDY

In this chapter, the pilot study and Experiment 1 will be described. Based on the evidence about early (visual) processing of categorical information (Chapter 3.1.1), the predictions of the present study can be described (Chapter 3.1.2). The experimental methodology of the initial experiment to investigate these predictions will be described (Chapter 3.1.3) and the results will be depicted (Chapter 3.1.4) and interpreted (Chapter 3.1.5). Due to the nature of the Bayesian approach Experiment 1 will follow the pilot study to replicate the results. Hence, the methodology of Experiment 1 will be described (Chapter 3.1.6) and the results of Experiment 1 will be depicted and interpreted (Chapter 3.1.7). The results of both experiments (i.e., pilot study and Experiment 1) are discussed in Chapter 3.1.8. Lastly, the chapter concludes with a summary about the findings (Chapter 3.1.9).

3.1.1 Introduction

Categorization is the ability to sort any one element into subsets (categories) based on either a prototype or a rule-based system that can be either known or inferred (Sowa, 2005). Concerning human perception, categorization refers to assigning sensory input to distinct groups based on cognitive and behavioral relevance. Typically, dividing stimuli into often arbitrary groups is taken as synonymous with the semantic relationship between objects within a category (Freedman & Assad, 2016). The categorization of auditory stimuli into relevant groups (e.g., stream of auditory input into syllables) is already observable 100–250 ms after stimulus onset in the activation of brain areas above the auditory cortex (for instance, Kujala, Tervaniemi, & Schröger, 2007). This early categorization is reflected in the mismatch negativity (MMN): an event-related brain potential (ERP) examined in the human electroencephalogram (EEG).

Conventionally, the MMN is elicited in oddball-like paradigms with two types of stimuli: a frequently presented auditory stimulus, the *standard*, and a deviation from this frequent stimulus, the *deviant*. The *standard* builds up an internal representation in the auditory system. Whenever a sound does not match this internal representation, the MMN, defined as the amplitude difference between deviant and standard, is elicited between 100 and 250 ms after stimulus onset (Kujala et al., 2007). Over the last years, it was demonstrated that the MMN can reflect more than changes in physical features between standard and deviant. For instance, the MMN is elicited by a violation of an expectation in a complex auditory environment (for a review, see Näätänen, Paavilainen, Rinne, & Alho, 2007). Several studies suggest that the system underlying the MMN categorizes a continuous auditory input at an abstract level (for a review, see Näätänen, Tervaniemi, Sussman, Paavilainen, & Winkler, 2001). Examples for this capacity include the processing of timbre (Christmann, Lachmann, & Berti, 2014) and harmonic categories (Koelsch, Gunter, Schröger, & Friederici, 2003), as well as linguistic categories such as speech-non-speech discrimination (Christmann, Berti, Steinbrink, & Lachmann, 2014), prosody (Kujala, Lepistö, Nieminen-von Wendt, Näätänen, & Näätänen, 2005), semantics (Pulvermüller & Shtyrov, 2006), and even statistical learning (Tsogli, Jentschke, Daikoku, & Koelsch, 2019). As the detection of irregularities does not depend on participants' awareness of the change, it is assumed that the auditory MMN reflects automatic and pre-attentive processing of information (Van Zuijen, Sussman, Winkler, Näätänen, & Tervaniemi, 2005).

Processing of visual categorical information

Similar to auditory categorization, visual categorization seems to occur both effortlessly and near instantaneously for well-learned categories (e.g., animal vs. non-animals; Fabre-Thorpe, 2011). Several studies have indicated that ERPs related to the categorization of visual objects are observed at parietal and occipital recording sites between 150–200 ms after stimulus onset (Curran, Tanaka, & Weiskopf, 2002). In contrast, automatic acquisition of novel visual categorical information, which is required to form a new representation in working memory, is evident in relatively late ERP components around 350–600 ms after stimulus presentation (see Berti, Geissler, Lachmann, & Mecklinger, 2000; Berti & Roeber, 2013). Hence, in the present study I assessed whether or not the acquisition of new categorical information in the visual domain over the short-term is evident in early ERP responses in sensory (pre-) processing similar to those in the auditory domain. In other words, I investigated whether the visual system exhibits such an early categorization as observed in the auditory system by the MMN. The overwhelming evidence and theoretical reflections on the MMN are based on auditory processing (Kujala et al., 2007). Nevertheless, in recent years, the concept of the MMN and the interpretation of its functional significance have been generalized across domains (olfactory: e.g., Krauel, Schott, Sojka, Pause, & Ferstl, 1999; tactile: e.g., Kekoni et al., 1997; nociceptive: Hu, Zhao, Li, & Valentini, 2013). Similarly, numerous studies have investigated the MMN in the visual domain (vMMN; e.g., Berti, 2011; Berti & Schröger, 2001; Czigler, 2007; Pazo-Alvarez, Cadaveira, & Amenedo, 2003; Tales, Newton, Troscianko, & Butler, 1999). The peak of the vMMN is observable around 200 ms after stimulus onset at parieto-occipital recording sites (Pazo-Alvarez et al., 2003; as reviewed by Czigler, 2007). It is commonly associated with the detection of changes in the basic features of visual input. However, the underlying processes involved in the vMMN generation are also assumed to be capable of deriving complex rules about regularities in visual features (Kimura, Schröger, & Czigler, 2011; Stefanics, Kremlácek, & Czigler, 2014; Winkler & Czigler, 2012). It has been argued that the vMMN (like its auditory counterpart) reflects *automatic* processing of changes in visual stimulation (Pazo-Alvarez et al., 2003), an assumption that has received empirical support in recent studies (Berti, 2011; Czigler, Weisz, & Winkler, 2007; Flynn, Liasis, Gardner, & Towell, 2016; Jack, Widmann, O'Shea, Schröger, & Roeber, 2017; Kogai, Aoyama, Amano, & Takeda, 2011). To date, it still remains debatable whether the vMMN reflects both automatic processing and the categorization of more complex information derived from visual features.

A generalization from the auditory domain to other sensory domains includes the implicit assumption that all sensory processes share fundamental characteristics. As sensory systems are optimized for processing different sensory properties, the inference of universal MMN functions could be challenged. For instance, light and sound sources are transduced differentially and consequently the sensory mechanisms are different. While the auditory system is specialized for processing over time, the visual system is specialized for spatial processing (compare Berti, 2018). In the most general sense, all modalities are adapted to process stimuli according to the needs of the respective system. It is, therefore, a reasonable question whether categorization is similar or differs between modalities.

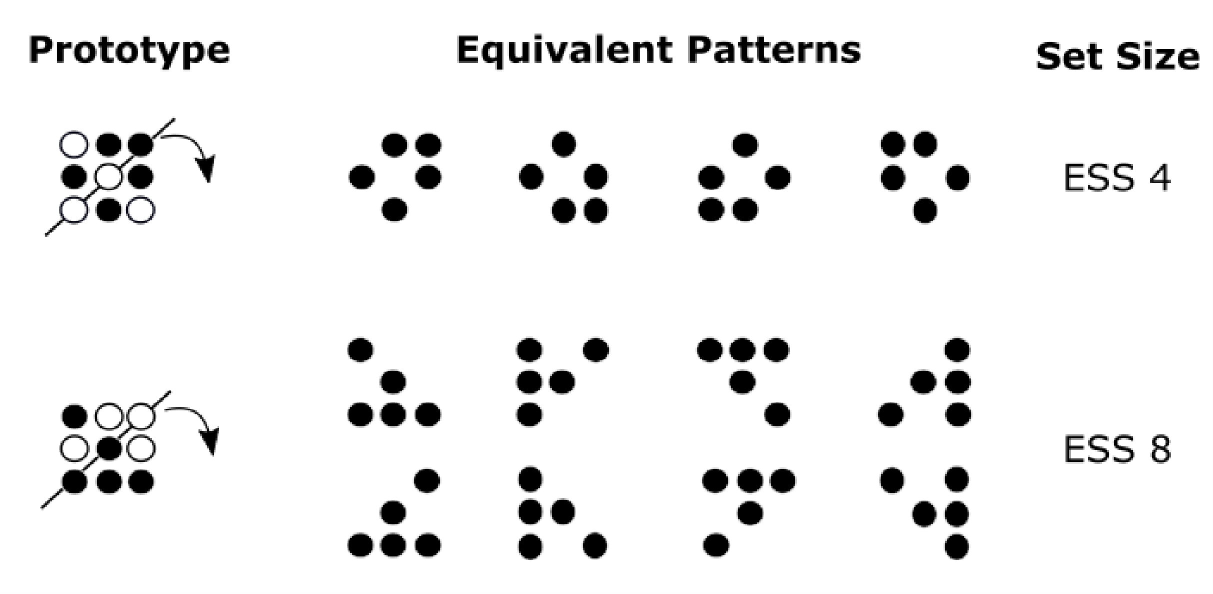
So far, there is no systematic research on whether a generalization across sensory domains is valid. Empirical evidence for the influence of categorical information on the vMMN has been reported for nameable categories such as facial emotions (Astikainen & Hietanen, 2009; Stefanics, Csukly, Komlósi, Czobor, & Czigler, 2012; Yu, Li, Mo, & Mo, 2017), lexical categories (Wei, Dowens, & Guo, 2018 for Chinese single-character word recognition; Wang, Liu, Wu, & Wang, 2013, for lexical tone phonology; Yu, Mo, Zeng, Zhao, & Mo, 2017, for novel shapes with lexical category labels), symmetry (Kecskés-Kovács, Sulykos, & Czigler, 2013) and color. For the latter, Clifford, Holmes, Davies, and Franklin (2010) used two different shades of blue colored squares and one green colored square as stimuli. One of the blue colored squares was presented as standard, the other blue colored square represented a *within-category deviant*, and the green colored square was used as a *between-category deviant*. When the deviant and standard belonged to different color categories, they elicited a larger vMMN in the time window of 100–250 ms compared to when the deviant and standard belonged to the same color category (Clifford et al., 2010). However, in this study two dimensions are potentially confounded: the physical dimension (i.e., the continuous physical property of wavelength of the reflected light), and the abstract semantic dimension (i.e., categories based on arbitrary linguistic boundaries associated with specific physical properties, for instance, *blue* corresponding to 450 nm; Athanasopoulos, Dering, Wiggett, Kuipers, & Thierry, 2010). To eliminate this potential confound, the physical characteristics of the stimuli should be kept as constant as possible. For example, Kecskés-Kovács et al. (2013) presented patterns consisting of seven black and nine grey squares in two 4 × 4 matrixes (i.e., the stimuli had the same physical characteristics). Kecskés-Kovács et al. (2013) hypothesized that vertical mirror symmetry serves as a perceptual category. Therefore, a vMMN was expected to be elicited by a random, asymmetrical stimulus (deviant) presented in a sequence of symmetrical stimuli (i.e., several *control* stimuli serving together as an equiprobable standard) but not vice versa (no vMMN for a symmetrical deviant in a sequence of asymmetrical control stimuli). As predicted, when the deviant was asymmetrical, two negative deflections were observed (between 112–120 ms and 284–292 ms). These were both identified as vMMNs by the authors and no vMMN was observed when a symmetrical deviant was presented in a sequence of asymmetrical control stimuli (see Kecskés-Kovács et al., 2013). Hence, only symmetry, and not the lack thereof, formed an internal representation and can be classified as a category. This supports the idea that an abstract visual category can elicit a vMMN. Accordingly, in the present study I relied on physically identical stimuli belonging to complex visual categories in order to compare categorization within and between abstract categories. Using these stimuli, I tested whether perceptual processing is affected by the categorical information inherent to the visual stimuli. I applied a Bayesian approach to derive a test statistic informed by prior independent evidence (Quintana & Williams, 2018) for evaluating the likelihood for both differences and similarities between conditions.

3.1.2 The present study

In the present study, I used a set of visual patterns consisting of five dots each (see Figure 1). These were arranged in an imaginary 3 × 3 squared grid with no empty rows or columns (as first used by Garner & Clement, 1963). These stimuli offer two major advantages for application in ERP studies. First, the physical energy of each pattern delivered to the sensory system is the same, since each pattern consists of five dots. Second, they comprise different categorical information as there are a total of 90 possible patterns belonging to 17 distinct subsets. These subsets were defined as transformational categories: each subset consists of patterns that can be transformed into each other by reflection and/or rotation and thus can be considered as categorically equivalent (equivalence set; ES; see Garner & Clement, 1963). The 17 subsets differ in size, containing either 1, 4, or 8 categorically equivalent patterns (equivalence set size, ESS; see examples in Figure 1). It was shown that all patterns of an ES share a common mental representation (Lachmann & Geissler, 2002; Lachmann & van Leeuwen, 2010). Since a smaller ES contains less information and thus a higher degree of redundancy (i.e., match of characteristics with the categorical representation), on have few alternatives; Lachmann & van Leeuwen, 2010) ratings are observed for smaller ESS patterns (Garner & Clement, 1963; Lachmann & Geissler, 2002). Moreover, several studies demonstrated that categorical information is encoded from these patterns even when the experimental task did not require this information for task performance (e.g., Berti & Roeber, 2013; Lachmann & Geissler, 2002, 2005a, 2005b), suggesting that the formation of these categories (i.e., ES) is an automatic and reliable process.

Figure 1

Stimulus Material



Note. The stimuli consisted of five dots arranged in an imaginary 3 × 3 grid with no empty rows or columns (first used by Garner & Cements 1963). Each stimulus prototype can be transformed into an equivalent pattern by rotation (90°) and/or reflection on any axis. An equivalent set size (ESS) of 4 is formed by a stimulus prototype that can be transformed into four equivalent patterns. An ESS of 8 is formed by a stimulus prototype that can be transformed into eight equivalent patterns.

The inherent characteristics of the stimulus material (i.e., equivalent patterns can be transformed into each other by reflection and/or rotation) are supposed to form the basis of categorization of each pattern in terms of the entire ES the pattern belongs to. However, humans tend to attribute meaning to otherwise meaningless patterns. This could also be the case for some of the dot patterns used here, resulting in abstract categories other than the ones defined by the ES structure. If meaning is indeed attributed to the dot patterns, the task may be solved effectively without ES based categorization. Lachmann (1998) asked participants to rate and to specify possible meaning for 17 patterns (i.e., one prototype for each ES). He found that only some patterns are consistently associated with a meaning (e.g., associations with letters and the "five of dice" pattern received the highest ratings). Nevertheless, a model assuming a mental pattern representation based on ES categorization (Lachmann & Geissler, 2002) was the best predictor for recognition performance; representational equivalence of rotated and/or reflected objects can hardly be ignored by humans (Lachmann & van Leeuwen, 2007, 2010; Pornstein & Krinsky, 1985). Hence, I use the ES structure of these dot patterns as compelling categorical information to examine a possible influence on the vMMN. For the purpose of this study, I use two out of 17 possible subsets; a smaller subset of ESS = 4 with four equivalent patterns as categorical elements, and a larger subset of ESS = 8 with eight equivalent patterns as categorical elements.

As described above, the visual stimuli used here control for one relevant non-cognitive influence on the ERPs, the variation of complexity and saliency of the physical stimulus. To avoid another potential misattribution, I used an equiprobable control condition (Schröger & Wolff, 1996; as used in Kecskés Kovács et al., 2013). In the traditional oddball paradigm, the standard stimulus is presented more frequently than the deviant stimulus and this difference in frequency affects the amplitude of ERP components (Kujala et al., 2007). In the equiprobable control condition, all stimuli are presented at an equal probability and thus effects due to frequency are controlled for. Hence, the vMMN difference wave is based on this equiprobable control condition, preserving the same physical characteristics as in the oddball condition but controlling for differences in the frequency of the presentation.

In addition, I used the three-stimulus oddball paradigm, as first used by Courchesne, Hillyard, and Galambos (1975), which is a variation of the classical oddball paradigm (see, for instance, Polich, 2007; Katayama & Polich, 1996; Rugg et al., 1993). Another rare stimulus, serving as a target, is introduced into the sequence of standard and deviant stimuli with the same probability as the deviant (e.g., standard stimulus $p = .75$, deviant stimulus $p = .125$, and target stimulus $p = .125$). This paradigm allows one to control for target effects (i.e., differences between the two relevant stimulus types, 'standard' and 'deviant', cannot be attributed to differences in the required cognitive processing connected with these targets, because neither standards nor deviants require any response). Hence, potential effects of further attentive processing steps are limited. In addition, all visual stimuli are presented in the same location on the screen, which keeps allocation of spatial attention constant for all three stimulus types. Therefore, differences between the stimulus types cannot be attributed to differences in the allocation of attention to the visual stimuli. However, it has been demonstrated that the vMMN is not modulated by attentional allocation (see, for instance, Berti, 2011; Czigler et al., 2007) and, therefore, effects in an early time-window (between 100 and 240 ms) likely indicate differences in perceptual processing of the visual input.

To address whether automatic encoding of the stimulus category can affect processing of early sensory processing steps, I will refer to the difference of the ERPs elicited by an ESS 4 deviant and ESS 8 equiprobable stimuli as *between-category vMMN*. Likewise, I will refer to the difference of the ERPs elicited by an ESS 8 deviant and ESS 8 equiprobable control stimuli as *within-category vMMN*.

Our main research question is whether categorical information affects the processes underlying vMMN generation (i.e., early perceptual processing of visual information). I address this question by investigating the vMMN and its potential categorical influences in two analyses: First, I test whether a vMMN is observed for *between-category* as well as *within-category* deviants. If a significant vMMN is obtained in both conditions, the second step is to then test whether the magnitude of the *between-category* vMMN and the *within-category* vMMN differs. Following the argumentation of the studies reviewed above (i.e., categorical processing as general feature of the MMN-process), I have two predictions regarding the elicitation of the respective vMMNs (1 and 2) and two predictions regarding the statistical comparison of the obtained vMMNs (3 and 4):

(1) *Between-category* deviants elicit a vMMN.

(2) *Within-category* deviants elicit a vMMN.

(3) *Between-* and *within-category* vMMNs differ in magnitude.

(4) Specifically, the *within-category MMN is smaller compared to the between-category vMMN.*

3.1.3 Method pilot study

Participants

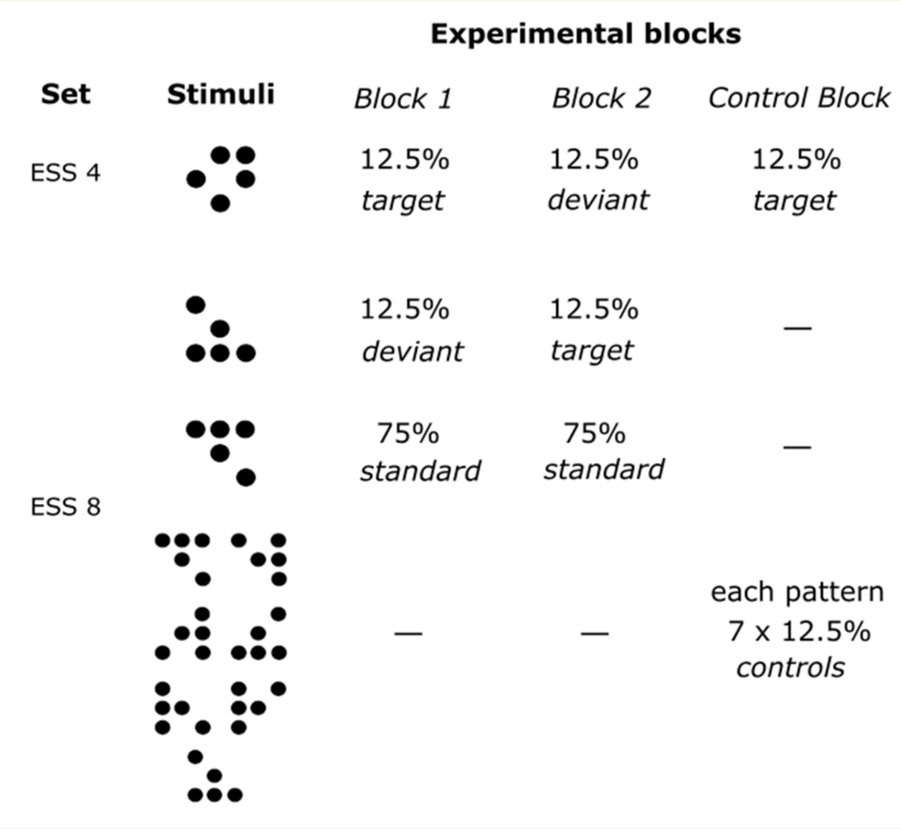
For this experiment, I recorded EEG data from 27 students from the University of Kaiserslautern who participated for course credits. I had to exclude three participants from the analysis due to low performance (error rate higher than 1 SD above group mean). Participants self-reported that they were right-handed, had normal or corrected-to-normal vision, have or had no diagnosis of psychological or neurological disorders, do not regularly consume psychoactive drugs or have not recently taken medication affecting the central nervous system. The study was conducted in accordance with the Declaration of Helsinki (World Medical Association, 2013) and approved by the ethical review board of the Faculty of Social Science of the University of Kaiserslautern. Every participant provided written informed consent in either German or English. Each participant generated an encrypted code word to ensure anonymity. In this experiment, EEG data from 24 students were analyzed (10 women; mean age: 25.8 years, *SD* = 2.3 years; English as instruction language: 11 participants).

Material

I presented patterns of two different ES (see Figure 2; Garner & Clement, 1963) according to the conditions. Each set contains patterns which can be transformed into each other by operations of rotation (90°) and/or reflection on any axis ("Rotation & Reflection sets", cf. Garner & Clement, 1963). The ES were chosen based on perceived perceptual complexity with the aim to keep them as comparable as possible (for ratings see Garner & Clement, 1963, as well as Lachmann & Geissler, 2002). The ESS 4 pattern employed here was rated with Goodness scores of 3.66 in Garner and Clement (1963) and 3.92 in Lachmann and Geissler (2002) on a nine-point scale from very complex = 9 to very simple = 1. The ESS 8 pattern employed here was rated with a 4.37 and 4.71, respectively. These specific patterns received very low ratings for meaning (Lachmann, 1998). In a number of experimental studies using these dot patterns, it was found that the ESS predicted (1) Goodness ratings for the individual patterns (Garner & Clement, 1963; Lachmann & Geissler, 2002), (2) reaction times (RTs) in speeded classification and recognition tasks (e.g., Carmo et al., 2017; Checkosky & Whitlock, 1973; Clement & Varnadoe, 1967; Hermens, Lachmann, & van Leeuwen, 2015; Lachmann & van Leeuwen, 2005a, 2005b, 2010), and (3) ERP amplitudes (e.g., the P3b: Berti et al., 2000; Berti & Roeber, 2013; Takahashi, Yasunaga, & Gyoba, 2019).

Figure 2

Experimental Procedure



Set	Stimuli	Experimental blocks *Block 1*	 *Block 2*	 *Control Block*
ESS 4		12.5% *target*	12.5% *deviant*	12.5% *target*
		12.5% *deviant*	12.5% *target*	—
		75% *standard*	75% *standard*	—
ESS 8		—	—	each pattern 7 x 12.5% *controls*

Note. In *Block 1* and *Block 2*, a three-stimulus oddball was employed with a repeated (standard) stimulus ($p = .75$), a deviant stimulus ($p = .125$), and a target stimulus ($p = .125$). The last block was a *Control Block* in which seven control stimuli, including those which were previously presented as standard and deviant stimuli from *Block 1*, were presented with an equal probability as the target pattern ($p = .125$).

Procedure

Figure 2 summarizes the stimulus material applied in this experiment. In all experimental blocks, participants were instructed to count how many times they saw a prespecified target. In *Block 1*, I presented a three-stimulus oddball design. Thus, three patterns were displayed: one ESS 8 pattern served as a standard (75 % of all trials), another ESS 8 pattern as deviant (12.5 % of all trials), and one ESS 4 pattern as the target (12.5 % of all trials). In *Block 2*, another ESS 8 pattern served as a target and the ESS 4 as a deviant. I did not change the ESS 8 standard in comparison to the first condition. Finally, I included a *Control Block* with an equiprobable condition. In this condition, I presented seven different ESS 8 control stimuli (7 × 12.5 %), thus matching the frequency of deviant and target stimuli for each stimulus presented. The target was again the ESS 4 pattern (12.5 %). As the neuronal response to a frequent stimulus is smaller compared to the neuronal response to a rare stimulus, differences in frequency of presentation may also affect the outcome of difference waves. In more detail, because the neurons processing the frequent stimulus are firing more frequently, the "exhausted" neuronal response is subtracted from the "fresh" neuronal response elicited by the rare stimulus. The resulting overestimated difference between the two conditions is the so-called refractoriness effect (see Schröger & Wolff, 1996). In other words, amplitude differences between standard and deviant ERPs do – at least to some degree – also reflect the different refractoriness of the related neuronal populations. Thus, in the *Control Block* all patterns were presented with the same probability.

Participants viewed a total of 400 trials per block, with a short break after 200 trials. The order of blocks was fixed: all participants started with *Block 1*, continued with *Block 2*, and finished with the *Control Block*. The sequence of trials within the blocks were randomized for each participant with the following two constraints: The first two blocks started with at least five standard trials and at least two standards were presented between two consecutive rare events, whereas the last block started with at least five control trials and at least two control stimuli were presented between two consecutive other events. Each pattern was constructed in an imaginary 50 × 47 mm frame. These patterns were presented sequentially at the center of the screen for 200 ms. A fixation cross was displayed between stimuli presentation for 300 ms, thus resulting in a total trial duration of 500 ms. Stimuli and the fixation cross were presented in black (luminance = 0.417 cd/m^2) on a white background (luminance = 161.1 cd/m^2). Participants were instructed to focus on the fixation cross to prevent eye-movements. Prior to the beginning of each block, participants were instructed to count how often the assigned target pattern occurred. In the instruction, I presented only the target patterns to the participants; the non-target patterns were not presented before the experimental trials. The counting task was introduced to ensure that participants attended the visual stimuli. Participants reported their results orally in each break and their answers were recorded by the experimenter.

EEG recording

For the EEG recordings, I used 27 Ag/AgCl cap-mounted electrodes (EasyCap GmbH; Gilching, Germany) positioned on an extended 10–20 system (plus two electrodes placed at the mastoids). The EEG was Gilching, Germany). All electrodes were recorded with impedances lower than 10 KΩ. Additionally, I used four electrodes (above, below, right, and left of the eyes) to record eye-movements. The ground electrode was placed at the forehead (AFz) and the reference electrode was placed at position FCz. The EEG signal was digitized with a sampling rate of 500 Hz. Stimuli were shown on a 14” VGA color monitor computer (1366 by 768 pixel), synchronized with the monitor refresh rate of 60 Hz. Participants perceived stimuli foveally (visual angel = 0.72°). Participants were seated 40 cm in front of the monitor without a chin rest. Stimulus presentation was controlled with Presentation Software (Version 18.0, Neurobehavioral Systems, Inc., Berkeley, CA, www.ne urobs.com). The study took place in a dimly lit room.

Data processing

The EEG was re-referenced offline to the averaged mastoids (M1/ M2) using Brain Vision Analyzer 2.1 (Brain Products GmbH, Gilching, Germany). All epochs with eye-movements (on average 15.3 % of trials per participant) were excluded from further analyses. Eye-movements were assessed manually by the frontal distribution and their unique change in amplitude. A band-pass filter was applied (1 Hz – 30 Hz; each with 24 dB/oct; Butterworth). For the three relevant stimulus types (equiprobable control, ESS 4 rare deviant, and ESS 8 rare deviant), EEG segments were based on a time window of 100 ms before and 400 ms after stimulus onset. Control stimuli directly following the ESS8 serving as the deviant in Block 1 and as the target in Block 2 or control stimuli directly following target trials were excluded from further analysis. Further artifacts (introduced, for instance, by muscle activity or body movements) were deleted automatically when a voltage step of 50 μV/ ms was detected, when a voltage difference of 100 μV occurred in any 200 ms interval, or when a low amplitude of 0.5 μV occurred in a 100 ms interval. On average, 0.3 % of all trials were rejected due to artifacts. A baseline correction was applied to the segmented signal, using the time window of 100 ms before the stimulus onset. On average, 191 (range: 106–227) control, 36 (range 18–51) ESS 4 deviant, and 42 (range 26–50) ESS 8 deviant trials entered statistical analyses. To report the results of the vMMN, I created difference waves by subtracting the ERPs elicited by control stimuli from those elicited by each deviant. A control stimulus is defined as a pattern being presented with the same frequency as all other patterns in this block. By contrast, a deviant stimulus is defined as a pattern deviating from a sequence of more frequently presented pattern. Thus, I compare across blocks to ensure that both demands regarding frequency are fulfilled. By using the equiprobable control stimuli for this comparison, I could control for frequency of presentation. This means that the differences in ERPs are not attributable to the lower frequency of presentation in one condition. To obtain the *within-category vMMN,* I subtracted the ERPs elicited by ESS 8 control stimuli from the ERPs elicited by the ESS 8 deviant (see Figure 2). Since both, the deviant and the control stimuli belong to the same ESS, I call this *within-category vMMN*. To obtain the *between-category vMMN,* I subtracted the ERPs elicited by ESS 8 control stimuli from the ERPs elicited by the ESS 4 deviant. This vMMN is called *between-category vMMN*, since I am comparing between two ESS, more specifically a deviant from ESS 4 and control stimuli from ESS 8. Note that these comparisons involve stimuli of different blocks for creating the vMMN difference waves.

For these two difference waves, I calculated the mean amplitude in the time window of 160–240 ms with the following criteria: First, I identified the individual negative peak in this time window and, second, I computed the mean amplitude within a 40 ms window centered around the peak. The selection of both time window and electrode site is in accordance with the literature. As reviewed by Czigler (2007), the MMN is defined as a negative peak observable around 200 ms after stimulus onset. In a number of earlier studies (Berti & Schröger, 2001, 2004, 2006), the highest amplitude for the vMMN was elicited at electrode site P8 (see, for instance, Figure 5 in Berti & Schröger, 2001). Therefore, the analysis was performed at electrode site P8. Diagrams shown in the following passages are figures from Brain Vision Analyzer edited with CorelDraw X7 (Corel GmbH, München, Germany).

Statistical analysis

In this study, I assess whether or not between- and within-category deviants elicit a vMMN, and if so, whether the two potentially differ in size. Inherent in this endeavor is the possibility to find no differences between conditions. Hence, I choose the Bayesian approach in analyzing the data, as "the traditional p-value approach is only concerned with disproving the null hypothesis, there is no way to assess if the data favors the null hypothesis compared to the alternative hypothesis. Even a 'large' non-significant *p*-value does not provide evidence for the null hypothesis" (Quintana & Williams, 2018, p. 1). Therefore, the Bayesian framework allows us to quantify how much more likely the data is under the null hypothesis compared to the alternative hypothesis, given a prior probability. Combining the prior probability with the observed data forms the posterior distribution. The results were analyzed with two Bayesian one-sample *t*-tests against zero (to test predictions 1 and 2: Do I observe reliable *within*-and *between-category vMMNs*?), one Bayesian two-sided paired sample *t*-test (to test prediction 3: Do both vMMNs differ in magnitude?) and one Bayesian one-sided paired sample *t*-test (to test prediction 4: Is the *between-category vMMN* larger than the *within-category vMMN*?). I used JASP (Version 0.9.1.0), which implements methods described by Rouder, Speckman, Sun, Morey, and Iverson (2009). For the two Bayesian one-sample t-tests, I used an informed normal-distributed prior. As I wanted to test our data against a specific value (i.e., 0), the mean of the prior effect size distribution was 0. Assuming that the variances of our samples do not systematically vary, I used Cohen's *d* from the literature (Berti, 2018) to predict a prior standard derivation of the effect in a δ distribution size. The calculated standard derivation (*SD*) was 0.2184. Under the same assumption, I calculated the prior distribution for the paired sample *t*-

tests. For this second prior normal distribution, I used partial eta-squared (η_p^2) from the studies by Athanasopoulos et al. (2010), Clifford et al. (2010), and Kecskés-Kovács et al. (2013) to calculate the mean (0.896) and *SD* (0.9255) of the distribution. Cohen's f^2 can be derived by dividing η^2 by 1- η^2 and Cohen's *d* can be calculated for multivariate comparisons with a minimum variability by multiplying Cohen's f^2 with the squared-root of two times the number of means (k; Cohen, 2008). I will report the Bayes Factor (*B*) for support of the alternative hypothesis (B_{10}/B_{+0}) or the null hypothesis (B_{01}/B_{0+}). A *B* value between 3 and 10 indicates a substantial evidence, between 10 and 100 indicates strong support (Kass & Raftery, 1995). Additionally, I report the Bayesian 95 % credibility interval (Bayesian 95 % CI; Wagenmakers, Lodewyckx, Kuriyal, & Grasman, 2010).

3.1.4 Results pilot study

Task performance

Participants' performance in the target counting task was highly accurate, with an average accuracy of 0.941 (standard error, *SE* = 0.027; Bayesian 95 % CI [0.884, 0.997]) in *Block 1,* 0.965 (*SE* = 0.011; Bayesian 95 % CI [0.942, 0.987]) in *Block 2,* and 0.98 (*SE* = 0.004; Bayesian 95 % CI [0.971, 0.989]) in the *Control Block*.

Event-related potential data

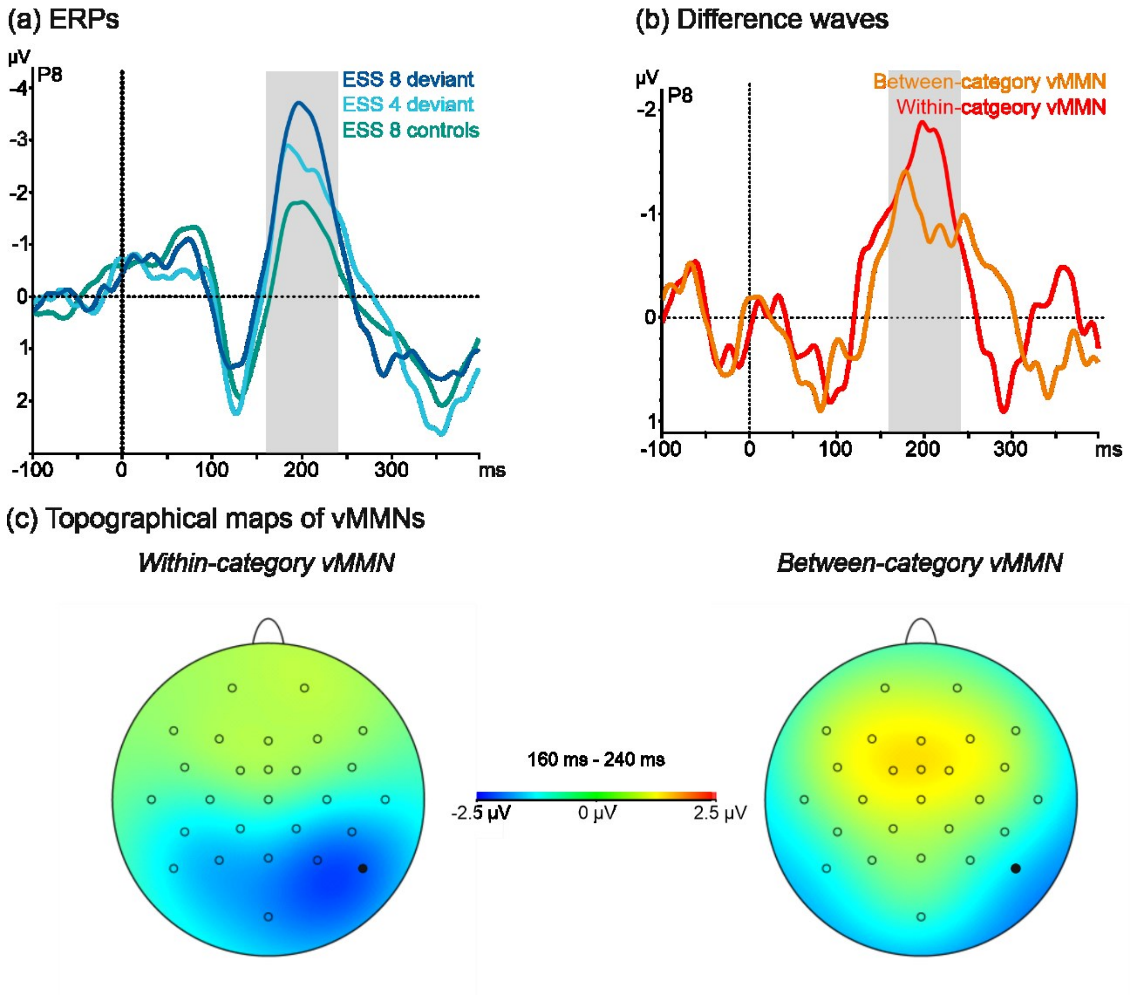
In the ERPs, I observed differences in the mean amplitude between the ESS 4 rare deviant, ESS 8 rare deviant, and ESS 8 equiprobable control stimuli. As illustrated in Figure 3a, both the ESS 4 rare deviant and the ESS 8 rare deviant elicited a more negative deflection in the vMMN time window (40 ms, centered around individual peak latencies identified between 160 – 240 ms) compared to ESS 8 controls. Both types of deviants elicited more negative ERPs (ESS 4 rare deviant: -2.16 µV, *SE*= 0.32 µV and ESS 8 rare deviant: -2.87 µV, *SE* = 0.36 µV) than ESS 8 control stimuli (-1.35 µV, *SE* = 0.22 µV).

To evaluate the vMMN (difference wave; see Figure 3b and c), I assessed whether the *between-category vMMN* (prediction 1) and the *within-category vMMN* (prediction 2) are different from zero. The support for prediction 1 is 60 time more likely than the support for the respective null hypothesis (B_{10} =

60.95; Bayesian 95 % CI [-0.812, -0.165]). I acquired a *between-category vMMN* in the time window of 160–240 ms with a mean peak amplitude of -1.18 μV (*SE* = 0.21 μV) and a mean peak latency of 197 ms (*SE* =6 ms). I also found strong support for prediction 2, demonstrating that the *within-category vMMN* (mean amplitude = -1.68 μV, *SE* = 0.28 μV; mean latency = 199 ms, *SE* = 5 ms) is different from 0 (B_{10} = 73.749; Bayesian 95 % CI [-0.825, -0.175]).

Figure 3

Results of pilot study



Note. (a) Grand average ERPs (N = 24) at one representative electrode (P8) for the ESS 8 deviant, the ESS 4 deviant, and the control stimuli. The grey area indicates the interval of 160 – 240 ms after stimulus onset, in which the peak detection analysis was performed. (b) Differences waves at one representative electrode (P8) for *between-* and the *within-category vMMN*. *Between-category vMMN* was calculated by subtracting the ERPs of the controls from the ERPs of the ESS 4 deviant. The *within-category vMMN* was calculated by subtracting the ERPs of the controls from the ERPs of the ESS 8 deviant. The grey area indicates the interval of 160 – 240 ms after stimulus onset, in which the peak detection analysis was performed. (c) Topographical maps of *between-category* and *within-*

category vMMN in the time window of 160 – 240 ms. Electrode sites are marked with circles and the filled circle indicate the P8 electrode used for analysis.

To test for a category-dependent modulation as specified in predictions 3 and 4, I compared the size of the *between-category vMMN* with the size of the *within-category vMMN*. Based on the literature, I considered a possible difference when comparing the vMMN in both conditions. The support for the prediction of a difference between the vMMNs (prediction 3) is 2 times more likely than the null hypothesis (B_{10} = 2.072; Bayesian 95 % CI [0.075, 0.895]) and thus does not provide sufficient evidence for prediction 3. I also found that the *within-category vMMN* could be smaller than the *between-category vMMN* (prediction 4). The alternative hypothesis is 2 times more likely than the null hypothesis (B_{+0} = 2.46; Bayesian 95 % CI [0.106, 0.896]), providing support that between-category and within-category vMMN did not differ in the present paradigm.

3.1.5 Discussion pre-study

The results of the pilot study clearly demonstrate the presence of both *between-* and *within-category vMMNs* (i.e., larger than 0; corresponding to prediction 1 and 2, respectively). However, I did not observe a difference between both vMMNs (corresponding to prediction 3). Hence, the *within-category vMMN* was not smaller than the *between-category vMMN* (corresponding to prediction 4). These results indicate that early perceptual processes, as reflected by the vMMN, do not comprise ad hoc visual categorical information, which is in contrast with the literature and the evidence obtained in the auditory domain.

Closer inspection of the existing literature reveals that categorization effects are typically based on already acquired categories and these previously unknown dot patterns used here. Regarding this point, the literature on the effect of categorical information in the vMMN is mainly based on categories like color (Athanasopoulos et al., 2010; Clifford et al., 2010; Thierry, Athanasopoulos, Wiggett, Dering, & Kuipers, 2009) and facial emotions (Astikainen & Hietanen, 2009; Stefanics et al., 2012). Compared to the dot patterns I used, this kind of categorical information is part of our everyday life. Thus, these categories are acquired early in life and are well-known to most of our participants. This can be also said about the literature of the auditory MMN (e.g., phonetic processing: Aulanko, Hari, Lounasmaa, Näätänen, & Sams, 1993). Thus, maybe our participants did not clearly perceive the categorical affiliation of the ES, even though behavioral evidence suggests that they should (Lachmann & van Leeuwen, 2010), in line with the notion of "To perceive is to know" (Garner, 1966).

Taking full advantage of the Bayesian logic requires that a prior, against which the empirical values are tested, is derived from a study closely resembling the evidence to be evaluated (Gronau, Ly, & Wagenmakers, 2019). By replicating our results, I can derive priors from the same experiment rather than relying on other studies with similar, but not identical topics. To additionally eliminate a potential confound, I changed the order of the blocks, such that the *Control Block* appears before *Block 1* and *Block 2*. Giving participants the chance to see all ESS 8 patterns beforehand may increase the likelihood that the ESS 4 pattern represents a deviation relative to the other patterns.

3.1.6 Methods experiment 1

Participants

For the first experiment, I recorded the EEG data of 28 students from the University of Kaiserslautern. In order to preclude carry-over effects, participants in Experiment 1 were naïve to the content of pilot study and recruited independently (i.e., no participants of Experiment 1 had already participated in pilot study). In Experiment 1, students participated for course credit or monetary compensation. I had to exclude four participants from the analysis due to low performance (error rate higher than 1 SD; $n = 2$), and excessive artifacts ($n = 2$). Participants self-reported that they were right-handed, had normal or corrected-to-normal vision, have or had no diagnosis of psychological or neurological disorders, do not regularly consume psychoactive drugs or have not recently taken medication affecting the central nervous system. The study was conducted in accordance with the Declaration of Helsinki (World Medical Association, 2013) and approved by the ethical review board of the Faculty of Social Science of the University of Kaiserslautern. Every participant provided written informed consent, in either German (13 participants) or English (11 participants). Each participant generated an encrypted code word, to ensure anonymity. In this experiment, EEG data from 24 students were analyzed (9 women; mean age: 25.5 years, *SD* = 2.4 years).

Procedure

Participants performed the same blocks as in the pilot study. However, in Experiment 1, the *Control Block* was presented first, containing seven control patterns with the same frequency (i.e., 12.5 % of trials) as the ESS 4 pattern serving as target. In the second block (corresponding to *Block 1* in pilot study), I presented a three-stimulus oddball sequence with the ESS 4 pattern as the target, an ESS 8 pattern as the deviant, and another ESS 8 pattern as the standard. The last block (corresponding to *Block 2* in pilot study) repeated the stimulus properties. The only difference was that the ESS 8 was assigned as the target and that the ESS 4 was assigned as deviant in this block.

Data processing and analysis

EEG acquisition procedures and data analysis were the same as described above. On average, 12.1 % of all trials had to be deleted due to eye-movements and 0.4 % of all trials were rejected due to artifacts. In this analysis, I had on average 201 control trials, 35 ESS 4 deviant trials and 40 ESS 8 deviant trials. The prior distribution for the Bayesian statistics was derived from the pilot study. The SD for the Bayesian one-sample *t*-test was calculated form the posterior distributions' median and the lower CI. Thus, the prior distribution of the two one-sampled *t*-tests are normally distributed around 0 with a *SD* of 0.165 for the *between-category vMMN* and a *SD* of 0.166 for the *within-category vMMN* (prediction 1 and 2). For the Bayesian paired sample *t*-tests, I used the results of our first experiment as priors, thus testing the results against our own previous results. The mean for the Bayesian two-sided paired sample *t*-test (prediction 3) was at 0.485 with a *SD* of 0.209. For the Bayesian one-sided paired sample *t*-test (prediction 4), I used a mean of 0.487 (*SD* = 0.194).

3.1.7 Results and discussion experiment 1

Task performance

Participants' overall performance in the target counting task was highly accurate, with an average accuracy of 0.976 (*SE* = 0.005; Bayesian 95 % CI [0.964, 0.987]) in the *Control Block*, 0.976 (*SE* = 0.007; Bayesian 95 % CI [0.961, 0.989]) in *Block 1*, and 0.828 (*SE* = 0.023; Bayesian 95 % CI [0.780, 0.875]) in *Block 2.*

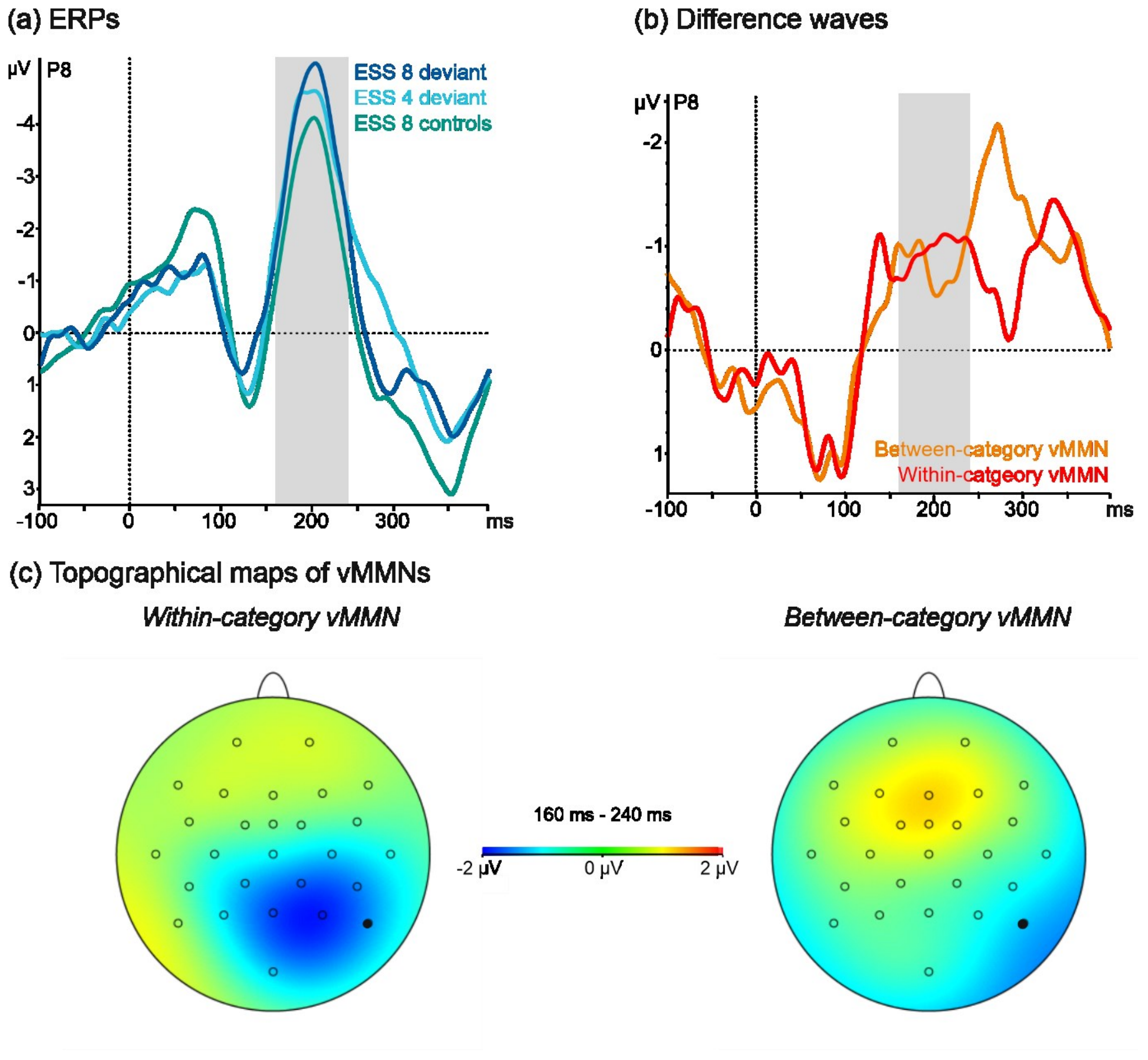
Event-related potential data

In the ERPs, I observed differences in mean amplitude between the ESS 4 deviant, the ESS 8 deviant, and the ESS 8 control stimuli. As illustrated in Figure 4a, both the ESS 4 deviant and the ESS 8 deviant elicited a more negative deflection in the vMMN time window (40 ms time window, centered around individual peak latencies identified between 160 and 240 ms) compared to the ESS 8 controls. The ESS 4 rare deviant had an average amplitude of -3.96 µV (*SE*= 0.69 µV) and the ESS 8 rare deviant of -4.00 µV (*SE* = 0.65 µV), compared to ESS 8 control stimuli with an average amplitude -3.11 µV (*SE* = 0.64 µV).

For the assessment of the vMMN (difference wave; see Figure 4b), I evaluated whether the *between-category vMMN* (prediction 1) and the *within-category vMMN* (prediction 2) were different from zero. The support for prediction 1 is 9 time more likely than the support for the respective null hypothesis (B_{10} = 9.417; Bayesian 95 % CI [-0.564, -0.034]). I acquired a *between-category vMMN* in the time window of 160–240 ms with a mean peak amplitude of -1.48 µV (*SE* = 0.33 µV) and a mean peak latency of 204 ms (*SE* =6 ms). I also found support for the assumption (prediction 2) that the *within-category vMMN* (mean = -1.27 µV, *SE* = 0.24 µV; mean latency =204 ms, *SE* =6 ms) is different from 0 (B_{10} = 14.639; Bayesian 95 % CI [-0.598, -0.060]).

Figure 4

Results of Experiment 1



Note. (a) Grand average ERPs (N = 24) at one representative electrode (P8) for the ESS 8 deviant, the ESS 4 deviant, and the control stimuli. The grey area indicates the interval of 160 – 240 ms after stimulus onset, in which the peak detection analysis was performed. (b) Differences waves at one representative electrode (P8) for *between-* and the *within-category vMMN*. *Between-category vMMN* was calculated by subtracting the ERPs of the controls from the ERPs of the ESS 4 deviant. The *within-category vMMN* was calculated by subtracting the ERPs of the controls from the ERPs of the ESS 8 deviant. The grey area indicates the interval of 160 – 240 ms after stimulus onset, in which the peak detection analysis was performed. (c) Topographical maps of *between-category* and *within-category vMMN* in the time window of 160 – 240 ms. Electrode sites are marked with circles and the filled circle indicate the P8 electrode used for analysis.

For our second step of analyses (predictions 3 and 4), I compared the size of the *between-category vMMN* and the *within-category vMMN*. Based on the literature, I considered a possible difference when comparing the vMMN in both conditions (prediction 3). The support for the null hypothesis of prediction 3 is 11 times more likely than the alternative hypothesis (B_{01} = 11.861; Bayesian 95 % CI [-0.130, 0.444]), hence not providing sufficient evidence for prediction 3. More specifically, I examined that the *within-category vMMN* could be smaller than the *between-category vMMN* (prediction 4). The null hypothesis is 15 times more likely than the alternative hypothesis (B_{0+} = 15.354; Bayesian 95 % CI [0.017, 0.464]), providing support that *within-category vMMN* is not smaller than the *between-category vMMN* in the present experiment 1.

Discussion

In the first experiment, I replicated the results of the pilot study with a different block order and a more refined statistical prior against which the empirical data were tested. Notably, block order did not modulate our effects. The chance to see all ESS 8 patterns from the start did not increase the likelihood that the ESS 4 pattern was perceived as a deviation relative to the other patterns. Thus, the main effect was not significantly influenced by block order and I again did not observe the difference between the *within-category vMMN* and the *between-category vMMN* described in the literature regarding well-learned, nameable categories and the findings from the auditory domain. Together, these data provide evidence that early and automatic processing steps, as reflected by the vMMN, are not affected by categorical information for previously unknown stimuli.

3.1.8 General Discussion

Does visual categorical information influence early perceptual processing and the associated ERP response as reflected in the vMMN? I investigated this question by using visual stimuli that have the same physical characteristics while belonging to different categories. Previous studies on categorization suggested that perceptual processing steps comprise categorical information and can therefore influence the vMMN (Athanasopoulos et al., 2010; Clifford et al., 2010; Mo, Xu, Kay, & Tan, 2011; Thierry et al., 2009). However, theoretical considerations regarding the functional significance of the MMN are largely confined to the auditory domain (Kujala et al., 2007). The present results contrast these considerations and suggest that the underlying MMN mechanism processes changes in visual stimuli based on perceptual differences even though the physical characteristics are equal. I choose this statistical approach to reflect both alternative answers to our research question (i.e., “yes” or “no”).

The first step of analysis (prediction 1 and 2) in our study was concerned with the presence of the *between-* and *within-category vMMN*, serving as an empirical measure for a general vMMN with the five-dot patterns employed here. As I found a pronounced *between-* and *within-category vMMN,* our data support this hypothesis. Hence, I can conclude that early processing steps in the visual domain can represent differences that are based on an abstract sensory rule. For our second hypothesis, I considered that *between-* and the *within-category vMMN* might differ (prediction 3). In more detail, the literature suggested that the *within-category vMMN* would be smaller in magnitude compared with the *between-category vMMN* (prediction 4). Such a difference would support the assumption that the vMMN also reflects processing of categorical information. Our results, however, do not support this hypothesis. In contrast, Bayesian statistics supports the null hypothesis. Note that in Bayesian statistics, the prior probability distribution is critical for a valid estimate of the statistical odds favoring or rejecting the null hypothesis. The choice of prior distribution often poses the challenge that no evidence is available in the literature that closely corresponds to the particular settings of the empirical investigation at hand. Therefore, default settings are typically used. For our pilot study, I reported the particular values underlying our prior distribution based on the literature. Crucially, in Experiment 1 I fully resolved this constraint by deriving new values for the prior distribution from our own results of pilot study. Replicating our own results enabled us to refine the Bayesian test statistic against which an independent new data set was tested, increasing both reliability and validity of our approach while taking full advantage of the Bayesian logic.

One factor influencing the present results is due to the stimulus material (Garner & Clement, 1963) I used. Studies about categorical information influencing the vMMN have been reported in facial emotions (Astikainen & Hietanen, 2009; Stefanics et al., 2012; Yu, Li et al., 2017), in lexical categories (Wei et al., 2018 for Chinese single-character word recognition; Wang et al., 2013, for lexical tone phonology; Yu, Mo et al., 2017, for novel shapes with lexical category labels), and in symmetry (Kecskés-Kovács et al., 2013). These types of categorical information are perceived regularly in daily life. Thus, these categorizations are learned over a long time period and are well-known to most participants. Additionally, some of these categories also resemble physical categories, which are potentially already encoded on the sensory level (for instance, by specialized retinal cells, see Dacey, 2000) or are hardwired in the organization of the visual pathways (i.e., by encoding the different sources of the information in the visual field, see Jack, Roeber, & O'Shea, 2015; for a related argument see also Berti, 2018). A critical feature of the different stimulus sets in this study is that they comprise different perceptual categories, but still have the same physical complexity. Thus, it is possible that our results differ from the literature due to either being less perceptually effective or by being not influenced by other cognitive processes.

Two additional factors that could have contributed to differences between our results and the literature concerns the choice of time window and the choice of electrode site in which the vMMN was evaluated. The time window and the choice of electrode site I chose to run the peak detection was strongly theory-based and therefore I looked strictly at the peak amplitude around 200 ms at P8. However, Figure 3 and Figure 4 suggest that there seems to be a later effect of categorical processing outside of the vMMN time window. Therefore, it remains to be established whether cognitive processes during this time window can still be characterized as pre-attentive. Additionally, the *within-category vMMN* seems to have a more central topographical distribution than the *between-category vMMN.* Therefore, it remains to be established whether the influence of categorical information is reflected also in the topographical distribution. Consequently, an analysis focusing on the topographical distribution instead of the magnitude difference might yield different results.

Originally, theories on the functionality of the MMN were mostly based on the auditory MMN (Kujala et al., 2007), which were then often generalized across other domains (olfactory: e.g., Krauel et al., 1999; tactile: e.g., Kekoni et al., 1997; nociceptive: Hu et al., 2013). This seems to be reasonable, as all sensory domains share the fundamental characteristic of processing sensory properties. However, functional differences between all sensory systems might challenge the generalization of the MMN across modalities. Thus, even if the processes underlying the auditory MMN are capable of an early and fast categorization of a continuous auditory input at an abstract level (for a review, see Näätänen et al., 2001), it is not necessarily generalizable to the visual domain and the vMMN. There does not seem to be much empirical evidence whether the generalization across sensory domains is valid. The results of our study indicate that the underlying mechanism of the vMMN may not be capable of general categorization at this automatic perceptual stage.

I acknowledge a number of limitations of the present investigation. Firstly, I did not randomize block order, but relied on two experiments with a pre-specified order of blocks. I replicated the results of the pilot study using a different block order, giving us evidence that the vMMN is elicited by these five-dot patterns and that block order did not have a major influence on our results. Note, however, that I cannot exclude another order effect in Experiment 1 for the *between-category vMMN,* as the ESS 4 pattern was attended (i.e., the target) in the block before it represented the deviant. According to this logic, the amplitude of the *between-category vMMN* may have been influenced by being more salient but not necessarily attended. Secondly, while a classic oddball paradigm is used in the majority of the literature, I employed a three-stimulus oddball paradigm in the present investigation. This change might have contributed to inconsistent findings in the present study compared to previous investigations. Thirdly, taking full advantage of Bayesian statistics resulted in a restricted analysis in terms of electrode location (using electrode site P8 only). Bayesian statistics were employed since I focused our analysis on the specific question of whether or not I would observe magnitude differences in the vMMNs, allowing for the statistical assessment of the null hypothesis. Based on the topographical distribution of the observed vMMNs, activity for the *within-category vMMN* appears to have a slightly more central-parietal distribution compared to the clearly right-parietal focus of the *between-category vMMN*. Because I did not predict this topographical difference and I did not have any means to account for this within the Bayesian logic, it remains to be evaluated in future research whether additional cognitive processes or potential differences in the timing of stimulus evaluation might account for this phenomenon.

The present results are in line with other studies applying these five-dot patterns: In a series of behavioral studies (Carmo et al., 2017; Lachmann & Geissler, 2002; Lachmann & van Leeuwen, 2005a, 2005b, 2007, 2010), it was shown that ESS of two successively presented patterns predict the time to decide whether or not they belong to the same ES category. Importantly, a strong response conflict was evident if the task requests a *different* response for two physically different patterns belonging to the same ES (physical comparison; Lachmann & van Leeuwen, 2005b). Furthermore, dual-task experiments with two overlapping choice reaction tasks (using the dot-pattern comparison as a secondary task following a simple independent tone choice reaction task) showed that the ESS effect is additive with varied asynchrony between the onset of the primary and the secondary tasks (Lachmann & van Leeuwen, 2007, 2008). Together, these studies suggest that the decision of whether two patterns belong to the same category (i.e., same ES) is made relatively late in the time course of information processing and that it requires limited central capacity (Pashler, 1994). The same effect was found for mental rotation of letters as a secondary task in a dual task setting (Ruthruff, Miller, & Lachmann, 1995).

3.1.9 Conclusion

Our data suggest that categorical classification is not reflected in the vMMN, indicating that early, automatic sensory processing (as indexed by the MMN) does not indicate ad-hoc perceptual categorization in the visual domain. In line with the notion that this finding is in contrast to findings in the auditory domain, in which abstract rules already affect sensory processing, reflecting perceptual classification at early processing steps. This might imply that visual categorization is affecting comparably later processing steps rather than the early perceptual processing steps under investigation here. On the contrary, it is also possible that auditory and visual categories are based on different perceptual features and rules, which might not be reflected in the two MMN subtypes. Both interpretations, however, suggest the auditory and the visual MMN are not fully functionally equivalent.

3.2 DO CATEGORICAL REPRESENTATIONS MODULATE EARLY PERCEPTUAL OR LATER COGNITIVE VISUAL PROCESSING? AN ERP STUDY

In the previous chapter (Chapter 3.1) it has been demonstrated that in a passive-oddball paradigm with a specific stimulus set, categorical information did not influence early perceptual processing steps. In this chapter, ERPs are used to differentiate distinct stages of visual processing. The goal of the present experiment is to assess at which stage of information processing the five-dot patterns are categorized, more specifically in early perceptual or later cognitive processes (in NT adults). Given the evidence about the modulation of later cognitive and early visual processing (Chapter 3.2.1), the predictions of the present study will be described (Chapter 3.2.2). The experimental methodology of the Experiment 2 to investigate these predictions will be explained (Chapter 3.2.3), followed by the depiction (Chapter 3.2.4) and discussion (Chapter 3.2.5) of the results. Lastly, the chapter concludes with a summary about the main findings (Chapter 3.2.6).

3.2.1 Introduction

Categorization is a central mechanism of perception and hence the foundation for constructing our knowledge about the world (Cohen & Lefebvre, 2017). Categorization can be defined as the mental process of classifying instances, objects, or events into distinct subsets (i.e., categories; Beck, Berti, Czernochowski, & Lachmann, 2021). Most notably, categorization is fast and seemingly effortless (Mandler, 2003), suggesting it relies on early neuro-cognitive processing. However, research in cognitive science often evaluates comparably late processing steps. The reason for this lies partly in the restriction of measuring response time data, which represents the end result of several cognitive processes, including the encoding, categorization, decision, and motor response phase of information processing (Massaro &

Cowan, 1993). The method of event-related brain potentials (ERPs) allows the investigation of distinct processing steps, including comparably early, perceptual processing (Rugg & Coles, 1995) and hence complements behavioral assessments. Here, I use ERPs to differentiate distinct stages of visual processing and categorization of a specific set of categorical patterns (i.e., five-dot patterns; see Garner & Clement, 1963). In more detail, I analyze the visual mismatch negativity (vMMN) and the P300 component of ERPs, associated with either early perceptual (i.e., vMMN component) or later cognitive (i.e., P300 component) processing, respectively. The goal of the present research is to assess at which stage effects of categorical information in these visual patterns can be observed, and specifically to evaluate the role of earlier perceptual processing stages for categorizing this specific stimulus material.

Perceptual categorization is based on perceptual similarities with a categorical representation of the category itself or other exemplars in the same category (Quinn et al., 2001). Perceptual similarities with a categorical representation refer to both similarities of an exemplar with category members and differences with category non-members (Cohen & Lefebvre, 2017). How categorical representations are encoded in the brain is an ongoing debate (for review see Hanson & Hanson, this specific category and the current processing goal of categorization (Gauthier, 2000). This implies that categorical encoding is modulated by task context, and hence, encoding differences between, for instance, pre-attentive and task-relevant processing of categorical information. Perceptual similarities with other instances refer to shared perceptive properties that are deemed equivalent for a set of instances (Reznick, 2000). To investigate these perceptive properties, the physical energy delivered to the sensory system needs to be controlled. For instance, Garner and Clement (1963) used visual patterns, consisting of five dots in an invisible 3 × 3 square grid, by leaving no row or column empty. In total, there are 90 possible five-dot patterns, which can be sorted into 17 distinct subsets (i.e., categories) of different sizes (containing either 1, 4, or 8 categorically equivalent patterns). Similarities within instances of a subset are deemed equivalent (equivalence set; ES) by transformational rules. The transformational rule implies that each pattern within the same category can be transformed to any other by reflection and/or rotation. In several studies it was shown that all patterns in an ES share a common mental representation (Lachmann & Geissler, 2002;

Lachmann & van Leeuwen, 2010; Lachmann & van Leeuwen, 2005b; see van Leeuwen & Lachmann, 2004, for a review). One important feature of these patterns is that the physical energy of each pattern delivered to the sensory system is the same (i.e., each pattern consists of five dots). In the following, I summarize prior research using these stimuli with respect to comparably late stage of information processing (P300), and then move on to research regarding earlier perceptual processing (vMMN).

The modulation of memory encoding by categorical information

Employing the five-dot patterns in a cognitive task demonstrated that late stages of information processing like memory encoding and maintenance are influenced by perceptual categorization (for instance, in Berti, Geissler, Lachmann, & Mecklinger, 2000; Berti & Roeber, 2013; Carmo et al., 2017 and Takahashi, Yasunaga, & Gyoba, 2014, 2019). Berti and colleagues (2000) employed a delayed memory comparison task, in which two patterns were presented sequentially, separated by a 1500 ms interstimulus-interval. Participants performed the task under two conditions: In the identity-matching task, they were instructed to decide whether both stimuli were identical; in the categorical-matching task they were instructed to judge whether both stimuli belonged to the same category (i.e., ES). The results of this study suggested that categorical information is immediately encoded into working memory when this information is task relevant. In more detail, Berti and colleagues reported a difference between the two task instructions in the 300 – 500 ms time window at electrode Pz (P300). The P300 (also labeled P3b) is interpreted as a correlate of memory encoding in a broad sense (e.g., Donchin & Coles, 1988) and it was suggested that the amplitude varies with the amount of information transferred into working memory (Johnson, 1986). The study by Berti et al. (2000) reported a more positive P300 amplitude in the categorical-matching compared to the identity-matching condition; therefore, the authors concluded that perceptual features were encoded and maintained in working memory in the categorical-matching, but not the identity-matching task. These results were, in principal, replicated in a study by Berti and Roeber (2013) and by Takahashi et al. (2019). In addition, Berti and Roeber (2013) also reported an effect of ES-size (ESS), with a larger P300 amplitude for ESS-8 compared to ESS-4 patterns. All three studies support the assumption that categorical information is encoded into working memory, especially when this categorical information is task relevant.

Taken together, perceptual categories are relevant during information processing. Nevertheless, it remains open at which point in information processing this effect can be observed. The studies employing five-dot patterns – representing inherent perceptual categories – demonstrate the earliest effect of categorical information at the level of memory encoding (as reflected in the P300 component). However, another line of research suggests that categorical information processing occurs already at perceptual levels.

Perceptual processing of categorical information

In the auditory domain, perceptual categorization is well documented (see Näätänen, Paavilainen, Rinne, & Alho, 2007, for review). For instance, the auditory system can encode categorical information already within the first 200 ms of stimulus processing (see Näätänen, Tervaniemi, Sussman, Paavilainen, & Winkler, 2001). This line of research makes use of the so-called mismatch negativity (MMN) component of the ERP, which is associated with sensory classification processes (see Näätänen & Winkler, 1999). More importantly, the MMN allows to tap into processes at an early stage of stimulus processing (between 150 and 250 ms post-stimulus), hence preceding memory encoding. Although the visual system also generates a visual MMN (vMMN, see Pazo-Alvarez, Cadaveira, & Amenedo, 2003; Czigler, 2007), it remains an open question whether early visual processing comprises the same capacity for perceptual categorization as the auditory system.

With respect to artificial categories, a study by Kecskés-Kovács, Sulykos, and Czigler (2013) reported results supporting the idea of early perceptual categorization in vision. In this study, vertical symmetry was used as categorical information by applying patterns consisting of nine grey and seven black squares, in two 4 × 4 squared grids, separated by a vertical line. The patterns in both squared grids were either symmetrical or non-symmetrical (Kecskés-Kovács et al., 2013). Stimuli were presented in a classical oddball sequence (i.e., one stimulus type serving as the frequent standard stimulus and one stimulus type serving as the rare deviant). With this protocol, Kecskés-Kovács et al. (2013) were able to analyze the vMMN (i.e., the difference between standard and deviant ERPs) when symmetrical patterns were presented as standards and non-symmetrical patterns as deviant, or vice versa. They observed two posterior negative deflections (early: 112 – 120 ms; late: 284 – 292 ms) in the symmetrical condition, both identified as vMMNs (Kecskés-Kovács et al., 2013). In contrast, a recent study by Beck et al. (2021) did not find an influence of category on the vMMN. In this study, the five-dot patterns were used as stimuli, which allowed for defining different categories (i.e., ES). Moreover, this study employed a three-stimulus oddball paradigm (see Courchesne, Hillyard, & Galambos, 1975), presenting one frequent (i.e., standard), one rare target, and one rare task-irrelevant (i.e., deviant) pattern. Participants were asked to count the occurrence of the rare target pattern and ignore the standard and deviant pattern (Beck et al., 2021). By applying five-dot patterns from different ES, two variants of vMMNs were computed: When the deviant and standard stimulus were in the same ES, a *congruence vMMN* was derived, whereas an *incongruence vMMN* was derived when the deviant and standard stimulus were from different ES (Beck et al., 2021). Thus, the influence of categorical information on earlier perceptual processing would be associated by a difference between the *congruence vMMN* and the *incongruence vMMN*. The main result was that the *congruence vMMN* and the *incongruence vMMN* did not differ, indicating no influence of categorical information (Beck et al., 2021). While these two studies reported inconsistent results, there is a notable difference in the two protocols. In the first study (Kecskés-Kovács et al., 2013) a binary category was used, in which a pattern is vertical symmetrical or not. This study indicates that symmetry could serve as a deviant and was able to elicit a vMMN. However, with this stimulus material categorical modulations on the vMMN cannot be investigated. In comparison, in the second study (Beck et al., 2021) two abstract categories were used, in which a pattern belongs to one of two classes defined by abstract rules (i.e., transformation and rotation). Here, no categorical modulation on the vMMNs was observed.

3.2.2 The present study

In the present study, I assess the influence of categorization on both early perceptual (vMMN) and later cognitive (P300) processing. For this purpose, I constructed a paradigm in which both processes –

early perceptual processing associated with sensory classification of categorical information and later cognitive processing associated with memory encoding of categorical information – could be observed. Thus, I combined an oddball paradigm with a delayed memory task. To investigate early perceptual processing, the stimuli were embedded in an oddball paradigm. This means that rare patterns (i.e., deviants) were presented within a sequence of more frequently presented patterns (i.e., standards). Note that the relationship between the standard and the deviant pattern does not need to be encoded to solve the task. In the delayed memory comparison task, participants performed an identity-matching task between two sequentially presented five-dot patterns. Each five-dot pattern belonged to a different category (i.e., ESS-4 or ESS- 8). In contrast to the studies summarized above, participants performed a continuous identity-matching (i.e., 1-back) task, resulting in a continuous comparison between the current and the previously presented target stimulus. Based on the literature, I predicted to observe both a *congruence* and an *incongruence vMMN* (i.e., difference between the standard ERP and the deviant ERP; Beck et al., 2021). Second, I assessed whether categorical information has an influence on vMMN and/or P300. Lastly, I hypothesized no effect of categorical information on early perceptual (Beck et al., 2021), but rather on later cognitive processes (Berti et al., 2000). Specifically, no unique activation of the *congruence vMMN* and *incongruence vMMN* is predicted (Beck et al., 2021). However, I expected an influence of category (i.e., ES) on the P300 at central-parietal electrode sites, with the ESS-8 pattern eliciting a larger amplitude than the ESS-4 pattern (Berti & Roeber, 2013).

3.2.3 Methods

Participants

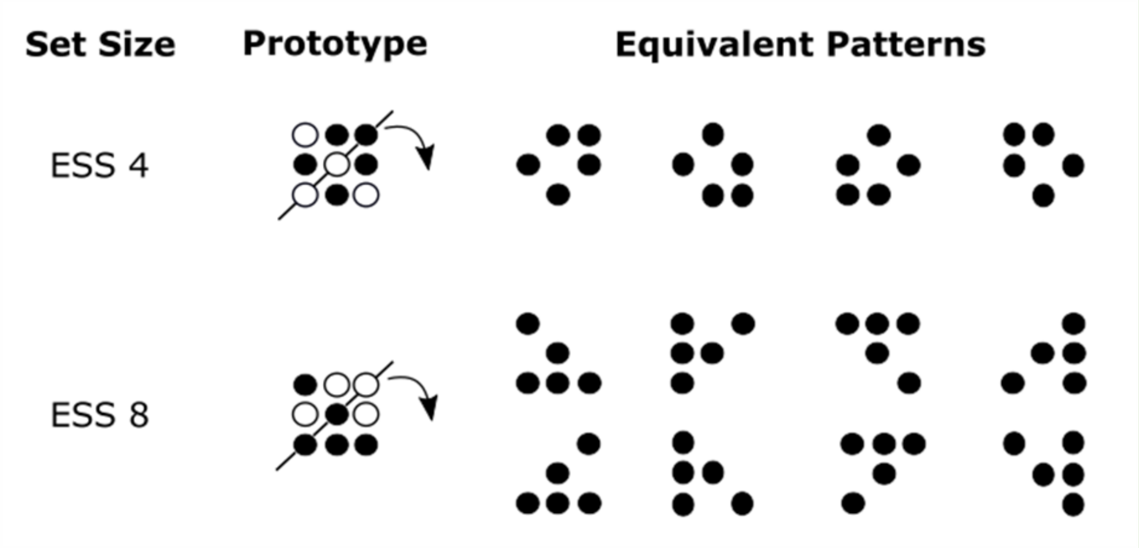
All participants were students from the University of Kaiserslautern, and, according to self-reports, were right-handed, had normal or corrected-to-normal vision, had no diagnosis of psychological or neurological disorder, and did not consume medication affecting the central nervous system. Every participant provided written informed consent after being informed about the procedure and having the possibility to ask questions. The study was conducted according to the Declaration of Helsinki (World Medical Association, 2013) and approved by the ethical review board of the Faculty of Social Science of the University of Kaiserslautern. I recorded EEG data from 30 students, who were compensated with course credits. After initial data analysis, I excluded participants due to low performance (*n* = 2; i.e., four standard deviations below group average) and incomplete data (*n* = 1). Thus, EEG data from 27 students were analyzed (17 female; *M*age: 24.96 years, *SD* = 1.85 years, range: 21–28 years).

Materials and procedure

I used a set of visual patterns, each consisting of five dots, constructed in a 3 × 3 squared grid, by leaving no row or column empty (first used by Garner & Clement, 1963). In this manner, 90 five-dot patterns can be constructed, which can be sorted into 17 distinct subsets (categories). Patterns within a subset can be transformed into each other by reflection and/or rotation (90°) operations and are therefore categorically equivalent (see Figure 5). Notably, since each pattern only consists of five dots, categorical characteristics are not due to differences in physical properties. In addition, I controlled for complexity of the categories and meaningfulness of the patterns. Complexity was controlled for by choosing two categories which received similar ratings for perceived perceptual complexity (see ratings in Garner & Clement, 1963 and Lachmann & Geissler, 2002). From each category, I used two patterns with low ratings for meaningfulness (see ratings in Lachmann, 1998). I used a smaller subset of ESS = 4 with four equivalent patterns as categorical elements, and a larger subset of ESS = 8 with eight equivalent patterns as categorical elements (see Figure 5). Additionally, the patterns were chosen based on a similar “direction” (upward). Between each stimulus, I presented either a black or red fixation cross at the center of the monitor.

Figure 5

Stimulus Material of Experiment 2

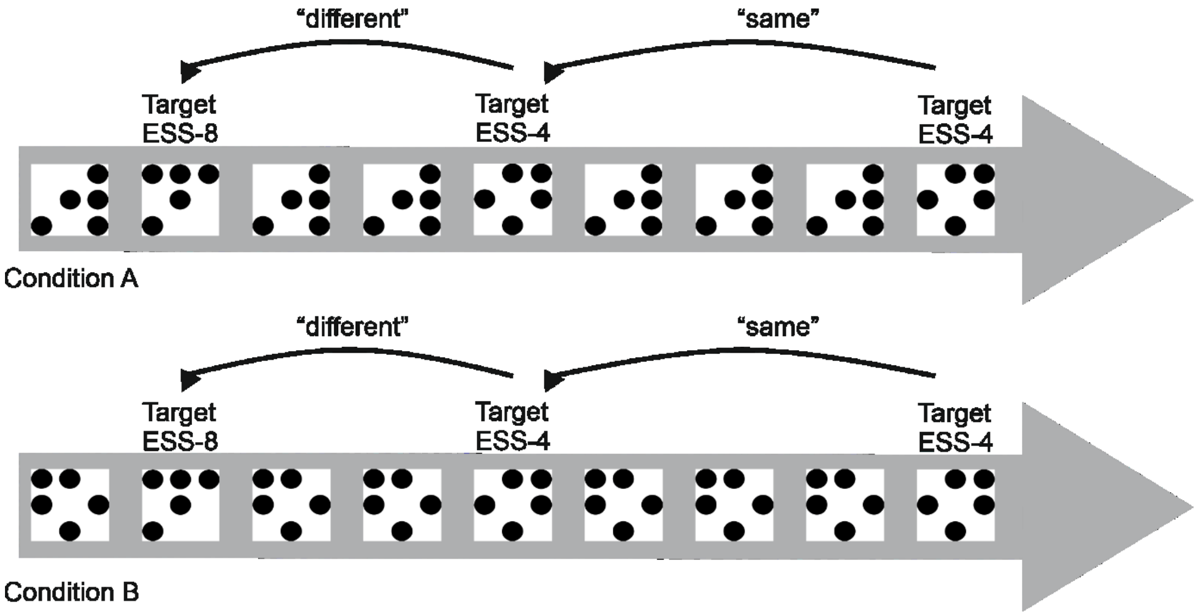


Note. I use two equivalent set sizes (ESS), ESS-4 and ESS-8. Each prototype consisted of five dots in an imaginary 3x3 matrix by leaving no row and no column empty stimuli (first used by Garner & Cements 1963). The prototype can be transformed into equivalent patterns by rotation (90◦) and/or reflection on any axis. A set of four equivalent patterns have an ESS of 4; a set of eight equivalent patterns have an ESS of 8.

Stimuli were presented on a 15.6′′ monitor with a resolution of 1920 × 1080 pixel and a refresh rate of 60 Hz. Dot patterns were presented in black (luminance = 0.417 cd/m^2) on a white (luminance = 161.1 cd/m^2) background. Instructions and stimuli were presented with the Software Presentation (Version 21.1, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com). I used two categories (ESS-8 and ESS-4; see Figure 5) and from each, two patterns (see Figure 6). One of the two patterns was presented frequently (standard pattern) and the other rarely (deviant pattern, 15 % of all trials). The standard pattern was presented in 85 % of all trials and counterbalanced blockwise between both categories. Standards were repeated randomly for four (20 %), five (30 %), six (30 %), or seven (20 %) consecutive trials. Presentation of the deviant pattern was counterbalanced between both categories. In each block, 50 rare patterns were presented. I realized two conditions (condition A and condition B; see Figure 6), since in each block I presented both deviant stimuli, but only one standard stimulus. In condition A the standard stimulus was from category ESS-8 and in condition B the standard stimulus was from category ESS-4. The six experimental blocks were presented randomly. In each trial, a stimulus was presented for 500 ms, followed by a fixation cross presented between 700 and 1100 ms (random variation).

Figure 6

Participants' task



Note. Participants performed a memory comparison task in two conditions (condition A and condition B). In both conditions I presented two rare stimuli but only one frequent stimulus. In condition A the frequent stimulus was from category ESS-8 and in condition B the frequent stimulus was from category ESS-4. The rare stimuli served as target stimuli and participants were asked to compare the actually presented target with the previously presented target and to indicate whether they were the same or different. The other, frequent stimuli were task-irrelevant and could be ignored.

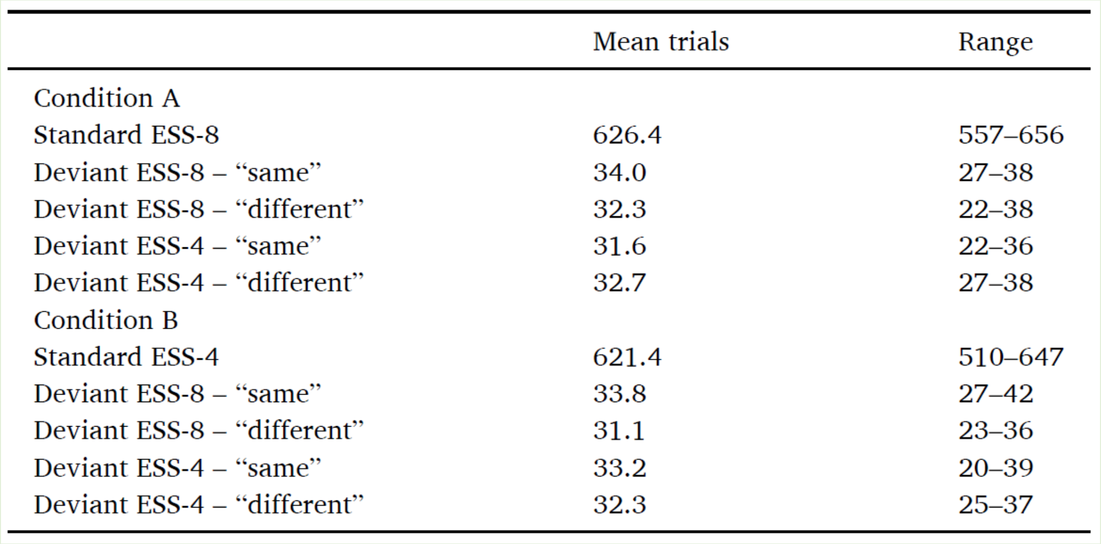
Participants were seated 40 cm in front of the monitor, using no chin rest, and perceived stimuli foveally (visual angel = 0.72°). Participants rested their index fingers on the left and right key of a response box, corresponding to a "same" and "different" response (counterbalanced across participants). Participants performed a memory task, which was an adaptation of the so-called n-back task (for information see Kirchner, 1958): Participants were instructed to perform a same-different memory comparison with sequentially presented rare stimuli (see Figure 6). In other words, rare stimuli served as targets; participants were asked to compare the current target with the previously presented target and to indicate whether they were the same or different. To complete this task, it is necessary to memorize the current rare stimulus until the next rare stimulus is presented and to continuously update the memory representation when the target changed. Responses could be given upon stimulus onset until the next stimulus was presented, resulting a response window between 1300 and 1600 ms due to the variable intertrial-interval (ITI). Frequent stimuli were task irrelevant and could be ignored. However, I added catch trials to ensure the processing of the frequent, task-irrelevant stimulus. Thus, participants were also instructed to press a foot pedal whenever the fixation cross changed to red (1.5 % of all trials). The red fixation cross only occurred after a standard stimulus. Overall, the trial duration did not depend on the responses. In the step-wise training blocks, participants had to respond with a 70 % accuracy to start the experimental blocks. Between each block, there was a break in which participants got feedback about their performance (mean accuracy and mean reaction time).

EEG recording

During practice and experimental blocks, electroencephalography (EEG) was recorded with 27 Ag/AgCl cap-mounted electrodes (EasyCap GmbH; Gilching, Germany) positioned on an extended 10 – 20 system (Jasper, 1958), plus two electrodes placed at the mastoids and four electrodes around the eyes, with the BrainVision EEG-System (BrainProducts GmbH; Gilching, Germany). I used four electrodes around the eyes (above and below the right eye, and beside the right and left eye) to record eye-movements. The ground electrode was placed at the electrode site AFz. The electrode positioned at electrode site FCz was used as online reference. The signal was recorded with electrode impedances lower than 10 KΩ. The sampling frequency was 500 Hz. I used Brain Vision Analyzer 2.1 (Brain Products GmbH, Gilching, Germany) to do a spline interpolation on electrodes with many artifacts (on average 0.5 electrodes per participant; ranging between 0 and 3 interpolated electrodes). The signal was re-referenced offline to the average of both mastoids. I used a Butterworth zero phase band-pass filter from 0.1 Hz to 30 Hz (with 24 dB/oct). I corrected for eye movement artifacts by using an independent component analysis (ICA) with the infomax restricted algorithm (Jung et al., 1998). For the ICA, I selected a 400 s interval from the fourth block of the experiment as a training data set for computing the unmixing matrix. ICA components were automatically identified by picking up blinks and saccades, as evidenced by their characteristic shape and location (at frontal electrode sites). After removing components manually (on average 2.7 per participant; ranging between 1 and 4 deleted components), the EEG signal was reconstructed. The EEG signal was segmented based on a time window 200 ms before and 1000 ms after the onset of the pattern presentation. Artifacts were removed automatically when (1) a voltage step of 50 μV/ms was detected, (2) a voltage difference of 100 μV occurred in any 200 ms interval, or (3) a low amplitude of 0.5 μV occurred in a 100 ms interval. Due to the artifact rejection on average 2.73 % (*SD* = 3.02 %) of all trials were removed. Segments were included in further analysis (1) when the response to a pattern was correct (i.e., no key press after frequent patterns and correct key press after rare patterns), (2) when the response to the rare patterns was slower than 200 ms, and (3) when the presentation of a frequent pattern was preceded by the presentation of a frequent pattern (number of average trials left per pattern can be found in Table 1).

Table 1

Trials per condition



	Mean trials	Range
Condition A		
Standard ESS-8	626.4	557–656
Deviant ESS-8 – “same”	34.0	27–38
Deviant ESS-8 – “different”	32.3	22–38
Deviant ESS-4 – “same”	31.6	22–36
Deviant ESS-4 – “different”	32.7	27–38
Condition B		
Standard ESS-4	621.4	510–647
Deviant ESS-8 – “same”	33.8	27–42
Deviant ESS-8 – “different”	31.1	23–36
Deviant ESS-4 – “same”	33.2	20–39
Deviant ESS-4 – “different”	32.3	25–37

Note. Mean trials and range per condition used in the ERP analysis, calculated for adults. Note that standard stimulus of category ESS8 and ESS4 are only used for the vMMN analysis.

Analysis of behavioral data

Response accuracy in the memory task (ACC) and reaction times of correct responses to target stimuli (RTs) were analyzed. I analyzed only responses to rare, target patterns. In 1.2 % of all trials, no response was given in the ITI (1300 – 1600 ms); no additional upper limit was used for RT analysis. Responses faster than 200 ms were excluded, corresponding to an average of 4.43 % (*SD* = 3.1 %) of all trials. For both, mean ACCs and mean RTs, I used a repeated measure Analysis of Variance (ANOVA) with the within-subject factors CONGRUENCY (congruent vs. incongruent), CATEGORY (category ESS-8 vs. category ESS-4), and RESPONSE (same vs. different). The interaction involving the category of the target and the irrelevant frequent pattern designated CONGRUENCY: a target from ESS-8 presented within the irrelevant pattern from ESS-8 and a target from ESS-4 presented within the irrelevant pattern from ESS-4 constitute congruence conditions; a target from ESS-8 presented within the irrelevant pattern from ESS-4 and a target from ESS-4 presented within the irrelevant pattern from ESS-8 constitute incongruence conditions. Behavioral data were aggregated in Python 3.6.5 (Van Rossum & Drake, 2009) and ACCs and RTs were analyzed with SPSS 26 (IBM Corporation, Armonk, NY). To clarify interaction effects, I compared congruence vs. incongruence for each response and each category using a planned comparison (repeated contrast). I report only effects and interactions with p-values below 0.05.

Analysis of event-related potentials

A baseline correction was applied to the segmented signal, using the time window of 200 ms before stimulus onset. All ERP components were analyzed with SPSS 26 (IBM Corporation, Armonk, NY). For the analysis of the vMMN, I computed difference waves by subtracting the ERPs of a frequent pattern from the ERPs of a rare pattern to obtain either a *congruence vMMN* or an *incongruence vMMN*. In more detail, for the *congruence vMMN*, I subtracted the standard pattern from category ESS-8 from the deviant pattern from category ESS-8 in condition A and the standard pattern from category ESS-4 from the deviant pattern from category ESS- 4 in condition B. For the *incongruence vMMN*, I subtracted the standard pattern from category ESS-8 from the deviant pattern from category ESS-4 in condition A and the standard pattern from category ESS-4 from the deviant pattern from category ESS-8 in condition B. For these two difference waves, I calculated the mean amplitude with the following rules: First, I identified the individual negative peak in an early (160 – 220 ms) and late (220 – 300 ms; based on visual inspection) time window and, second, I computed the mean amplitude within a 20 ms window, centered around individual peak latencies. The analysis was performed by averaging electrode sites P7 and P3 for the left region of interest (ROI) and P8 and P4 for the right ROI for each participant. For statistical analysis of the vMMN, I used (1) a one-sided *t*-test against 0 to verify that both vMMNs (congruence and incongruence) in each ROI (left and right) in each time window (160 – 220 ms and 220 – 300 ms) were elicited and (2) a repeated measures Analysis of Variances (ANOVA) with CONGRUENCE (congruence vs. incongruence) and LATERALITY (left vs. right) as within-subject factors, for both time windows separately. To clarify interaction effects, I compared the congruence vMMN with the incongruence vMMN for each ROI using a planned comparison (repeated contrast). As in the behavioral analysis, I report only those effects and interactions with p-values below the conventional significance value of 0.05; all remaining analyses are not listed in the result section.

For the analysis of the P300 component, I used ERPs of both target patterns. In more detail, I used ERPs elicited by the presentation of correctly identified target patterns from category ESS-8. The same was done with ERPs elicited by the presentation of the rare ESS-4 target pattern. I averaged ERPs across condition A and B. To analyze the P300 component, I calculated the mean amplitude in the time windows of 300 – 500 ms (early) and 500 – 650 ms (late) at the electrode sites CP1, CP2, P3, P4, and Pz. For statistical analyses, I used a repeated measures ANOVA with CATEGORY (category ESS-8 vs. category ESS-4), TIME (early vs. late) and ELECTRODES (CP1 vs. CP2 vs. P3 vs. P4 vs. Pz) as within subject factors. To clarify interaction effects, I compared ESS-4 vs. ESS-8 for each time window using a planned comparison (repeated contrast). In addition, to investigate interaction effects with ELECTRODES I averaged the electrode sites CP1 and P3 for the left ROI and CP2 and P4 for the right ROI. As in the analysis of the vMMN, I report only those effects and interactions with p-values below the conventional significance value of 0.05; all remaining analyses are not listed in the result section.

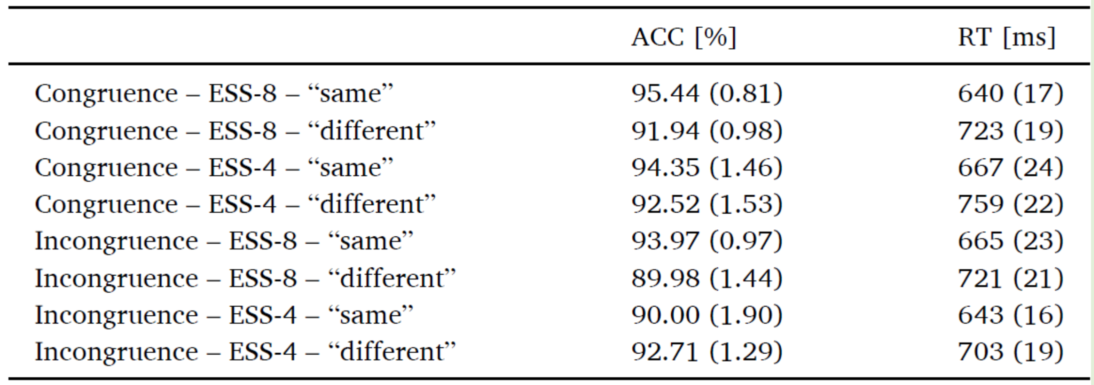
3.2.4 Results

Results of behavioral data

Overall, participants responded correctly to an average of 92.62 % of all trials in the memory task (*SE* = 0.6 %; for details see Table 2). Thus, the overall error rate was 7.38 %. In the ANOVA of mean ACC, I observed a main effect of the factor CONGRUENCY, $F(1, 26) = 9.98$, $p < .005$, $\eta_p^2 = 0.28$. Participants responded more correctly to *congruent* (*M* = 93.57 %, *SE* = 0.71 %, 95 % CI [92.11, 95.04]) than to *incongruent* targets (*M* = 91.67 %, *SE* = 0.75 %, 95 % CI [90.12, 93.21]). I observed a triple interaction effect between CONGRUENCY, CATEGORY, and RESPONSE, $F(1, 26) = 4.96$, $p < .05$, $\eta_p^2 = 0.16$. Planned contrasts revealed that response accuracy was higher to *congruent* (*M* = 94.38 %, *SE* = 1.46 %, 95 % CI [91.38, 97.38]) than to *incongruent* targets (*M* = 90.00 %, *SE* = 1.90 %, 95 % CI [86.10, 93.92]); $p < .005$) when participants responded to an ESS-4 target with *same* as compared to *different* responses.

Table 2

Accuracy and reaction time results



	ACC [%]	RT [ms]
Congruence – ESS-8 – “same”	95.44 (0.81)	640 (17)
Congruence – ESS-8 – “different”	91.94 (0.98)	723 (19)
Congruence – ESS-4 – “same”	94.35 (1.46)	667 (24)
Congruence – ESS-4 – “different”	92.52 (1.53)	759 (22)
Incongruence – ESS-8 – “same”	93.97 (0.97)	665 (23)
Incongruence – ESS-8 – “different”	89.98 (1.44)	721 (21)
Incongruence – ESS-4 – “same”	90.00 (1.90)	643 (16)
Incongruence – ESS-4 – “different”	92.71 (1.29)	703 (19)

Notes. Mean activity of accuracy (ACC) and reaction time (RT; standard error in brackets) was calculated for adults.

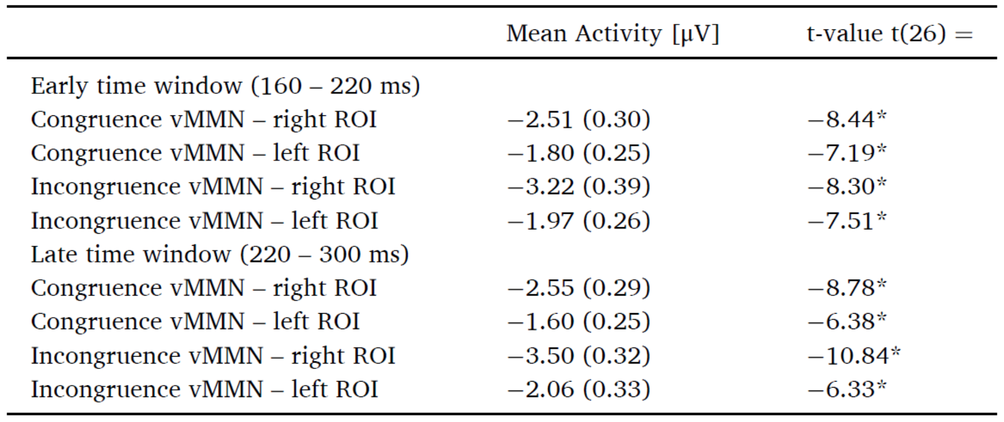
Overall, participants responded on average after 690 ms (*SE* = 17 ms) after target presentation (for details see Table 2). In the ANOVA of mean RTs, I observed a main effect in CONGRUENCE, $F(1, 26) = 7.62$, $p < .05$, $\eta_p^2 = 0.23$. Participants responded slower to *congruent* (*M* = 697 ms, *SE* = 17 ms, 95 % CI [662, 733]) than to *incongruent* targets (*M* = 683 ms, *SE* = 17 ms, 95 % CI [648, 719]). I observed a main effect in CATEGORY, $F(1, 26) = 13.02$, $p < .005$, $\eta_p^2 = 0.33$. Participants responded faster to the ESS-8 target pattern (*M* = 677 ms, *SE* = 15 ms, 95 % CI [646, 709]) than to the ESS-4 target pattern (*M* = 703 ms, *SE* = 19 ms, 95 % CI [663, 743]). I observed a main effect in RESPONSE, $F (1, 26) = 58.92$, $p < .001$, $\eta_p^2 = 0.69$. *Same* responses (*M* = 653 ms, *SE* = 17 ms, 95 % CI [619, 688]) were faster than *different* responses (*M* = 726 ms, *SE* = 19 ms, 95 % CI [688, 765]). Additionally, I observed an interaction between CONGRUENCY and RESPONSE, $F(1, 26) = 14.21$, $p < .001$, $\eta_p^2 = 0.35$. Planned contrasts revealed no difference between *congruent* and i*ncongruent* targets ($p = .94$) when the response was *same*, whereas responses were slower to *congruent* (*M* = 741 ms, *SE* = 19 ms, 95 % CI [701, 780]) than to *incongruent* targets (*M* = 712 ms, *SE* = 19 ms, 95% CI [674, 750]; $p < .001$) when the response was *different*.

Results of event-related potential data

First, I focus on the results of the vMMN. Table 3 summarizes mean activity of all vMMNs (each condition, ROI, and time window) and their deviation from zero. The more positive activation of the *congruence vMMN* than the *incongruence vMMN* is shown for individual electrodes sites (P7, P3, P4, and P8) in Figure 7A and for the ROIs (left and right) in Figure 7B. As illustrated in Figure 7C, differences between both vMMNs were observed only in the right hemisphere in both time windows.

Table 3

Mean activity of vMMN and results of t-test against 0



	Mean Activity [μV]	t-value t(26) =
Early time window (160 – 220 ms)		
Congruence vMMN – right ROI	−2.51 (0.30)	−8.44*
Congruence vMMN – left ROI	−1.80 (0.25)	−7.19*
Incongruence vMMN – right ROI	−3.22 (0.39)	−8.30*
Incongruence vMMN – left ROI	−1.97 (0.26)	−7.51*
Late time window (220 – 300 ms)		
Congruence vMMN – right ROI	−2.55 (0.29)	−8.78*
Congruence vMMN – left ROI	−1.60 (0.25)	−6.38*
Incongruence vMMN – right ROI	−3.50 (0.32)	−10.84*
Incongruence vMMN – left ROI	−2.06 (0.33)	−6.33*

Note. Mean activity (standard error in brackets) of the vMMN was calculated for adults in μV. Note that the vMMN is the difference wave between the ERPs elicited by a standard and a deviant stimulus.

* $p < .001$.

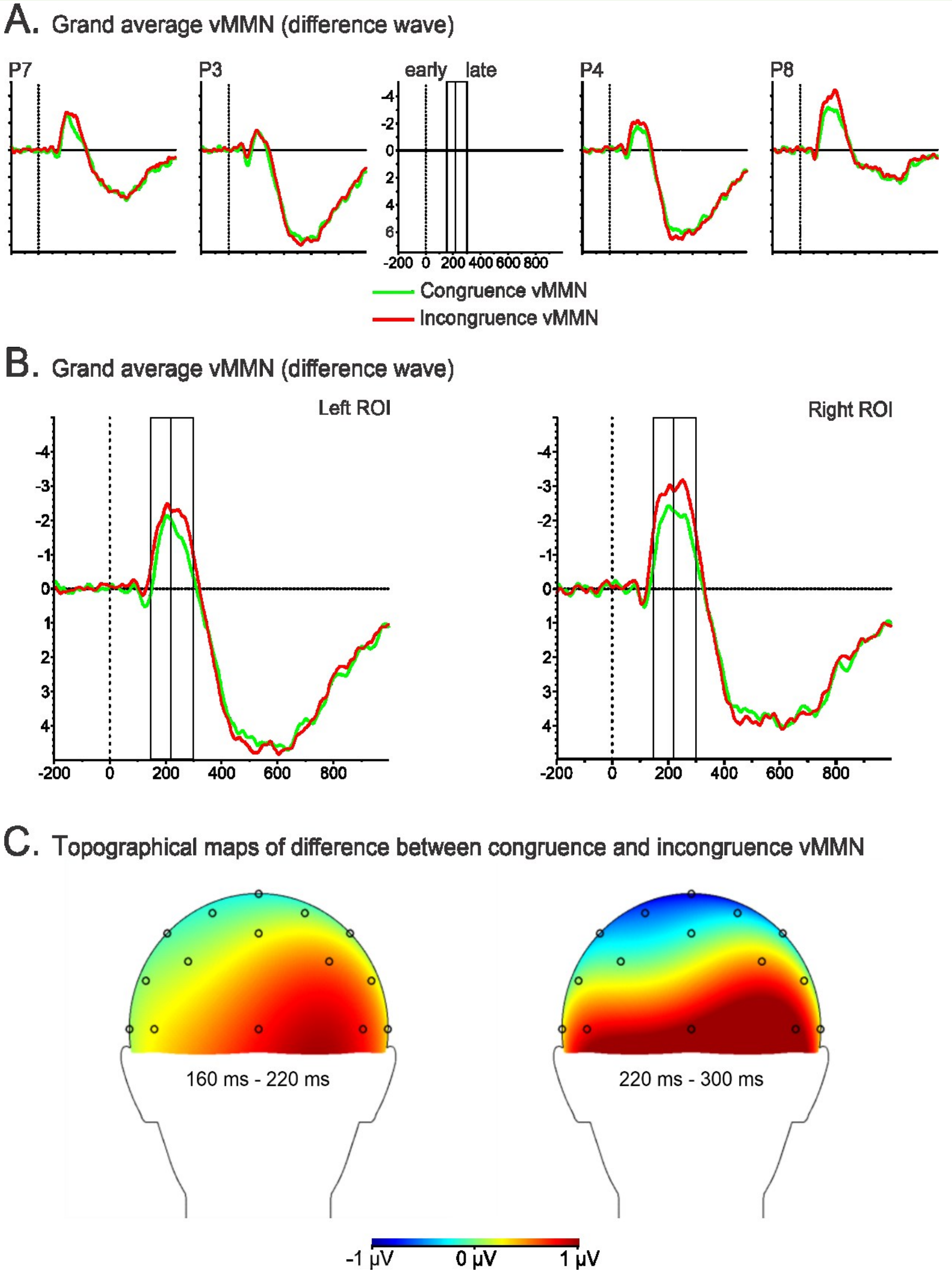
For the vMMNs in the early time window (160 – 220 ms), I observed a main effect in CONGRUENCE, $F(1, 26) = 8.37$, $p < .01$, $\eta_p^2 = 0.24$. Mean amplitudes at both ROIs were more negative for the *incongruence vMMN* (M = -2.59 μV, SE = 0.28 μV, 95 % CI [-3.16, -2.03]) than for the *congruence vMMN* (M = -2.15 μV, SE = 0.24 μV, 95 % CI [-3.16, -2.03]). I observed a main effect in

LATERALITY, $F(1, 26) = 9.72$, $p < .005$, $\eta_p^2 = 0.27$. Mean amplitudes of both vMMNs were more negative at the right ROI ($M = -2.87$ µV, $SE = 0.33$ µV, 95 % CI [-3.55, -2.18]) compared to the left ROI ($M = -1.88$ µV, $SE = 0.24$ µV, 95 % CI [-2.38, -1.38]). Additionally, I observed an interaction effect between CONGRUENCE and LATERALITY, $F(1 ,26) = 8.32$, $p < .01$, $\eta_p^2 = 0.24$. In the right ROI, I observed a more negative amplitude for the *incongruence vMMN* than the *congruence vMMN* ($p < .001$), whereas in the left ROI there was no difference between the *congruence vMMN* and the *incongruence vMMN* ($p = .28$).

For the vMMNs in the late time window (220 – 300 ms), I observed the same pattern of results. I observed a main effect in CONGRUENCE, $F(1, 26) = 15.28$, $p < .001$, $\eta_p^2 = 0.37$. The mean amplitudes at both ROIs was more negative for the *incongruence vMMN* ($M = -2.78$ µV, $SE = 0.26$ µV, 95 % CI [-3.32, -2.25]) than for the *congruence vMMN* ($M = -2.08$ µV, $SE = 0.22$ µV, 95 % CI [-2.53, -1.62]). I observed a main effect in LATERALITY, $F(1, 26) = 12.56$, $p < .005$, $\eta_p^2 = 0.33$. The mean amplitudes of both vMMNs was more negative at the right ROI ($M = -3.03$ µV, $SE = 0.30$ µV, 95 % CI [-3.63, -2.42]) compared to the left ROI ($M = -1.83$ µV, $SE = 0.27$ µV, 95 % CI [-2.38, -1.28]). Additionally, I observed an interaction effect between CONGRUENCE and LATERALITY, $F(1,26) = 5.93$, $p < .05$, $\eta_p^2 = 0.19$. In the right ROI, I observed a more negative amplitude for the *incongruence vMMN* than the *congruence vMMN* ($p < .001$), whereas in the left ROI I observed a marginal difference between the *congruence vMMN* and the *incongruence vMMN* ($p = .06$).

Figure 7

Results vMMN



Note. Grand average difference wave at the electrode sites P7, P3, P4, and P8 (A.) and at the left and right ROI (B.) for the *congruence vMMN* and *incongruence vMMN*. The *congruence vMMN* refers to the difference between ERPs of the frequent stimulus and the deviant of the same category (e.g., ESS-8 frequent and ESS-8 rare stimulus in condition A). The *incongruence vMMN* refers to the difference between ERPs of the frequent stimulus and the deviant of the different category (e.g., ESS-8 frequent and ESS-4 rare stimulus in condition A). The squares indicate the interval of 160–220 ms (early) and 220–300 ms (late) after stimulus onset, in which the peak detection was performed. (C.) The topographical maps of the difference between the *congruence vMMN* and *incongruence vMMN* in the time window 160–220 ms and 220–300 ms.

Second, I focus on the results of the P300. The activation of P300 for the ESS-4 and ESS-8 target is shown for the electrodes (CP1, CP2, P7, P3, Pz, P4, and P8) in Figure 8A and for the ROIs (left and right) in Figure 8B. A reversed polarity of activation between left and right ROIs regarding ESS-4 and ESS-8 targets was observed only in the early time window, as shown in Figure 8C. For mean activity of the specific P300s for each target category, electrode, and time window, see Table 4.

Table 4

Mean activity of the later central-parietal component

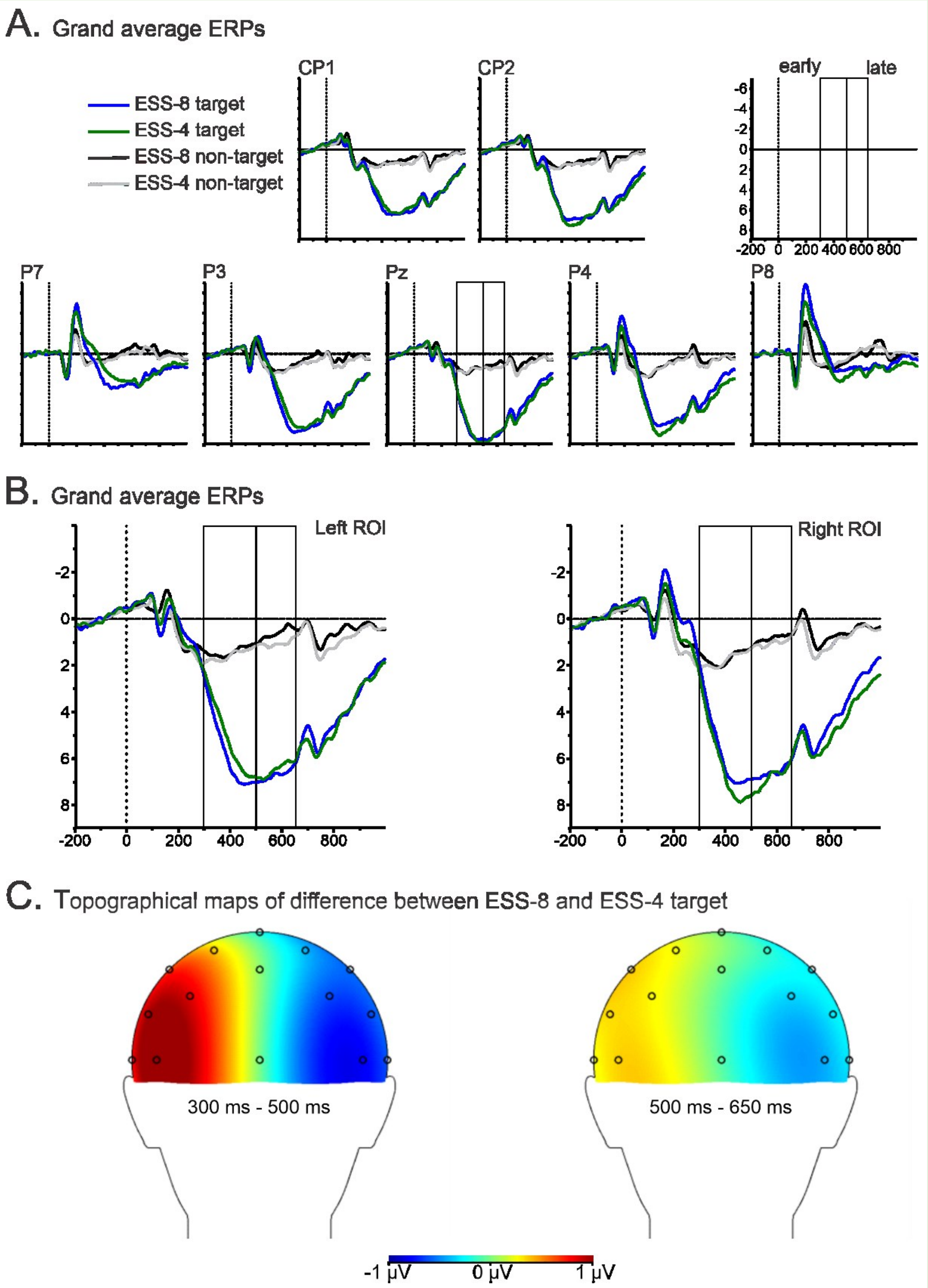
Mean Activity [µV]	ESS-8 target	ESS-4 target
Early time window (300–500 ms)		
CP1	5.21 (0.60)	4.83 (0.58)
CP2	5.69 (0.58)	6.01 (0.57)
P3	6.23 (0.61)	5.39 (0.62)
P4	5.59 (0.67)	6.28 (0.63)
Pz	6.94 (0.68)	6.88 (0.67)
Late time window (500–650 ms)		
CP1	6.16 (0.75)	5.95 (0.71)
CP2	6.70 (0.75)	6.80 (0.67)
P3	7.22 (0.65)	6.95 (0.64)
P4	6.50 (0.69)	6.90 (0.62)
Pz	8.13 (0.77)	8.14 (0.70)

Note. Mean activity (standard error in brackets) was calculated for adults in µV.

For the P300, I observed a main effect in TIME, $F(1, 26) = 5.71$, $p < .05$, $\eta_p^2 = 0.28$, with a smaller P300 amplitude in the early ($M = 5.91$ µV, $SE = 0.57$ µV, 95 % CI [4.74, 7.01]) than in the late ($M = 6.95$ µV, $SE = 0.64$ µV, 95 % CI [5.62, 8.27]) time window. I observed an interaction effect between CATEGORY and ELECTRODES, $F(1,26) = 15.41$, $p < .001$, $\eta_p^2 = 0.37$. Planned contrasts revealed no difference between categories at Pz ($p = .90$) and in the right ROI ($p = .13$), whereas a tendency for a larger amplitude in ESS-8 ($M = 6.21$ µV, $SE = 0.58$ µV, 95 % CI [5.01, 7.41]) than ESS-4 ($p = .061$; $M = 5.78$ µV, $SE = 0.56$ µV, 95 % CI [4.64, 6.92]) was observed in the left ROI. Additionally, I observed an interaction between TIME, CATEGORY, and ELECTRODES, $F(1,26) = 16.05$, $p < .001$, $\eta_p^2 = 0.38$. Planned contrasts revealed no effect of CATEGORY or TIME on the P300 at Pz ($p = .99$). However, I observed an interaction between CATEGORY and ELECTRODES in the early, but not the late time window. More specifically, I observed a larger amplitude in the ESS-4 than in the ESS-8 ($p < .05$) in the right ROI. Reversely, in the left ROI I observed a larger amplitude in the ESS-8 than in the ESS-4 ($p < .01$).

Figure 8

Results P300



Notes. Grand average ERPs for the ESS-8 target, ESS-4 target, ESS-8 irrelevant and ESS-4 irrelevant at the electrode sites CP1, CP2, P7, P3, Pz, P4, and P8 (A.) and at the left and right ROI (B.). The squares indicate the interval of 300–500 ms (early) and 500–650 ms (late) after stimulus onset, in which the mean amplitude was calculated. (C.) The topographical maps of the difference between the ESS-8 target and ESS-4 target in the time window 300–500 ms and 500–650 ms.

3.2.5 Discussion

The pattern of behavioral results confirms that categorical information was processed even though it was not necessary for successful task performance. The present study observed faster responses to *same* compared to *different* targets (fast-same effect; see Farell, 1985, for review) and to ESS-4 compared to ESS-8 targets (see Lachmann & van Leeuwen, 2004, for review). The ESS effect is in line with a number of earlier studies reporting RTs in successive *same*-*different* tasks increasing with the ESS of the pattern to be compared. The finding that processing time for a pattern depends on the number of equivalent patterns belonging to same set (of rotational and reflexional transformations) suggests categorical representation for each (Lachmann & Geissler, 2002). This explains also why I found, as in earlier studies (Lachmann and van Leeuwen, 2005a, 2008), a strong effect of ESS even though it was not task-relevant; the categorical representation in terms of ES makes it hard to ignore the equivalence of patterns (e.g., response conflict for patterns from the same set that require a *different* response in earlier studies, Lachmann & van Leeuwen, 2004). Furthermore, I found that targets incongruent to non-targets received faster, but less accurate responses compared to congruent targets. This also indicates that a categorical representation affects processing, even though it is task-irrelevant.

Prior EEG studies using these five-dot patterns focused on the influence of categorical information on later cognitive processing. The literature indicates no influence of categorization in early perceptual (Beck et al., 2021), but later cognitive processing (Berti & Roeber, 2013; Berti et al., 2000). The goal of this study was to assess effects of categorical information on both the early perceptual and later cognitive processing within one paradigm. For this purpose, I combined an oddball paradigm with a delayed memory task. In turn the results of the early perceptual (i.e., vMMN component) and later cognitive (i.e., P300 component) processing will be discussed.

Perceptual processing of categorical information

The vMMN component is defined as the difference between ERPs elicited by deviant and ERPs elicited by standard patterns and mirrors perceptual processing of visual input. Here were compare the *congruence vMMN* with the *incongruence vMMN*, connotating the categorical relation between deviant and standard patterns. As in the study by Beck and colleagues (2021), I observed both vMMNs, indicating that early perceptual processing encodes abstract information. However, in contrast to our previous study, I observed a unique activation for both vMMNs, which suggests encoding of categorical information in early perceptual processing. This inconsistent result might be explained by a notable difference in both paradigms: In the study by Beck and colleagues (2021), the deviant pattern was task-irrelevant in a three-stimulus oddball paradigm, whereas in the present study, the deviant pattern was task-relevant. Hence, categorical encoding in early perceptual processes might depend on the processing goal (i.e., task; Gauthier, 2000).

In more detail, I observed a more negative amplitude for the *incongruence vMMN* than for the *congruence vMMN* in the right ROI (i.e., P8 and P4), in both early (160 – 220 ms) and late (220 – 300 ms) time window. First, observing unique vMMNs only in the right ROI is in line with a source location analysis, demonstrating that the main sources to elicit a vMMN are located in the right occipital visual extrastriate areas (Kimura, Ohira, & Schröger, 2010). Second, since unique vMMNs are observed in both time windows, one might conclude the same underlying evoked potential (i.e., the vMMN). However, it is important to note that ERPs indicate dissimilar underlying evoked potentials (i.e., the vMMN or the visual N1; see Kimura, Schröger, & Czigler, 2011). To distinguish the evoked potentials of the vMMN and the visual N1, an equiprobable control sequence could be introduced in a future study. Thus, the standard would be represented by several equiprobable stimuli rather than a single stimulus. Presenting several equiprobable stimuli would eliminate a neuronal refractoriness effect. The refractoriness effect describes the observation that the neurons processing a frequent stimulus (i.e., standard) are firing more frequently, resulting in a “exhausted” neuronal response (see Schröger & Wolff, 1996). Hence, subtracting an “exhausted” neuronal response from a “fresh” neuronal response, elicited by the rare stimulus (i.e., deviant), would result in a confounded difference. This effect influences in particular the visual N1, which would be clearly distinguishable from the vMMN. Third, the more negative amplitude for the *incongruence vMMN* than the *congruence vMMN* can be associated with studies investigating the influence of color categories on early perceptual processing. Clifford, Holmes, Davies, and Franklin (2010) investigated a *congruence vMMN* and an *incongruence vMMN,* considering the color of the standard in contrast to the color of the deviant stimuli (i.e., in the *congruence vMMN* the standard and the deviant stimulus had the same color). They used a three-stimulus oddball paradigm in which the target differed from the standard and deviant by shape (i.e., standard and deviant were circles, the target was a square). By using color as a category, a more negative deflection was observed for the *incongruence vMMN* than *congruence vMMN*, like in the present study. While such a congruency effect is surprising with regard to color as relevant category, with regard to our stimulus material the congruency effect supports the perceptual processing of categorical information at this early stage of processing: Here, rare stimuli, which are congruent to the standard, deviate with regard to one feature from the standard presentation (i.e., sensory information) while incongruent rare stimuli deviate with regard to two features (i.e., sensory and categorical information). In other words, the vMMN seems to mirror the degree of deviation, as proposed by the predictive coding model of the vMMN (for instance, see Czigler, 2007; Kimura et al., 2011). In contrast, this hardly fits to color as categorical information. Therefore, more research is required to solve this puzzle.

The modulation of memory encoding by categorical information

In the present study I applied the P300 component as a measure of memory encoding. I compared ERPs for ESS-8 and ESS-4 targets, because in order to perform the memory comparison task the current target need to be encoded into working memory. Therefore, as suggested by earlier studies (Berti & Roeber, 2013; Berti et al., 2000), categorical information should modulate the P300 component. In contrast to the literature (Berti & Roeber, 2013; Berti et al., 2000), I observed no effect of categorical information at Pz in either time window (300 – 500 ms and 500 – 650 ms). This lack of effect indicates no encoding of categorical information at this stage of cognitive processing. From this perspective, our results suggest that categorical information might be encoded already at an early stage of processing, in line with the behavioral results demonstrating that this information was also processed. I can only speculate at this point that categorical information might be processed at the stage of perceptual processing as indicated by the vMMN results. In this case an additional encoding into working memory would not be necessary.

However, when investigating laterality effects, I observed the predicted larger amplitude for ESS-8 compared to ESS-4 (Berti & Roeber, 2013) in the early time window and right ROI, whereas I observed a reversed effect in the left ROI. To consider the inconsistency between the prior and the current results in more detail, I want to point out the three main modifications in the methods: inter-target interval, task, and the EEG analysis. First, in the study by Berti and colleagues (2000) the interval between each target stimulus was 1.5 s, whereas in the present study the interval varied between 5.2 and 11.2 s. A longer inter-target interval might result in an interference of the encoded information in working memory with the information of the stimuli presented in between. Another explanation could be that categorical information is encoded during a shorter interval, whereas categorical information about the target is not encoded during a longer interval. Second, in the present study I used a continuous matching task, which results in a less differentiated observation of retrieval and encoding processing of information. In prior studies (Berti & Roeber, 2013; Berti et al., 2000) the matching task was not continuous, making it possible to investigate only the encoding of information. Thus, our results might either only represent or be confounded by the retrieval process. Note that no categorical information needs to be retrieved in the identity-matching task. Third, during the processing of the EEG data, both prior studies (Berti & Roeber, 2013; Berti et al., 2000) used the left mastoid as reference. In the present study I used the linked averaged (right and left) mastoids as offline reference. Using a one-sided reference might create an imbalance between the electrodes in the left and right hemisphere. This modification might explain the laterality effect obtained in the present study and maybe even the null-finding at the electrode site Pz. Irrespective of these modifications, I would like to emphasize that encoding of categorical information into working memory is especially prominent when categorical information is task relevant (Berti & Roeber, 2013). In the present study, to solve the task, pattern categorization was not relevant for the task.

Implications

Overall, I obtained behavioral results consistent and ERP results inconsistent with prior literature. Behaviorally, I observed the fast-same and the ESS effect as reviewed by Farell (1985) and Lachmann and van Leeuwen (2004), respectively. Both effects seem persistent irrespective of the differences in the participants' task in the current and the prior studies. Note that RT analysis represent the end result of multiple cognitive processes (Massaro & Cowan, 1993). Hence, changes in the paradigm did not influence the end result of cognitive processing. To investigate distinct processing steps, I used the method of ERPs. In additional to prior ERP studies (Beck et al., 2021; Berti et al., 2000; Berti & Roeber, 2013) that focused on early perceptual processing, I also assessed later stages of cognitive processing. The main modification in the current study is participants' task, which was a more demanding task than those employed previously: In prior studies participants performed either a counting task (Beck et al., 2021) or a delayed memory comparison task (Berti & Roeber, 2013; Berti et al., 2000; Carmo et al., 2017; Takahashi et al., 2014; Takahashi et al., 2019), whereas in the present study a continuous delayed memory comparison task was performed. Hence, the encoding of categorical information might be more variable and dynamic with respect to the participants' task than expected based on earlier paradigms.

Limitation and future directions

Two major aspects could be considered in the future to examine the potentially variable, dynamic encoding of categorical information. The first aspect to be considered is the generalization of stimuli to other instances, objects, or events. In the current study I used a specific stimulus set (five-dot patterns by Garner & Clement, 1963) to control the physical energy delivered to the sensory system. This was done since early perceptual ERP components might be influenced by this factor. However, by using this specific set of stimuli, our results are difficult to be generalized across other visual categories, for instance, more namable categories such as facial emotions (e.g., Stefanics, Csukly, Komlósi, Czobor, & Czigler, 2012), lexical categories (e.g., Yu, Mo, Zeng, Zhao, & Mo, 2017), or colors (Clifford et al., 2010). Additionally, our results are difficult to be generalized across other sensory domains, such as auditory, olfactory, or tactile categories. Therefore, future studies could investigate the potentially variable and dynamic encoding of categorical information with stimuli across different sensory modalities. The second aspects to be considered is the influence of task demands and strategies to solve the task. Since task demand was not varied in the current study, its potential role can be inferred only implicitly. In future studies, it would be interesting to investigate whether encoding of categorical information is influenced by task demands or the participants' strategy to solve the task.

3.2.6 Conclusion

Categorical information is encoded even when it is not task relevant. While behavioral correlates of visual categorization generalize across paradigms, closer inspection of brain activity suggests that the encoding of categorical information can occur in different processing stages. Together, our results suggest that task demands play a major role to fine-tune the order in which perceptual categories contribute to visual categorization.

3.3 OPEN ISSUES

The first set of empirical investigations (Chapter 3.1 and Chapter 3.2) focused on perceptual categorization in visual processing using ERP analysis. More specifically, using stimuli with the same sensory information (Chapter 3.1), I addressed the question whether categorical information affects early perceptual processing of visual information. Experiment 2 investigated the stage at which visual categorical information is encoded and concluded that subtle changes in task and experimental context determine whether early perceptual or later cognitive processes play a more prominent role (Chapter 3.2).

In the following chapters, I will discuss the results and consider open issues regarding well-defined perceptual categories (Chapter 3.3.1), and categorical information processing based on the processing goal (Chapter 3.3.2).

3.3.1 Well-defined structure of perceptual categories

The first research objective was to investigate the processing of categorical information in well-defined categories. Well-defined categories are defined based on features that are both singularly necessary and jointly sufficient (Nakamura, 1985). Hence, there are clear category boundaries (i.e., a clear, well-defined associations of members or non-members) and all category members are equally representative (McCloskey & Glucksberg, 1978; Nakamura, 1985). The categories in both investigations (Chapter 3.1 and Chapter 3.2) were artificial and well-defined; based on a limited number of features (i.e., constellation of five dots in a 3 x 3 matrix and reflection/rotation transformations; Garner, 1978).

In contrast to the pilot study and Experiment 1, the results suggest that early visual processes (160 – 300 ms after stimulus onset over posterior brain areas) were sensitive to well-defined category membership in Experiment 2. This is in line with results from ill-defined categories. Evidence was provided by Curran, Tanaka, and Weisskopf (2002), who investigated similarity-based perceptual categorization of visual shapes. The visual shapes were computer-generated, two-dimensional polygons. An ill-defined category was created by generating a polygon as a category prototype, and multiple polygons as category members (by distorting the category prototype). After extensive training, participants were asked to indicate whether a stimulus belonged to the same category as the category prototype or not. The results indicate that early visual processes (around 156 – 200 ms after stimulus onset over posterior brain areas) were sensitive to ill-defined category membership (Curran et al., 2002). Hence, for both well- and ill-defined perceptual categories, the representation of categorical information can be observed in early visual processing. This might suggest that processing of categorical information is not only associated with activity in the ITC (i.e., ventral visual stream) and LPFC, but also in the visual cortex. Thus, it does not contradict the existing literature but rather adds the perspective that the processing of categorical information for perceptual categories is encoded in much earlier processes. Additionally, the early visual representation of categorical membership can influence the information processing in the ITC and the LPFC.

Because of the high temporal resolution of EEG, changes in electrical activity can be observed (almost) instantly after stimulus presentation in the current studies. However, due to the low spatial resolution, no firm conclusions can be drawn about the source of the electrical activity. Hence, to estimate the origin of the cortical electrical activity low resolution brain electromagnetic tomography analysis (LORETA; Pascual-Marqui, Michel, & Lehmann,1994; Pascual-Marqui, 2002) could be used. For instance, Wang and colleagues (2013) investigated the categorization of phonological features embedded in Chinese single characters. They observed that a violation of lexical tone phonology evoked an early electrical response, labeled as vMMN. They used Low-Resolution Electromagnetic Tomography Analysis (LORETA) as a source analysis and observed that neural activations of the visual cortex were involved (Wang et al., 2013). Therefore, using LORETA for the data of the current investigations the involvement of the visual cortex could be indicated. Another possible future direction could be to investigate whether there is a difference between well- and ill-defined perceptual categories. For instance, Garner (1978) emphasized the simplicity of the presented dot patterns, since the categorical information vary only in a limited number of separable dimensions and are artificially produced (to control for various confounding factors; as in Curran et al., 2002). This in turn does not only raise the question whether the same results would be present with a different stimulus material but also whether natural categories would be represented in the same manner.

3.3.2 Categorical information processing based on processing goal

The second research objective was to investigate a more automatic encoding of categorical information, since categorical representations in the brain are suggested to be dependent on experience and processing goals (Gauthier, 2000). The former is associated with expertise in specific object categories (Harel, 2016), whereas the latter is defined by how the categorical information is used (Gauthier, 2000).

In the current set of investigations, the change of the participants’ task resulted in a modification of the encoding of categorical information in early processing steps. In more detail, in the pilot study and Experiment 1, categorical information was not encoded in the early perceptual processing during a counting task, whereas in the second investigation categorical information was encoded during an identity comparison task. Note, however, that in both studies the encoding of categorical information was task-irrelevant. Still, the encoding of categorical information seems to be independent of whether the categorical information itself is task-relevant or irrelevant, or whether the task is related to categorization, but rather dependent on the processing goal of the visual information as a whole. The results emphasize the flexibility of the neuronal processes to encode categorical information depending on the overall processing goal of information. To put it differently, the overall processing goal of the presented information plays an important role for the encoding of perceptual categorical information.

The inconsistent results between the first investigation (Chapter 3.1) and the second investigation (Chapter 3.2) might indicate the effects of experience. More specifically, participants in the pilot study and Experiment 1 did not observe the stimuli prior to the main task, whereas those in Experiment 2 received considerable training prior to the main task. Even though behavioral evidence (for instance, Lachmann & van Leeuwen, 2010) suggests that categorical information of dot patterns is perceived automatically ("To perceive is to know"; Garner, 1966), an analysis comparing the neuronal responses in the first and last trials could assess whether (or not) behavior or neuronal activation changes with experience (i.e., over time/trials).

CHAPTER 4: CATEGORICAL REPRESENTATIONS OF SEMANTIC CATEGORIZATION IN VISUAL PROCESSING

In this chapter, the second set of investigations is described. They are concerned with the investigation about when and where more detailed information for semantic categorization is implicitly encoded (in ASD and NT adults). In Chapter 4.1, Experiment 3A aims to examine the effects of image presentation duration and typicality on the shapes of reaction time and accuracy distributions in an ultra-rapid superordinate (i.e., "animal") categorization paradigm, comparing adults with and without ASD. In Chapter 4.2, Experiment 3B aims to dissociate distinct phases of semantic categorization and to observe whether these phases are modulated differently by category boundaries, presentation duration, and typicality in NT and ASD adults.

4.1 THE ROLE OF PRESENTATION DURATION IN SUPERORDINATE CATEGORIZATION: A DISTRIBUTIONAL RESPONSE TIME STUDY.

In this chapter, the evidence about feedforward and recurrent feedback processing for superordinate categorization, as well as superordinate categorization in individuals with ASD will be described (Chapter 4.1.1), followed by the predictions of the present study (Chapter 4.1.2). The experimental methodology to investigate the predictions of the shapes of reaction time and accuracy distributions will be explained (Chapter 4.1.3). The results will be depicted (Chapter 4.1.4) and discussed (Chapter 4.1.5). Lastly, the chapter concludes with a summary about the findings (Chapter 4.1.6).

4.1.1 Introduction

Objects can be categorized at different levels of abstraction, including the basic level (e.g., dog or face), the superordinate level (e.g., animal or human face), and the subordinate level (e.g., German Shepard or Caucasian face). Traditionally, the basic level was considered as the entry point into the semantic system as the categorization performance was most efficient for the basic level (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). More recently, this notion has been adjusted because the entry level can shift downward to subordinate levels due to learning processes (Tanaka, 2001) and performance can be better under certain circumstances for superordinate categorization compared to basic-level categorization (Mack & Palmeri, 2015).

Feedforward processing for superordinate categorization

A number of studies have suggested that feedforward processing can explain superordinate categorization performance in so-called ultra-rapid superordinate categorization tasks in which stimulus presentation times are very short. For example, Thorpe, Fize, and Marlot (1996) used a go/no-go categorization task in which participants had to decide whether an image presented for 20 ms contained an animal or not. They found that the performance was remarkably good, as the average proportion of correct responses equaled 94 %, and the average median reaction time (RT) on "go" trials equaled 445 ms (range across subjects: 382 – 567 ms). Furthermore, frontal event-related potentials generated on correct "go" trials and correct "no-go" trials diverged around 150 ms after stimulus onset. They concluded that such fast performance must be based on essentially feed-forward neural mechanisms (Thorpe, Fize, and Marlot, 1996).

More recent studies have measured the minimal RT needed to complete an ultra-rapid superordinate categorization task with short presentation times (Fabre-Thorpe, Richard, & Thorpe, 1998). In studies with human participants, the minimal RT was found to equal 250 – 280 ms for animal images (Delorme, Rousselet, Macé, & Fabre-Thorpe, 2004; Fize, Fabre-Thorpe, Richard, Doyon, & Thorpe, 2005; Macé, Joubert, Nespoulous, & Fabre-Thorpe, 2009; Rousselet, Fabre-Thorpe, & Thorpe, 2002) and ~288 ms for man-made object images (Joubert, Rousselet, Fize, & Fabre-Thorpe, 2007).

Various mid- and high-level visual features have been proposed to account for the fast recognition of animals, including the global outline (Lloyd-Jones & Luckhurst, 2002), diagnostic animal parts including eyes, mouth, and limbs (Delorme, Richard, & Fabre-Thorpe, 2010), and intermediate curvilinear features (Zachariou, Del Giacco, Ungerleider, & Yue, 2018). Together with the anatomical segregation of various category-selective neurons in the ventral temporal cortex (Lindh, Sligte, Assecondi, Shapiro, &

Charest, 2019; Wiggett, Pritchard, & Downing, 2009), these findings suggest that feedforward connections in the visual system are sufficient for fast superordinate categorization.

Recurrent processing for superordinate categorization

Other studies, however, suggest that a bi-directional or recurrent processing framework is a more appropriate framework to understand visual processing and categorization (Bar, 2003; Kar & DiCarlo, 2021; O'Reilly, Wyatte, Herd, Mingus, & Jilk, 2013; Rüter, Kammer, & Herzog, 2010; Schyns, 1997). For example, Kar and DiCarlo (2021) used a two-choice object discrimination task and showed that inactivation of the ventro-lateral prefrontal cortex produces deterioration in the quality of the inferior-temporal (IT) population code and deteriorations in behavioral performance that were significantly higher for so-called late-solved images (>150 ms from image onset) than for the early-solved images (<150 ms from image onset). In other words, while some images can be recognized based on the early phase of the IT responses (90 – 120 ms) established presumably by feedforward-only processing, other images can only be recognized based on the late phase of the IT response (>150 ms) which depends on recurrent processing (see also Wyatte, Jilk, & O'Reilly, 2014; Zhang, Sun, Liu, Zhang, & Wu, 2020).

Gerlach and colleagues (Gerlach et al., 2002; Gerlach, Law, & Paulson, 2004; Gerlach, Law, & Paulson, 2006) have developed a theory to understand when and why a processing advantage for animated objects emerges during object recognition. They suggested that in regard to accessing a stored object shape representation, the structural similarity between stored exemplars of different categories affects the grouping processes in a fundamentally different way than the matching processes. High structural similarity between stored exemplars can be advantageous for integrating local object segments and parts into whole object representations because the global and local features of these exemplars are more stable and more highly correlated than the features of exemplars from categories with low structural similarity. At the same time, however, high structural similarity may hinder matching operations, because the activated integral units for object selection or covert identification will compete (i.e., deciding that a single match has been found with stored object information in visual long-term memory). As a result, Gerlach et al. (2002, 2004, 2006) found that, under optimal grouping conditions, i.e., with complete line drawings and unlimited exposure, high complex objects (with low structural similarity, e.g., artefactual objects) are named faster and more accurately because there is less competition at the level where activated object representations compete for selection (a matching advantage), compared to low complex objects (with high structural similarity, e.g., natural objects including animals). In contrast, in tasks where the demand for perceptual differentiation is not too high (e.g., superordinate categorization) and under suboptimal grouping conditions (e.g., limited exposure duration or fragmentation), low complex objects (with high structural similarity, e.g., animals) can be named faster and more accurately. This occurs because: (1) under such conditions, task performance tends to depend on global shape information carried by low spatial frequencies and (2) the outlines and silhouettes of natural objects are better identifiable than those of artefacts, which are believed to rely more on a part-based description (Riddoch & Humphreys, 2004), while the global shape of natural objects might contain more salient features or less 2D/3D ambiguity (Lloyd-Jones & Luckhurst, 2002). As a result, early feedback information from the (current set of) activated candidate object representations can influence difficult grouping and segmentation processes in posterior IT (Gerlach et al., 2002), while the global shape characteristics of activated natural object representations will produce a grouping advantage under suboptimal grouping conditions, which can outweigh their disadvantage during matching under optimal conditions (Gerlach et al., 2004, 2006).

Superordinate categorization in Autism Spectrum Disorder

Individuals with autism spectrum disorder (ASD) tend to perceive the environment on a more detailed level than neurotypical (NT) adults. According to the Perceptual Hypothesis, individuals with ASD have enhanced discrimination abilities (Plaisted, 2001). Enhanced discrimination abilities lead to the perception of seemingly irrelevant details that are not important for NT adults. Additionally, enhanced discrimination leads to reduced generalization, over-selectivity, and poorer categorization (for review see Brown & Bebko, 2012).

Vanmarcke et al. (2016) investigated the possible differences in categorization abilities between ASD and NT adults in an ultra-rapid semantic categorization task. The authors presented animal and vehicle images for 33ms. After each presentation, participants were asked to categorize whether the image displayed an animal or a vehicle (“go”/”no-go” task). In contrast to the prediction by the Perceptual Hypothesis, the authors did not observe any differences between individuals with ASD and NT adults, in neither the mean reaction times nor the overall accuracy. However, other studies did find a behavioral difference in ultra-rapid superordinate categorization between individuals without and with ASD when considering the typicality structures of items in a category (Gastgeb & Strauss, 2012). Objects can not only belong to different categories, they can also be more or less typical for a certain category (Panis, Vangeneugden, & Wagemans, 2008), and it has been shown that atypical category exemplars are easier to spot in visual search tasks (Kayaert, Op de Beeck, & Wagemans, 2011), generate a larger neural object-selective response in ventral occipito-temporal cortex compared to more prototypical exemplars (Panis, Wagemans, & Op de Beeck, 2011), and are identified slower on average (Gastgeb, Strauss, & Minshew, 2006).

A few behavioral studies suggest that individuals with high-functioning ASD (HF-ASD) have difficulties with atypical members of a category (Carmo, Duarte, Pinho, Filipe, & Marques, 2016; Gastgeb et al., 2006). For example, Carmo et al. (2020) presented six images in a rapid serial visual presentation (RSVP) paradigm while varying presentation times across RSVPs (13, 27, 53, and 80 ms). Participants had to detect a target item belonging to a basic level category that was presented after each RSVP (mammals, birds, vehicles, and fruits). Detection in terms of d-prime was found to improve with presentation duration, and typical items were detected better than atypical ones for each image presentation duration. Additionally, they observed that NT adults detected atypical images only with the longest presentation duration (80 ms), whereas adults with HF-ASD were never able to detect atypical images above chance. Carmo et al. (2020) hypothesized that a single feedforward pass through the visual system might not be sufficient to categorize atypical items, because only the longest presentation duration allows sufficient top-down information to reach and change the tuning of visual neurons needed to categorize atypical items. In contrast to NT adults, HF-ASD adults might thus fail to categorize atypical items due to malfunctioning feedback mechanisms (Carmo et al., 2020).

4.1.2 The present study

The current study is motivated by two goals. Firstly, most studies so far have investigated performance differences by comparing mean performance measures such as overall detection rate or mean correct RT (e.g., Grill-Spector & Kanwisher, 2005; Mack, Gauthier, Sadr, & Palmeri, 2008). However, mean performance measures conceal the underlying behavioral dynamics (Panis, Schmidt, Wolkersdorfer, & Schmidt, 2020), with previous studies showing that recognition performance changes over time (Panis, Torfs, Gillebert, Wagemans, & Humphreys, 2017; Panis & Wagemans, 2009). Therefore, I will employ a distributional method known as *discrete-time event history analysis* to statistically describe and model the response times measured in an ultra-rapid categorization paradigm. This will allow us to study *at which time after image onset* an advantage for animated objects is present, and how the effect of parameters such as presentation duration (PD) might change over time. In this first distributional study of ultra-rapid superordinate categorization, I avoid the use of masks as the effect of masking itself changes over time (Panis, Wagemans, & Schmidt, 2019).

Secondly, I want to test multiple hypotheses regarding visual categorization. I hypothesized that there is an advantage (i.e., earlier response occurrence and higher response accuracy) for processing (A) animal over man-made images (Thorpe, 1998) and (B) long over short presented images (Gerlach et al., 2002). Additionally, I am expecting (C) a difference between typical and atypical images in the long presentation duration (Panis, 2011). Lastly, (D) I hypothesize that HF-ASD adults might fail to categorize atypical items due to malfunctioning feedback mechanisms (Carmo et al., 2020). This hypothesis implies that a difference in HF-ASD adults would only be observed in atypical item categorization for longer response times, i.e., for responses based on recurrent processing that occur later than 300 ms after image onset.

To answer these questions, I presented NT and HF-ASD adults with pictures of animal and man-made object images displayed for a short or long duration, manipulated the typicality of the animal images, and used distributional analyses to statistically describe and model the RT and accuracy data.

4.1.3 Methods

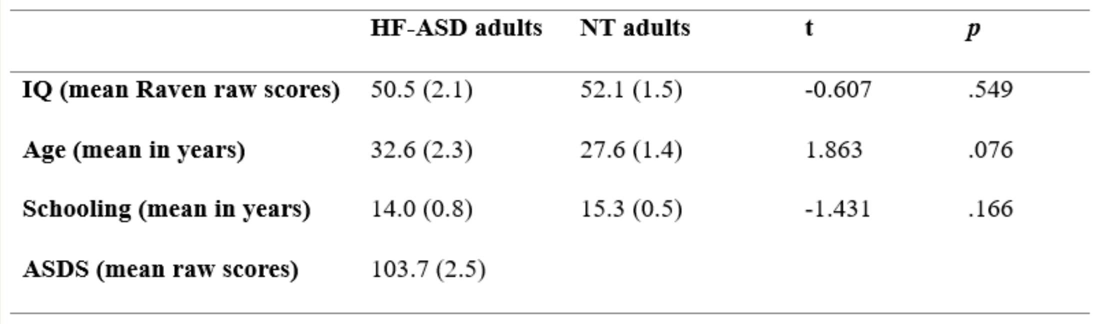
Participants

All participants were male, had normal or corrected-to-normal vision, had more than nine years of formal education, and were compensated with a voucher. Participants gave their written consent after being informed about the study procedures and had been given the possibility to ask questions. I recruited 15 male adult participants with high-functioning autism spectrum disorder (HF-ASD) diagnosed according to Diagnostic and Statistical Manual of Mental Disorders (DSM-V; American Psychiatric Association, 2013) and a score above 70 points on the verbal subscale of the Wechsler Adult Intelligence Scale. I used the Asperger's Syndrome Diagnostic Scale (ASDS; Myles, Bock, & Simpson, 2001) to confirm the clinical evaluation and diagnosis.

HF-ASD adults were matched for age, years of schooling, and general cognitive ability (assessed with Raven's progressive matrix) with neurotypical (NT) adults with no known psychological or neurological disorder. Twenty NT adults were selected to group-wise match the 14 HF-ASD adults. Quality of matching was tested with an independent t-test. Table 5 shows demographic details of both groups and the results of the t-test. This study was approved by the ethical review board of the Faculty of Psychology at the University of Lisbon and was conducted according to the Declaration of Helsinki (World Medical Association, 2013).

Table 5

Overview of the demographic information



	HF-ASD adults	NT adults	t	*p*
IQ (mean Raven raw scores)	50.5 (2.1)	52.1 (1.5)	-0.607	.549
Age (mean in years)	32.6 (2.3)	27.6 (1.4)	1.863	.076
Schooling (mean in years)	14.0 (0.8)	15.3 (0.5)	-1.431	.166
ASDS (mean raw scores)	103.7 (2.5)			

Note. Demographic information and estimated mean IQ scores of both groups of participants (standard error in brackets), calculated for adults with high-functioning autism spectrum disorder (HF-ASD) and neuro-typical (NT) adults separately. T-value of pairwise t-test in independent groups.

Apparatus

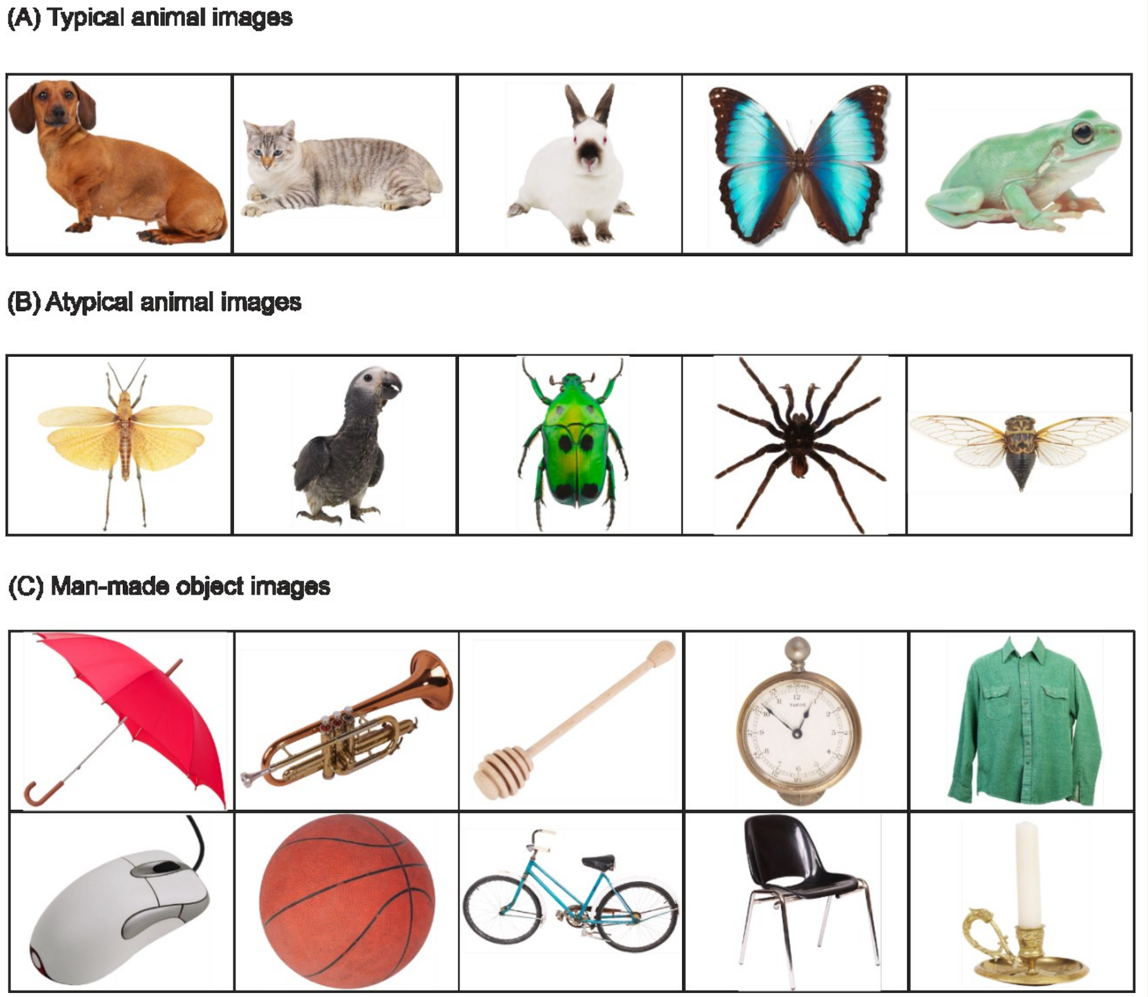
Stimuli were presented on a CRT monitor with a resolution of 1024 x 768 pixels and a refresh rate of 85 Hz. The instructions and stimuli were presented with Presentation Software (Version 18.0, Neurobehavioral Systems). Responses to the stimuli were given on a QWERTY keyboard, by pressing either the F or J key. Participants were seated 40 cm in front of the monitor, with no chin rest, in a dimly lit and shielded room.

Stimuli

Stimuli were presented inside a black fixation frame at the center of the screen, with a size of 10° x 10° visual angle (as described in VanRullen & Thorpe, 2001). I used 1600 colored photographs taken from the Photo Objects database by Hemera. Stimuli were presented for either 23.5 ms (2 frames) or 82.3 ms (7 frames). Half of the images represented animals and the other half were man-made objects. See Figure 9 for examples of animal and man-made object images.

Figure 9

Stimulus Material of Experiment 3A



Notes. Examples of typical (A) and atypical (B) animal, as well as man-made object (C) images used in the superordinate ultra-rapid categorization task. Stimuli were colored images.

Design

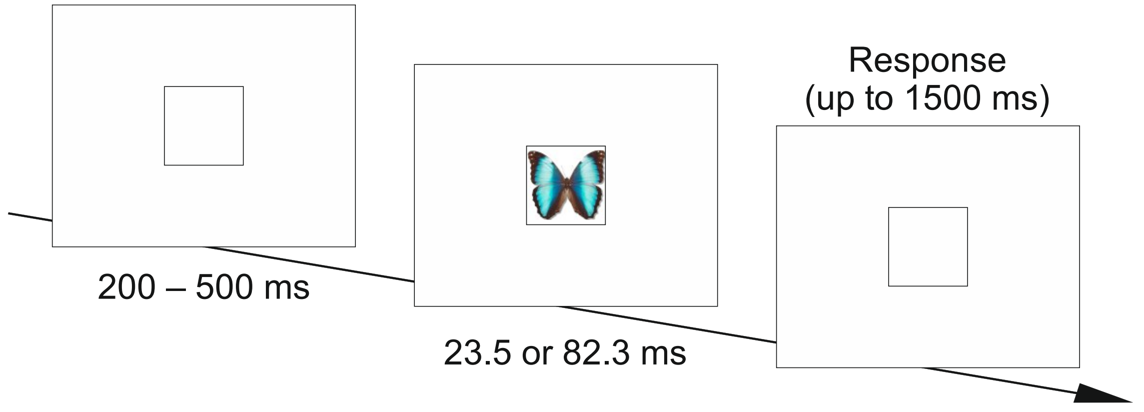
I used 400 photographs that contained an animal and 400 photographs that contained a man-made object. Participants saw each image only once in a randomized order. In each condition, half of the images were presented for 23.5 ms and the other half for 82.3 ms. Additionally, half of the animal images were typical, while the other half were atypical animal images (for examples see Figure 9). Typicality ratings were assessed following Rosch and Mervis (1975) in a prior study of young neurotypical adults. Participants were asked to indicate how well each image represented a given category (i.e., animal) on a 7-point scale with 7 being more representative and 1 being less representative (for ratings and results, see Beck et al., submitted).

Procedure

In each trial, one image was presented inside this black fixation frame for either 23.5 or 82.3 ms. Participants performed a visual superordinate categorization task in which they indicated whether the image belonged to the animal category or not. Thus, animals were used as targets and objects as non-targets. The response keys ("F" & "J") and their corresponding answers ("Yes" & "No") were counterbalanced between participants. Participants had up to 1500 ms to respond, following which the next stimulus was presented after a random interval between 200 ms and 500 ms (Figure 10). After every 100 trials, a break was offered to the participants.

Figure 10

Trial design



Notes. For the whole trial and during each block a fix square was displayed. In each trial, images were presented in a square for either 23.5 or 82.3 ms. Participants could respond until 1500 ms after stimulus offset to a two forced-choice task, answer the question “Did you see an animal image?” – “Yes”/”No”. Participants were asked to respond as accurate and as fast as possible.

Analysis of Mean Error Rate and Mean Correct RT

To compare our results with the literature, I examined the mean error rate (ER) and mean correct reaction time (RT) using a repeated-measures analysis of variance (ANOVA) with one between-subject variable GROUP (NT vs. HF-ASD adults), and two within-subject variables: Presentation Duration (PD; 23.5 vs. 82.3 ms), and Type (typical animal vs. atypical animal vs. no-animal images). P-values were Greenhouse-Geisser corrected, when needed (Geisser & Greenhouse, 1958). I excluded responses faster than 200 ms, corresponding to an average of 3.1 % of all trials in the NT group and 4.5 % in the HF-ASD group. In one out of all trials, no response was given after 1500 ms; no additional upper limit was used for RT analysis. For the average correct RTs, I excluded responses that were erroneous, leading to the exclusion of an average of 9.7 % of all trials in the NT group and 12.2 % in the HF-ASD group. ERs and RTs were aggregated in Python 3.6.5 and analyzed using SPSS 26.

Event History Analysis and Conditional Accuracy Analysis

Event history analysis (EHA), a.k.a. survival, hazard, duration, transition, and failure-time analysis, is the standard set of statistical methods for studying the occurrence and timing of events in many scientific disciplines (Allison, 1982, 2010; Austin, 2017; Singer & Willett, 2003; Willett & Singer, 1993). Examples of time-to-event or survival data include RT data, saccade latencies, fixation duration, time-to-force-threshold data, perceptual dominance duration when viewing a bi-stable stimulus, neural inter-spike duration, etc. (Panis et al., 2020). In general, to apply EHA one must be able to define the event-of-interest (any qualitative change that can be situated in time; here: a button-press response), to define a time point zero (here: image onset), and to measure the passage of time between time zero and event occurrence in continuous or discrete units (here: discrete time bins). As discussed by Whelan (2008) the use of a distributional method can maximize the return from the collected data, which is important in view of the costs and time required to run an experiment.

I used R (R Core Team, 2014) to set up life tables for each combination of participant and experimental conditions, to calculate the descriptive statistics provided by discrete-time EHA (see Table 6). The first 1000 ms after image onset was divided in twenty bins of 50 ms. While the starting point is not part of the interval, the endpoint is – the first and last bins are (0,50] and (950,1000], respectively. The hazard function of response occurrence is one of the most diagnostic functions when describing the distribution of a sample of (right-censored) RT data (Luce, 1986; Townsend, 1990)[1]. The discrete-time hazard function, $h(t) = P(T = t \mid T \geq t)$, represents for each bin the conditional probability that a response

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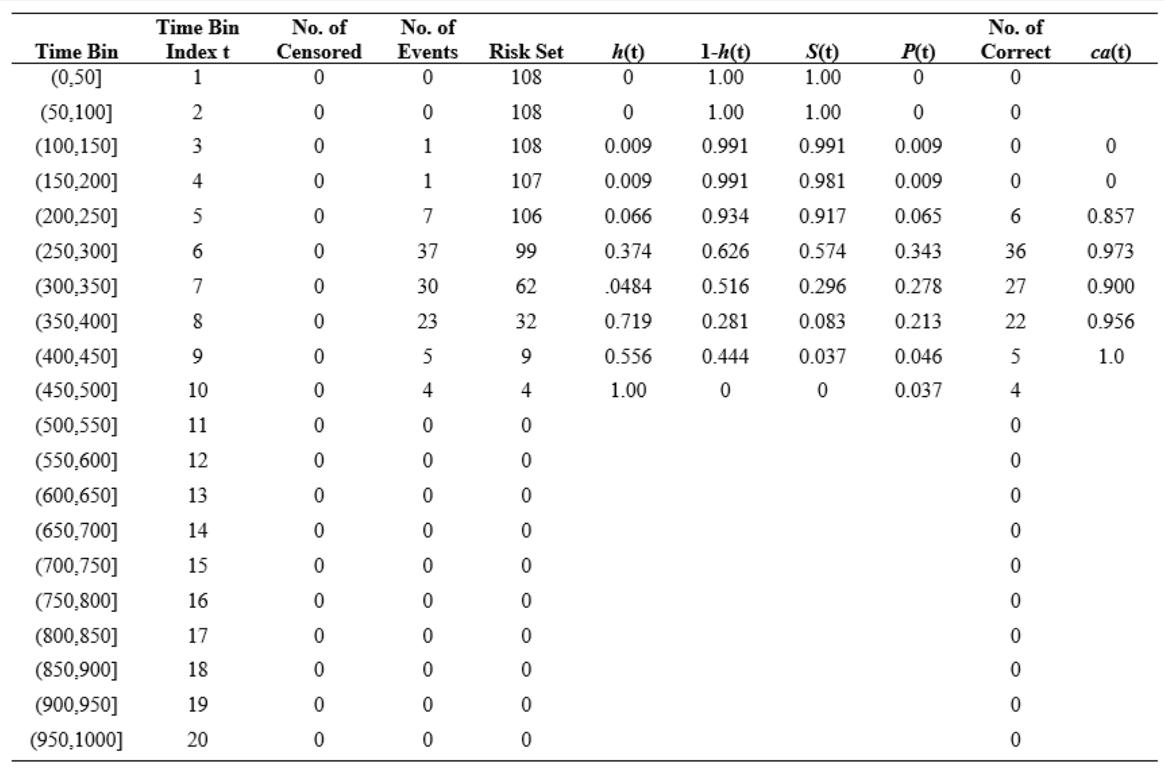
[1] Right-censoring occurs when all you know about an observation on a variable T is that it is *larger* than some value. Interval censoring means that all you know about T is that $a < T < b$, for some values of a and b – as in Table 6 (Allison, 2010). The most common type of right-censoring is “singly Type I censoring” which applies when the experiment uses a fixed response deadline for all trials. "Type I" means that the censoring time is fixed and under the control of the experimenter, and "singly" refers to the fact that all observations have the same censoring time (Allison, 2010).

will occur in bin t given that it has not yet occurred in any of the past bins (Allison, 2010). It is estimated by dividing the number of responses in bin t by the risk set for bin t, i.e., the number of trials that are still response-free at the start of bin t (see Table 6). All trials without a response in the first 1000 ms are treated as right-censored observations (i.e., I only use the information that RT > 1000 ms for these trials).

Table 6

Life table participant 104 the condition of typical animal images presented for 82.3 ms.



Time Bin	Time Bin Index t	No. of Censored	No. of Events	Risk Set	*h*(t)	1-*h*(t)	*S*(t)	*P*(t)	No. of Correct	*ca*(t)
(0,50]	1	0	0	108	0	1.00	1.00	0	0	
(50,100]	2	0	0	108	0	1.00	1.00	0	0	
(100,150]	3	0	1	108	0.009	0.991	0.991	0.009	0	0
(150,200]	4	0	1	107	0.009	0.991	0.981	0.009	0	0
(200,250]	5	0	7	106	0.066	0.934	0.917	0.065	6	0.857
(250,300]	6	0	37	99	0.374	0.626	0.574	0.343	36	0.973
(300,350]	7	0	30	62	.0484	0.516	0.296	0.278	27	0.900
(350,400]	8	0	23	32	0.719	0.281	0.083	0.213	22	0.956
(400,450]	9	0	5	9	0.556	0.444	0.037	0.046	5	1.0
(450,500]	10	0	4	4	1.00	0	0	0.037	4	
(500,550]	11	0	0	0					0	
(550,600]	12	0	0	0					0	
(600,650]	13	0	0	0					0	
(650,700]	14	0	0	0					0	
(700,750]	15	0	0	0					0	
(750,800]	16	0	0	0					0	
(800,850]	17	0	0	0					0	
(850,900]	18	0	0	0					0	
(900,950]	19	0	0	0					0	
(950,1000]	20	0	0	0					0	

Notes. No. of Events = number of observed responses in bin t; hazard function *h*(t) = P(T = t | T ≥ t); survivor function *S*(t) = P(T > t); probability mass function *P*(t) = P(T = t) = *h*(t) * *S*(t-1); conditional accuracy function *ca*(t) = P(correct | T = t); NA = undefined. 0 trials were right-censored at 1000 ms (i.e., 1000 < RT ≤ 1500 ms or no response occurred during the entire 1500 ms response collection period).

A second useful function is the survivor function $S(t) = P(T > t) = [1-h(t)] * [1-h(t-1)] * \ldots * [1-h(1)]$. The survivor function is the complement of the cumulative distribution function, $S(t) = 1-F(t) = 1-P(T \leq t)$, and gives for each bin the probability that the response does not occur before the end of bin t. Note that $S(0) = 1$. The estimated median RT – the time point when half of the trials have experienced a response – equals the quantile $S(t)_{.50}$ and can be obtained using linear interpolation. Equally noteworthy is that when $S(t)$ approaches 0 (i.e., a low risk set since the probability that a response does not occur before the end of bin t is low), larger error bars are expected in $h(t)$. I also plot the corresponding probability mass function or $P(t) = P(T = t) = h(t) * S(t-1)$.

To study the shape of the accuracy distribution, I estimate the discrete-time conditional accuracy function $ca(t) = P(\text{correct} \mid T = t)$, by dividing the number of correct responses in bin t by the total number of observed responses in bin t (see Table 6; Pachella, 1974; Wickelgren, 1977).

Finally, to test *whether and when* the main and interaction effects including GROUP (NT vs. HF-ASD adults), Presentation Duration (23.5 vs. 82.3 ms), and Type (typical animal, atypical animals, man-made objects) are significant across participants, I fitted discrete-time hazard and conditional accuracy models to the data. An example discrete-time hazard model with three predictors and the complementary log-log (cloglog) link function can be written as follows[2]:

$$\text{cloglog}[h(t)] = \ln(-\ln[1-h(t)]) = [\alpha_0\text{ONE} + \alpha_1(\text{TIME} - 1) + \alpha_2(\text{TIME} - 1)^2 + \alpha_3(\text{TIME} - 1)^3] + [\beta_1X_1 + \beta_2X_2 + \beta_3X_2(\text{TIME} - 1)].$$

---

[2] The complementary log-log link is preferred over the logit link for a discrete-time hazard model when the events can in principle occur at any time during each time bin (Allison, 2010), which is the case for RT data: $\text{cloglog}[h(t)] = \ln\{-\ln[1-h(t)]\}$. Inverse of the link: $h(t) = 1 - \exp\{-\exp\{\text{cloglog}[h(t)]\}\}$. Although the cloglog link function is asymmetrical it is similar to the logit link function for proportions below about 0.4.

The main continuous predictor variable TIME is the time bin index t (see Table 6) which is centered on value 1 in this example. The first set of terms within brackets, the alpha parameters multiplied by their polynomial specifications of (centered) time, represents the shape of the cloglog-hazard function in the chosen baseline condition (i.e., when all predictors X_i take on a value of zero). The second set of terms (beta parameters) represents the vertical shift in the baseline cloglog-hazard for a 1 unit increase in the respective predictor. For example, the effect of a 1 unit increase in X_1 is to vertically shift the whole baseline cloglog-hazard function with β_1 cloglog-hazard units. However, if the predictor interacts linearly with time (see X_2 in the example), then the effect of a 1 unit increase in X_2 is to vertically shift the predicted cloglog-hazard in bin 1 to β_2 cloglog-hazard units (when TIME-1 = 0), in bin 2 to $\beta_2 + \beta_3$ cloglog-hazard units (when TIME-1 = 1), etc. To interpret the effects of the predictors, the parameter estimates are exponentiated, resulting in a hazard ratio (HR). The parameters of a discrete-time hazard model can be estimated using population-averaged methods (e.g., Generalized Estimating Equations), Bayesian methods, or generalized linear mixed models (Allison, 2010).

I proceeded as follows for the current data set. First, I chose to fit the hazard models by implementing generalized linear mixed-effects regression models in R (R Core Team, 2014; function glmer of package lme4; Bates, Mächler, Bolker, & Walker, 2015) using the cloglog link function. I selected a time range where all participants provided enough data in each of the 12 conditions and followed the general advise to create between 10 and 20 bins for modeling purposes (Singer & Willett, 2003). Thus, I selected the time range (150,800] and created 13 bins of 50 ms each for modeling purposes. Thus, all trials with a RT ≤ 150 ms were discarded, and all trials were right-censored at 800 ms when fitting hazard models.

Second, the condition “NT adults – short PD – typical animal images” was chosen as the baseline condition. The main continuous predictor variable TIME was the time bin rank centered on bin (250,300], the reference bin during model selection. The intercept, the linear effect of TIME, and their correlation were treated as random effects to deal with the correlated data resulting from the repeated measures on the same participant.

Next to dummy-coding the relevant levels of our experimental factors (HF-ASD, long PD, atypical animal, man-made object), I also included the continuous predictor trial number (TRIAL) to model across-trial changes in the hazard of response occurrence, due to synaptic learning processes (Schöner et al., 2016) or proactive cognitive control processes (Braver, 2012), for example, that play out on this longer time scale. The TRIAL was centered on 1000, and rescaled by dividing by 1000. Thus, with all effects set to zero, the cloglog-hazard model's-intercept refers to the estimated cloglog[$h(300)$] in trial 1000 when a typical animal image is presented to NT adults with a short presentation duration.

Third, to estimate the parameters of the $h(\mathrm{t})$ model, I must create a data set where each row corresponds to a time bin of a trial of a participant (a person-trial-bin oriented data set). Specifically, each time bin that was at risk for event occurrence in a trial was scored on the dependent variable OUTCOME (0 = no response occurred; 1 = response occurred), the centered covariates TIME and TRIAL, the variable PARTICIPANT, and the dummy-coded dichotomous experimental predictor variables (HF-ASD, long PD, atypical animal, man-made). Thus, each trial without an observed response before 800 ms contributes 13 rows, and each row has a value 0 for OUTCOME. The resulting person-trial-bin oriented data set contained 274,958 rows.

Fourth, I started with a full multilevel cloglog-hazard model (43 fixed parameters; with bins at level 1 nested within the participant at level 2) encompassing the following effects at level 1: (a) a 3rd order polynomial for the shape of the cloglog-hazard function in the baseline condition (4 parameters), (b) the effects of being having ASD ('HF-ASD'), increasing presentation duration ('LONG'), changing to atypical animals ('ATYPICAL'), and to man object ('MANMADE') images were allowed to interact with time in a linear, quadratic, and cubic fashion (16 parameters), (c) the five first-order interaction effects involving HF-ASD, LONG, ATYPICAL, and MANMADE could vary over time in a linear and quadratic fashion (15 parameters), (d) the two second-order interaction effects involving HF-ASD, LONG, ATYPICAL, and MANMADE could vary linearly over time (4 parameters), and (e) the linear effects of TRIAL could interact with time in a linear, quadratic, and cubic fashion (4 parameters).

I used an automatic backward selection procedure to select the final model to report. Specifically, during each iteration, the effect with the largest *p*-value that was not part of any higher-order effect was deleted, and the model refitted. This continued until each of the remaining effects that was not part of any higher-order effect had a $p < .05$ (expect for the effect TIME^3 : TRIAL with $p = .052$ in the cloglog-*h*(t) model).

Finally, after model selection, I refitted the selected cloglog-hazard model twice with TIME centered each time on a different reference bin (550 and 750), to make explicit what values the parameter estimates of effects not involving TIME take on according to the selected model in these other time bins, and whether they represent a significant effect or not.

To select a conditional accuracy model, I used the same multilevel modeling procedure except that I used the original person-trial oriented data set (27,200 trials), and only included trials with observed RTs within the time segment (150,800] (25,583 trials or rows). I predicted the accuracy (1/0) in each bin and used the symmetric logit link function.

4.1.4 Results

Mean error rate

One HF-ASD participant was excluded from the analysis due to a high error rate (higher than 2 SD above the group mean). Overall, participants responded erroneously on 6.5 % of all trials (*SE* = 0.83 %). The ANOVA on the mean error rates showed a significant main effect of PD, $F(1,32) = 24.00$, $p < .001$, $\eta_p^2 = .43$. Participants made more mistakes when images were presented for 23.5 ms (*M* = 7.6 %, *SE* = 1.0 %) than when presented for 82.3 ms (*M* = 5.4 %, *SE* = 0.8 %)[3]. The mean error rates are displayed in Figure 11a.

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[3] For direct comparison with Carmo et al. (2018) I analyzed category discrimination using d prime (d') and an ANOVA with three variables: GROUP (NT vs. HF-ASD adults; between subject factor), Presentation Time (PT; 23.5 vs. 82.3 ms; within subject factor), and TYPICALITY (typical animal vs.

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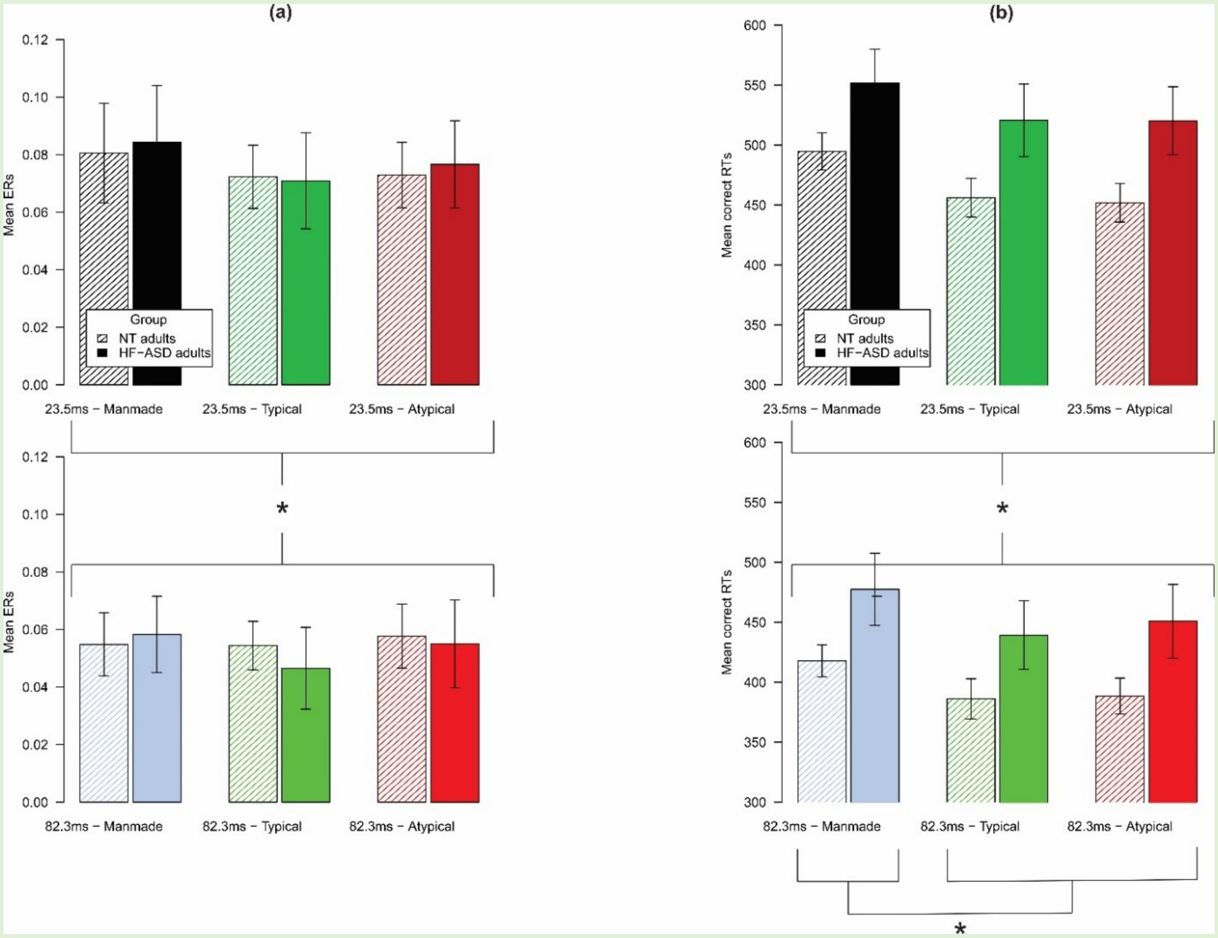
atypical animal image; within subject factor). D' was calculated by using the z-score of the probability of hits minus the z-score of the probability of false alarms. The probability of hits was obtained by dividing the amount of hits by the sum of the hits and the misses. The probability of false alarms was obtained by dividing the amount of false alarms by the sum of the false alarms and the correct rejections. In the absence of misses or false alarms, I applied the formula by Macmillan & Creelman (2004). A d' of 0 indicates no discrimination, whereas a d' of 4 indicates nearly perfect performance (Macmillan & Creelman, 1991). I found a main effect in PT, $F(1,32) = 24.74$, $p < .001$, $\eta_p^2 = .44$. Detecting animal images was more difficult when the presentation time was short ($M = 3.13$, $SE = 0.15$) than when the presentation time was long ($M = 3.51$, $SE = 0.15$).

Figure 11

Mean performance measures



Notes. (a) Mean error rate and (b) mean correct RT for neurotypical (NT) adults and adults with high-functioning autism spectrum disorder (HF-ASD) depending each on presentation time (23.5 ms or 82.3 ms) and presented image (man-made objects, typical animals, and atypical animals). Error bars represent standard error.

* $p < .001$.

Mean correct RT

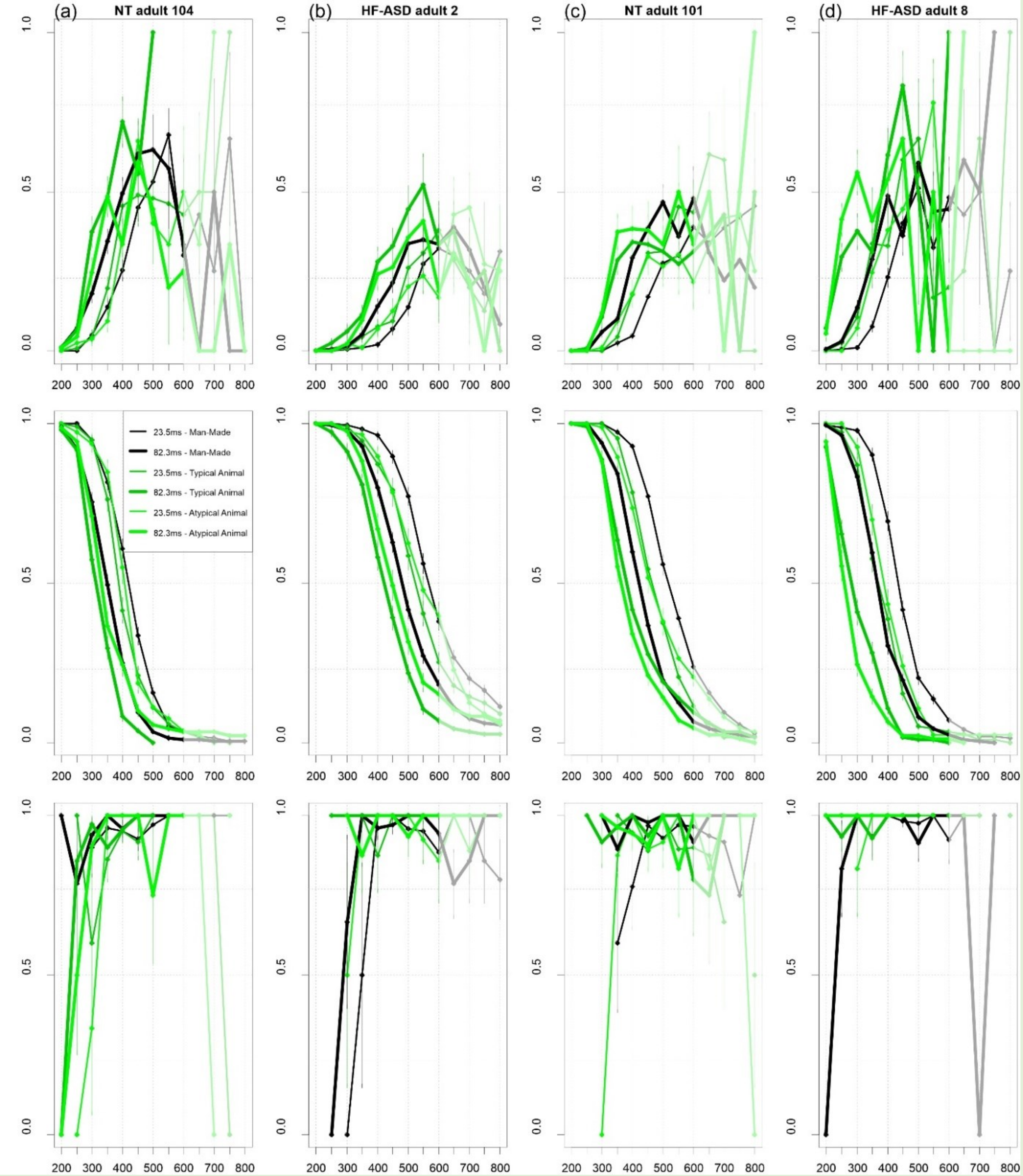
In the correct RTs, as in the ANOVA of the ERs, I observed a significant main effect of PD, $F(1,32) = 643.1$, $p < .001$, $\eta_p^2 = .95$. When images were presented for 23.5 ms it took participants on average 494 ms (*SE* = 16 ms; *Median* = 465 ms) to respond, whereas when images were presented for 82.3 ms participants were on average 72 ms faster (*M* = 422 ms, *SE* = 15 ms; *Median* = 405 ms). Additionally, I observed a significant main effect of Type, $F(2,64) = 41.54$, $p < .001$, $\eta_p^2 = .57$. In more detail, participants answered slower to man-made object images (*M* = 480 ms, *SE* = 15 ms; *Median* = 455 ms) than to typical (*M* = 445 ms, *SE* = 16 ms; *Median* = 420 ms) and atypical (*M* = 447 ms, *SE* = 16 ms; *Median* = 429 ms) animal images. A post hoc t-test showed a significant difference between man-made object images and all animal images, $t(33) = 7.5$, $p < .001$. I observed a marginally significant main effect of the between-subject factor GROUP, $F(1,32) = 4.12$, $p = .051$, $\eta_p^2 = .11$. NT participants gave correct responses faster (*M* = 433 ms, *SE* = 19 ms; *Median* = 421 ms) than HF-ASD adults (*M* = 493 ms, *SE* = 29 ms; *Median* = 464 ms,). The mean correct RTs are presented in Figure 11b.

Event history analysis: Descriptive statistics

In Figure 12 I present the data of four representative participants to study interindividual differences. Let´s first focus on a NT adult and long image presentation durations (dotted lines in Figure 12a). Imagine traveling with time starting at image onset. If, for example, the waiting time has increased until 250 ms without event occurrence, then the conditional probability that the response occurs in bin (250,300] is estimated to be 0.37 when a typical animal image was presented (37 observed responses with a risk set equal to 99; Table 6). Thus, of all trials that survive until (i.e., are still response-free at) 250 ms, about 57.4 percent will experience a response during the next 50 ms (i.e., they will „die“, and drop out of the risk set). In short, $h(300) = .37$ (I refer to each bin by using its endpoint). Moreover, if a response occurs in bin (250,300], then the probability that it will be correct equals $.97 = ca(300)$.

Figure 12

Descriptive statistics



Notes. Sample-based estimates of (top to bottom) *h*(t), *S*(t), & *ca*(t) for the NT adult 104 (a), HF-ASD adult 2 (b), NT adult 101 (c), and HF-ASD adult 8 (d). Displays the first 20 bins (or 1000 ms) after target onset. Bin width equals 50 ms. Black lines represent man-made object images, dark green lines typical animal images, and light green lines atypical animal images. Thin lines represent images presented for 23.5 ms, whereas thick lines represent images presented for 82.3 ms. Error bars are depicted for each time bin. Less visible lines (from 600ms) indicate a low risk set.

However, if the waiting time has increased until 400 ms, for example, then $h(450) = .56$ and $ca(450) = 1.0$. The hazard and conditional accuracy functions thus show how the performance changes over time. For atypical images, $h(300) = .25$ and $ca(300) = .90$. For man-made images, $h(300) = .18$ and $ca(300) = .94$. This NT adult thus shows an early advantage for typical animals compared to atypical animals and man-made objects.

In Figure 12b I show the data of an HF-ASD adult that also shows an advantage for typical over atypical animals when the image presentation duration is long. Figure 12c shows the data of a NT adult who shows an advantage for atypical over typical animals with the longest presentation duration. Figure 12d shows the data of an HF-ASD adult who shows an advantage for atypical over typical animals with the longest presentation duration.

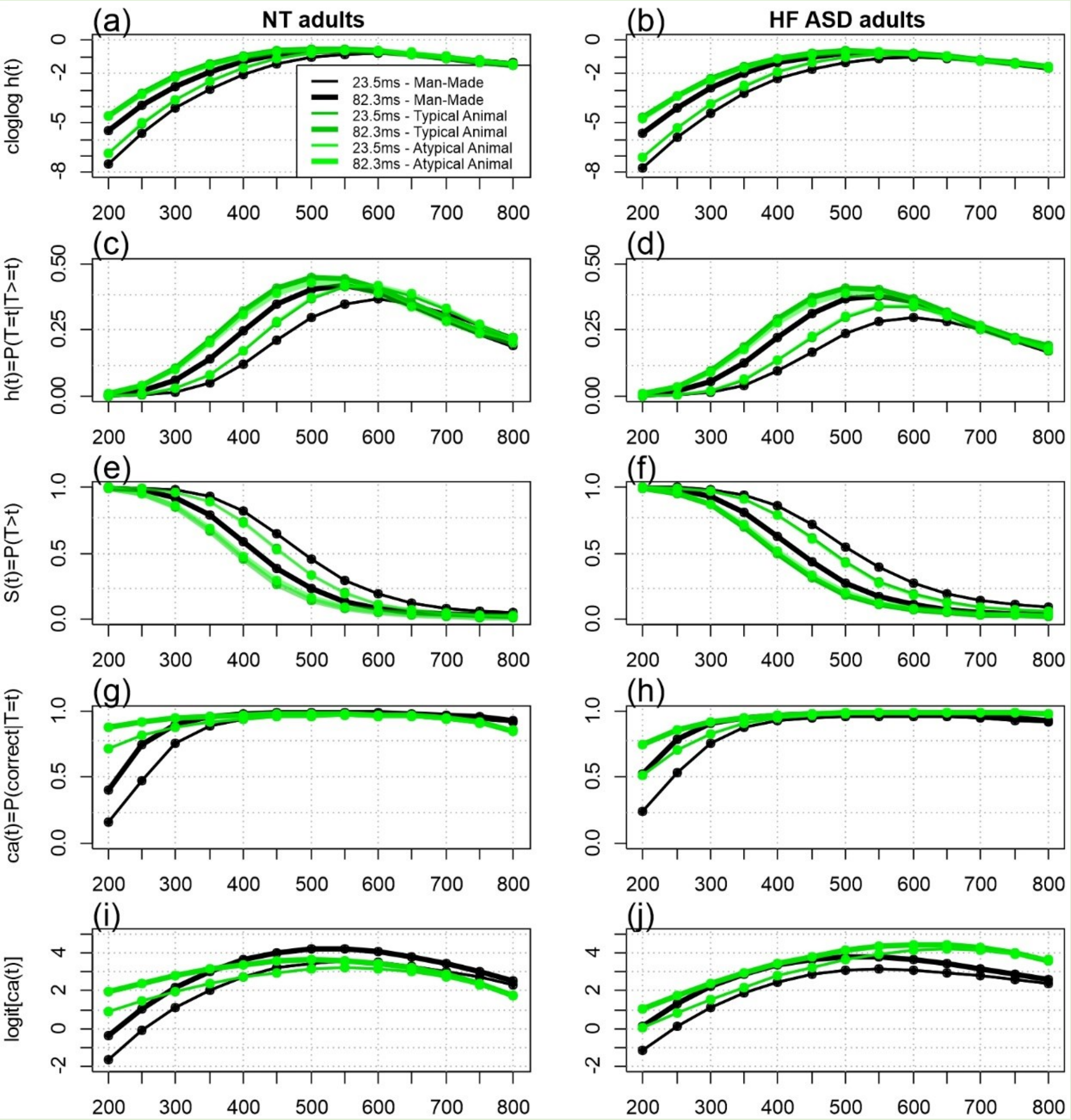
Note that when the presentation duration is short, all participants show a minimal difference between the hazard functions for typical and atypical animals. Furthermore, most responses emitted after about 350 ms have a high conditional accuracy.

Event history analysis: Inferential statistics of the discrete-time hazard model

Table 7 shows the selected hazard model, and Table 8 shows the selected conditional accuracy model. Figure 13 shows the model-based hazard, survivor, and conditional accuracy functions.

Figure 13

Model-based functions

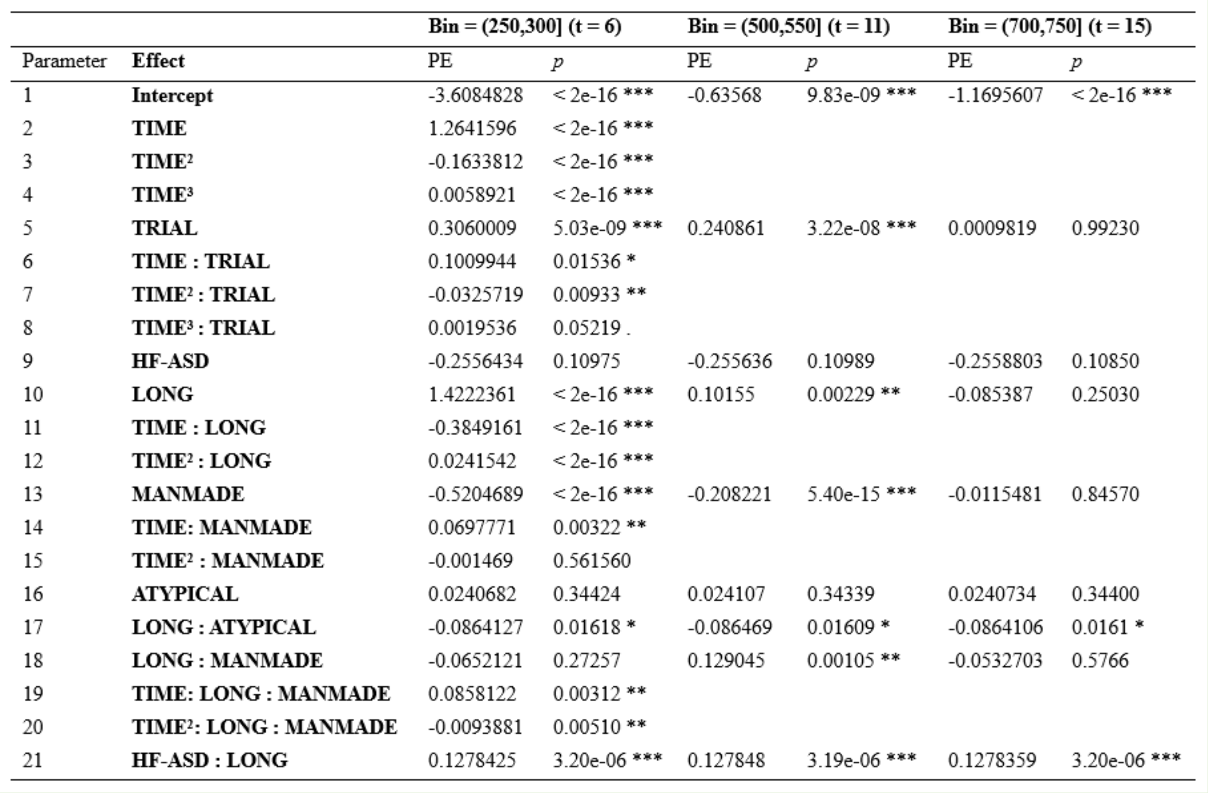


Notes. The model-based estimates of (top to bottom) cloglog[*h*(t)] (a, b), *h*(t) (c, d), *S*(t) (e, f), *ca*(t) (g, h), and logit[*ca*(t)] (i, j) for each experimental group (columns) at trial 1000 in the selected discrete time hazard model for reaction times between 200 ms and 800 ms. Bin width equals 50 ms. Black lines represent man-made object images, dark green lines typical animal images, and light green lines atypical animal images. Thin lines represent images presented for 23.5 ms, whereas thick lines represent images presented for 82.3 ms. Error bars are depicted for each time bin. Less visible lines (from 600ms) indicate a low risk set.

The first four parameter estimates (PE) in column 3 of Table 7 model the shape of the cloglog[*h*(t)] function in the baseline condition for trial 1000 of a NT adult responding to a typical animal image being presented for 23.5 ms. The intercept (Table 7, parameter 1) equals -3.61 cloglog-hazard units, corresponding to an estimated hazard value, *h*(300), of (1-exp[-exp(-3.61)] =) .03. This intercept changes in a linear, quadratic, and cubic fashion (parameters 2-4). Thus, the PE of the intercept increases to -0.64 in bin 550, and then decreases to -1.17 in bin 750, corresponding to *h*(550) = .41 and *h*(750) = .26 for the baseline condition in trial 1000.

Table 7

Selected cloglog-h(t) model



		Bin = (250,300] (t = 6)		Bin = (500,550] (t = 11)		Bin = (700,750] (t = 15)	
Parameter	Effect	PE	*p*	PE	*p*	PE	*p*
1	**Intercept**	-3.6084828	< 2e-16 ***	-0.63568	9.83e-09 ***	-1.1695607	< 2e-16 ***
2	**TIME**	1.2641596	< 2e-16 ***				
3	**TIME^2**	-0.1633812	< 2e-16 ***				
4	**TIME^3**	0.0058921	< 2e-16 ***				
5	**TRIAL**	0.3060009	5.03e-09 ***	0.240861	3.22e-08 ***	0.0009819	0.99230
6	**TIME : TRIAL**	0.1009944	0.01536 *				
7	**TIME^2 : TRIAL**	-0.0325719	0.00933 **				
8	**TIME^3 : TRIAL**	0.0019536	0.05219 .				
9	**HF-ASD**	-0.2556434	0.10975	-0.255636	0.10989	-0.2558803	0.10850
10	**LONG**	1.4222361	< 2e-16 ***	0.10155	0.00229 **	-0.085387	0.25030
11	**TIME : LONG**	-0.3849161	< 2e-16 ***				
12	**TIME^2 : LONG**	0.0241542	< 2e-16 ***				
13	**MANMADE**	-0.5204689	< 2e-16 ***	-0.208221	5.40e-15 ***	-0.0115481	0.84570
14	**TIME: MANMADE**	0.0697771	0.00322 **				
15	**TIME^2 : MANMADE**	-0.001469	0.561560				
16	**ATYPICAL**	0.0240682	0.34424	0.024107	0.34339	0.0240734	0.34400
17	**LONG : ATYPICAL**	-0.0864127	0.01618 *	-0.086469	0.01609 *	-0.0864106	0.0161 *
18	**LONG : MANMADE**	-0.0652121	0.27257	0.129045	0.00105 **	-0.0532703	0.5766
19	**TIME: LONG : MANMADE**	0.0858122	0.00312 **				
20	**TIME^2: LONG : MANMADE**	-0.0093881	0.00510 **				
21	**HF-ASD : LONG**	0.1278425	3.20e-06 ***	0.127848	3.19e-06 ***	0.1278359	3.20e-06 ***

Notes. Parameter estimates (PE) and test statistics (*p*) for the selected hazard model. During model selection TIME was centered on bin 300. The selected model was refitted two times with TIME centered on bin 550 and bin 750. HF-ASD = High-functioning autism spectrum disorder; TIME^2 = TIME * TIME. TIME^3 = TIME * TIME * TIME.

. $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Relative to the reference condition, I observed a main effect of a LONG presentation duration (parameter 10, reference bin PE = 1.42, $p < .001$). Thus, presenting typical animal images for 82.3 ms to NT adults increases the estimated cloglog[*h*(t)] by 1.42 units in bin (250,300], corresponding to a hazard ratio, HR(300), of (exp[1.42] =) 4.14. The fact that the parameter estimate is positive indicates a higher probability of response occurrence in bin (250,300] when a typical animal image is presented for 82.3 ms than for 23.5 ms to the NT adults. Importantly, this effect changes significantly with TIME in a linear and quadratic fashion (parameters 11 and 12). The PE decreases with increasing waiting time, equaling 0.10 in bin 550 (HR = 1.12, $p < .005$) and -0.09 in bin 750 (HR = 0.92, $p = .25$). Hence, the early positive effect of a longer presentation duration on response occurrence decreases over time and is gone around 700 ms. In other words, if the waiting time has increased until 700 ms (or longer), then there is actually no effect anymore of presentation duration on response occurrence.

Relative to the reference condition, I also observed a main effect of MANMADE (parameter 13, reference bin PE = -0.52, $p < .001$). This means that in comparison to presenting typical animal images for 23.5 ms, the cloglog-hazard of response occurrence decreases by 0.52 cloglog-hazard units in bin 300 (HR = 0.6) when presenting an image of a man-made object. This effect changes in a linear and quadratic fashion over time (parameters 14 and 15), so that the PE equals -0.21 in bin 550 ($p < .001$, HR = 0.81), and -0.01 in bin 750 ($p = .85$, HR = 0.99). Thus, the effect of man-made versus typical animal images on the hazard function of response occurrence decreases over time and is gone around 700 ms.

While the time-invariant main effects of HF-ASD and ATYPICAL are not significant (parameters 9 and 16), three interaction effects are significant. The first interaction effect between LONG and ATYPICAL is time-invariant (parameter 17, PE = -0.09, $p = .016$). It shows that the insignificant main effect of ATYPICAL becomes negative with a longer presentation time. This effect was partly expected: only with a longer presentation time do I see a decrease in categorization response occurrence for atypical compared to typical animal images. However, this effect of typicality does not change over time, in contrast to the hypothesis of Carmo et al. (2020).

The second interaction effect between LONG and MANMADE changes in a linear and quadratic fashion over time (parameters 18 – 20), resulting in a non-significant negative PE value in bin 300 (PE = -0.07, $p = .27$), a significant positive PE value in bin 550 (PE = 0.13, $p < .005$), and a non-significant negative PE in bin 750 (PE = -0.05, $p = .58$). Thus, compared to the effect of MANMADE for a short image presentation duration (parameters 13 – 15) – which decreases over time and is gone around 700 ms

–the effect of MANMADE for a long image presentation duration is gone a bit earlier due to this significant positive interaction effect in bin 550. This illustrates the relevance of comparing hazard functions instead of mean performance measures.

The third interaction effect between LONG and HF-ASD is positive and time-invariant (parameter 21, PE = 0.13, $p < .0001$). It shows that the positive effect of a longer presentation time (parameters 10 – 12) is larger and lasts a bit longer for HF-ASD adults compared to NT adults.

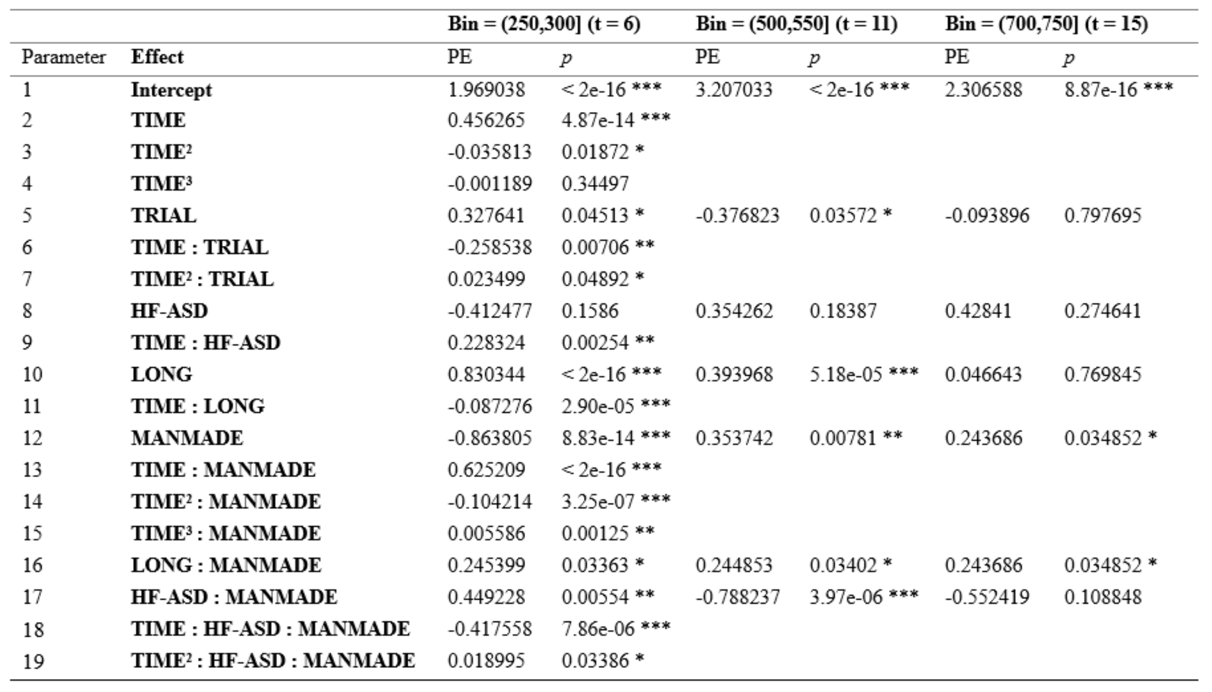
Finally, the hazard changes on the across-trial time scale, and this effect differs depending on the time bin (parameters 5 – 8). Each series of 1000 trials will increase the predicted cloglog-hazard with .31 units in bin 300, but only with .24 units in bin 550. The across-trial learning effect thus only affects responses emitted before ~700 ms.

Event history analysis: Inferential statistics of the discrete-time conditional accuracy model

The first four parameters in column 3 of Table 8 model the shape of the logit[*ca*(t)] function in the baseline condition for trial 1000 (green, i.e., red, dotted line in Figure 13i). The intercept (Table 8, parameter 1) equals 1.97 logit units, corresponding to an estimated conditional accuracy value in bin 300 of (exp(1.97)/[1+exp(1.97)] =) .88 = *ca*(300). This intercept changes in a linear and quadratic fashion (parameters 2 – 4). Thus, the PE of the intercept increases to 3.21 in bin 550 – *ca*(550) = .96 –, and then decreases to 2.31 in bin 750 – *ca*(750) = .91. This shows that the predicted conditional accuracy of the emitted responses is highest when they are emitted around 500 ms after image onset.

Table 8

Selected logit-ca(t) model



		Bin = (250,300] (t = 6)		Bin = (500,550] (t = 11)		Bin = (700,750] (t = 15)	
Parameter	Effect	PE	*p*	PE	*p*	PE	*p*
1	**Intercept**	1.969038	< 2e-16 ***	3.207033	< 2e-16 ***	2.306588	8.87e-16 ***
2	**TIME**	0.456265	4.87e-14 ***				
3	**TIME^2**	-0.035813	0.01872 *				
4	**TIME^3**	-0.001189	0.34497				
5	**TRIAL**	0.327641	0.04513 *	-0.376823	0.03572 *	-0.093896	0.797695
6	**TIME : TRIAL**	-0.258538	0.00706 **				
7	**TIME^2 : TRIAL**	0.023499	0.04892 *				
8	**HF-ASD**	-0.412477	0.1586	0.354262	0.18387	0.42841	0.274641
9	**TIME : HF-ASD**	0.228324	0.00254 **				
10	**LONG**	0.830344	< 2e-16 ***	0.393968	5.18e-05 ***	0.046643	0.769845
11	**TIME : LONG**	-0.087276	2.90e-05 ***				
12	**MANMADE**	-0.863805	8.83e-14 ***	0.353742	0.00781 **	0.243686	0.034852 *
13	**TIME : MANMADE**	0.625209	< 2e-16 ***				
14	**TIME^2 : MANMADE**	-0.104214	3.25e-07 ***				
15	**TIME^3 : MANMADE**	0.005586	0.00125 **				
16	**LONG : MANMADE**	0.245399	0.03363 *	0.244853	0.03402 *	0.243686	0.034852 *
17	**HF-ASD : MANMADE**	0.449228	0.00554 **	-0.788237	3.97e-06 ***	-0.552419	0.108848
18	**TIME : HF-ASD : MANMADE**	-0.417558	7.86e-06 ***				
19	**TIME^2 : HF-ASD : MANMADE**	0.018995	0.03386 *				

Notes. Parameter estimates (PE) and test statistics (*p*) for the selected conditional accuracy model. During model selection TIME was centered on bin 300. The selected model was refitted two times with TIME centered on bin 550 and bin 750. HF-ASD = High-functioning autism spectrum disorder; TIME^2 = TIME * TIME. TIME^3 = TIME * TIME * TIME.

. $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Relative to the reference condition, I observe a main effect of a LONG image presentation duration (parameter 10, reference bin PE = 0.83, $p < .001$), which changes linearly with time (parameter 11). Presenting typical animal images for 82.3 ms to NT adults instead of 23.5 ms increases the estimated logit[*ca*(t)] with 0.83 units in bin (250,300], corresponding to an odds ratio – OR(300) – of 2.3. In other words, the odds of a correct response are 2.3 times higher for responses emitted in bin (250,300] when the presentation time is long compared to short (for NT adults in trial 1000 in response to typical animal images). Just as in the hazard model, this positive effect decreases over time and is gone around 700 ms.

Relative to the reference condition, I observe a main effect of MANMADE (parameter 12, reference bin PE = -0.86, p < .001), that changes with increasing waiting time (parameters 13 – 15). Compared to typical animals, categorizing images of man-made objects decreases the estimated logit-*ca*(t) with 0.86 units in bin 300, or OR(300) = 0.42 (*p* < .001). However, for bins 550 and 750 the odds ratios are larger than 1 so that the odds of a correct response are larger for man-made compared to typical animal images when responses are emitted after 500 ms (OR(550) = 1.42; OR(750) = 1.28). A late advantage for man-made objects has also been observed by Panis et al. (2017). Relative to the reference condition, I observe a main effect of HF-ASD that changes linearly with time but is not significant in any bin (parameters 8 and 9).

Two additional interaction effects are significant. The first interaction effect between LONG and MANMADE is positive and time-invariant (parameter 16, PE = 0.25, *p* = .034). The effect of MANMADE for a short presentation time (parameter 12) becomes less negative for bin 300 and more positive for bins 550 and 750 with a long presentation time.

The second interaction effect between HF-ASD and MANMADE changes over time (parameters 17 – 19). As a result, the effect of MANMADE for NT adults (parameters 12 – 15) becomes less negative for bin 300 when HF-ASD adults are performing the task and stays negative for bins 550 and 750. The HF-ASD adults thus never show the late advantage for man-made objects shown by NT adults.

Finally, each additional series of 1000 trials increases the logit[*ca*(t)] in bin 300 by 0.33 units (parameter 5, *p* < .05), but decreases it in bin 550 with 0.38 logit units (*p* < .05).

4.1.5 Discussion

To study how the superordinate categorization performance in adults with and without HF-ASD depends on presentation duration, natural image typicality, and the passage of waiting time, I analyzed the response times with event history analysis, and the accuracy with conditional accuracy analyses. Thus, I investigated how the superordinate categorization performance and the effects of our experimental manipulations change over time, and if additional processing time is needed to categorize atypical animal images. Our findings bring together several lines of research.

Ultra-rapid superordinate categorization in NT adults

Fabre-Thorpe (2011) concluded that response times of around 250 to 290 ms are the lower limits needed to categorize images and argued that this fast performance is based on the feedforward sweep through the ventral pathway after image onset. Our findings in bins 250 and 300 are consistent with this proposal. The hazard model shows that the advantage of natural over man-made objects, for both short and long presentation durations, and for both NT and HF-ASD adults, in terms of response occurrence is present in the fast responses (< 300 ms). One can additionally observe an advantage for the longer than shorter presentation duration for all images. While this advantage did not change with category (natural vs. man-made), it did change, however, with typicality. The advantage of longer presentation duration decreased for atypical in comparison to typical animal images. Furthermore, whenever such an early response occurs, its accuracy is above chance, but lower for man-made compared to animal images and lower for short compared to long presentation duration. The advantage of natural over man-made objects increases with longer presentation duration. Overall, these findings are consistent with the idea that feedforward mechanisms (extraction of global shape, diagnostic features, or curvilinear features) are sufficient to perform our ultra-rapid superordinate categorization task for early-solved images.

However, the advantage for animal images was also present for responses emitted after 300 ms, for both the response occurrence and response accuracy. These findings are consistent with the theory of Gerlach and colleagues (2002, 2004, 2006), which states that early feedback information from the (current set of) activated candidate object representations after the feedforward sweep can influence difficult grouping and segmentation processes in the posterior IT and that the global shape characteristics of activated natural objects will produce a grouping advantage under suboptimal grouping conditions, which can outweigh their disadvantage during matching under optimal conditions. In other words, categorizing late-solved images (> 300 ms) likely depends on recurrent processing involving the visual system (Kar & DiCarlo, 2021).

As in Carmo et al. (2020), I observed an advantage for long over short presentation duration was observed for response occurrence and accuracy (before and after 300 ms). Overall, I observed higher information integration of information with longer presentation duration. The advantage of information integration was due to longer presentation duration was larger for responses before than after 300 ms. Hence, feedforward processes are more influenced by presentation duration than recurrent processes. Presentation duration affects recurrent processes, since they are associated with the activation of object representation (Gerlach et al., 2002, 2004, 2006).

Interestingly, the advantage for animal images for the short presentation duration lasted longer than for the long presentation duration in response occurrence. Clarke (2020) suggests that semantic information becomes available around 200 – 400 ms after image onset. In response accuracy, the advantage for animal images for the short presentation duration increases for the long presentation duration for both feedforward and recurrent processes. Hence, our findings strongly suggest that superordinate visual categorization can also be influenced recurrently by emerging semantic information, especially for the short presentation duration.

Ultra-rapid superordinate categorization of ASD adults

The goal of this study was to test the hypothesis of Carmo et al. (2020) that HF-ASD adults might fail to categorize atypical items due to malfunctioning recurrent processes. The malfunctioning recurrent processes were observed by looking at the results of the longest presentation duration. Hence, for the current study this has two implications. Firstly, it might imply that differences in HF-ASD adults would only be observed in the categorization of atypical items with longer response times, i.e., for responses based on recurrent processing that occur after about 300 ms after image onset. Even though I did not observe an effect of typicality in HF-ASD adults in the averaged sample, I observed contracting results on the individual level. For instance, in the HF-ASD adult 2 I observed an advantage for typical images, while in the HF-ASD adult 8 I observed an advantage for atypical animal images. This might indicate for some HF-ASD adults malfunctioning recurrent processes. However, since this pattern of results was also observed in the NT adults, these results might not be due to individual differences in the HF-ASD adults but rather to the typicality ratings used in the current study. Therefore, I want to emphasize that the typicality ratings were not administered to the participants in the current study but to a pre-study sample of participants. The typicality ratings from the pre-study might be not representative or reliable. For instance, the pre-study sample consisted of younger NT adults than the current study and the number of participants in the pre-study sample was quite low ($n = 17$). Secondly, it implies that differences in HF-ASD adults would be observed in the categorization with longer presentation duration. I did observe the influence of longer presentation duration in HF-ASD adults on response occurrence. This effect is time-invariant indicating no difference between feedforward and recurrent processing but rather that longer presentation duration made enhanced discrimination possible for HF-ASD adults in comparison to NT adults. This is inconsistent with the results by Carmo et al. (2020), since they observed no enhanced discrimination for HF-ASD adults but rather for NT adults. This might be due to the changes in paradigm and the obvious difference in the performance level. In the study by Carmo et al. (2020) a RSVP paradigm was used resulting in an overall low detection rate, while in the current study the performance was high. Hence, both results might reflect two sides of a coin.

Unexpectedly, I observed that the late advantage for man-made objects in comparison to animal images in NT adults was not observed in HF-ASD adults. Therefore, the recurrent processes in individuals with HF-ASD adults did not contribute as positively as in the NT adults. This might indicate malfunctioning recurrent processes in HF-ASD adults when categorizing man-made images. Nevertheless, with the current paradigm and methodology, I did not find clear evidence for the hypothesis of malfunctioning recurrent processes.

Limitations

I think that our results do suggest a number of improvements for future studies that want to examine why HF-ASD adults have difficulties with atypical members of visual object categories (Carmo et al., 2020; Gastgeb et al., 2006). First, future studies might want to consider using a small-N design, in which much more trials are administered to less subjects. Having more power per individual is important if I want to understand individual behavior (Smith & Little, 2018). Moreover, it can help in understanding interindividual differences because subject information can be added to level 2 of multilevel hazard and conditional accuracy models, which is important given the possible heterogeneity of the visual processing differences that have been described in ASD.

Second, instead of dichotomizing typicality ratings to select typical and atypical images, one can include the original average typicality ratings as continuous predictors in a hazard model. Future studies might also want to quantify various other informational aspects of images (e.g., outline complexity, curvilinearity, etc.) and add these relevant predictors to a hazard model to study whether and when categorization performance is affected by them.

Third, the fact that I used no masks made our task relatively easy for the participants. Future studies might consider image degradation procedures such as fragmentation (Burnett, Panis, Wagemans, & Jellema, 2015; Panis & Wagemans, 2009), as well as using masks to make the task more difficult. Fourth, comparing categorization performance at different levels of categorization using event history analysis is another necessary research direction for future studies (Grill-Spector & Kanwisher, 2005; Mack et al., 2008).

Finally, instead of selecting existing images from a database, one might use artificially created visual object categories and exemplars (see Panis et al., 2008). This will allow researchers to independently manipulate typicality (i.e., the location of an exemplar in a low-dimensional shape space that is close or far from the prototype) and familiarity (i.e., number of repeated presentations in an experiment). This is important as I can have no control over the amount of familiarity and typicality of independently selected images for each participant in an experiment.

4.1.6 Conclusion

Studying how performance changes over time is crucial to be able to behaviorally distinguish feedforward-only from recurrent processing mechanisms. By using event history analysis extended with conditional accuracy analysis, I have shown that NT and HF-ASD adults categorize certain object images on a superordinate level quickly, while other images are categorized more slowly, and that the effects of experimental manipulations such as image presentation duration changes with increasing waiting time. Interestingly, the presentation duration influences the information processing based on feedforward-only rather than based on feedback connection.

4.2 IS THE DOLPHIN A FISH? ERP EVIDENCE FOR THE IMPACT OF TYPICALITY DURING EARLY VISUAL PROCESSING IN ULTRA-RAPID SEMANTIC CATEGORIZATION IN AUTISM SPECTRUM DISORDER

In the previous chapter (Chapter 4.1) the effects of presentation duration on the shapes of reaction time and accuracy distributions were observed. However, the results of the behavioral analysis did not give a clear indication about the effect of typicality, about the difference between ASD and NT adults, nor about why ASD adults have difficulties with atypical members of visual object categories. Hence, in this chapter, ERP analyses are used to differentiate distinct stages of visual processing. The goal of the present research is to dissociate distinct stages of semantic categorization and to be observed whether these stages are modulated differently by category boundaries, presentation duration, and typicality in NT and ASD adults. Based on the evidence about the neuronal activity during semantic categorization (Chapter 4.2.1), the predictions of the present study will be described (Chapter 4.2.2). The methodology to investigate these predictions will be explained (Chapter 4.2.3). The results will be depicted (Chapter 4.2.4) and interpreted (Chapter 4.2.5). Lastly, the chapter concludes with a summary about the findings (Chapter 4.2.6).

4.2.1 Introduction

Imagine a dolphin – based on its fins or its habitat in the water it could be classified as a fish; however, unlike other marine animals it belongs to the category of mammals. While this particular common misconception contradicts a rule-based biological taxonomy, some semantic categories remain subjective, as multiple (hierarchical) levels of categorical membership are possible. Notably, individuals on the autistic spectrum have been shown to prefer more specific, local features for categorization (Plaisted, 2001). In this study, I investigate how neurotypical adults and those on the autism spectrum categorize typical vs. atypical exemplars of two semantic categories (animals and food). I focus on the temporal order of categorization processes by using event-related potentials (ERPs) to investigate early processing stages of semantic categorization of visually presented stimuli.

Neural activity during semantic categorization within the first 300 milliseconds

Neural activity as measured by ERPs during categorization distinguishes between several categorization processes very early on. The first modulation is observed in the N1 component (about 140 milliseconds after target presentation at fronto-central electrodes) mirroring different levels of categorization. Visual input can be semantically categorized either on a general, superordinate level (e.g., “animal”), on a less general, basic level (e.g., “dog”), or on a more detailed, subordinate level (e.g., “poodle”; Kiefer, 2001). Tanaka, Luu, Weisbrod, and Kiefer (1999) found that N1 was larger when images were categorized based on the subordinate level compared to categorizations on the basic or superordinate level. The authors concluded that subordinate categorization requires more perceptual processing. A second ERP modulation, the anterior P2, is observed when targets are discriminated based on simple features (Luck, 2005). When categorization is more difficult, P2 amplitude (between 190 and 240 ms) has been found to be smaller (Chen et al., 2008). A third ERP component, the anterior N2 (between 240 and 300 ms) indexes, among other cognitive processes, categorization and object recognition (Woodman, 2010). As part of the brain’s action monitoring system, N2 is enhanced by conflict eliciting stimuli, for instance, those difficult to classify (Yeung & Cohen, 2006), but is not affected by categorization levels (superordinate, basic or subordinate; Maguire et al., 2009; for review see Folstein & Van Petten, 2008). Finally, the P3 occurs when distinguishing complex, sometimes arbitrary target features (Luck, 2005) and has been associated with memory and attentional processing leading to event classification (Kok, 2001; Rac-Lubashevsky & Kessler, 2019). Proverbio, Del Zotto, and Zani (2007) asked participants to decide whether pairs of stimuli representing animals and/or man-made objects belonged to the same category. A larger centro-parietal P3 component was observed for animals compared to objects, even when salience was controlled for, suggesting smaller processing demands for animal recognition or greater involvement of visual sensory areas responsible for distinguishing complex features (Proverbio et al., 2007).

Ultra-rapid Semantic Categorization

Under time pressure as implemented by ultra-rapid stimulus presentation (~ 20 ms), the earliest difference in ERP components related to semantic categorization was found 150 ms after stimulus onset over the frontal and occipital cortex (ultra-rapid categorization; first investigated by Thorpe, Fize & Marlot, 1996). In this paradigm, participants are asked to release a button if they see an animal image ("go" trials) and to keep their finger on the button if the image does not represent an animal ("no-go" trials). The difference between animal and non-animal images (dN150) was characterized by a positive peak at 186 ms over frontal electrode sites. Using this paradigm, similar results were reported for animals and vehicles (VanRullen & Thorpe, 2001), animal and non-animal pictures (i.e., mountains, rivers, buildings, fruits, and vehicles; Antal et al., 2001), man-made and natural objects (Joubert et al., 2007), and with extensively trained but newly established categories (Faber-Thorpe, Delorme, Marlot & Thorpe, 2001). Together, these results suggest that ultra-rapid semantic categorization is based on a coarse visual representation (Fabre-Thorpe, 2011).

Categorization in Autism Spectrum Disorder

In Autism Spectrum Disorder (ASD), the semantic system, including semantic categorization, has not received much attention. However, differences in the mechanisms underlying categorization may contribute to the pattern of social, communication, and behavioral characteristics of ASD (Gastgeb & Strauss, 2012). For instance, during speech acquisition, infants form categories of sounds. If this ability is impaired in infants, secondary difficulties in acquiring speech may arise, and indeed impaired or delayed development of communicative speech is one of the main characteristics of many individuals on the autistic spectrum (e.g., Tager-Flusberg, Paul, & Lord, 2005).

Prior research on the semantic categorization of pictorial information in ASD has predominantly relied on indices of behavioral performance (for neuroimaging findings during word categorization see e.g., Gaffrey, Kleinhans, Haist, Akshoomoff, Campbell, Courchesne & Müller, 2007). Based on the paradigm by Thorpe and colleagues (1996) detailed above, Vanmarcke et al. (2016) explored differences between adults with and without ASD, depending on categorization levels (superordinate, basic, and subordinate). In line with the behavioral findings of Tanaka and colleagues (1999), Vanmarcke et al. (2016) found differences between levels of categorization. Of particular relevance for the present study, they did not observe any behavioral differences between individuals with ASD and neurotypical (NT) adults. However, this study does not provide information about the underlying mechanisms of semantic categorization. One hint regarding the mechanisms underlying semantic categorization may be found in a study by Carmo et al. (2016). In their study, individuals with and without a diagnosis of ASD participated in a dot-pattern matching task. They performed either an identity matching task (the patterns are the same in shape and orientation) or a category matching task (the patterns are the same in shape but of different orientation). They observed, in both tasks, a group effect, with slower reaction times (RTs) for individuals with ASD compared to NT adults. This result suggests overall slower category learning in individuals with ASD (Carmo et al., 2016). Minshew, Meyer, & Goldstein (2002) suggest that high-functioning adults with ASD (HF-ASD) categorize items based on simple, rule-based features, but seem to have difficulties when distinguishing input based on more complex, less perceptually apparent features. In line with this, Gastgeb & Strauss (2012) found that HF adults with ASD have difficulties in forming abstract categorical prototypes, due to enhanced discrimination and reduced generalization.

Typicality in ASD

Since most natural categories have no distinct boundaries, they are not distinguished based on simple features but rather based on “typicality structures” (Gastgeb & Strauss, 2012). Recent behavioral studies suggest that individuals with HF-ASD have difficulties with the outer edges of a category (Gastgeb, Strauss, & Minshew, 2006; Carmo, Duarte, Pinho, Filipe, & Marques, 2016). In more detail, some members of a category are more representative and therefore more *typical* for a specific category (e.g., sparrow as a bird) than other, less representative and therefore *atypical* members (e.g., ostrich as a bird). Gastgeb, Strauss, & Minshew (2006) investigated how typicality structures influence categorization of an artificial (e.g., furniture) and a natural (e.g., animal) category in adolescents with HF-ASD. Responses for both categories were slower and more error-prone for atypical than for typical items in adolescents with and without HF-ASD. Hence, atypical stimuli require additional processing – attentional, perceptual, memory-related, or decision-related (or multiple) – in order to be categorized, specifically in adolescent with HF-ASD. In other words, individuals with HF-ASD processed typical exemplars as efficiently as NT adolescents, but required additional processing for atypical exemplars, in line with the notion that categorization on a superordinate level can occur without detailed visual processing, whereas both basic and subordinate categorization rely on further perceptual information. Thus, atypical items need to be categorized on a more detailed level than typical items (Jolicoeur, Gluck, & Kosslyn, 1984). To examine this in more detail, Carmo et al. (2020) presented six images in a rapid-serial visual presentation paradigm with different presentation times (13, 27, 53, and 80 ms). Participants were asked to identify a target item belonging to a basic-level category (typical and atypical mammals, birds, vehicles, and fruits). Performance was strongly affected by typicality, with a higher detection rate for typical items. Atypical items were only detected by NT adults in the condition with the longest presentation time, since the extraction of more perceptual information requires additional processing. Contrary to NT participants, adults with HF-ASD were not able to detect atypical items even in the condition with the longest presentation time, suggesting qualitative differences in categorization.

4.2.2 The present study

To the best of our knowledge, to date no study combined all potentially relevant aspects introduced above. Hence, I assessed typicality effects in ultra-rapid categorization in individuals with HF-ASD and NT adults using EEG. I adapted the paradigm introduced by Thorpe et al. (1996) and tested a sample of participants with high-functioning ASD and a neurotypical control group matched for age, schooling and general cognitive abilities. To investigate the influence of category boundaries in individuals with HF-ASD (based on Minshew, Meyer, & Goldstein, 2002), I added a second semantic category (food) with even less distinct boundaries than animals and presented the stimuli with two different presentation times. Finally, participants were introduced to a “yes” – “no” task, rather than a Go

– No-Go task, to avoid the possibility of an early target – no-target ERP difference due to motor preparation or response inhibition (Antal et al., 2001).

With respect to behavioral performance, I combine several factors investigated previously in isolation: (1) typicality (2) level of categorization and (3) presentation times. Regarding typicality, I expect responses to typical items of both categories to be faster and more accurate (Gastgeb, Strauss, & Minshew, 2006). Since the superordinate level of categorization is more general, I predict that answers will be faster and more accurate for animals than in the food category with a less distinct category boundary. This effect might be enhanced in individuals with HF-ASD (Minshew, Mayer, & Goldstein, 2002). Additionally, I predict that longer presentation times will lead to more accurate performance and faster responses (Carmo et al., 2020; see also Mack & Palmeri, 2015). I expect that there will be no behavioral difference between groups regarding typical or atypical items at short presentation times (Vanmarcke et al., 2016), but at longer presentation times differences between the experimental groups may be observed for atypical items (Carmo et al., 2020).

With respect to the cognitive processes indexed by ERPs, I investigate whether early processing stages of extracting semantic meaning from visual input are influenced by (1) typicality, (2) level of categorization, and (3) presentation time in each experimental group. Our first goal was to conceptually replicate the effects in ultra-rapid categorization described by Thorpe et al. (1996; dN150). In a second step, I explored which aspects of early visual categorization (N1, P2, N2, P2 and P3) are modulated by the cognitive processes under investigation. Specifically, I compare categorization processes across food and animal categories. Our expectation was that early semantic processing of a category with less distinct category boundaries might be different from that of a more distinct category, with items possibly categorized on a different hierarchical level. Moreover, I investigate whether typicality modulates the P2 and P3 components. The anterior P2 component is observed when targets are discriminated based on simple features (Luck, 2005), whereas the P3 seems to be elicited based on arbitrary feature categorization (Proverbio et al., 2007). Since P2 amplitude varies inversely with task difficulty (Chen et al., 2008), I expect to find lower P2 amplitudes for atypical items compared to typical ones. Finally, I assess whether the level of categorization modulates the N1 and N2 components by including a moderating effect of presentation time, as categorizing visual input on a more detailed level is only possible with longer presentation times.

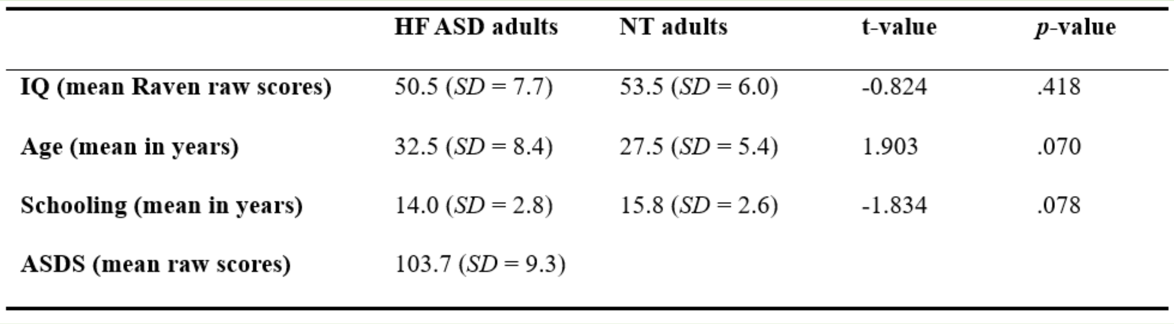
4.2.3 Methods

Participants

I recruited two groups of participants, NT adults and adults with HF-ASD. All participants were male, reported normal or corrected-to-normal vision, and had more than 9 years of formal education. Participants with HF-ASD scored above 70 points in the verbal subscale of the Wechsler Adult Intelligence Scale and had been diagnosed with HF-ASD (based on DSM-V criteria of the American Psychiatric Association, 2013). I used the Asperger's Syndrome Diagnostic Scale (ASDS; Myles, Book, & Simpson, 2001) to confirm the clinical evaluation diagnosis. The study was conducted according to the Declaration of Helsinki (World Medical Association, 2013) and was approved by the ethical review board of the Faculty of Psychology at the University of Lisbon. All participants gave their written consent after being informed about the procedure and were given the opportunity to ask questions. The data from one participant with HF-ASD were excluded from further analyses due to low performance (d' lower than 2 SD below group mean), and the data from one NT adult were excluded due to extensive artifacts (81.7 % of all trials had to be removed). The two groups were matched for age, schooling, and general cognitive abilities (assessed with Raven's progressive matrixes) by excluding 4 NT adults with extreme values in age and general cognitive abilities. Thus, the data of 17 NT participants and 14 participants with HF-ASD were included in the analysis (for details see Table 9).

Table 9

IQ and demographic information



	HF ASD adults	NT adults	t-value	*p*-value
IQ (mean Raven raw scores)	50.5 (*SD* = 7.7)	53.5 (*SD* = 6.0)	-0.824	.418
Age (mean in years)	32.5 (*SD* = 8.4)	27.5 (*SD* = 5.4)	1.903	.070
Schooling (mean in years)	14.0 (*SD* = 2.8)	15.8 (*SD* = 2.6)	-1.834	.078
ASDS (mean raw scores)	103.7 (*SD* = 9.3)			

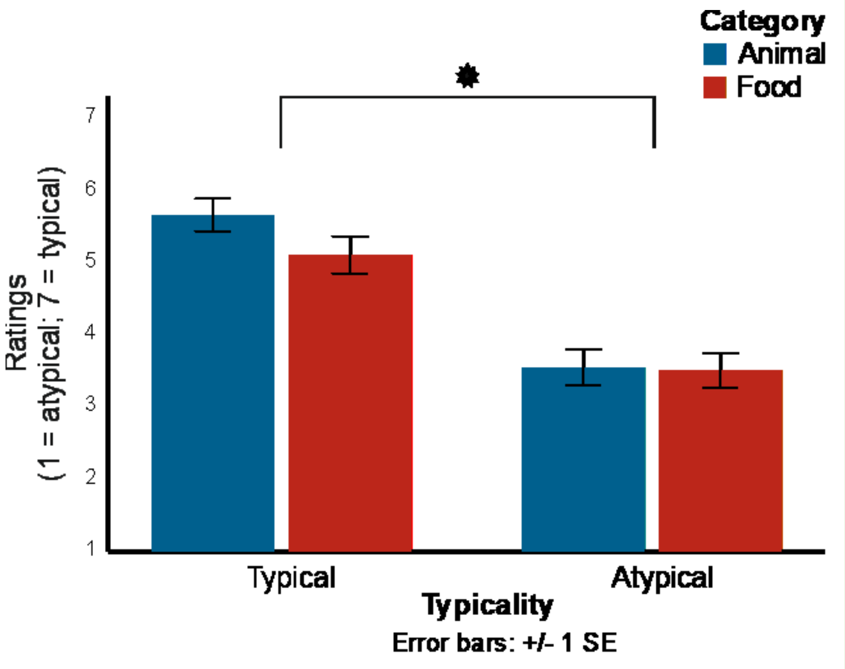
Notes. There are only male participants in both groups, indicated separately for adults with high-functioning autism spectrum disorder (HF ASD) and neuro-typical (NT) adults. Asperger's Syndrome Diagnostic Scale (ASDS; Myles, Book, & Simpson, 2001) was used to confirm clinical diagnosis. T-value of pairwise t-test for independent groups. IQ: Intelligence Quotient; *SD*: standard deviation.

Materials and Procedure

Stimuli were 1600 color photographs taken from the Photo Objects database by Hemera; animals and food items were used as targets, objects as non-targets. In each trial, one of these pictures was presented. Throughout the experimental blocks, a black fixation frame at the center of a 10° x 10° visual angle (as described in VanRullen & Thorpe, 2001) was visible on a CRT monitor with a refresh rate of 85 Hz and a resolution of 1024 x 768 pixel. Each picture was presented only once. In a prior rating test 17 NT students (mean age = 19.4 years, 2 male) were asked to indicate how well each item represents a given category on a 7-point scale, i.e., "animal" or "food", respectively. The z-transformed means served to define typicality level; values below 0 were used as atypical items, and those above 0 as typical items. Based on this definition, the mean original typicality ratings (1 – 7) were significantly different for both categories (Figure 14).

Figure 14

Results of prior rating test



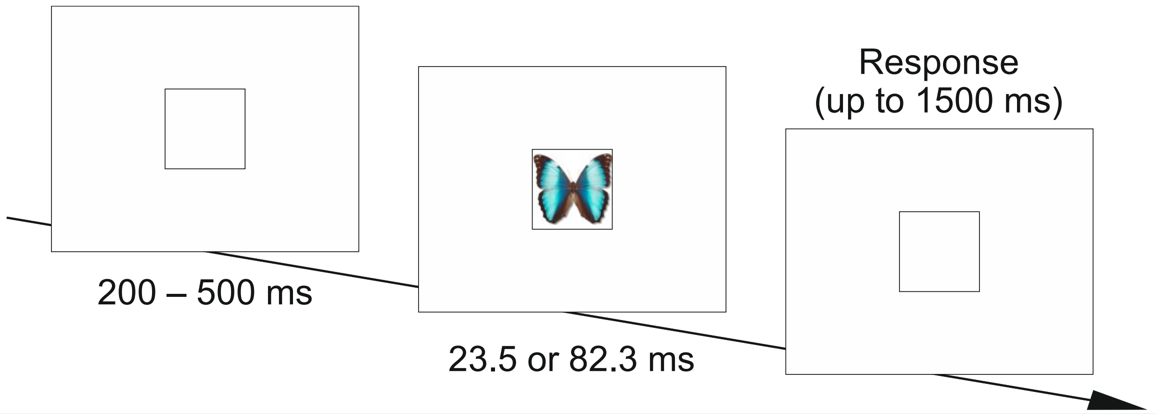
Notes. Mean typicality rating of students (*n* = 17) after dividing images in each category (animals in red, food in blue). The asterisk indicates a significant difference between typical and atypical items in both categories.

Stimuli were presented with Presentation Software (Version 18.0, Neurobehavioral Systems). Participants were seated in front of a computer screen, placed at eye level and at an average distance of 40 cm on a table in a dimly lit and shielded room. Participants rested their index fingers on the F and J keys of a QWERTY keyboard and responded by pressing one of the keys. Participants performed a visual categorization task, in which they indicated, for each item, whether or not it belonged to the animal or food category, respectively. Each relevant category was presented in blocks, and the order of these blocks and the response keys (yes, no) were counterbalanced.

Targets and non-targets were presented in random order with equal probability (50 %). Presentation times (23.5 ms or 82.3 ms) were varied randomly, with equal proportions of targets and non-targets. Each subsequent stimulus was presented after a random interval between 200 and 500 ms following the response, with a maximum of 1500 ms (displayed in Figure 15). After every 100 trials, a short break was offered.

Figure 15

Trial design of Experiment 3B



Notes. For the whole trial and during each block a fix square was displayed. In each trial, images were presented in the square for either 23.5 or 82.3 ms. Participants could respond until 1500 ms after stimulus offset to a two-option forced choice (“Yes”/”No”), answering the question “Did you see an animal image?”. Participants were asked to respond as accurately and as fast as possible.

EEG recording

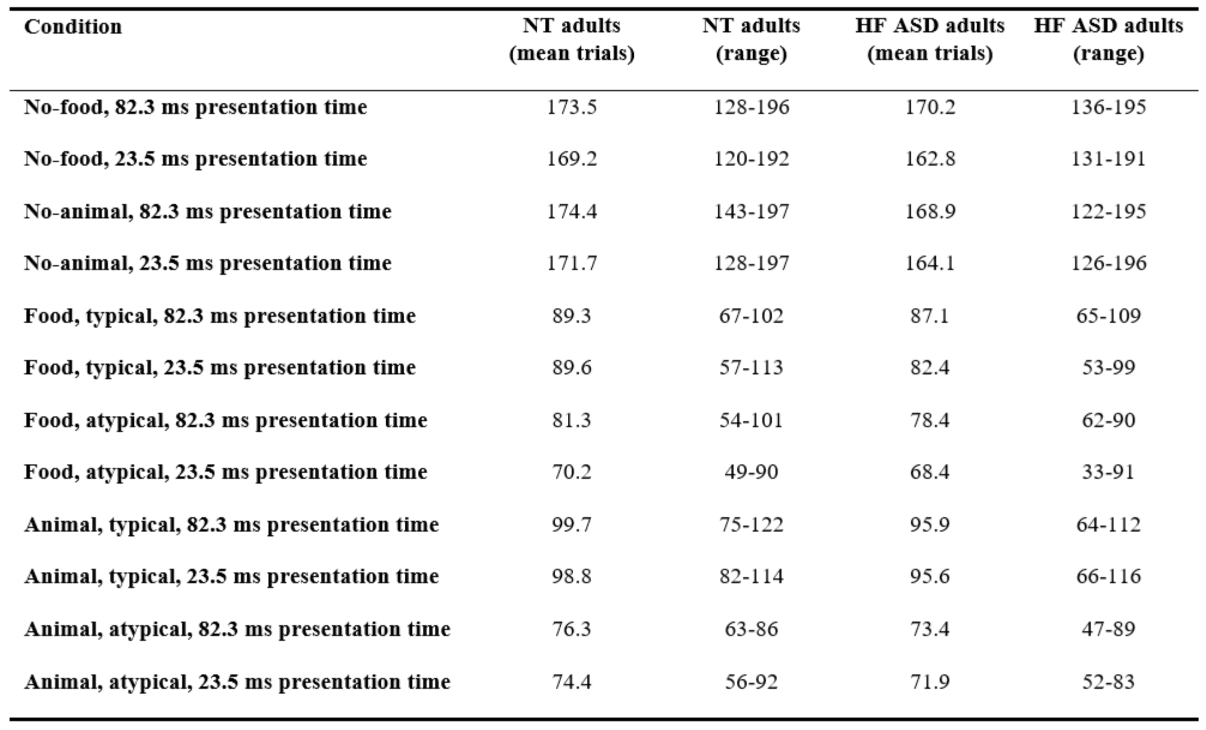
For the EEG recording, I used 64 Ag/AgCl cap-mounted electrodes, plus two placed at the mastoids and four around the eyes, positioned on an extended 10-20 system (Jasper, 1958). The EEG was recorded with the BioSemi EEG-System (BioSemi B.V., Amsterdam, Netherlands). All electrodes were recorded with an electrode offset within a 40 µV range. The electrode offset is generated at the junction of the skin and electrolyte solution under the electrodes. It is a by-product of the direct current potentials and results in a voltage at the amplifier input (Jones, 2015). I used the electrodes around the eyes (above and below the right eye, and beside the right and left eye) to record eye-movements. The ground electrode was placed with the Common Mode Sense (CMS) active electrode and the driven right leg (DRL) passive electrode at the electrode positions PO1 and PO2, respectively, in the 10-20 system. The CMS is also used as online reference. The sampling frequency was 2048 Hz. EEG signal was filtered online with a 0.16 Hz high-pass filter and a 100 Hz low-pass filter.

EEG Data processing

I used the spherical spline method (Perrin et al., 1989) for interpolation of electrodes with many artifacts, since this method makes no assumption about the conductivity of the head tissues (Cohen, 2014; on average in NT adults: 1.9 electrodes; in adults with HF-ASD: 2.6 electrodes; ranging for both groups between 0 and 8 interpolated electrodes). The signal was re-referenced offline to the average of all cap-mounted electrodes using Brain Vision Analyzer 2.1 (Brain Products GmbH, Gilching, Germany). The choice of reference depends on a variety of factors, including the number of electrodes, location of electrodes, cognitive task, analyses to be performed and brain regions to be investigated (see Cohen, 2014). Since most of the relevant portions of ERPs in cognitive neuroscience consist of frequencies between 0.01 Hz and 30 Hz (Luck, 2005), the EEG signal was filtered using a zero-phase shift Butterworth filter (most common used filter; Cohen, 2014) with a high cutoff at 30 Hz at 48dB/oct. I corrected for eye movement artifacts by using an independent component analysis (ICA) with the Infomax Restricted algorithm (Jung et al., 2000), where possible. For the ICA, I selected a 100 s interval from the 16th block of the experiment as a training data set for computing the unmixing matrix. ICA components were automatically identified by picking up blinks and saccades, as evidenced by their characteristic shape and maximum at frontal sites. After removing these components, the EEG was reconstructed. Two participants with HF-ASD did not blink during most of the blocks, thus a suitable amount of data for the ICA was not available (Hoffmann & Falkenstein, 2008). Therefore, I manually deleted all blinks for these participants, which amounted to 38 and 49 blinks, resulting in 1.38 % and 2.21 % deleted trials, respectively. EEG segments were based on a time window of 200 ms before and 800 ms after stimulus onset. Artifacts were removed automatically when: (1) the amplitude difference between two sample points exceed 50 μV, (2) the amplitude difference was more than 150 μV in an interval of 100 ms, or (3) a low amplitude of 0.5 µV occurred in a 100 ms interval (Cohen, 2014). Due to the artifact rejection, on average 2.48 % of all trials had to be removed in the NT group and 5.07 % in the HF-ASD group. On average there were 114 (range: 49 – 197) trials left per condition per participant for the NT adults and 109.9 (range: 33 – 196) for the participants with HF-ASD (for more details see Table 10).

Table 10

Trials per condition of Experiment 3B



Condition	NT adults (mean trials)	NT adults (range)	HF ASD adults (mean trials)	HF ASD adults (range)
No-food, 82.3 ms presentation time	173.5	128-196	170.2	136-195
No-food, 23.5 ms presentation time	169.2	120-192	162.8	131-191
No-animal, 82.3 ms presentation time	174.4	143-197	168.9	122-195
No-animal, 23.5 ms presentation time	171.7	128-197	164.1	126-196
Food, typical, 82.3 ms presentation time	89.3	67-102	87.1	65-109
Food, typical, 23.5 ms presentation time	89.6	57-113	82.4	53-99
Food, atypical, 82.3 ms presentation time	81.3	54-101	78.4	62-90
Food, atypical, 23.5 ms presentation time	70.2	49-90	68.4	33-91
Animal, typical, 82.3 ms presentation time	99.7	75-122	95.9	64-112
Animal, typical, 23.5 ms presentation time	98.8	82-114	95.6	66-116
Animal, atypical, 82.3 ms presentation time	76.3	63-86	73.4	47-89
Animal, atypical, 23.5 ms presentation time	74.4	56-92	71.9	52-83

Notes. Mean number of trials and range, per condition, used in the ERP analysis, calculated for adults with high-functioning autism spectrum disorder (HF ASD) and neuro-typical (NT) adults separately. Note that No-food and No-animal conditions were only used for the dN150 analysis.

Analysis of Behavioral data

Category discrimination (d’) and reaction times (RTs) were analyzed. Responses faster than 200 ms were excluded; RT analyses were based on correct answers only. Due to incorrect responses, an average of 10.29 % of all trials had to be excluded in the NT group and 9.64 % in the HF-ASD group. Based on RTs, an average of 2.82 % of all trials had to be excluded in the NT group and 2.64 % in the HF-ASD group. For statistical analyses I only used responses to the target category.

Category discrimination was analyzed using d prime (d'). D' was calculated by using the z-score of the probability of hits minus the z-score of the probability of false alarms. In the absence of false alarms or misses, I applied the formula by Macmillan & Creelman (2004). A d' of 0 indicates no discrimination, whereas a d' of 4 indicates nearly perfect performance (Macmillan & Creelman, 1991). For both, mean d' and mean RTs, I used a repeated measure analysis of variance (ANOVA) with Category (animal vs. food), Typicality (typical vs. atypical), and Presentation Time (23.5 vs. 82.3 ms) as within subject factors, and Group (NT vs. HF-ASD participants) as between subject factor. For the sake of brevity and to ease readability, I report only those effects and interactions with p-values below the conventional significance value of .05; all remaining analyses are not listed in the result section. All recorded p-values were Greenhouse-Geisser corrected, when needed (Geisser & Greenhouse, 1958).

Analysis of EEG data

A baseline correction was applied to the segmented signal, using the time window of 200 ms before stimulus onset (as recommend by Luck, 2005). The signal was averaged per condition and participant. For the first part of the EEG analysis, I compared the averaged signal of correct responses to target and distractor images to replicate the results by Thorpe et al. (1996). I also followed the statistical approach used in that study, i.e., I tested when the onset of the differential activity (targets – non-targets), dN150, diverges from 0 (15 consecutive t-test values below $p < .01$; Rugg, Doyle & Wells, 1995 as used by Thorpe et al., 1996). Since Thorpe et al. (1996) recorded with a sampling rate of 1000 Hz, I down sampled our EEG signal to this value. Similar to Thorpe et al. (1996; VanRullen & Thorpe, 2001), I grouped the signal of seven electrodes (Fp1, Fp2, F3, F4, F7, F8, and Fz) for a frontal region of interest (ROI) and six electrodes (O1, O2, Oz, PO7, PO8, and POz) for an occipital ROI with Python 3.6.5. To calculate the peak latency of the differential activity, I selected individual peaks, for both ROIs, occurring between 150 and 200 ms with Brain Vision Analyzer. To assess whether the peak latencies differed between conditions in each group, I used a repeated measure ANOVA with two variables of two levels, ROI (frontal vs. occipital) and Category (animal vs. food) with SPSS 26.

In the second part of the EEG analysis, I focused on the N1, P2, N2, and P3 components based on the literature. For these analyses, I only used target stimuli to which participants responded correctly with a minimum RT of 200 ms, in line with the criteria used for behavioral data. These effects were evaluated at pre-specified ROIs according to the literature. The N1 component peaks at around 140 ms after stimulus onset, therefore, I chose a time window between 120 ms and 170 ms (similar to Proverbio et al., 2007) to calculate the peak latency and mean amplitude. The ROI for this analysis comprised the average signal of F3, F4, Fz, C3, C4, and Cz (similar to Antal et al., 2001). I calculated the peak latency and mean amplitude for the anterior P2 between 180 – 240 ms (similar to Chen et al., 2008), at an anterior ROI including F1, F2, Fz, FC1, FC2, FC5, FC6, FCz, C3, C4, C5, C6 and Cz (Chen et al., 2008). For the anterior N2, I used the time window between 240 – 300 ms (similar to Chen et al., 2008) with a ROI containing Fpz, Fp1, Fp2, AFz, AF3, AF4, Fz, F1, and F2 (Maguire et al., 2009). The P3 was analyzed between 300 – 500 ms (Proverbio et al., 2007) after stimulus onset at a central-parietal ROI (averaged P1, P2, Pz, CP1, CP2, CPz, C1, C2, and Cz; similar to Proverbio et al., 2007).

Event-related potentials assess the average EEG activity across many trials in order to enhance systematic activity associated specifically with cognitive processing related to a stimulus. This approach effectively reduces the impact of unsystematic fluctuations in the ongoing EEG (i.e., improving the signal to noise ratio). However, this approach does not control for factors unrelated to cognitive activity that do not vary across trials (i.e., morphological differences between individuals like skull thickness or myelination), but still can have considerable influence on amplitude differences as measured on the skull. Therefore, comparing microvolt differences in amplitude between individuals does not allow to make inferences about the underlying cognitive processes (c.f. McCarthy & Wood, 1985; Urbach & Kutas, 2006). Moreover, numerous neuroanatomical differences have been described for individuals with ASD as compared to neurotypical individuals (for review see Amaral, Schumann, & Nordahl, 2008). As these differences in morphology are unlikely to be randomly distributed, EEG waveforms vary systematically in morphology across participant groups. Hence, ERP analyses were performed for each group separately, as statistical interactions between groups of participants may reflect anatomical differences rather than different cognitive processes employed in each group. I used a repeated measure ANOVA with the factors: Category (animal vs. food), Typicality (typical vs. atypical), and Presentation Time (23.5 vs. 82.3 ms) for each group. Similar to behavioral analyses, I report effects with p-values below the conventional significance criterion of .05. This also includes significant interaction effects that did not reveal any significant differences between conditions in Bonferroni-corrected post-hoc comparisons. In addition, I report all results of special interest (i.e., those explicitly based on the hypotheses or effects that reach statistical significance in one group, but not in the other.) Figures shown in the following passages are figures from Brain Vision Analyzer (using a 20 Hz high cutoff at 48dB/oct and a 50 Hz notch zero phase shift Butterworth filter) edited with CorelDraw X7 (Corel GmbH, München, Germany).

4.2.4 Results

Results of Behavioral data

For d’ I found a main effect of Category, $F(1,29) = 43.74$, $p < .001$, $\eta_p^2 = .60$, Typicality, $F(1,29) = 19.66$, $p < .001$, $\eta_p^2 = .40$, and Presentation Time, $F(1,29) = 96.33$, $p < .001$, $\eta_p^2 = .76$. Participants were better in detecting animal than food images, with a mean d’ of 3.23 ($SE = 0.14$) and 2.72 ($SE = 0.13$), respectively. Discrimination performance was higher for typical items ($M = 3.05$, $SE = 0.14$) than for atypical items ($M = 2.91$, $SE = 0.13$). Performance was lower for short presentation times ($M = 2.73$, $SE = 0.13$) than when presentation time was long ($M = 3.22$, $SE = 0.13$). I found an interaction effect between Category and Typicality, $F(1,29) = 22.15$, $p < .001$, $\eta_p^2 = .43$, with differences between typical ($M = 2.86$, $SE = 0.15$) and atypical images ($M = 2.58$, $SE = 0.12$; $p < .001$) occurring only in the food category, and not in the animal category ($p = .99$). I also found an interaction between Category and Presentation Time ($F(1,29) = 7.46$, $p < .05$, $\eta_p^2 = .21$), with a significant difference between the two presentation times ($p < .001$) for both animal and food stimuli. This difference was larger for the food ($M_{\text{Difference}} = 0.58$) than the animal ($M_{\text{Difference}} = 0.37$) category.

For RT, as for d', I found a main effect of Category, $F(1,29) = 38.65$, $p < .001$, $\eta_p^2 = .57$, Typicality, $F(1,29) = 16.21$, $p < .001$, $\eta_p^2 = .35$, and Presentation Time, $F(1,29) = 659.43$, $p < .001$, $\eta_p^2 = .95$. Participants were faster for animal than for food images, with mean reaction times of 453 ms (SE = 16 ms) and 514 ms (SE = 17 ms), respectively. Additionally, responses to typical items were faster (M = 479 ms, SE = 15 ms) than responses to atypical items (M = 487 ms, SE = 16 ms). Responses were considerably slower for short (M = 523 ms, SE = 16 ms) compared to long presentation time (M = 444 ms, SE = 16 ms). Moreover, I found an interaction between Category and Presentation Time ($F(1,29) = 10.88$, $p < .01$, $\eta_p^2 = .27$), with the shortest RTs observed when participants responded to animal images presented for 82.3 ms (M = 417 ms, SE = 16 ms), and the longest RTs observed when food images were presented for 23.5ms (M = 558 ms, SE = 18 ms). As described for d', for both animal and food stimuli, category, I observed difference between presentation times ($p < .001$), with larger differences found for food stimuli ($M_{\text{Difference}}$ = 87 ms) than for stimuli from the animal category ($M_{\text{Difference}}$ = 71 ms).

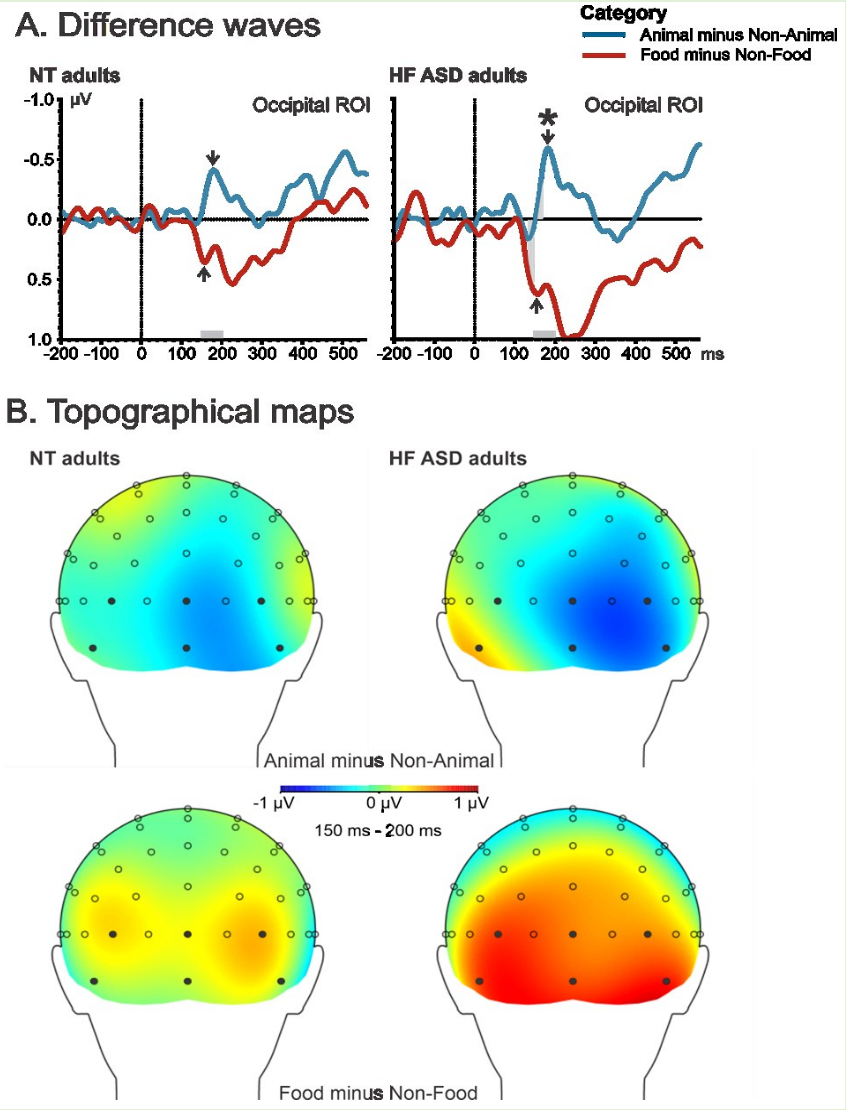
Taken together, behavioral data indicate faster and more accurate responses to typical than to atypical items, and for the animal compared to the food category. I did not observe differences in behavioral performance between the NT and HF-ASD group. Consequently, ERP data – which are analyzed for correct responses only (see Table 10) – have a comparable signal-to-noise ratio in both groups. This contributes to the reliability of ERP waveforms in both groups, simultaneously ruling out a potential confound of lower performance for the clinical population in particular.

Results of EEG data

I calculated the difference wave between target and non-target stimuli and observed no significant differences in any ROI for the NT adults, nor in the frontal ROI for the HF-ASD adults. In the occipital ROI, for individuals with HF-ASD only, animal and non-animal stimuli started to diverge at 170 ms after stimulus onset, whereas food and non-food items diverged at 154 ms (Figure 16).

Figure 16

Difference (dN150) between target and non-target stimuli



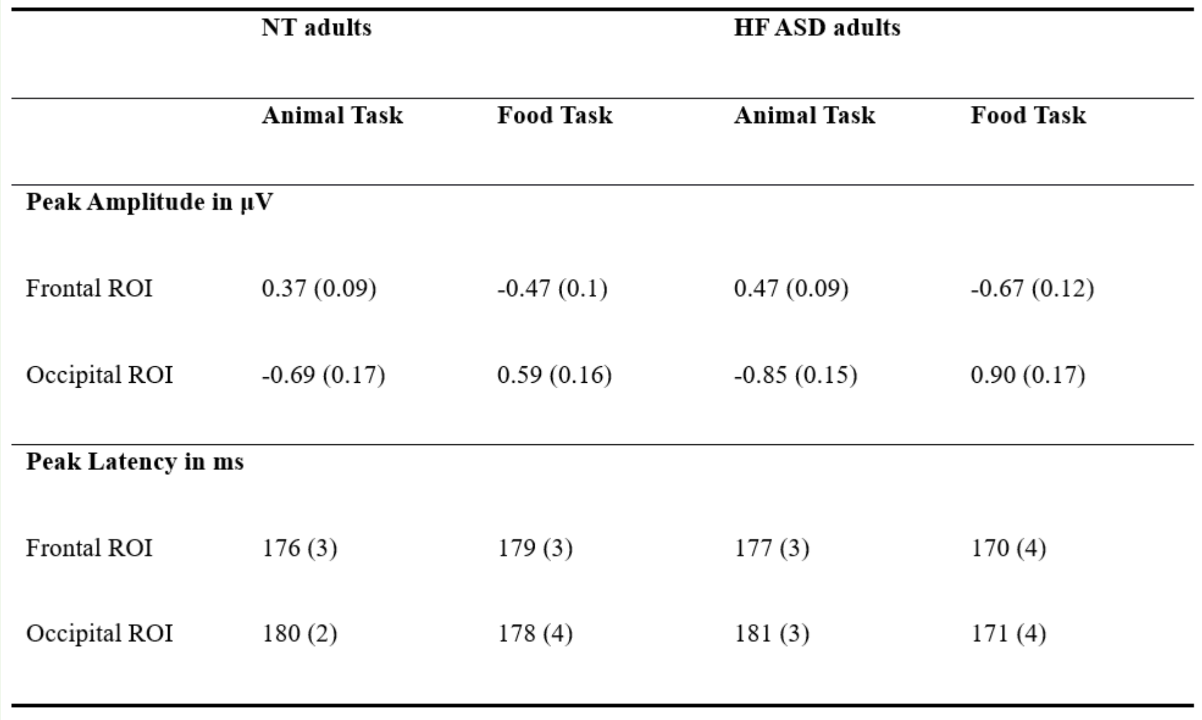
Notes. dN150 in the occipital ROI (including electrode sites O1, O2, Oz, PO7, PO8, and POz) for HF ASD and NT adults. Only for HF ASD adults, a reliable divergence between target and non-target was observed. A. Difference waveforms. The onset of a reliable divergence (i.e., 15 significant consecutive t-test) is illustrated by a grey square inside the difference waveforms. The time window used for the peak detection is illustrated by the grey bar over the x-axis (i.e., ms). In HF ASD adults, peak amplitude difference between animal (blue) and food (red) items, as indicated by the asterisk. B.

Topographical maps. Electrode sites are marked with circles, filled circle indicate the ROI for this analysis.

In addition, I analyzed peak amplitudes and latencies of the divergence between target and non-target stimuli. The most obvious feature of the dN150 at visual inspection was that the difference waves for targets minus non-targets differed in polarity depending on category and ROI. Hence, peak detection identified maximal distance from zero, i.e., positive peaks in the frontal ROI for the difference between animal and non-animal images and negative peaks for food/ no-food images, and the reverse in the occipital ROI. I observed no significant difference in the NT adults, in neither the peak amplitude nor the peak latency, $F(1,16) = 0.01$, $p = .94$ (see Table 11). Likewise, in the HF-ASD adults, I observed no difference in peak amplitudes. However, with respect to peak latency, I observed a main effect of Category, $F(1,13) = 15.48$, $p < .001$, $\eta_p^2 = .54$, in both ROIs. The difference between both categories was due to a later peak latency in the animal task compared to the food task (Table 11, Figure 16). Notably, the onset of the divergence was earlier in the animal task than in the food task, suggesting a flatter increase of the neuronal activity in the animal task.

Table 11

Mean peak amplitudes and latencies of the divergence between target and non-target stimuli in the 150 and 200 ms time window



	NT adults		**HF ASD adults**	
	Animal Task	**Food Task**	**Animal Task**	**Food Task**
Peak Amplitude in µV				
Frontal ROI	0.37 (0.09)	-0.47 (0.1)	0.47 (0.09)	-0.67 (0.12)
Occipital ROI	-0.69 (0.17)	0.59 (0.16)	-0.85 (0.15)	0.90 (0.17)
Peak Latency in ms				
Frontal ROI	176 (3)	179 (3)	177 (3)	170 (4)
Occipital ROI	180 (2)	178 (4)	181 (3)	171 (4)

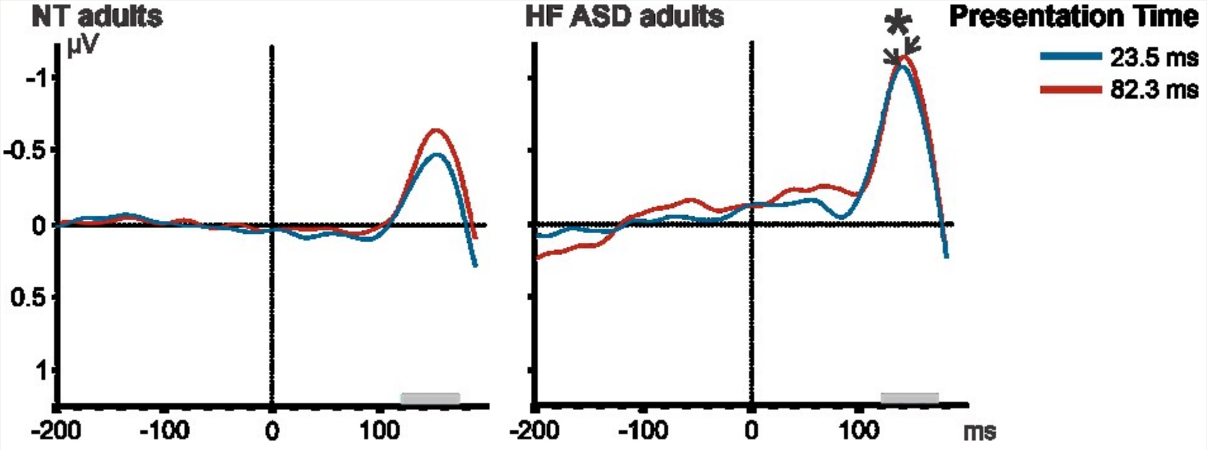
Notes. Mean values were calculated for adults with high-functioning autism spectrum disorder (HF ASD) and neuro-typical (NT) adults separately (standard error in brackets). Values of peak amplitude are in µV, whereas peak latencies are in ms. The frontal ROI included the following electrode sites: Fp1, Fp2, F3, F4, F7, F8, and Fz. The occipital ROI included the following electrode sites: O1, O2, Oz, PO7, PO8, and POz. In the Animal Task I compared animal and no-animal images; in the Food Task I compared food and no-food images.

Complementing the classic approach of Thorpe and colleagues, I also analyzed mean amplitudes and mean peak latencies for the N1, P2, N2 and P3 component in each group. With respect to peak latencies of the N1 component, I did not observe a main effect of Presentation Time in NT adults, $F(1,16) = 0.52$, $p = .48$, but I observed a main effect of Presentation Time in HF-ASD individuals, $F(1,13) = 9.08$,

$p < .01$, $\eta_p^2 = .41$, with an earlier peak for the short (*M* = 146 ms, *SE* = 3 ms) compared to the long presentation time (*M* = 149 ms, *SE* = 3 ms; Figure 17).

Figure 17

N1 ERP component

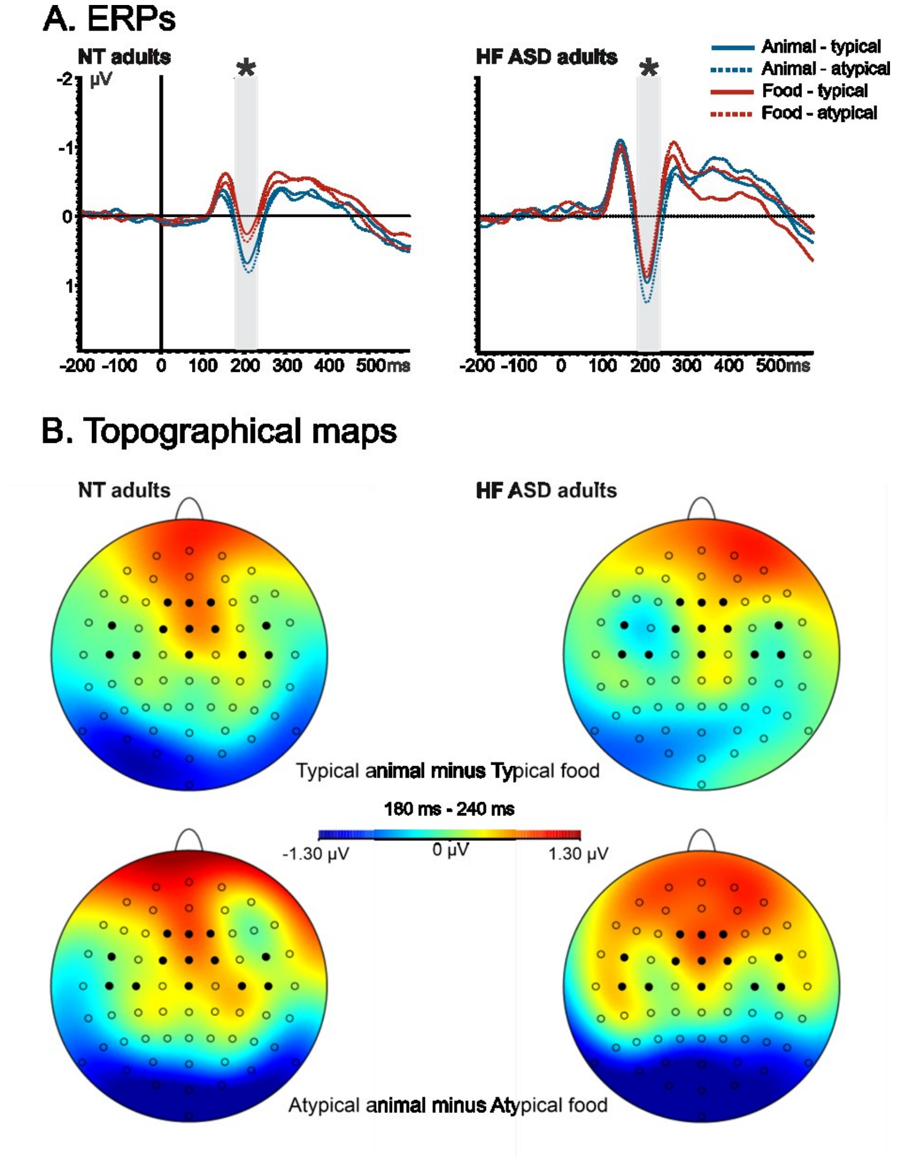


Notes. N1 for target stimuli in a frontal ROI using the following electrode sites: F3, F4, Fz, C3, C4, and Cz for HF ASD and NT adults. The time window used for the peak detection is illustrated by the grey bar over the x-axis (i.e., ms). In HF ASD adults, a peak latency (indicated by arrow) difference was observed between short (blue) vs. long (red) presentation time, as indicated by the asterisk

For the mean amplitude of the anterior P2 component in NT adults, the ANOVA showed a main effect of Category, $F(1,16) = 16.41$, $p < .001$, $\eta_p^2 = .51$, with a more positive value for animal images (*M* = 0.44 μV, *SE* = 0.14 μV) than food images (*M* = 0.08 μV, *SE* = 0.15 μV). I also found a main effect of Typicality, $F(1,16) = 9.72$, $p < .001$, $\eta_p^2 = .38$, with a smaller amplitude for typical (*M* = 0.19 μV, *SE* = 0.15 μV) than for atypical images (*M* = 0.33 μV, *SE* = 0.13 μV). I did not observe an interaction effect between Category and Typicality, $F(1,16) = 0.72$, $p = .41$. In the HF-ASD adults, I also observed a larger (i.e., more positive) P2 for animal images (*M* = 0.74 μV, *SE* = 0.33 μV) than for food images (*M* = 0.43 μV, *SE* = 0.34 μV). This main effect of Category, $F(1,13) = 5.78$, $p < .05$, $\eta_p^2 = .31$ was modulated by an interaction effect between Category and Typicality, $F(1,13) = 16.07$, $p < .001$, $\eta_p^2 = .55$, with no effect of category in typical images ($p = .99$), but a significant difference between atypical animal images (M = 0.91 μV, SE = 0.33 μV) and atypical food images (atypical: M = 0.38 μV, SE = 0.34 μV; $p < .05$; Figure 18). In contrast to the NT adults, I did not observe a main effect of Typicality in HF-ASD adults, $F(1,13) = 1.55$, $p = .24$.

Figure 18

P2 ERP component

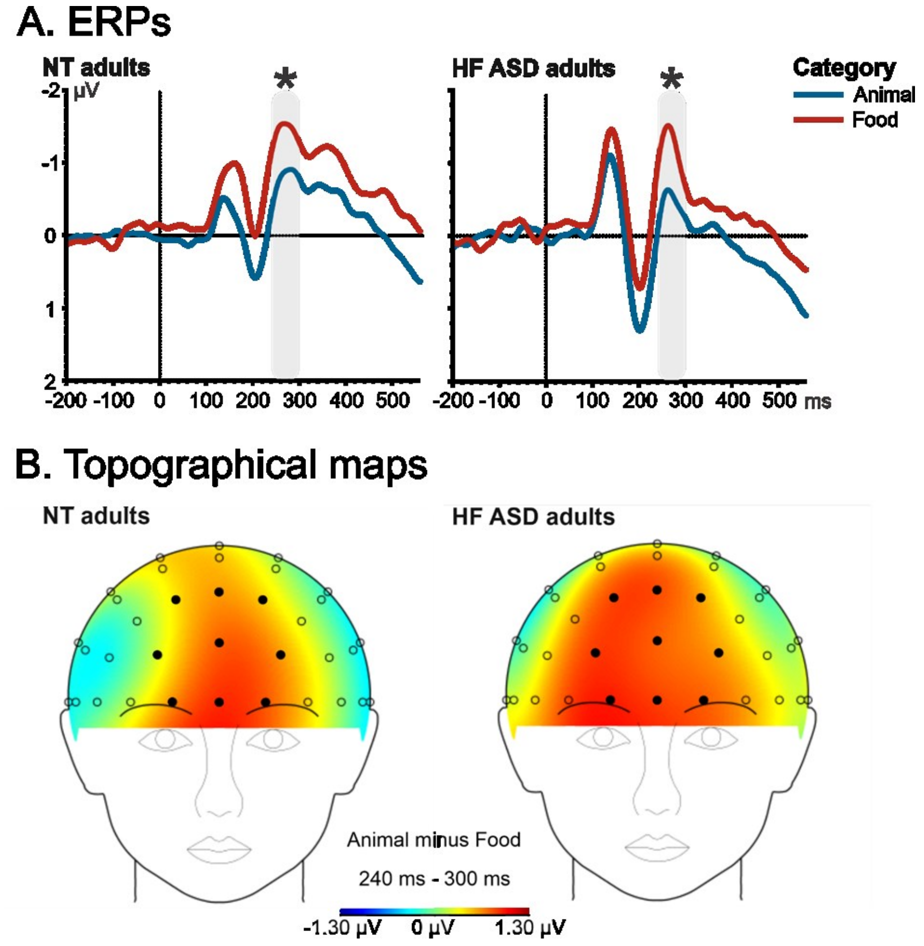


Notes. P2 for target stimuli in a ROI using the following electrode sites: F1, F2, Fz, FC1, FC2, FC5, FC6, FCz, C3, C4, C5, C6 and Cz for HF ASD and NT adults reflect influences of category (food vs. animal) and typicality (typical vs. atypical). A. ERPs. The time window used for the mean activity is illustrated by the grey bar over the x-axis (i.e., ms). In both groups, I observed effects of typicality and category, as indicated by the asterisk. In NT adults, I observed differences between animal (blue) vs. food (red) and typical (continuous) vs. atypical (dotted) images. B. Topographical maps. Electrode sites are marked with circles, filled circle indicate the ROI for this analysis. In HF ASD adults, I observed a difference between atypical animal vs. atypical food images, but not between typical animal vs. typical food images.

In the anterior N2 component (240 – 300ms), in NT adults mean amplitude was influenced by Category, $F(1,16) = 5.34$, $p < .05$, $\eta_p^2 = .25$, and Presentation Time, $F(1,16) = 9.97$, $p < .001$, $\eta_p^2 = .38$. I observed a smaller N2 in the animal task ($M = -0.7$ µV, $SE = 0.36$ µV) than in the food task ($M = -1.29$ µV, $SE = 0.5$ µV), in addition to a smaller N2 amplitude for the short ($M = -0.72$ µV, $SE = 0.37$ µV) than the long ($M = -1.26$ µV, $SE = 0.55$ µV) presentation time. In the analysis of the neuronal activity of the HF-ASD adults, I observed a main effect of Category, $F(1,13) = 6.36$, $p < .05$, $\eta_p^2 = .33$. This effect indicates a smaller mean N2 amplitude for animal ($M = -0.43$ µV, $SE = 0.48$ µV) than for food ($M = -1.2$ µV, $SE = 0.41$ µV) images (Figure 19). Additionally, I observed a trend in the main effect of Presentation Time, $F(1,13) = 3.89$, $p = .07$, $\eta_p^2 = .23$, with a smaller N2 amplitude for the short ($M = -0.54$ µV, $SE = 0.36$ µV) than the long ($M = -1.09$ µV, $SE = 0.52$ µV) presentation time. Both effects are similar to the pattern observed in NT adults.

Figure 19

N2 ERP component

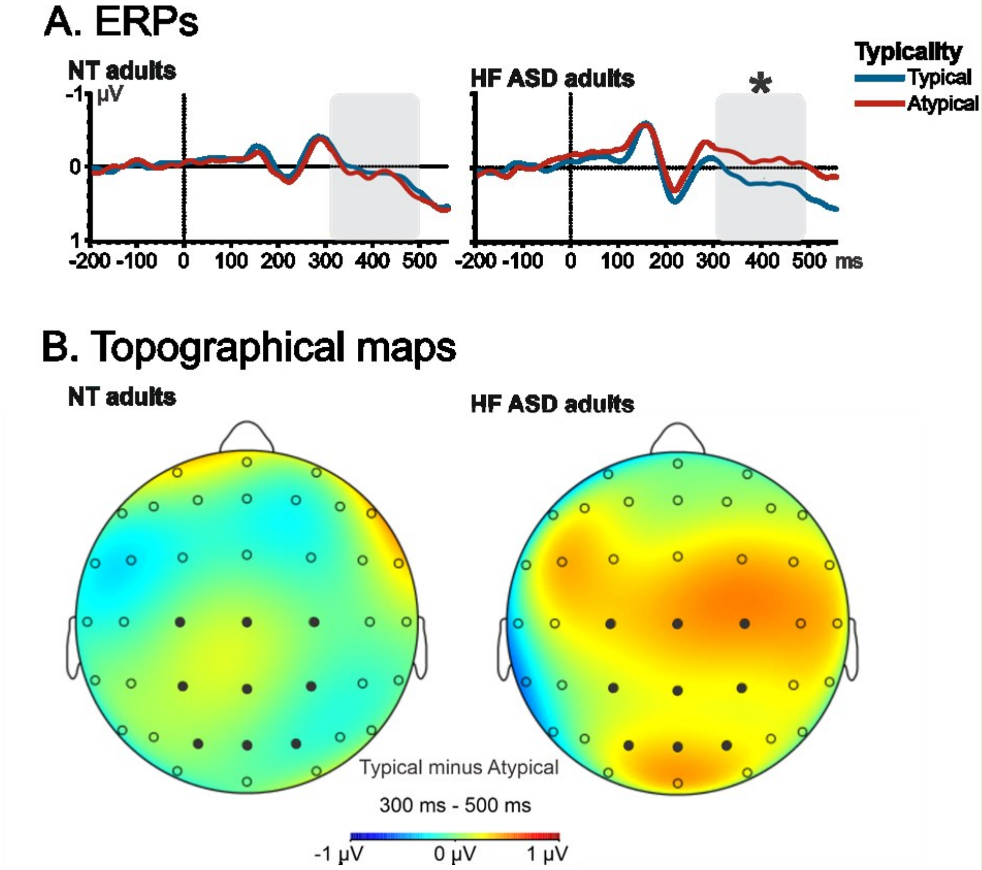


Notes. N2 for target stimuli in a ROI using the following electrode sites: Fpz, Fp1, Fp2, AFz, AF3, AF4, Fz, F1, and F2 for HF ASD and NT adults. In both groups, I observed differences between the animal vs. the food category. A. ERPs. The time window used for the mean activity is illustrated by the grey bar over the x-axis (i.e., ms). In both groups, I observed differences between animal (blue) vs. food (red) images, as indicated by the asterisk. B. Topographical maps. Electrode sites are marked with circles, filled circle indicate the ROI for this analysis.

For P3 (300 – 500ms) amplitudes, I observed no significant effect in Typicality for NT adults, $F(1,16) = 0.01$, $p = .95$, but I found a significant effect, $F(1,13) = 4.71$, $p < .05$, $\eta_p^2 = .27$, in the HF-ASD adults. I observed a larger P3 in typical (*M* = 0.17 µV, *SE* = 0.35 µV) compared to atypical (*M* = -0.13 µV, *SE* = 0.36 µV) images (Figure 20).

Figure 20

P3 ERP component

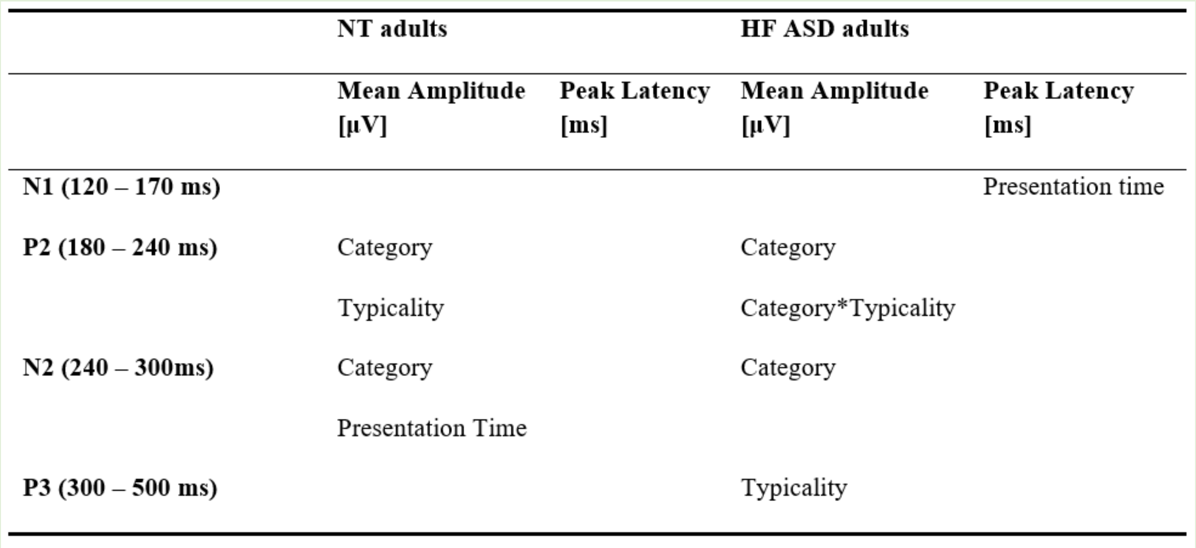


Notes. P3 for target stimuli in a ROI using the following electrode sites: P1, P2, Pz, CP1, CP2, CPz, C1, C2, and Cz for HF ASD and NT adults. Only for HF ASD adults, reliable differences between typical vs. atypical images were observed. A. ERPs. The time window used for the mean activity is illustrated by the grey bar over the x-axis (i.e., ms). In HF ASD adults, I observed differences between typical (blue) vs. atypical (red) images, as indicated by the asterisk. B. Topographical maps. Electrode sites are marked with circles, filled circle indicate the ROI for this analysis.

To summarize, I found evidence that all three factors under investigation - category, typicality and presentation time – modulated specific aspects of semantic categorization (see Table 12). In both groups, I observed similar effects of Category in the mean amplitude of P2 and N2, specifically smaller P2 and larger N2 amplitudes for food stimuli compared to animal stimuli. In contrast, the effect of Typicality manifested as smaller P2 amplitudes for typical images in NT adults, and larger P3 amplitudes for typical images in HF-ASD adults. Finally, presentation times affected the amplitude of N2 in NT adults, and the latency of N1 in HF-ASD adults: I observed a larger mean N2 amplitude for longer presentation times in NT adults, and a shorter N1 peak latency for short presentation times in HF-ASD adults.

Table 12

Summary of statistically significant (p < .05) ERP results



	NT adults		**HF ASD adults**	
	Mean Amplitude [µV]	**Peak Latency [ms]**	**Mean Amplitude [µV]**	**Peak Latency [ms]**
N1 (120 – 170 ms)				Presentation time
P2 (180 – 240 ms)	Category		Category	
	Typicality		Category*Typicality	
N2 (240 – 300ms)	Category		Category	
	Presentation Time			
P3 (300 – 500 ms)			Typicality	

Notes. Analyses were done separately for each group (HF ASD, NT adults), including the factors Category (animal vs. food), Typicality (typical vs. atypical), and Presentation Time (23.5 vs 82.3 ms).

4.2.5 Discussion

In the present study I assessed how category, typicality, and presentation time (23.5 vs. 82.3 ms) affect behavioral and neural responses in ultra-rapid categorization. Specifically, I assessed semantic categorization of animal vs. non-animal (discrete category boundaries) and food vs. non-food (fuzzy category boundaries) stimuli in NT and HF-ASD adults. I (1) conceptually replicated the ultra-rapid design introduced by Thorpe et al. (1996; dN150), (2) evaluated potential effects of a less distinct category (animal vs food stimuli), and (3) assessed whether typicality influences simple (anterior P2) or abstract (P3) feature categorization. Finally, I (4) used the N1 and N2 component as reference point to assess the association between presentation time and hierarchical level of categorization.

Both discrimination ability and RTs confirm that it is more difficult to categorize food compared to animal stimuli, as well as atypical compared to typical images. Longer stimulus presentation times enhanced behavioral performance, particularly for the food category with less specific category boundaries. Notably, I did not observe performance differences between HF-ASD and NT adults. In a rapid-serial visual presentation paradigm, however, Carmo et al. (2020) reported group differences in semantic categorization, with HF-ASD participants unable to detect atypical items even with the longest presentation times. Simplified response requirements and overall longer presentation times in the present paradigm made the task easier for all participants, eliminating a potentially confounding effect of lower performance on ERP results in the ASD group. In the following sections, I will discuss the role of typicality as well as category boundaries and the level of categorization as indexed by ERPs.

Role of Task Characteristics during Ultra-Rapid Semantic Categorization

I determined the earliest evidence of semantic categorization in the EEG signal by using the difference wave between target and non-target images. Unlike Thorpe et al. (1996), I did not observe a frontal modulation of the difference wave after 150 ms in NT adults. A number of modifications in our paradigm may have contributed to this result: (1) Response requirements. In contrast to the Go – No-Go task used by Thorpe and colleagues, in our paradigm participants were asked to press a button after each image. Thus, I eliminated the need for motor inhibition of non-targets, which may be less intuitive for participants and requires cognitive control processes. The frontal difference wave presumably reflects neural activity underlying response inhibition during No-Go trials (Thorpe et al., 1996), and is thus absent in our modified paradigm. (2) Stimuli. The original non-animal images were natural pictures (e.g., forests, mountains, lakes, buildings, flowers, and fruits; Thorpe et al., 1996), whereas in the present study pictures of man-made objects were presented. Prior work has shown a different onset of neuronal responses to artificial vs. natural pictures (Joubert et al., 2007), and thus I cannot exclude that our results may reflect our choice of stimulus materials. (3) Presentation times. The temporal characteristics of the difference wave may be influenced by differences in the rate of presentation, as images in this study were presented for 23.5 ms and 82.3 ms, and both presentation durations were included in the dN150 analysis.

Despite all these changes in the paradigm, for individuals with HF-ASD I did observe divergences at occipital recording sites for both the animal and food category. Likewise, I also observed peak differences in the dN150 for individuals with HF-ASD. Together, these findings suggest that the clinical population relied on different cognitive processes and/ or brain areas to complete the task.

Less Distinct Category Boundaries

I found that less distinct category boundaries affect reaction times and performance both in individuals with HF-ASD and in NT adults, with longer reaction times and less accurate responses for food images, where boundaries between targets and non-targets were generally less distinct. Moreover, I found evidence for different early semantic categorization of food and animal images in HF-ASD adults in terms later onset of change and a shorter peak latency of the dN150. In line with behavioral results, I observed smaller P2 amplitudes in both groups in response to food images compared to animal images, again reflecting higher task difficulty with the former set of stimuli. In fact, P2 amplitude has been shown to correlate inversely with task difficulty in general (Chen et al., 2008). Our results thus suggest that ultra-semantic categorization is more difficult when objects belong to a category with fuzzier boundaries. Additionally, I also found a more negative N2 for food stimuli than for animal stimuli in both groups, replicating the findings of Antal et al. (2001), who also found more negative deflections of the N2 component for non-animals compared to animal stimuli.

Typicality effects in ASD

Previous studies showed that HF-ASD adults have difficulties with the outer edges of a category. This is important since most natural categories cannot be distinguished by simple features, but rather by typicality structures (Gastgeb & Strauss, 2012). In other words, categorizing atypical images requires a more detailed level of categorization, and thus needs longer and is less accurate (Jolicoeur, Gluck, & Kosslyn, 1984). In the present paradigm, both NT adults and HF-ASD adults showed comparable effects of typicality in behavior, with answers to atypical images being slower and less correct. In line with Vanmarcke et al. (2016), I found no group differences in mean RT and d'. To substantiate our behavioral findings, I assessed the influence of typicality on the P2 and P3 components and observed a typicality effect in P2 for NT and in P3 for ASD adults. Whereas the P2 component reflects categorizing targets based on simple features, the P3 reflects categorizing targets based on complex, more arbitrary features. This difference in target discrimination is also reflected in the timing of their occurrence. NT adults displayed a more positive P2 component for atypical images in comparison to typical images whereas HF-ASD adults showed a more positive P3 component for typical images in comparison to atypical images. These findings suggest that atypical images are more likely to be categorized based on their simple features by NT adults and based on arbitrary features by HF-ASD adults. There are two caveats in this interpretation of our findings. First, since typicality was assessed and rated by NT adults, the apparent difference in the response to or processing of typicality itself may actually reflect differences in the individual representation of typicality. So far, there is no study that addresses this issue. Instead of being rated by a separate group of NT adults, in future research it would be valuable to measure typicality ratings by adults with HF-ASD. This approach could shed light into the question of whether typical vs. atypical items are defined differently in ASD. Second, I should also consider that atypical images with perceptual similarity to typical images tend to be categorized as quickly as typical images, leading to an under-estimation of typicality effects. Notwithstanding, I did observe slower and less accurate responses to atypical images in both groups, and qualitative differences in ERPs, substantiating our approach.

Level of Categorization

Visual input can be categorized on three hierarchical semantic levels - superordinate, basic, and subordinate level. Categorizing visual input on a lower level, i.e., in more detail, depends on the time available to perceive images (Carmo et al., 2020). In the present study, when an image was presented for a longer duration, participants responded faster and more accurately; A longer duration of visual presentation was associated with an earlier N1 latency in the ASD group and a larger N2 amplitude in the NT group. The N1 component reflects differences between subordinate and basic level categorization (Tanaka et al., 1999), which I did not observe in NT adults. Together, these results suggest that HF-ASD adults use additional presentation time to categorize images on the subordinate level, even though they engaged in a superordinate level categorization task. However, interpretations of the N1 need to be taken cautiously, since I did not specifically control for multiple low-level visual properties (for instance, luminance energy and spatial frequency composition). In NT adults only, I found larger N2 amplitudes for the long presentation time, which may index object recognition (Woodman, 2010), suggesting that NT participants used the additional presentation time for qualitatively different cognitive processes relative to a shorter presentation time. For ASD individuals, this comparison appeared as a trend, tentatively suggesting increased variability in cognitive processing when more time was available. In sum, in HF-ASD adults, longer presentation times lead to more detailed processing of images, supporting the notion of enhanced visual discrimination in HF-ASD adults as suggested for standard viewing times.

In addition to the classic triad of impairments, qualitative differences in visual processing have been consistently described over the last decades in individuals with ASD (Plaisted, 2001). The enhanced discrimination ability is shown, for example, by the fact that apparently minor changes in the environment, which are overlooked by NTs, are noticed by individuals with ASD (O'Riordan & Plaisted, 2001). Enhanced discrimination abilities in ASD may contribute to a difficulty and/or reluctance in forming a prototype (Plaisted, 2001), supporting the notion that HF-ASDs prefer to categorize on a rule-based system rather than using prototypes (Minshew et al., 2002).

4.2.6 Conclusion

Our results regarding cognitive processes during ultra-rapid semantic categorization may reflect findings of the social, communicative, and behavioral characteristics of ASD. Enhanced discrimination abilities could interfere with categorization, which depends on the ability to treat some object features within a category as similar despite perceptual dissimilarity (Soulières, Mottron, & Saumier, 2007). Our results suggest that ASD individuals categorize images based on complex features, whereas NT adults categorized based on simple features. The use of complex features to categorize images is an indication of enhanced discrimination abilities. Together with the difficulty of categorizing based on similarity (Klinger & Dawson, 2001), it may contribute to the preference for categorizing in a clear-cut, rule-based system in HF-ASD. This raises the question of whether an intervention program tailored to train similarity-based categorization could be helpful, possibly enabling ASD individuals to employ rules in effort to compensate for their limited ability to use prototypes.

Furthermore, longer N1 latencies suggest that HF-ASD individuals – but not NT adults – examined images in greater detail when they had the opportunity. However, it can be assumed that the use of this additional information has no advantage on performance, based on our behavioral data demonstrating that HF-ASD adults did not outperform NT adults, at least under the task parameters employed here. Hence, a more detailed examination of objects might be used without any noticeable positive effect on their behavior. Failure to disengage from certain objects features in the environment is a frequently observed behavioral pattern of individuals with HF-ASD. Furthermore, the ability to quickly categorize is important to reduce the demands on memory capacity, releasing resources to focus on more pragmatically important aspects of our environment (Gastgeb & Strauss, 2012). However, if not enough resources are available to focus on these other aspects of the environment, individuals on the autistic spectrum will either feel overwhelmed or miss out on these aspects altogether, both of which are observed in ASD.

4.3 OPEN ISSUES

The second set of empirical investigations (Chapter 4.1 and Chapter 4.2) focused on semantic categorization based on information from (mostly) early stages of visual processing. Faber-Thorpe (2001) suggested that in ultra-rapid categorization tasks, the encoding of superordinate level categorical information is mostly based on coarse visual representations, activated with the first available (magnocellular) visual information. The aim was to investigate how presentation duration, typicality, and cognitive processing style of individuals can affect information processing. Information processing was studied by observing the temporal course of behavior using the EHA (Chapter 4.1), as well as the electrophysiological activity using an ERP analysis (Chapter 4.2). In the following chapters the results and open issues on typicality in ill-defined categories (Chapter 4.3.2) and how detailedness affects the processing of semantic categorical information (Chapter 4.3.3) will be elaborated.

4.3.1 Typicality in ill-defined categories

The second research objective was to investigate the influence of typicality on the encoding of categorical information (based on information from early visual processing). Atypical members of a category are more likely to be processed in more detail in contrast to typical members (Jolicoeur et al., 1984; Murphy & Brownell, 1985). In an ultra-rapid categorization task, as employed in the current investigation, the encoding of typicality is suggested to be based on information from the early stages of visual processing (Carmo et al., 2020).

Surprisingly, the results of both the mean behavioral analyses and the neurophysiological analyses (as well as the analysis of mean reaction time of the prior typicality rating test) indicate that the typicality structures are different across the employed ill-defined semantic categories (i.e., “animal” and “food”). This finding could be a by-product of the stimulus material. The stimuli in the current investigation were not controlled for any confounding factors, such as for example, familiarity, visual complexity, aesthetic appeal, arousal, or valence. The variable typicality structure across the ill-defined categories might be due to an interplay of these confounding factors. However, when considering evidence for categorization based on artificiality or animacy, the variable structure can be explained and is in line with the literature. Since, artificial entities are more structurally variable than natural entities, due to their more challenging shape configuration, it was expected that artificial entities would be more structurally variable than natural ones (Gerlach et al., 2006). Regarding animacy, it was proposed that animate entities are composed of more categorical similarities (e.g., legs and eyes) than inanimate entities (Moss, Tyler, & Jennings, 1997; Tyler & Moss, 2001). Both artificiality and animacy explain variable typicality structures based on the type of the ill-defined category. Nevertheless, controlled stimulus material as well as additional ill-defined categories could be adopted in future studies to shed more light on the variability of the typicality structure.

4.3.2 Categorical information processing based on detailedness

The research question was to investigate when and where more detailed information for semantic categorization is implicitly encoded based on information from (mostly) early stages of visual processing. Some factors that implicitly affect the detailedness of the information processing are presentation duration, typicality, and the cognitive processing style of participants. More specifically, the detailedness of information processing increases for longer presentation duration (due to an increasing number of available perceptual features or information from feedback connections; Rogers & Patterson, 2007; Carmo et al., 2020), for atypical images (due to needing more information to be correctly categorized; Jolicoeur et al., 1984; Murphy & Brownell, 1985), and for individuals with HF-ASD (due to having overall enhanced discrimination abilities and therefore extremely detailed categorical representations; Brown & Bebko, 2012; Church et al., 2010).

The results of both analyses, the advanced analysis of the behavioral data (i.e., EHA; Chapter 4.1) and the analysis of EEG data (i.e., ERP analysis; Chapter 4.2), suggest that the categorical information of a stimulus material is encoded flexible, depending on the level of detail. Additionally, the results of the ERP analysis indicate that this effect is associated with activity over frontal brain areas (i.e., PFC) and over central and parietal areas (i.e., the parietal cortex, which is associated with the processing of information for action). This is in line with results from functional neuroimaging studies regarding similarity-based categorization (as employed in the current investigations). Results of these studies indicate that the activation in the (anterior) PFC can be associated with the successful retrieval of information from long-term memory (Buckner et al., 1998; Lepage, Ghaffar, Nyberg & Tulving, 2002), such as previously encountered exemplars or a category prototype (Koenig et al., 2005). In contrast, the activation in (inferior) parietal brain areas was associated with feature integration necessary for categorical judgment (Wilkinson, Halligan, Henson, & Dolan, 2002; Grossman et al., 2002).

More information is needed to understand how both processes are affected, for instance, by examining independently the effect on the retrieval of information from long-term memory as well as the influence on the integration of features. One behavioral evidence can be found in a study by Souza, Garrido, Horchak, and Carmo (2021), who investigated the effect of typicality on long-term memory (by using a Remember-Know paradigm). They observed that typical images were mostly answered to with 'Guess' responses. 'Guess' responses involve a low confidence level and uncertainty about conscious awareness while reexperiencing memories. Hence, they are suggested to involve semantic memory and, more specifically, can be associated with the activation of a category prototype. In contrast, they observed that atypical images were mostly answered to with 'Remember' responses. 'Remember' responses involve a vivid memory and conscious awareness of the reexperiencing memories. Hence, they are suggested to involve of episodic memory and, more specifically, can be associated with the activation of a previously encountered exemplar (Souza et al., 2021). A study conducting neuronal activity could shed more light on the specific influence on the retrieval of information from long-term memory (i.e., category prototype or previously encountered exemplars).

CHAPTER 5: GENERAL DISCUSSION

In the following chapters, I will recapitulate the research questions, discuss the results and implications, and consider the future objectives based on the current investigations (Chapter 3 and Chapter 4). First, the results gained by using the advanced analysis of behavior (i.e., EHA) and by the analysis of EEG data (i.e., ERP analysis) will be compared (Chapter 5.1). After this comparison, the discussion of the processing of visual information during categorization (Chapter 5.2) is followed by the discussion regarding the processing differences for categorization in ASD (Chapter 5.3) and regarding categorical representations in the brain (Chapter 5.4).

5.1 ANALYSIS OF BEHAVIORAL COMPARED TO ELECTROENCEPHALOGRAPHICAL DATA

In the current investigations, both the advanced analysis of behavioral data (i.e., EHA) and the analysis of EEG data (i.e., ERP analysis) were applied separately. Results regarding the shape of reaction time and accuracy distribution indicated that presentation duration influenced feedforward connections more than feedback connections. Furthermore, the usage of feedback connections and longer presentation duration enhanced the categorization of atypical images, as well as that there are individual differences in both HF-ASD and NT adults. These individual differences are in line with the proposal that the cognitive style (i.e., based on the WCC theory by Firth, 1989) ranges from weak to strong in a bell-shaped curve in the population (Happé, 1999). Results regarding the ERPs indicated that atypical images are more likely to be categorized based on their simple features by NT adults and based on arbitrary features by HF-ASD adults. Additionally, the results indicate that in HF-ASD adults longer presentation times lead to more detailed processing of images. Hence, the results of both analyses are not contradicting, but are complementary perspectives to semantic categorization based on information from (mostly) early visual areas.

However, this assumption has limits since both analysis techniques are not directly comparable. Firstly, in the behavioral analysis man-made and animal images were compared, whereas in the electrophysiological analysis food and animal images were compared. Secondly, due to the limitations of the electrophysiological analysis, there is no statistical comparison between the HF-ASD and NT adults (and any interaction). Lastly, due to a lower signal-to-noise ratio in EEG studies compared to behavioral studies, individual differences are more likely to be observed in the analysis of behavioral data. Additionally, behavioral data collection is more economical and might even enhance participation (e.g., due to sensory sensitivity during EEG data collection in individuals with ASD), in contrast to collecting electrophysiological data. Nevertheless, the usage of both analyses did enrich the insight into the encoding of semantic categorical information based on information from early visual areas. Hence, it would be of even greater benefit to combine both analyses. For instance, participants could be divided into subgroups based on the results of the behavioral analysis, like individuals' performance or timing of solved stimuli, and the corresponding electrophysiological activity could be investigated. More specifically, a comparison of early- and late-solved images in the EEG could shed light on the processing based on feedforward connections as well as feedforward *and* feedback connections, respectively.

5.2 PROCESSING OF VISUAL INFORMATION DURING CATEGORIZATION

The first research question was to investigate whether the representation of perceptual categorical information can be observed already in early visual processing. In the pilot study and Experiment 1, the representation of categorical information in early visual processing was not observed. In contrast, in Experiment 2 the representation of categorical information was observed. As discussed, it seems like the encoding of perceptual categorical information in early visual processing is influenced by the overall processing goal of the information.

One implication of these results for visual processing could be that the ventral stream (i.e., information about 'what') and the dorsal stream (i.e., information about 'where' and 'how') interact in a flexible manner. The interaction might be depended on the processing goal and categorical information, resulting in the encoding of categorical information in the visual cortex or later processing steps (e.g., ITC or PFC). Literature suggests that due to faster processing of information from the magnocellular cells, information from the parvocellular cells (dominating the ventral stream) might be influenced via feedback connections. The current results add evidence to this assumption by showing the flexibility of encoding categorical information.

The question arises whether the encoding of categorical information is influenced during the recombination of information from the magno-, parvo- and koniocellular cells in the retina in the V1 and V2 areas or whether feedback connections of areas related to later processes are involved. To shed more light on the interaction between information processing in the ventral and dorsal stream, further studies need to be employed. The investigation of the interaction could be done by using a masking condition. Here, an additional stimulus is presented to make the target stimulus less perceptible or even invisible, and it is suggested that masking disrupts feedback processing (Fahrenfort, Scholte, & Lamme, 2007). Hence, by comparing a masking and non-masking condition, the activity related to feedback processing can be investigated.

It's worth noting that the research questions were all concerned with the categorical information encoding in visual processing. As indicated in the introduction to the pilot study and Experiment 1, each sensory modality is optimized in a specific domain of information. For instance, the auditory system is optimized to process temporal information, whereas the visual system is optimized to process spatial information (Berti, 2018). Due to this optimization it can be assumed that the processing goal between sensory modalities might be different. Furthermore, the findings of the first study (Chapter 3.1) suggest that the encoding of categorical information may differ across domains. However, future studies might compare across sensory modalities to disentangle domain-specific and domain-general encoding of categorical information.

5.3 PROCESSING DIFFERENCES FOR CATEGORIZATION IN ASD

The second research question was related to the cognitive style of sensory information processing in individuals with ASD. There are two main theories on the processing of sensory information in ASD: the WCC theory (Frith, 1989) and the perceptual hypothesis (Plaisted, 2001). The WCC theory describes the preference of individuals with ASD for local rather than global information, while the perceptual hypothesis provides an explanation for this preference (Plaisted, 2001). The perceptual hypothesis states that individuals with ASD have enhanced discrimination abilities on a perceptual level (Plaisted, 2001), which results in reduced generalization, overselectivity, and poor categorization (Brown & Bebko, 2012).

In contrast to the literature, neither a decrease in mean performance nor an increase in mean reaction times indicated poor categorization abilities in HF-ASD adults in comparison to NT adults. Even more so, the EHA results suggest that HF-ASD adults performed better in slower RTs than NT adults. Additionally, the results of the EHA suggest that an advantage in slower RTs depending on artificiality (i.e., man-made object vs. animal images) was not observed in HF-ASD adults in comparison to NT adults. The results of the ERP analysis indicate that in HF-ASD adults, the influence of presentation duration was observed over fronto-central brain areas, whereas in NT adults it was observed in later processing steps over frontal areas. Additionally, the ERP results indicate that the categorization of atypical images is based more on arbitrary features in HF-ASD adults, whereas in NT adults it is based on simple features. No difference was observed in the processing between animal and food images. Hence, not only behavioral but also neuronal differences were observed regarding the influence of presentation duration and typicality in HF-ASD adults for the encoding of categorical information and, due to the usage of more arbitrary features to categorize atypical images, a more detailed categorical representation in HF-ASD adults can be assumed (like proposed by Church et al., 2010).

Having more detailed or hyper-specific categorical representations, it means that the similarities between objects decreases (Church et al., 2010) while the number of critical features for categorical judgments increases. As a result, this type of representation reduces the similarities in social settings, the ability to learn, and increases memory demands. Hyper-specific categorical representations, regarding social settings, would result in a reduced perception of similarities between situations and social cues. Similarities between complex perceptual inputs (that vary on a number of dimensions) are required to recognize to correctly understand social cues (McCann & Peppé, 2003; Sasson, 2006). Hence, communication skills and reciprocal social interaction might be more difficult for individuals with ASD, which are core features of the ASD diagnosis. Additionally, hyper-specific categorical representations might decrease the ability to learn and transfer learning to novel situations (Church et al., 2010). For instance, to speak and understand languages, children need to stop differentiating among all experienced morphemes but continue only to differentiate among the ones that are relevant for their native language (Brown & Bebko, 2012). Hence, was observed that children with ASD differentiate between morphemes that do not belong to their native language (Happé & Frith, 2006). Furthermore, the ability to define a minimum of needed critical features is important to reduce the demands on memory capacity and releasing resources to focus on more pragmatically important aspects of the environment (Gastgeb & Strauss, 2012). However, if not enough resources are available to focus on these other environmental aspects, individuals on the autistic spectrum will either feel overwhelmed or miss out on these aspects altogether (both are observed in ASD). Hence, it is necessary to investigate categorical representations and categorization of individuals with ASD in more detail, to better understand their communication skills and reciprocal social interactions as well as their restricted, repetitive, and stereotyped patterns of behavior (American Psychiatric Association, 2013).

Furthermore, adults with HF-ASD participated in the current studies. Due to the varying behavioral manifestations of ASD, three main subtypes are defined (i.e., LF-ASD, HF-ASD, and AS). Future studies could examine the behavior and neuronal activity of individuals with AS and LF-ASD during categorization. This would give an insight into whether encoding of categorical information is influenced by intellectual disability (LF-ASD in comparison to HF-ASD and AS) as well as a delay in language development (LF-ASD and HF-ASD in comparison to AS). In addition, existing studies investigated categorization while comparing the behavior of children, adolescence, and adults with ASD. For instance, Gastgeb, Strauss, and Minshew (2006) observed that, in the mean reaction time, the typicality effect decreased with age (i.e., the largest typicality effect in children with ASD). As a result, a number of questions arise, including whether the larger typicality effect is mirrored in neuronal activity, how categorical information is encoded in children and adolescents with ASD, and whether adults with ASD discovered a compensatory strategy reflected in the brain.

Lastly, the local processing preference can not only be observed in individuals with ASD but also in individuals with schizophrenia spectrum disorder (Cutting, 1989; Phillips and Silverstein, 2003; for review see Watson, 2013). In both neurodevelopmental disorders, cognitive impairments, deficit symptoms, and motor symptoms are core features (American Psychiatric Association, 2013; for review see Nylander, Lugnegård, & Hallerbäck, 2008). To date, the association between both disorders is still under debate (for a review see De Crescenzo et al., 2019). As a result, in future studies comparing individuals with ASD and those with schizophrenia spectrum disorder, the encoding of categorical information may highlight their common features. These studies may also reveal whether changes in sensory and categorical information processing are caused by similar underlying mechanisms.

5.4 CATEGORICAL REPRESENTATIONS IN THE BRAIN

I examined models for categorical judgment and categorical representations in the brain, in the literature review on object categorization in cognitive science (Chapter 2.3). Models regarding the representation of categorical information suggest that the representation can be category-selective (in which a specific *category* is associated with specific brain structures; Martin & Chao, 2001), feature-specific (in which a specific *feature* is associated with specific brain structures: Martin & Chao, 2001), or process-specific (in which a specific *process* is associated with specific brain structures; Gauthier, 2000). A process can be defined by how information is used, for instance, by the level of categorization (Rosch, 1987).

The first set of investigations (Chapter 3) aimed to answer if the representation of categorical information can be observed already in early visual processing, whereas the second set of investigations (Chapter 4) aimed to answer when and where more detailed information for semantic categorization, (which is mostly based on information from the early stages of visual processing) is implicitly encoded. The results suggest that perceptual categorization depends on the processing goal, while semantic categorization depends on the level of detail. The question arises if this would be also observed for conceptual categorization. One indication can be found in a recent study observing the representation of numbers. They observed that the representation was influenced by multiple unrelated factors (i.e., spatial effects; Nikolaev, Beck, Theobald, Lachmann, & van Leeuwen, 2020).

Nevertheless, the results of both research questions are similar, in the sense that both imply that encoding of categorical information is flexible (depending on the processing goal and the level of detail). This result can be interpreted as not only being in line with the model of the process-specific representation by Gauthier (2000), but also as an extension. The current results emphasize that not only the processing goal itself might influence the representation of categorical information, but also the circumstances in which the processing goal should be achieved (e.g., presentation duration, typicality of the stimulus material, or cognitive processing style).

Future investigations will need to examine the interaction between the processing goal and the circumstances (in which the processing goal should be achieved) on the representation of categorical information. There is neuroscientific research available on the impact of each of the factors. On the one hand, for instance, Tanaka and colleagues investigated the effect of processing goals on neuronal responses. They asked participants to categorize the same stimulus material either on a superordinate, basic, and subordinate level. They observed that categorical information was represented in different temporal and spatial locations depending on the level of categorization (i.e., processing goal; Tanaka et al., 2001). On the other hand, for instance, Mohsenzadeh, Qin, Cichy, and Pantazis investigated the effect of circumstances in which categorical judgments are made. They asked participants to indicate whether an image in a serial visual presentation was a member of a category using a presentation rate of 500, 34, or 17 ms. They observed that with longer presentation rates an earlier representation of categorical information was observed (i.e., 136, 169, and 197 ms after stimulus onset onward, respectively; Mohsenzadeh et al., 2018). However, the interaction between both factors, processing goals and the circumstance (in which the processing goal should be achieved), should be assessed in a future study.

CHAPTER 6: CONCLUSION

Overall, the current investigations contributed to the understanding of the processing underlying categorization and categories might be even more complex than assumed. In the first set of investigations, categorical representations during perceptual categorization were examined. The results suggest that the processing of categorical information can be already encoded in early visual processes. Additionally, the results emphasize the flexibility of the neuronal processes to encode categorical information depending on the overall processing goal of information. In the second set of investigations, categorical representations during semantic categorization were inspected. The results suggest that the structure of semantic categories can differ and that the categorical information of a stimulus material is encoded differently depending on the level of detail. Taken together, the results of both sets of investigations are similar, in that both imply that the encoding and representation of categorical information is more flexible than assumed. The current findings emphasize that not only the processing goal itself, but also the circumstances under which the processing goal should be achieved (e.g., presentation duration, typicality of the stimulus material, or cognitive processing style), can influence the representation of categorical information. Additionally, the findings demonstrate a close association between categorization and social, communicative, and behavioral characteristics of ASD. Thus, differences in categorization processes can profoundly alter all aspects of cognition and behavior, as well as how we perceive our environment.

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APPENDIX

Appendix I: Comorbid features of ASD

Even though most of the symptoms of ASD lead to difficulties in adjustment to the environment, chronic and debilitating difficulties often co-occur (Matson & Goldin, 2013). The most co-occurring difficulties are intellectual disability (prevalence rate: 70%), behavioral problems (e.g., aggression, self-injury, or disruptive behavior), physical impairments (e.g., epilepsy, sleep disturbances, or gastrointestinal disorder), and various forms of psychological disorders (Matson & Goldin, 2013). Individuals with ASD have a higher risk of developing psychological disorders (Hollocks, Lerh, Magiati, Meiser-Stedman, & Brugha, 2019) prior to the age of 30 than neurotypical individuals (Levy & Perry, 2011; independent of gender, Mannion & Leader, 2013). The most common comorbid psychological disorders are anxiety disorders (42% of all adults with ASD during of a lifetime; Hollocks et al., 2019), major depressive disorder (37% of adults with ASD during of a lifetime; Hollocks et al., 2019), and attention-deficit/hyperactivity disorders (30% of adults with ASD during of a lifetime; Kim & Lord, 2013). However, the high prevalence of comorbidities might be influenced by diagnostic overshadowing (Hollocks et al., 2019). For example, there are behavioral similarities between individuals with social phobias and ASD. In both, reduced social motivation, difficulties in social interaction, and avoidance of social situations can be observed (Hollocks et al., 2019).

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Appendix II: Neuroscience of ASD – Gray and white matter volume

Investigations about gray matter volume revealed differences between individuals with and without ASD in multiple brain regions (Stigler & McDougle, 2013). An increase in gray matter volume was observed, for instance, in regions of the medial temporal gyrus, superior temporal gyrus, fusiform gyrus, parahippocampal gyrus, and parts of the basal ganglia (caudate head; for review see Cauda et al., 2011 and Yang et al., 2016). A decrease in gray matter volume was observed, for instance, in regions of the right hemisphere in the medial temporal gyrus and parts of the basal ganglia (caudate tail; for review see Cauda et al., 2011 and Yang et al., 2016). Differences in gray matter are associated with multiple cognitive functions, mostly related to social, communicative, and motor deficits (for review see Cauda et al., 2011 and Yang et al., 2016). For example, differences in the superior temporal gyrus, the medial temporal gyrus, and the parahippocampal gyrus are associated with social perception (Zilbovicius et al., 2006).

Investigations on white matter volume reported no global difference (Hyde et al., 2009), but regional differences were observed in multiple regions (Stigler & McDougle, 2013). White matter tracts connect both hemispheres (i.e., corpus callosum) and also regions within a hemisphere. The corpus callosum facilitates inter-hemispheric connectivity (Stigler & McDougle, 2013) and is linked to processing speed (Moseley, Bammer, & Illes, 2002), motor skill, complex information processing as well as working memory (Zahr, Rohlfing, Pfefferbaum, & Sullivan, 2009). In the corpus callosum a reduction was observed for individuals with ASD in the left splenium (for review see, Di, Azeez, Li, Haque, & Biswal, 2018). This reduction might be associated with abnormalities in higher visual processing (e.g., processing of faces; Pelphrey et al., 2002; Hubl et al., 2003; Bölte, Hubl, Dierks, Holtmann, & Poustka, 2008). White matter tracts connecting regions within a hemisphere facilitate intra-hemispheric connectivity (Stigler & McDougle, 2013). On the one hand, an increase in volume was observed, for instance, in temporal cortices (Schumann et al., 2010), temporal-parietal area (Cody, Pelphrey, & Piven, 2002), medial-temporal gyrus, and in the superior temporal sulcus (Irimia, Torgerson, Jacokes, & Van Horn, 2017). On the other hand, a decrease in volume was observed in parts of the parietal lobe

(Courchesne, Press, & Yeung-Courchesne, 1993) and the right pole of the temporal lobe (Boddaert et al., 2004). Multiple cognitive functions are associated with differences in the intra-hemispheric connectivity between individuals with and without ASD, for example, the processing of auditory stimuli, like speech and social cognition (Irimia et al., 2017). Overall, results suggest a deficient inter-hemispheric and excessive intra-hemispheric white matter connectivity (Stanfield et al., 2008; Stigler & McDougle, 2013).

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Appendix III: Theory of Mind hypothesis

Theory of Mind (ToM) describes the ability to attribute mental states to oneself and others, as well as to predict the behavior of others based on their mental states (first by Premack & Woodruff, 1978). To put it differently, ToM promotes self-awareness and enables individuals to identify the intentions and emotions of others (Frith & Frith, 1999). Additionally, ToM facilitates the consideration and explanation of the behavior of others (Samson, Mottron, Jemel, Berlin, & Ciocca, 2006), such as goals, feelings, and beliefs (Fernández, 2013). Over the last decades, three levels of ToM have been differentiated: First-order ToM is the ability to identify the mental state of another person (e.g., Peter thinks …; first by Baron-Cohen, Leslie, & Frith, 1985), while second-order ToM is the ability to identify the mental state of another person referring to the mental state of others (e.g., Peter thinks that Jana thinks …; first by Bowler, 1992). Advanced ToM is the ability to interpret complex social situation based on subtle information (Spek, Scholte, & Van Berckelaer-Onnes, 2010). There is an ongoing debate about the underlying neurological mechanisms of ToM. For example, the Mirror Neuron Theory states that the set of neurons activated during performance of actions and during observation of action performance (i.e., mirror neurons; Rizzolatti & Craighero, 2004) might be associated with ToM (for review see Andreou & Skrimpa, 2020).

Studies observed a connection between the impairment of social-communication skills of children with ASD and performance in ToM tasks (Shamsi, Hosseini, Tahamtan, Bayat, 2017). Individuals with HF-ASD successfully performed first- and second-order ToM (for review see Baron-Cohen, Wheelwright, Skinner, Martin, & Clubley, 2001; Senju, 2012; Senju, Southgate, White, & Frith, 2009). However, a deficit was observed in the spontaneous usage of advanced ToM, as for example in everyday settings (Spek et al., 2010).

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Appendix IV: Executive Dysfunction hypothesis

Executive functioning (EF) describes a broad range of goal-directed, future-oriented, higher-order cognitive processes (Stuss, 2011; Barkley, 2014; Baggetta & Alexander, 2016). The identified EF processes vary from two (Miyake & Friedman, 2012) to over 30 (Baggetta & Alexander, 2016) depending on the task. However, the core processes are set shifting, response inhibition, and working memory (Miyake et al., 2000; Baggetta & Alexander, 2016), which might contribute to the higher-order EF processes like reasoning, planning, and problem solving (Demetriou, DeMayo, & Guastella, 2019). Over the last decades, two subsets of EF have been differentiated, cool and hot EF. Cool EF processes can be conducted independently of the contextual framework as well as of affective and motivational influences (Zelazo & Müller, 2002), whereas hot EF processes are mediated by affective and motivational demands (Zelazo & Carlson, 2012). Note that both, cool and hot EF processes are independent (Zimmerman, Ownsworth, O'Donovan, Roberts, & Gullo, 2016; Poon, 2018). EF is associated with activity in the frontoparietal (for review see Rommelse, Geurts, Franke, Buitelaar, & Hartman, 2011) and frontal cortical areas (for review see Buchsbaum, Greer, Chang, & Berman, 2005) as well as with functional connectivity (Alvarez & Emory, 2006; Otero & Barker, 2014).

Individuals with ASD were reported to have difficulties with all core processes of EF (Miyake et al., 2000), independent of the diagnostic group (for review see Demetriou et al., 2018) and age (for review see Demetriou, DeMayo, & Guastella, 2019). One explanation might be the atypical brain connectivity of individuals with ASD. For differences in distinct EF processes, atypical activity in the neuronal networks of working memory (Koshino, Kana, Keller, Cherkassky, Minshew, & Just, 2008) and response inhibition (Kana, Keller, Minshew, & Just, 2007) have been observed. Studies observed a link between an EF deficit in ASD with the severity of repetitive behaviors (Turner, 1997; 1999), but not restrictive behavior patterns (Boyd, McBee, Holtzclaw, Baranek, & Bodfish, 2009). However, there is substantial heterogeneity in the performance in individuals with ASD of EF tasks. The heterogeneity was proposed to be associated with the heterogeneity of the impaired of hot rather than cold EF processes (Demetriou, DeMayo, & Guastella, 2019).

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‘The author has, nevertheless, long derived pleasure from the prosecution of [her] task … [but] while the execution is generally accomplished portion by portion, [s]he is compelled to admit that instead of a history [s]he furnishes only materials for one. These materials consist in translations, extractions, original and borrowed comments, hints, and notes; a collection, in short, which, if not answering all that is required, has at least the merit of having been made with earnestness and interest’

(Goethe, Zur Farbenlehre, 1810, p. xxxv-xxvi)

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DECLARATION

Hiermit versichere ich,

- dass ich die vorgelegte Arbeit selbst angefertigt und alle benutzten Hilfsmittel in der Arbeit angegeben habe,
- dass ich diese Dissertation nicht schon als Prüfungsarbeit für eine staatliche oder andere wissenschaftliche Prüfung eingereicht, und
- dass weder die gleiche noch eine andere Abhandlung der Dissertation bei einer anderen Universität oder einem anderen Fachbereich der Technischen Universität Kaiserslautern veröffentlicht wurde.

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