THE ROLE OF PERCEIVED MATERIAL IN ASSOCIATIVE RECOGNITION OF FAMILIAR AND UNFAMILIAR OBJECTS

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ABSTRACT

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Previous research suggests that object features such as color or shape enhance memory processes, but none of them specifically focus on the material of objects, which is a crucial feature. This thesis seeks to understand how object features such as shape, material, surface texture, and reflectance influence the encoding and retrieval of objects in associative memory. Associative memory refers to how associations are formed across items either strategically, semantically, or perceptually. Specifically, I used a recognition task to understand the nature of associations formed when perceiving familiar and unfamiliar objects with congruent and incongruent materials. The stimuli in Experiment 1 contained three-dimensional (3D) model images of four familiar objects (jug, water glass, goblet, mug) rendered with four materials (wood, metal, glass, stone). The stimuli in Experiment 2 contained images of unfamiliar 3D models rendered with the same material categories as in Experiment 1. The stimuli in Experiment 3 contained images of one unfamiliar object rendered with seven texture categories (wood, metal, glass, stone, copper, plastic, and jelly) and two surface reflectance categories (matte, glossy). The findings revealed that recognition sensitivity (*d'*) was higher for material, shape, and reflectance congruent conditions than incongruent ones. There was no significant difference between material congruency and shape congruency as a memory facilitator in Experiment 1. On the other hand, for unfamiliar objects, the material feature was significantly better remembered than the shape and reflectance features. These findings shed light on the crucial role of the object material, complementing shape and reflectance, in associative recognition.

Keywords: Material perception, associative recognition, object perception, object memory

ÖZ

MALZEME ALGISININ BİLİNEN VE BİLİNMEYEN OBJELERDE ÇAĞRIŞIMSAL BELLEĞE ETKİSİ

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Önceki araştırmalar, renk veya şekil gibi belirgin nesne özelliklerinin hafıza süreçlerini güçlendirebileceğini göstermiştir, ancak hiçbiri nesnelerin malzemesine özel olarak odaklanmamıştır. Bu çalışma, şekil, malzeme ve yüzey dokusu ve yansıması gibi nesne özelliklerinin çağrışımsal nesne belleğinin kodlanması ve hatırlanması üzerindeki etkisini anlamayı amaçlamaktadır. Özellikle, eşleşen ve eşleşmeyen malzemelerle işlenmiş tanıdık ve tanıdık olmayan nesnelerin belleğe kodlanmasında oluşan ilişkilerin doğasını anlamak için bir tanıma görevi kullandım. Deney 1'deki uyaranlar, dört tanıdık nesnenin (sürahi, su bardağı, kadeh, kupa) dört malzeme (ahşap, metal, cam ve taş) ile oluşturulmuş üç boyutlu (3B) model görüntülerini içeriyordu. Deney 2'deki uyaranlar, Deney 1'dekiyle aynı malzeme kategorileriyle oluşturulmuş tanıdık olmayan 3B model görüntülerini içeriyordu. Deney 3'teki uyaranlar, yedi malzeme kategorisiyle (ahşap, metal, cam, taş, bakır, plastik ve jöle) ve iki yüzey yansıma kategorisiyle (mat, parlak) oluşturulmuş tanıdık olmayan nesne görüntülerini içeriyordu. Bulgular, tanıma duyarlılığının (d’) malzeme, şekil ve yansıma uyumlu koşullarda uyumsuz koşullara kıyasla daha yüksek olduğunu ortaya koydu. Tanıdık nesnelerde, malzeme ve şekil özelliklerinin tanıma duyarlılığı arasında anlamlı bir fark bulunmadı. Öte yandan, tanıdık olmayan nesnelerde, malzeme özelliği şekil ve yansıma özelliklerine kıyasla önemli ölçüde daha iyi hatırlandı. Tezdeki bulgular nesnelerin malzeme özelliklerinin, şekil ve yansıma özelliklerine kıyasla ilişkisel tanımada kritik rolünü ilk kez ortaya koymaktadır.

Anahtar Kelimeler: Malzeme algısı, çağrışımsal bellek, obje algısı, obje hafızası

To all the animals whose suffering goes unseen

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CHAPTER 1

INTRODUCTION

1.1. Material Perception

Our daily experiences involve interacting with numerous objects, made of various materials, some familiar and others not. We can identify and recognize these materials and infer their physical characteristics at a glance (Wiebel et al., 2013; Sharan et al., 2009). An object's material properties offer vital cues about its identity, usefulness, and affordance, hence determining our interaction with the object. For this reason, material perception studies explore how humans visually perceive and understand the properties of different object materials automatically and effortlessly (Adelson, 2001; Buckingham et al., 2009; Liu et al., 2010; Fleming, 2017). The range of materials we encounter daily is rich: Each of wood, stone, metal, and glass has distinct object properties such as roughness, heaviness, reflectance, translucency, and geometry, with practical affordances that influence how we interact with them. This interaction depends on our perception of the material properties often before we physically touch it. Hence, without touching the object, we have a general understanding and expectation about how the object would feel and even what the object would be used for in daily life (Nagai et al., 2015).

1.1.1. Surface Features of Objects

The way a material looks is influenced not just by how it reflects light but also by the combination of the three-dimensional (3D) shape, surrounding illumination, texture, and color of its surface (Motoyoshi et al., 2007; Ho et al., 2008; Marlow et al., 2011; Sharan et al., 2013; Sawayama & Nishida, 2018). These features provide valuable details about the object.

Surface reflectance is a property of the material that describes how light interacts with its surface. It is specifically about how the surface bounces or reflects light (Nishida & Shinya, 1998; Fleming et al., 2003; Motoyoshi et al., 2007; Doerschner et al., 2010). Reflectance is just one of several surface features that influence how a material appears, alongside texture, color, and 3D shape (Ho et al., 2008; Olkkonen & Brainard, 2010). Especially the shape of a surface is a crucial factor in determining how light reflects off it, and this plays a significant role in the material's final visual appearance (Lagunas et al., 2021; Serrano et al., 2021). Hence, our ability to recognize materials relies on surface features like shape, color, and texture.

Shape has been the focus of object recognition for some time (Logothetis & Sheinberg, 1996). However, the shape of an object does not always provide enough information to determine its material identity, and material estimation does not merely depend on the perception of shape-based object identity. ImageNet-trained CNNs were found to recognize objects based on local textures rather than global object shapes (Liang, 2018), contrary to human participants, who relied primarily on shape information (Serrano et al., 2021). Moreover, material recognition cannot be explained by surface characteristics such as shape, reflectance, texture, and color alone. For instance, surfaces made of different materials can display similar reflectance characteristics, and surfaces with similar texture patterns can be made of different materials. Hence, it is possible to have two different materials look the same (Sharan et al., 2013; Vangorp et al., 2007).

Local surface information, such as color or texture, does not always benefit material perception and recognition (Xiao & Brainard, 2008; Sharan et al., 2009; Giesel & Gegenfurtner, 2010). In the perception of static unfamiliar objects, shape was found to play a significant role only when the material of the objects was held constant, but when the material varied, observers no longer relied on shape cues to judge the object's stiffness (Schmidt, 2017). Here, instead of relying on ambiguous cues (unfamiliar objects), the visual system focuses on the more reliable information provided by the optical nature of the material. Various visual cues, such as color, fine details (high spatial frequencies), contrast, texture, and shape, appear to play a role in how we categorize materials. However, relying on any single one of these cues is not enough to fully explain how we accurately identify and recognize different materials. In summary, the visual system exploits multiple low-level cues in combination with high-level object knowledge to recognize materials.

1.1.2. Material Perception in the Visual System Hierarchy

Our visual experience is built upon perceiving a variety of surfaces and objects. Each has its own 3D shape, material composition, and way of reflecting light, influenced by the illumination (Lagunas et al., 2021). To understand how we perceive materials, we need to look at the mid-level vision, part of the visual perception hierarchy that tries to understand how the visual system derives such information from images. This complex process involves organizing visual data into a complete picture of surfaces and materials. It is a multi-sensory process with a hierarchical structure, meaning it builds upon simpler visual perceptions to achieve a deeper understanding (Anderson et al., 2009). Our ability to effortlessly recognize a wide range of materials despite their potentially limitless visual appearances is worth noting: How does the brain decipher the multitude of factors that contribute to the images we see, allowing us to perceive the world around us? This question is a compelling example of an essential but unresolved challenge in visual neuroscience (Adelson, 2000; Fleming et al., 2001; Schmid et al., 2023).

There are three stages in the visual processing hierarchy involved in material perception. The first stage is low-level image feature extraction, in which basic local feature elements from an image, such as shapes, colors, textures, and illusory contours, are collected and then used to build a more comprehensive version of what is being seen. For instance, material categories, such as wood and stone, can be discriminated around 100 ms stimulus onset, likely due to differences in the low-level image material surface features (Wiebel et al., 2014).In the second stage, mid-level surface computations, the visual system starts interpreting the collected features to estimate material properties; thus, it involves understanding and differentiating the surface characteristics of materials, such as reflectance, texture, and color. In the final stage, high-level recognition, the visual system uses the information processed in the previous stages to categorize materials into various classes based on their estimated properties. This level of processing allows for the organization and recognition of various materials quickly and accurately in different contexts; therefore, in this stage, more complex top-down processes are in place (Sharan et al., 2009; Fleming, 2017; Alley et al., 2020).

Neural processing in material perception was found to incorporate recognizing low-level image attributes in the early visual areas like primary and secondary visual cortex (Baumgartner & Gegenfurtner, 2016) to categorizing surface materials in higher-level category areas, such as the parahippocampal gyrus, fusiform gyrus, and collateral sulcus (Komatsu & Goda, 2018). Moreover, neurophysiological evidence also shows that the primary processing and categorizing visual perception of materials occur via a hierarchical structure within the ventral visual pathway (Komatsu & Goda, 2018), which is crucial for object recognition. Activities related to texture and materials are not restricted to a single area but are dispersed along the collateral sulcus, extending into adjacent gyri in the medial-lateral direction (Cant et al., 2009; Cavina-Pratesi et al., 2010). In summary, from basic low-level image feature detection to sophisticated material recognition and categorization, our visual system undercovers complex visual information to understand and interact with different materials in our environment (Fleming, 2017; Schmid et al., 2023).

1.1.3. Models of Material Perception

There are different levels of how we visually perceive materials. According to the model developed by Schmidt et al. (2017), there are two main routes of material perception: the association route and the estimation route. The estimation route allows material recognition to be achieved through the direct estimation of material properties from image features. This process happens without the need for explicit material identification and relies on the analysis of visual cues alone, such as surface reflectance, to infer material properties (Van Assen & Fleming, 2016). For instance, gloss was found to be a material property that takes effect via the estimation route (Vangorp et al, 2017).

Another way we identify materials is by using learned associations. The association route facilitates linking visual cues, like the texture of a surface, with the properties of that material, like whether it is soft or hard, based on the material identity formed with learned object–material associations (Fleming et al., 2013; Schmidt et al., 2017). Hence, over a lifetime, we develop strong connections between the visual appearance of an object and its typical material properties, and we depend on these associations when identifying materials (Sharan, 2009; Alley et al., 2020). Therefore, visual priors about materials can shape our expectations and modify how we perceive them. The shape-based identity of an object can trigger associations with specific material properties, meaning that recognizing an object's shape can lead to strong predictions about its material composition. This means that via the association route, we do not just passively receive visual material information but actively interpret it based on prior experience.

1.2. Material and Object Category Recognition

Material category membership is formed based on the similarities of both perceptual and semantic qualities binding the gap between sensory perception and semantic interpretation (Sharan et al., 2013). Fleming et al. (2013) demonstrated that individuals can make consistent and accurate judgments about the visual properties of materials when presented with photographic stimuli. They tested nine distinct perceptual qualities, and participants were able to reliably assess each one suggesting a strong relationship between the visual assessment of material qualities and the semantic representation of different material classes. However, materials can be incredibly diverse in their physical forms. For example, the material category of glass can include a broad range of appearances, from water glass to a magnificent chandelier. This introduces a challenge for our cognitive system. The numerous ranges of shapes a material can adopt make it difficult to establish clear boundaries for material categorization only based on perceptual or semantic similarity (Fleming et al., 2015; Caputa et al., 2010). Consequently, it is tempting to simplify the concept of material recognition to the field of object recognition. For instance, expecting a mug to be made of ceramic rather than wood is highly basic. Although there is a fair, statistically relevant correlation between object identity and material identity, shape-based object identity does not account for material recognition. It is important to emphasize that their relationship is not directly symmetrical. Objects with the same identity can be made of different materials, while objects from different identities can belong to the same material category (Bileschi et al., 2005; Sharan, 2009, Figure 1.1). Recognizing materials involves unique processes that go beyond simply identifying objects.

Sharan and colleagues (2009) demonstrated that our ability to visually identify and classify everyday materials from images is rapid and precise, even with a short presentation time of 40 ms. Moreover, they also reported that in addition to the fast and accurate material category estimation, people reliably evaluate different aspects of material surface features, such as whether it is soft or rough, matte or glossy, opaque or translucent. Thus, they concluded that material perception can be as fast as object recognition. Conversely, a study by Wiebel et al. (2013) revealed that material recognition is accurate but slower than object recognition, and discriminating materials is more complicated than objects.

Figure 1. 1. Objects that belong to the same identity category and are made of different materials are shown on the left side. Objects that belong to different identity categories and are made of the same materials are shown on the right side. Here, the shape-based object identity of the fish does not provide any cue for the glass material identity. On the other hand, the shape-based object identity of the goblet provides relevant information on its material identity, which is glass.

In addition to this, the findings of Nagai and colleagues (2015) revealed that evaluations of features like glossiness and transparency were linked to enhanced performance in discriminating materials for short reaction times, and non-visual feature ratings such as heaviness and warmness were associated with longer reaction times. The authors concluded that visual surface features are the primary source of material recognition compared to non-visual features in everyday life. For instance, we rarely estimate gloss and translucency only from haptic information without visual input (Okamoto et al., 2013; Xiao et al., 2014). According to the study conducted by Sharan et al. (2013), relying solely on local image details such as texture, local shape, and color was found to be insufficient for accurately recognizing material categories. The authors report that participants performed better at recognizing the material category when they were given global image information (object-relevant details).

1.3. Object Memory

When interacting with objects, we combine different types of information, such as their semantic function, technical/mechanical, and sensorimotor elements, in a continuous feedback loop (Federico et al., 2023). Even though we see objects from various angles and situations, we can still identify them as the same object. This means many different "views" of an object are mapped and encoded to a single, unique identity as a unitary configuration called object files (Schacter et al., 1990; Mitroff & Alvarez, 2007; Osiurak et al., 2020). Object files store and update episodic visual representations (surface features such as shape, color, and texture) of objects over time and motion (Mitroff & Alvarez, 2007). Studying an object activates and strengthens the memory file of that object, which makes it more accessible and requires less effort to retrieve when reencountered. Information about global and local object features is very beneficial in the overall retrieval process, even though learning and remembering stimuli with multiple properties increases the cognitive load and makes retrieval more demanding (Olson & Jiang, 2002; Alvarez & Cavanagh, 2004; Eng et al., 2005).

1.3.1. Object Memorability

Studies exploring how people remember images have revealed that specific pictures consistently stick in people's minds while others fade from memory. Participants show remarkably similar patterns in which images they memorize or forget (Isola et al., 2011; Isola et al., 2011; Isola et al., 2013; Khosla et al., 2015; Bainbridge et al., 2017). Research suggests that an image's ability to be remembered is fundamentally built into its characteristic features (Shoval et al., 2023). And if an image is memorable, remembering that image will also be relatively more straightforward (Bainbridge et al., 2017). Object memorability refers to how effectively an object will be stored in a person's memory following a brief single exposure (Basavaraju et al., 2019). While earlier studies examined what makes images stick in memory, they did not explicitly investigate which individual objects within those images are most memorable. The initial investigation of object memorability was conducted by Dubey and colleagues (2015). Their research revealed that images that people tend to remember well usually include at least one inherently memorable object. And not all object features have the same memorability. According to their findings, visual attributes such as hue, saturation, shape, and pixel measurements fail to reliably predict object memorability (Dubey et al., 2015). On the other hand, they showed that object category plays an important role in determining visual object memorability. For example, while animals, people, and vehicles were found to be more memorable, furniture, buildings, and devices were generally less memorable. They also showed that object memorability decreases as the number of objects and the other object categories increase (Dubey, 2015).

Other research discovered that the features related to an object's semantic meaning are the strongest predictors of object memorability compared to visual features like color and shape (Khosla et al., 2015; Konkle et al., 2010; Hovhannisyan et al., 2021; Kramer et al., 2022; Kramer et al., 2023; Schiffer, 2023). The research findings also suggest that object memorability appears to be more dependent on conceptual distinctiveness than perceptual distinctiveness (Konkle et al., 2010; Kramer et al., 2023). Moreover, the most typical examples within an object category were found to be slightly more memorable than others (Lee et al., 2023; Kramer et al., 202).

One study indicated that object memorability can be purely based on visual characteristics, even without any semantic content (Lin et al., 2021). This was demonstrated by keeping low-level visual elements while removing semantic features. Furthermore, the placement of objects within an image significantly affects object memorability (Basavaraju et al., 2019). Items positioned in the middle of images are more memorable than those placed in corner areas (Basavaraju et al., 2019). Also, it was found that larger objects are more memorable than smaller ones, with a clear positive correlation between size and memorability (Basavaraju et al., 2019). Therefore, a single object's memorability can vary depending on its location and size within the image (Basavaraju et al., 2019). When real-world objects, colored photographs, or black-and-white line drawings were used as stimuli in an object recognition task, the real objects were found to be more memorable than pictorial stimuli (Snow et al., 2014). In summary, object memorability depends on semantic features more than perceptual ones. However, if we cannot access meaningful or semantic characteristics, then we start to depend on perceptual features for object memorability.

1.3.2. The Role of Shape and Color in Object Memory

When the memory system has access to both semantic and visual shape information of objects, it prioritizes and relies on the semantic aspects, however, when semantic interpretation is not possible, memory defaults to storing objects based on their physical form (Van Weelden et al., 2015). According to shape perception research, the visual system depends on the fundamental 3D components as the main elements for identifying objects (Hayward, 1998; Lloyd-Jones & Luckhurst, 2002; Lloyd-Jones et al., 2012). The outer edge of an object plays a crucial role in object recognition, even when we view it from different angles. This outline shape allows for maintaining consistent object identification despite changes in perspective. Thus, among visual properties, shape is believed to be the prevalent feature in object recognition (Biederman, 1987; Hummel & Biederman, 1992; Hayward et al., 1999). According to a study conducted by Lloyd-Jones et al. (2012), the visual processing system uses object shape as the fundamental gateway for other object features such as color and texture.

Examples from the literature also report that basic color properties such as hue and saturation have minimal impact on object memorability (Dubey et al., 2015). Also, it was found that people tend to remember colors more reliably and accurately when they represent clear, typical examples of specific color categories. For instance, a pure, distinct red is more likely to be remembered correctly than an ambiguous shade between red and orange (Bae et al., 2015). Considering the role of color in object recognition, a meta-study conducted by Bramão et al. (2011) found that the effect of color on object recognition was moderate (Cohen's $d = 0.28$). According to a study conducted by Cave et al. (1996), when the same-colored and different-colored pictures were used in the study and test phases, no performance difference was observed between the same-color and different-color conditions. Hence, they concluded that object recognition was not influenced by the changes in color.

When participants were shown object pictures whose colors were typical, moderately atypical, or bizarre, color bizarreness was found not to affect the object recognition memory (Morita & Kambara, 2021). On the other hand, some studies showed that objects whose color is strongly associated with their shape-based object identity play an important role in object recognition, which is called color typicality or color diagnosticity (Redmann et al., 2019; Reppa et al., 2020; Nagai & Yokosawa, 2003). Tanaka and Presnell (1999) demonstrated that color has a significant role in recognizing high-color diagnostic objects and has no effect on recognizing objects with non-color diagnosticity. Ovalle-Fresa et al. (2021) found that visual associative recognition memory was better for concrete object–color associations than abstract fractal–color associations. Yet another study found that recognition of shape and color function independently, relying on distinct sensory and memory processes, contradicting the abovementioned evidence for color typicality (Stefurak & Boynton, 1986). One study suggests that color helps us recognize pictures not because we remember the colors themselves but because color highlights distinctive surface features and contours (Suzuki & Takahashi, 1997; Lewis et al., 2013). In short, when we store information about objects, we process color and shape characteristics and these two visual properties are integrated into how we remember objects we encounter.

1.3.3. The Role of Familiarity in Object Memory

Our everyday experience suggests that we effortlessly recognize familiar objects even when the visual information we receive about them changes significantly. Familiar objects often have distinct features that make them stand out from unfamiliar ones, such as consistent shape-color associations (Tanaka & Presnell, 1999; Reppa et al., 2020), established object-material associations (Sharan et al., 2009; Schmidt et al., 2017) and learned semantic associations (Martin & Chao, 2001; Martin, 2007). Having familiarity and prior knowledge about an object creates a mental representation that can be used to enhance perception and memory processing of that object (Boucart & Bonnet, 1991; Kahneman, 2011). The ease of recognizing familiar objects might be partially attributed to our ability to access semantic information, such as the object's name and its associated meaning or shape nameability (Craddock & Lawson, 2008; Walker & Cuthbert, 1998). For instance, it was found that when objects are not familiar enough, we attempt to identify the familiar elements of the unfamiliar object as much as possible (Schmidt et al., 2020). If the object is familiar or has mostly familiar elements like global shape information, we base our judgments on semantic information (Schmidt et al., 2020). New-association priming refers to the phenomenon where exposure of two unrelated items together can lead to the creation of links between the items that were previously unrelated (Musen et al., 1999). It was found that object familiarity increases new association priming, as it allows individuals to access the already existing memory representations for both elements and focus on merging the new association (Musen et al., 1999). However, if the stimuli are unfamiliar new-association priming does not occur (Musen et al., 1999). Hence, it is easier to associate if representations already exist; otherwise, memory representations must be created first.

The strong connection between object meaningfulness and object memorability suggests that people rely on an object's semantic content to indicate how likely they will remember it later. Objects with greater meaningful content were less perceived by their visual features and more by their semantic features (Shoval et al., 2023). Memory improves when we can attach verbal descriptions to what we see. Specifically, when people are provided with labels for unfamiliar or ambiguous objects, they tend to remember them more effectively than those without labels (Koutstaal et al., 2003). This could be due to the familiarity that object meaningfulness holds, and the more familiar an object is, the more increased memory performance is observed (Blalock, 2015; Xie, 2017). Overall, these findings indicate that familiarity, typicality, and co-occurrence were found to have enhancing effects on object memory (Green & Hummel, 2005, 2006; Ngo et al., 2018; Schiffer, 2023; Kramer et al., 2023).

1.3.4. The Role of Visual Saliency in Object Memory

When images are simple - containing minimal objects or objects with few notable features - visual saliency effectively predicts how memorable those objects will be. However, this predictive power diminishes significantly in more complex images where multiple objects with different object features are observed. Hence, visual saliency was found to reliably predict object memorability only when the image has minimal complexity (Dubey et al., 2015; Bainbridge, 2019). Therefore, an image's ability to be remembered depends not solely on its visual attention-grabbing features. Highly memorable images do not necessarily stand out immediately or catch our eye - their memorability derives from factors beyond just attention-capturing visual elements (Bainbridge, 2020). On the other hand, images depicting noticeable or distinctive salient movements were found to be better remembered (Basavaraju et al., 2018). In conclusion, contrary to common thinking, visual saliency is not a universal indicator of memorability (Isola et al., 2011). Similarly, images that are considered particularly unique or aesthetically appealing do not demonstrate a strong connection with being more memorable (Dubey et al., 2015; Isola et al., 2013). Nevertheless, to my knowledge, no study has investigated the role of material in object memorability.

1.4. Perception and Memory

Is it too daring to say memory is perception? In other words, we have memory-driven expectations, how objects are perceived depends on their representation over experience; hence, perception is memory (Buckingham, 2009). According to visual sensory memory, later called iconic memory (Neisser, 1978), object recognition is an active process where the current visual input of an object is constantly being compared with existing perceptual representations of similar objects. Thus, many detailed memory representations are the very representations that underlie visual object perception. Moreover, grounded cognition (Barsalou, 2005) argues that this comparison is modal, not amodal, as it is assumed by classic approaches. According to the embodied theory of memory, perception and memory are deeply interconnected operations, both being constructive processes influenced by the observer's experiences, interpretations, and categorizations. They are closely linked because perceiving an object is not merely about gathering perceptual data, but it also involves comparing sensory features of objects and materials with stored representations of these sensory inputs. In other words, what we perceive or remember is shaped by previous experiences and the meanings we attribute to them rather than being direct reflections of reality. Thus, it boils down to what is remembered depends on how it was recorded into memory, suggesting that our memory results from our perception that can influence and be influenced by perceptual experiences (Barsalou, 1999). Both memory and perception involve categorization to manage the vast amount of information, a necessary process based on the observer's knowledge and experience. These categorizations may create prototypes, omitting some of the specific details that, in return, could lead to perceptual and memory illusions, also highlighting the connection between the two (Quirago, 2016). As perceptual inferences can lead to visual illusions, memory can also be distorted, leading to false memories, such as falsely recognizing a word associated with a list (Roediger & McDermott, 1995).

Memory is spread throughout the same neural networks engaged in sensory-motor activities (Slotnick, 2004). The view that perception and memory share mutual neural pathways is supported by neuroimaging research that shows activation of sensory-motor areas during memory tasks (Martin & Chao, 2001; Weinberger, 2004; Versace et al., 2009).

There are many studies investigating how memory traces can actively influence perceptual processing. For example, a shape associated with a sound in a learning phase was found to influence the perception of that related auditory property in the test phase, even when only the shape was present, and the sound was not present (Brunel et al., 2010). In another study, when a sensory property (like sweetness) was associated with a visual pattern, it was found that the pattern previously associated with the property of sweetness had a facilitatory effect on the categorization of the pictures of sweet products (Rey et al., 2013). In their experiment involving a visual search task where the typical size and perceptual size of objects were manipulated, Riu et al. (2011) found that participants had faster reaction times when there was congruency between the typical size of objects (stored information) and their perceived size in the task. Contrariwise, when there was incongruency between these two aspects of size, reaction times in the visual search task increased.

One study examined working memory's role in maintaining material constancy (Tsuda et al., 2020), referring to the ability to consistently perceive materials under varying lighting conditions. The study revealed that when perceptual and memory congruent performances were directly compared, working memory representation was less accurate than perception, highlighting the need to consider memory processes in understanding, perceiving, and remembering material properties (Tsuda et al., 2020). Memory plays a vital role in constancy: To make a successful match, one needs to compare presently perceived input with an encoded representation seen previously. Constancy was also found in working memory for glossiness perception, which is robust to illumination changes (Tsuda & Saiki, 2018). Nevertheless, it should be noted that not many studies examine how perceptual mechanisms interplay in a memory-related task.

1.5. Associative Recognition Memory

The concept of association is fundamental to learning and memory. Associations formed between sensory stimuli, such as surface texture or material of objects, provide information about environmental regularities and are crucial for predicting and interpreting future sensory inputs and defining the semantic properties that are stored in the memory (Albright, 2012). Associative memory can be influenced by how items are semantically organized or clustered, leading people to remember items that are related in meaning, such as those in the same taxonomic group, thereby creating a network of semantic associations. Two main experimental techniques are commonly used to investigate associative memory. The first technique, *the cued-recall task*, involves participants studying pairs of items and then being prompted with one item, from which they must recall the corresponding pair (Tulving, & Thomson, 1973). The second technique, *the associative recognition task*, requires participants to study item pairs and then identify whether presented pairs are the same as those studied by answering "yes" for recognized pairs and "no" for unrecognized ones (Clark et al., 1993; Rotello & Heit, 2000; Cohn & Moscovitch, 2007; Kahana, 2012).

In associative recognition task, three different types of pairs are used during the retrieval stage to test memory. Each type serves a specific purpose and requires different responses from participants. Intact pairs are exactly the same as what participants saw during the study phase; both the items and their pairing remain unchanged. When participants see these pairs, they should respond "yes" because these are the original pairs they have learned. Unstudied pairs are completely new pairs that participants have never seen either of the items before. These pairs appear for the first time during the retrieval stage and serve as new information. Participants should respond "no" to these pairs since they were not in the original study list. Rearranged pairs contain individual items from the study list, but these items have been mixed up to create incorrect combinations in the retrieval stage to serve as lures. Participants should respond "no" to these pairs since they did not appear in the study list as a pair (Rotello & Heit, 2000; Cohn & Moscovitch, 2007).

According to dual-process theory, recognition memory is the ability to distinguish between old (previously encountered) and new information. It is thought to be based on two fundamentally different processes: 1) A subjective sense of familiarity without remembering specifics is often used to make swift memory judgments, and 2) the recollection which is an effortful process of retrieving precise details (Yonelinas, 2002; Nagai & Yokosawa, 2003).

Intact pairs are used because they activate both familiarity and recollection processes simultaneously. When participants see an intact pair, they can recognize it through both the familiarity of individual items and their recollection of the specific association between them. These pairs activate both the item and associative information. Rearranged pairs serve a crucial methodological purpose; they force participants to rely on associative memory rather than just item memory. To correctly reject these pairs, participants must use one item to retrieve its original partner (Humphreys,1978). Therefore, the rearranged pairs depend on not just the individual item memory but also the associations formed between two individual items (Cohn & Moscovitch, 2007). The unstudied pairs serve as a baseline control condition; they contain completely new items. This allows pure novelty detection and false alarm rates.

1.6. Why Study the Role of Material Perception on Associative Recognition of Familiar and Unfamiliar Objects

The influence of material perception on visual object memory has been largely neglected in research despite the ecological significance of recognizing materials and their properties (Adelson, 2001; Wiebel, 2014; Fleming, 2014; Fleming et al., 2015; Nagai et al., 2015). To my knowledge, no previous study directly investigated the role of object material and compared this to the role of object shape in memorability. There is a gap in the literature about which material features are more memorable and whether material memorability is superior for familiar vs. unfamiliar objects. Hence, I focus on the impact of perceptual features such as material, shape, and reflectance on object memorability. I used a set of objects that change in perceptual congruency with familiar and unfamiliar objects. By perceptual congruency, I mean choosing two objects that have the same perceptual components as pairs. For instance, when two objects in a pair have the same shape or material, they are perceptually congruent. When they have different shapes or materials, they are perceptually incongruent. Therefore, this thesis focuses on how material information is stored and retrieved from associative object memory compared to other surface characteristics such as shape and reflectance. Moreover, this thesis is interested in how shape-based familiarity and unfamiliarity play a role in associative object memory.

This type of research can provide valuable insights into the interplay between shape perception and material perception in associative object recognition, shedding light on how these aspects of visual processing influence each other. Hence, building paired samples that vary in material, shape, and reflectance in a controlled and systematic way will be useful for studying the relationship between these variables.

Also, investigating how people interact with novel, functionless objects with no familiarity, such as spherical objects called Glavens (Phillips, 2004; Phillips et al., 2009) -similar to Gibson's feelies (Gibson, 1962)- can provide valuable insights into the cognitive mechanisms that underlie our ability to perceive and recognize materials as well as objects. Understanding how incoming familiar and unfamiliar sensory evidence is combined with high-level expectations is essential to understanding how the human visual system executes material perception and forms shape–material associations (Alley et al., 2020).

1.7. Aims and Hypotheses

In this thesis, I investigate the role of perceived material on the associative recognition memory of familiar and unfamiliar objects compared to other object features, such as shape and surface reflectance. To do this, a set of familiar objects with different object identities made of everyday materials were chosen as stimuli in the first experiment. A set of unfamiliar objects with different shapes made of the same everyday materials were chosen as stimuli in the second and third experiments. The aim of Experiment 1 was to investigate how participants form associations between two familiar objects based on their shared object features like material and shape-based object identity. The main research question was whether participants rely on the material or the shape information when forming associations between two familiar objects. The hypotheses of Experiment 1 are as follows: (1) The shape-congruent and material-congruent familiar object pairs will be recognized better than the shape-incongruent and material-incongruent familiar object pairs, showing a congruency effect. (2) The shape information of familiar objects will predominate the material information when forming associations in memory.

The aim of Experiment 2 was to investigate whether the congruency effect transfers to unfamiliar objects. I investigated how participants form associations between two unfamiliar objects based on their shared object features, such as material and shape. The main research question was whether participants rely on the material or the shape information when forming associations between two unfamiliar objects. The hypotheses of Experiment 2 are as follows: (1) The shape-congruent and material-congruent unfamiliar object pairs will be recognized better than the shape-incongruent and material-incongruent unfamiliar object pairs, showing a congruency effect. (2) The material information of unfamiliar objects will predominate the shape information when forming associations in memory.

Finally, the aim of Experiment 3 was to investigate how people form associations between two unfamiliar objects (when shape is kept constant) based on their shared surface properties like texture and reflectance. The main research question was whether people rely on the texture or the reflectance information when forming associations between two unfamiliar objects. It is expected that (1) a surface congruency effect of unfamiliar objects with identical geometries will also be observed here. The reflectance-congruent and texture-congruent unfamiliar object pairs will be recognized better than the reflectance-incongruent and texture-incongruent unfamiliar object pairs. Also, (2) the texture information of unfamiliar objects will predominate the reflectance information when forming associations due to distinctive surface patterns and visual cues that textures can offer, which can make them easier to discriminate.

CHAPTER 2

EXPERIMENT 1

2.1. Experiment 1: Shape vs. Material of Familiar Objects

2.1.1. Method

In the first experiment, participants completed an associative recognition task where they studied paired images of familiar objects with varying congruency of object features (material, shape). Congruent and incongruent material and shape properties were tested to investigate whether congruency would enhance recognition performance.

2.1.2. Participants

The study was approved by the Human Studies Ethical Committee of Middle East Technical University. A post G-Power calculation was conducted to determine the sample size. For the experiment to have 0.95 power, 0.25 effect size, and 0.05 alpha level for two-way Repeated Measures ANOVA within factors, the estimated sample size was 54 (Faul et al., 2009). Seventy-four participants (54 females, 18 males, 2 non-binary) aged between 19-30 (M= 21.9, SD= 2.16) from Middle East Technical University took part in the experiment in exchange for course credit or voluntarily. Participants were native Turkish speakers with normal or corrected vision. All participants gave written informed consent after a brief outline of the study's nature, methods, and ensuring the privacy of the participants' responses before participating.

2.1.3. Experimental Setup

The experiment was written and carried out using Python (Psychopy v2023.2.3) software and presented on an HP 24f (2XN60AA) monitor at a resolution of 1,920 ×

1,080 pixels. The experiment was conducted in a sound-proof laboratory setting to avoid any disturbance that could distract participants from the task. The distance from the computer (50 cm) and the illumination of the room was kept constant for all participants.

2.1.4. Materials

The experimental stimuli in this study consisted of 32 images of familiar objects under four shape categories (jug, goblet, water glass, mug) and four material categories (wood, metal, glass, stone). In other words, in every shape category, there were 4 images of an object rendered with four different materials (and vice versa) that were generated using the program Blender 4.1.1, an open-source 3D computer graphics application (Blender, 2024; Figures 2.1, 2.2).

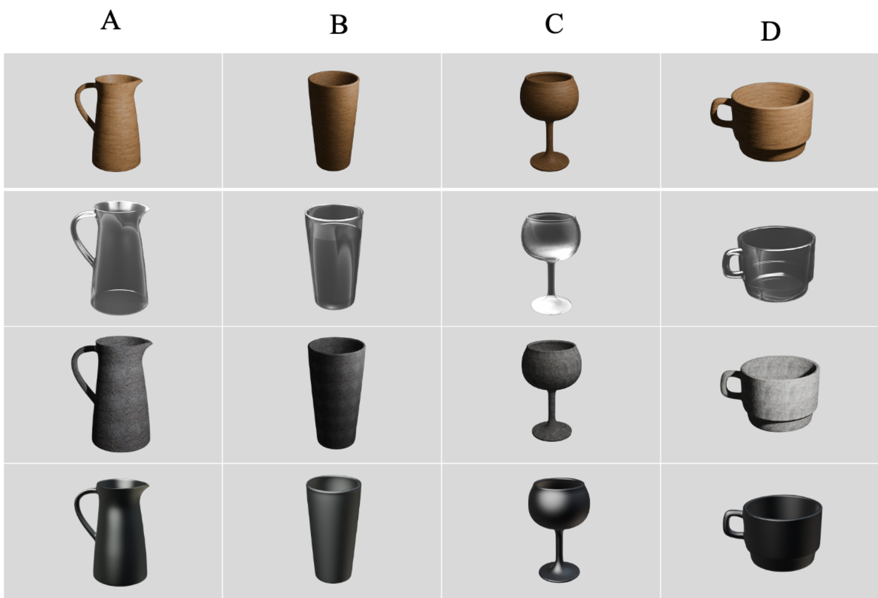

Figure 2. 1. The study list stimuli of Experiment 1, four familiar objects rendered with four materials: wood jug, glass jug, stone jug and metal jug (A); wood water glass (WG), glass WG, stone WG, and metal WG (B); wood goblet, glass goblet, stone goblet, and metal goblet (C); wood mug, glass mug, stone mug, and metal mug (D).

The four objects and materials were selected from the assets of BlenderKit, an open extension of Blender that provides assets for models, materials, scenes, etc. The rotation of the jug was (0°, 0°, 54.8°), the rotation of the goblet was (2°, 2°, 2°), the rotation of the mug was (0°, 0°, -120°), and the rotation of the water glass was (1°, 1.3°, 0.5°) on the XYZ plane. The location of the jug, goblet, and water glass was (0.5m, -0.4m, -0.8m), and the location of the mug was (0.2m, -0.2m, -0.5m) on the XYZ plane. The luminance properties used when rendering the four materials were selected and modeled by the eye to portray the reflectance, transparency, translucency, and texture characteristics of each material optimally. For the glass renderings, the rectangle area light engine had a 200000 W- 500000 W power interval; for the wood and stone renderings, the point light engine had a 200-700 power interval; for the metal renderings, the sunlight engine had a 50-200 power interval (no shadow option was used). The camera viewed the objects from the front and slightly from above with the perspective projection and a 50 mm focal length. The objects with glass, wood, and stone materials were rendered with the EEVEE render engine with a sampling level of 16 and 64 samples per pixel. The objects with metal material were rendered with the Workbench render engine with eight samples and specular reflections.

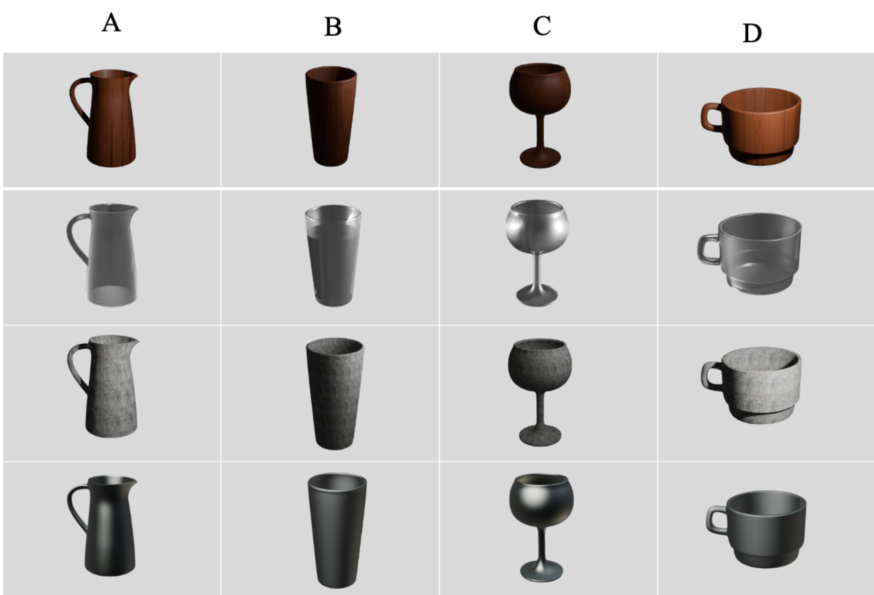

Figure 2. 2. The new unstudied experimental stimuli that did not appear on the study list and was only shown in the test list. Four familiar objects rendered with four materials: wood jug, glass jug, stone jug and metal jug (A); wood WG, glass WG, stone WG, and metal WG (B); wood goblet, glass goblet, stone goblet, and metal goblet (C); wood mug, glass mug, stone mug, and metal mug (D).

These images of objects were listed as pairs in an associative recognition task to further assess the associative object memory of participants. There was a total of four conditions: in the material-congruent item condition (MC, Figure 2.3A), paired items were the images of either the same or different object shapes made of the same material. In the shape-congruent item condition (SC, Figure 2.3B), paired items were the objects with identical shapes made of either the same or different materials. In material-incongruent condition (MI, Figure 2.3C), paired items were images of either the same or different shapes made of different materials. Lastly, in the shape-incongruent condition (SI, Figure 2.3D), paired items were images of objects made of either the same or different material categories with different shapes.

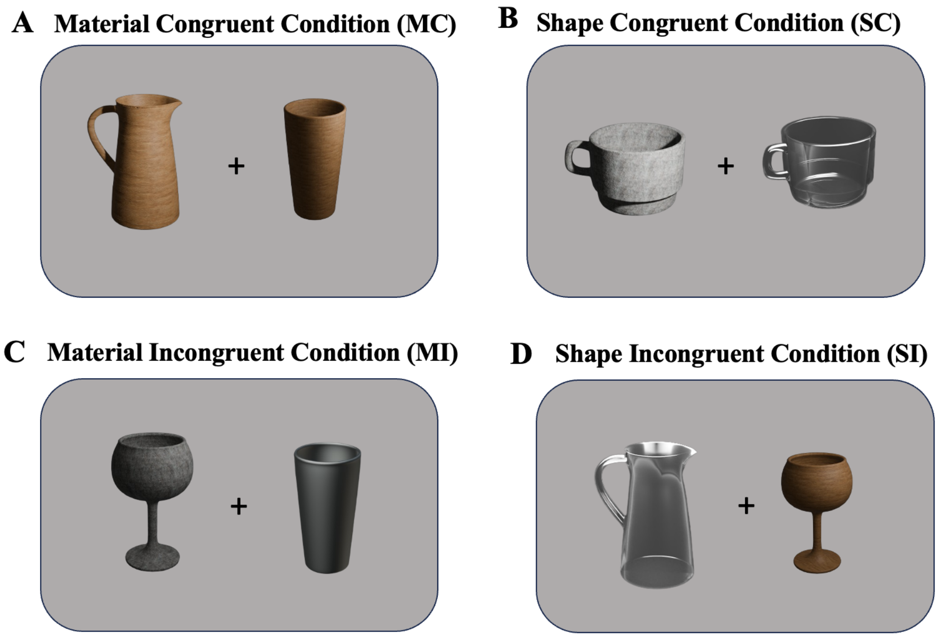

Figure 2. 3. This figure illustrates examples from the four conditions in the associative recognition task of Experiment 1.

In the original design, each main condition (material-congruent, material-incongruent, shape-congruent, and shape-incongruent) contained repeating object pairs that appeared across conditions. In material-congruent (MC) conditions, half the pairs were material-congruent but shape-incongruent, and half were both material and shape-congruent. In shape-congruent (SC) conditions, half the pairs were shape-congruent but material-incongruent, and half were both material and shape-congruent. In material-incongruent (MI) conditions, half the pairs were material-incongruent but shape-congruent, and half were both material and shape-incongruent. Similarly, in shape-incongruent (SI) conditions, half the pairs were shape-incongruent, but material-congruent and half were both material and shape-incongruent.

While these repeating pairs were equally distributed across conditions and did not confound the experimental design, they could potentially influence the results by increasing memory sensitivity overall. An alternative approach would have been to use four distinct conditions without overlap: material-congruent shape-incongruent condition, shape-congruent material-incongruent condition, material and shape congruent condition, and material and shape incongruent condition. However, the current design was chosen for all three experiments to independently examine how associative memory changes between congruent and incongruent conditions for individual object and surface features (material vs. shape, texture vs. reflectance) rather than studying their combined effects.

2.1.5. Procedure

Before the experiment started, the experimenter instructed the participants about the experiment, explaining every stage of the study in detail using instruction slides with visuals. After the instructions, the experimenter left the room, and the experiment started. Instructions were also provided on screen for the participants to read between each stage during the experiment.

The experiment consisted of three stages: the study stage, the distraction stage, and the retrieval stage. In the study stage, participants were shown a study list containing 16 pairs for every four conditions (MC, SC, MI, SI). A total of 64 pairs were randomly presented for 4 seconds and a four-second inter-stimulus interval prior to the presentation of the next pair. Participants were instructed to study these pairs in the study list for a later memory test. The study stage was followed by the distraction stage, which included a distractor task in which participants completed addition and subtraction calculations in a random order for two minutes. Immediately after the distractor stage, the retrieval stage took place with an associative recognition task. Participants were shown a test list containing 15 pairs for each of the four conditions (MC, SC, MI, SI) in a random order. A total of 60 pairs were shown, containing 32 intact pairs that were in the study list and 16 new, unstudied pairs that were not in the study list (Figure 2.2). Material and shape combinations of the objects in the unstudied pairs were shown for the first time in the retreival stage. Also, there were

12 rearranged pairs consisting of objects that were in the study list but belonged to different pairs and were rearranged in the retrieval stage. Participants were required to press the key "e" on the keyboard if they had recognized the pair from the study list or "h" if they had not recognized the pair from the study list with no time limit. This study used a within-subject design with an associative recognition task, and all responses were collected using a keyboard (Figure 2.4).

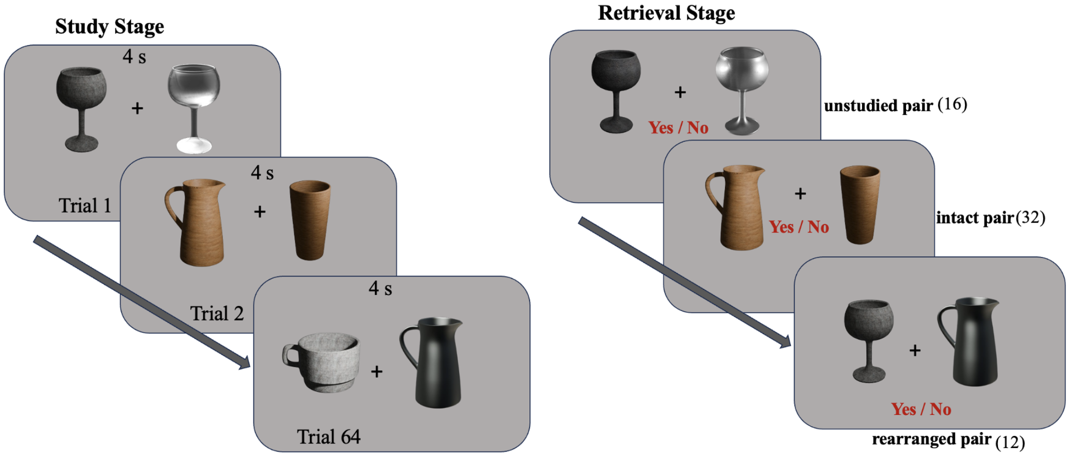

Figure 2. 4. The experimental procedure of the study stage and the retrieval stage of Experiment 1.

2.1.6. Results

A Python code was written to organize the data (Visual Studio Code version 1.91, 2024) using the SciPy package. Each participant's hit rate for intact pairs in every four conditions (MC, SC, MI, SI) and false alarm rate for rearranged and new pairs in every four conditions (MC, SC, MI, SI) were calculated. Hence, the sensitivity *d′* scores of every four conditions (MC, SC, MI, SI) for each participant were computed by subtracting z-scores of the false alarm rates from the hit rates (MacMillan & Creeman, 1991). Inferential statistics were run in JASP (JASP Team, 2024) and figures were plotted in R (R Core Team, 2021).

The response bias is the different range of memory evidence that participants require to call an item "old" free of any experimental manipulation. The measure of response bias is the criterion value (*c*), which is the decision threshold to distinguish old from new items and is calculated by -1/2 (z(H) + z(F)). A neutral bias has a 0 value of c; hence, the overall error rate is minimized. A conservative bias has a positive c value, and a liberal bias has a negative c value (Macmillan & Creelman, 1990). A one-sample t-test was conducted to examine the response bias of participants on associative recognition of familiar objects. The normality assumption was not violated; the Shapiro-Wilk test indicated that differences between participants were normally distributed, $W(74)= 0.97$, $p= 0.13$. The findings revealed a significant main effect of response bias (M=-0.32, SD=0.34) between participants, $t(73)= -8$, $p< 0.001$, $d= -0.93$, which means that participants had a liberal bias in Experiment 1.

A two-way 2 (congruency) x 2 (object feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and object feature (material, shape) on the d-prime scores. The findings revealed a significant main congruency effect on associative object recognition memory, meaning that material and shape congruent pairs were better recognized than material and shape incongruent pairs, $F(1, 73) = 14.3, p < 0.001$, $\eta^2 p = 0.16$, mean difference = 0.2, standard error = 0.05, 95%CI [0.09, 0.29], $p < .001$. I did not observe a difference between the object features (material vs. shape, Table 2.1).

Table 2. 1. Repeated Measures ANOVA for Experiment 1

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object feature	0.00553	1	0.00553	0.459	0.500	0.006
Residual	0.87802	73	0.01203			
Congruency	2.68953	1	2.68953	14.307	< .001	0.164
Residual	13.72349	73	0.18799			
Surface feature ∗ Congruency	0.55639	1	0.55639	1.921	0.170	0.026
Residual	21.14301	73	0.28963			

There was no significant main effect of the object feature on the associative recognition of familiar objects, $F(1, 73) = 0.45, p = 0.05$, $\eta^2_p = 0.006$, mean difference = -0.008, standard error = 0.01, 95% CI [-0.03, 0.17], $p = .05$. Hence, there was no significant difference between sensitivity *d′* scores of material congruent and shape congruent conditions as well as the material incongruent and shape incongruent conditions. This might indicate that both the material and the shape features of familiar objects affect the associative object recognition equally. There was no significant interaction effect between congruency and object feature on associative recognition of familiar objects, $F(1, 73) = 1.92$, $p = 0.17$, $\eta^2_p = 0.02$. This means that the effect of congruency on associative object recognition was similar for the material and the shape of the object (Figure 2.6).

Table 2. 2. Mean of Hit Rates, False Alarm Rates and Sensitivity d' Scores of Conditions in Experiment 1

	MC	MI	SC	SI
HR	0.80	0.65	0.80	0.63
FAR-unstudied	0.53	0.25	0.48	0.29
FAR-rearranged	0.70	0.63	0.72	0.62
FAR-total	0.59	0.44	0.56	0.46
Sensitivity d'	0.70	0.59	0.79	0.50

Post hoc tests using Bonferroni correction revealed that the recognition sensitivity *d′* score of the shape congruent (*M*=0.78, *SD*=0.57) condition was higher than the shape incongruent (*M*=0.50, *SD*=0.47) condition, mean difference = 0.3, standard error = 0.07, 95% *CI* [0.08, 0.47], $p < .001$. This means that shape congruent pairs were better recognized than incongruent pairs in the associative recognition of familiar objects (Figure 2.5).

A two-way 2 (congruency) x 2 (object feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and object feature (material, shape) on the hit rates of familiar objects. The findings revealed a significant main congruency effect on the hit rates of familiar objects, $F(1, 73) =$

83.1, $p < 0.001$, $\eta^2p = 0.53$ (Table D.1). There was no significant main effect of the object feature on the hit rates of familiar objects, $F(1, 73) = 1.499\times10\text{-}13$, $p = 1$, $\eta^2p = 2.054\times10\text{-}15$ (Table D.1). Meaning that both the material and the shape features of familiar objects affect the hit rates equally. There was no significant interaction effect between congruency and object feature on the hit rates of familiar objects, $F(1, 73) = 0.98$, $p = 0.32$, $\eta^2p = 0.01$. This means that the effect of congruency on hit rates was similar for the material and the shape of the object (Figure 2.7). Post hoc analysis with a Bonferroni adjustment revealed the hit rate of congruent conditions (M=0.80, SE=0.01) were higher than the incongruent conditions (M=0.64, SE=0.02), mean difference = 0.16, standard error = 0.01, $p < .001$ (Table D.2).

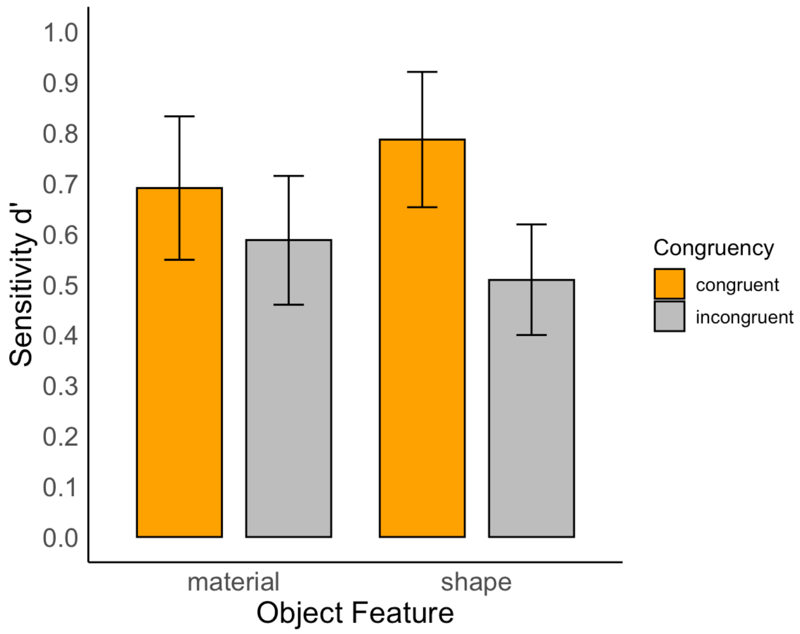

Figure 2. 5. The recognition sensitivity of four conditions (MC, SC, MI, SI) with familiar objects. The X-axis represents object features, the Y-axis represents the sensitivity d' scores. The yellow bars display congruent and the gray bars display incongruent conditions, and the error bars represent standard errors of the mean.

A two-way 2 (congruency) x 2 (object feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and object feature (material, shape) on the false alarm rates of familiar objects. The findings revealed a significant main congruency effect on the false alarm rates of familiar objects, $F(1, 73) = 84.9$, $p < 0.001$, $\eta^2p = 0.54$ (Table D.3). There was no significant main effect of the object feature on the false alarm rates of familiar objects, $F(1, 73)$

= 1.25, p = 0.27, η^2p = 0.017. Meaning that both the material and the shape features of familiar objects affect the false alarm rates equally. There was no significant interaction effect between congruency and object feature on the false alarm rates of familiar objects, $F(1, 73) = 1.25$, $p = 0.27$, $\eta^2p = 0.017$. This means that the effect of congruency on false alarm rates was similar for the material and the shape of the object (Figure 2.7). Post hoc analysis with a Bonferroni adjustment revealed the false alarm rate of congruent conditions (M=0.57, SE=0.02) were higher than the incongruent conditions (M=0.45, SE=0.02), mean difference = 0.13, standard error = 0.01, $p < .001$ (Table D.4).

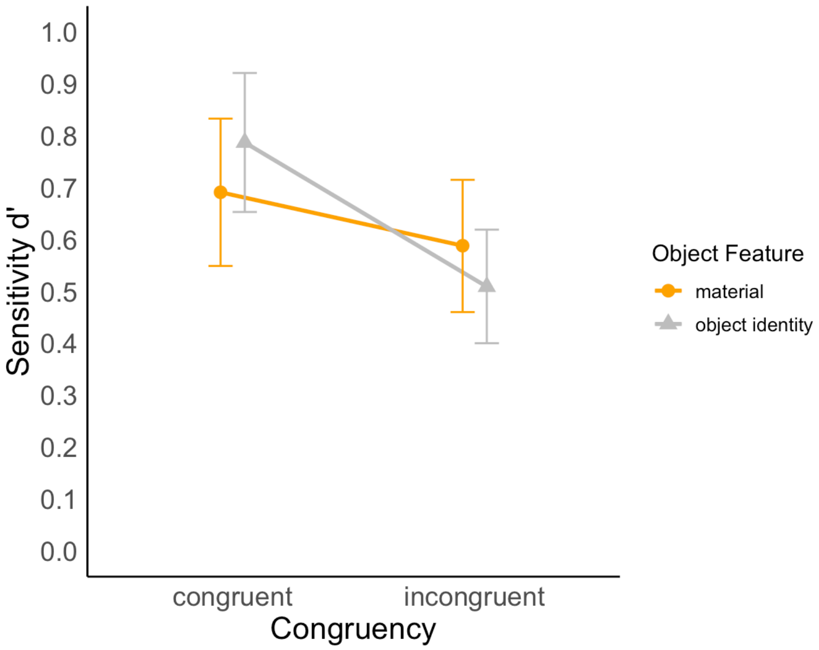

Figure 2. 6. The recognition sensitivity of four conditions (MC, SC, MI, SI) with familiar objects. The X-axis represents congruency, the Y-axis represents the sensitivity d' scores. The yellow line displays material and the gray line displays shape conditions, and the error bars represent standard errors of the mean.

Furthermore, a two-way 2 (congruency) x 2 (object feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and object feature (material, shape) on the false alarm rates of rearranged pairs. The findings revealed a significant main congruency effect on the false alarm rates of rearranged pairs, $F(1, 73) = 25.5$, $p < 0.001$, $\eta^2p = 0.26$ (Table D.5). Post hoc analysis with a Bonferroni adjustment revealed the false alarm rate of rearranged pairs in congruent conditions (*M*=0.71, *SE*=0.02) were higher than in the incongruent conditions (*M*=0.62, *SE*=0.02), mean difference = 0.09, standard error = 0.02, $p < .001$ (Table D.6).

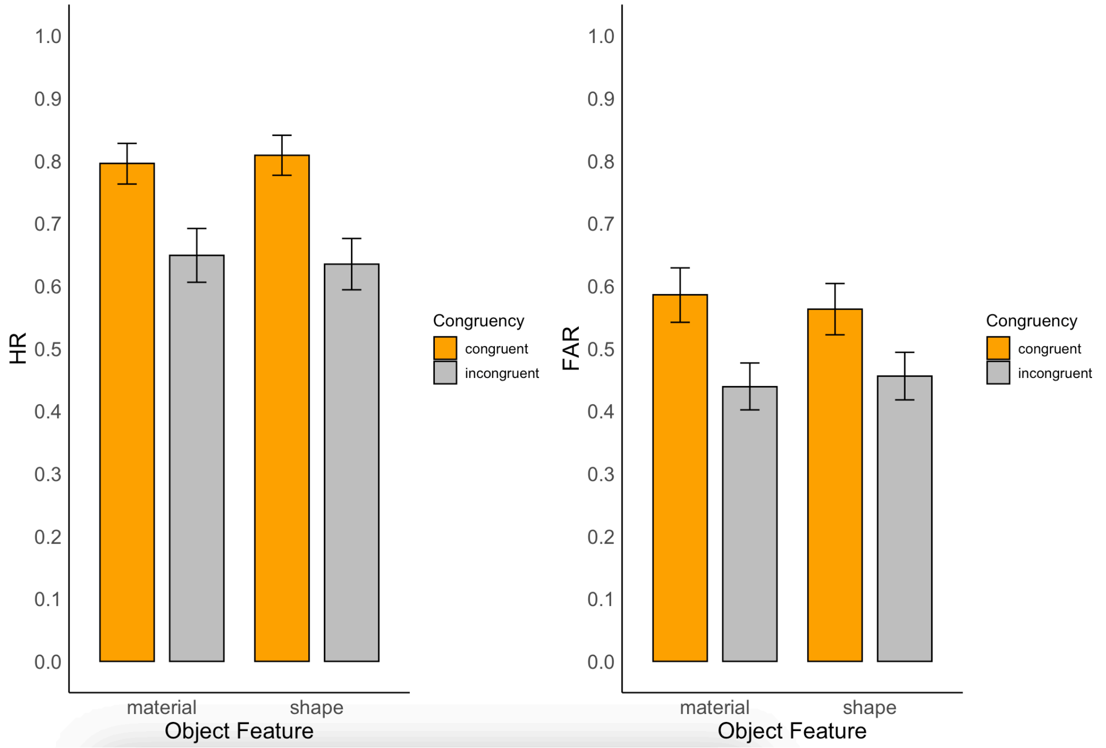

Figure 2. 7. The hit rates (HR) and false alarm rates (FAR) of four conditions (MC, SC, MI, SI) of familiar objects. The X-axis represents object features, the Y-axis represents the HRs and FARs. The yellow bars display congruent and the gray bars display incongruent conditions, and the error bars represent standard errors of the mean.

CHAPTER 3

PRELIMINARY STUDY AND EXPERIMENT 2

3.1. Preliminary Study

3.1.1. Method

Data from Experiment 1 suggest that for familiar objects, shape is an important feature in object recognition, as sensitivity scores for shape-congruent pairs were found to be remembered better than shape-incongruent pairs. This was not the case for the material feature in Experiment 1. So in Experiment 2, I used unfamiliar shapes to diminish the strong effects of familiar object shapes and tested the role of material information in unfamiliar object recognition.

Before conducting Experiment 2, an online preliminary study was carried out using Google Forms to see whether an unfamiliar object rendered with four different material categories (wood, metal, stone, glass) was, in fact, perceived as the intended materials by the participants.

3.1.2. Participants

The study was approved by the Human Studies Ethical Committee of Middle East Technical University. Thirty-one participants (18 females, 13 males) aged between 18-40 (M= 23.3, SD= 4.37) from Middle East Technical University took part in this experiment in exchange for course credit or voluntarily. Participants were native Turkish speakers with normal or corrected vision. All participants gave written informed consent after a brief outline of the study's nature, methods, and ensuring the privacy of the participants' responses before participating.

3.1.3. Materials

The experimental stimuli in this study consisted of 19 images of unfamiliar objects based on the glaven models provided by Philips (2004) under four material categories (wood, metal, glass, stone). The stimuli were generated using Blender 4.1.1, an open-source 3D computer graphics application (Blender, 2024).

The four material categories were selected from the assets of BlenderKit, an open extension of Blender that provides assets for models, materials, and scenes. The glaven model (Glaven2) was chosen from the Glaven Set provided by Philips on GitHub (2004). There were four versions of the material category of glass and stone, five versions of the material metal, and six versions of the material wood (Figure 3.1).

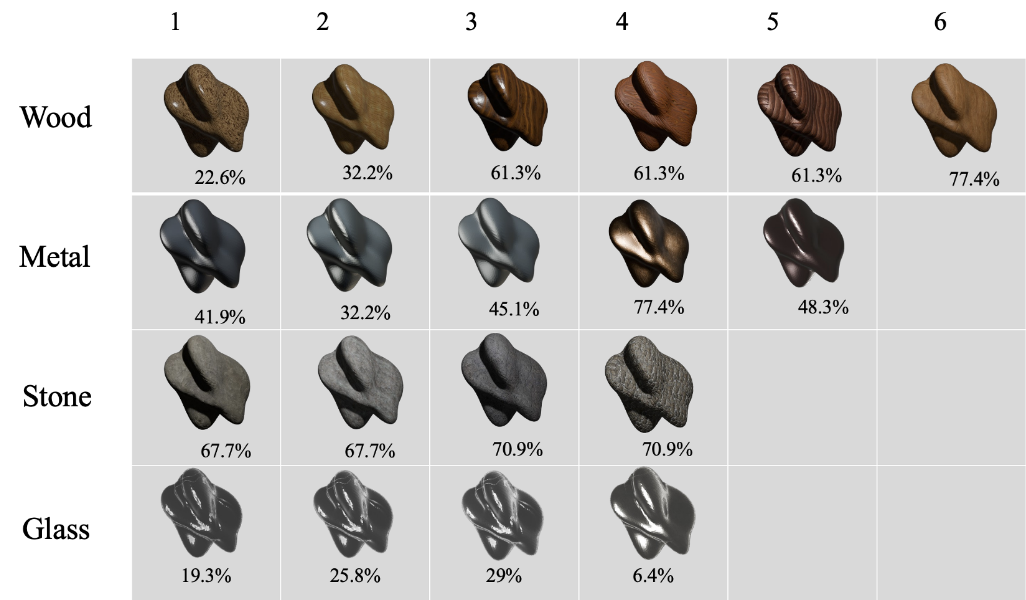

Figure 3. 1. The stimuli of the preliminary study, glaven2 rendered with different versions of four material categories with the percentage of participants correctly identifying the material category of each object.

The location of glaven2 was (0, 0, 0). The luminance properties used when rendering the four materials were selected and modeled by the eye to portray the reflectance, transparency, translucency, and texture characteristics of each material most optimally. For the glass renderings, the rectangle area light engine had a 200000-500000 W power interval; for the wood and stone renderings, the point light engine had a 200-700 W power interval; for the metal renderings, the sun light engine had a 50-200 W power interval without shadow option were used. The camera viewed the objects from the front and slightly from above with the perspective camera type and a 50 mm focal length. The objects with glass, wood, and stone materials were rendered with the EEVEE render engine with a sampling level of 16 and 64 samples per pixel. Workbench render engine with eight samples and specular reflections.

3.1.4. Procedure

This study was conducted online using Google Forms. On the top of the screen, the instructions for the task were given to the participants: "Please write down the material of the objects you will see" (Tr., “Lütfen ekranda göreceğiniz objelerin hangi malzemeden yapıldığını düşünüyorsanız yazınız”). Nineteen images of glaven2 with different versions of four material categories (wood, metal, stone, glass) were displayed for the participants to write down which materials they thought the objects were made of.

3.1.5. Results

Results revealed that for the wood material category, wood1 was correctly identified by 22.6%, wood2 was correctly identified by 32.2%, wood3 was correctly identified by 61.3%, wood4 was correctly identified by 61.3%, wood5 was correctly identified by 61.3%, and wood6 was correctly identified by 77.4% of participants (Figure 3.1, top row). Hence, wood6 and wood4 were chosen as the wood material category for the object renderings in Experiment 2. For the stone material category, stone1 was correctly identified by 67.7%, stone2 was correctly identified by 67.7%, stone3 was correctly identified by 70.9%, and stone4 was correctly identified by 70.9% of participants (Figure 3.1, second row). Hence, stone3 and stone4 were chosen as the stone material category for the object renderings in Experiment 2. For the metal material category, metal1 was correctly identified by 41.9%, metal2 was correctly identified by 32.2%, metal3 was correctly identified by 45.1%, metal4 was correctly identified by 77.4%, and metal5 was correctly identified by 48.3% of participants (Figure 3.1, third row). Thus, metal4 and metal5 were chosen as the metal material category for the object renderings in Experiment 2. Finally, for the glass material category, glass1 was correctly identified by 19.3%, glass2 was correctly identified by 25.8%, glass3 was correctly identified by 29%, and glass4 was correctly identified by 6.4% of participants (Figure 3.1, bottom row). Due to the insufficient percentage of correct identifications of the glass material, none of the versions in this study were chosen as the glass material category in the second experiment. Instead, I used an improved method to render shapes in glass for Experiment 2.

3.2. Experiment 2: Shape vs. Material of Unfamiliar Objects

The findings of Experiment 1 suggested that the material feature could be as crucial as the shape feature in familiar object memory. Prior knowledge of the familiar objects could have improved the shape recognition in Experiment 1. Therefore, I used unfamiliar objects without prior knowledge in Experiment 2. This way, only the perceptual impact of material and shape features on object memory could be observed without the semantic intrusions.

3.2.1. Method

A new group of participants completed a similar experiment to Experiment 1, this time with unfamiliar shapes. In an associative recognition task, they studied paired images of unfamiliar objects under different object features (material, shape) in congruent and incongruent conditions to investigate which factors would yield higher recognition performance.

3.2.2. Participants

The study was approved by the Human Studies Ethical Committee of Middle East Technical University. A priori G Power calculation was conducted to determine the sample size. For the experiment to have 0.95 power, 0.25 effect size, and .05 alpha level for Repeated Measures ANOVA within factors, the estimated sample size was 54 (Faul et al., 2009). Fifty-seven participants (51 females, 4 males, 2 non-binary) aged between 18-30 (*M*= 21.1, *SD*= 1.93) from Middle East Technical University took part in this experiment in exchange for course credit or voluntarily. Participants were native Turkish speakers with normal or corrected vision. All participants gave written informed consent after a brief outline of the study's nature, methods, and ensuring the privacy of the participants' responses before participating.

3.2.3. Experimental Setup

The experimental setup was the same as Experiment 1.

3.2.4. Materials

The experimental stimuli in this study consisted of 32 images of unfamiliar objects. I used four object curvature categories (glaven1, glaven4, glaven7, glaven8) based on the glaven models provided by Philips (2004) and four material categories (wood, metal, glass, stone). In every object shape and material category, there were 4 images of each object rendered with four different materials which were generated using Blender 4.1.1, an open-source 3D computer graphics application (Blender, 2024, Figure 3.2, 3.3).

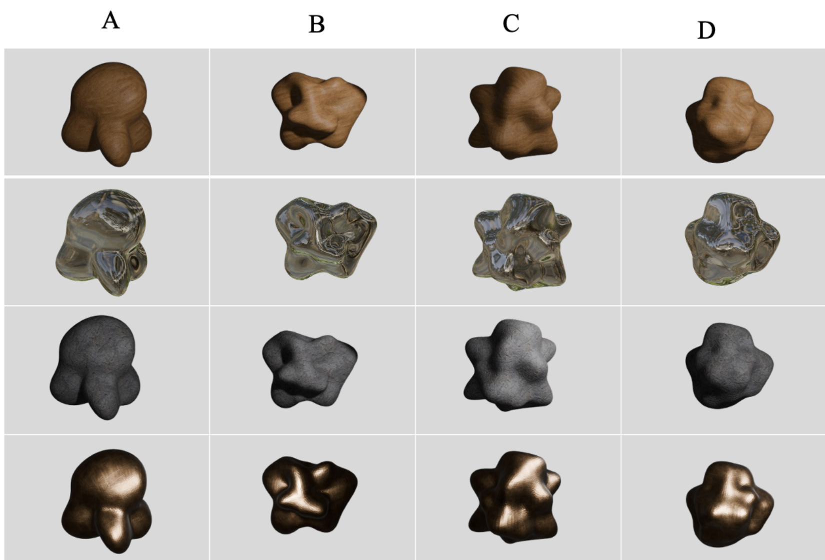

Figure 3. 2. The study list stimuli of Experiment 2, four unfamiliar objects rendered with four materials: wood glaven1, glass glaven1, stone glaven1and metal glaven1 (A); wood glaven4, glass glaven4, stone glaven4, and metal glaven4 (B); wood glaven7, glass glaven7, stone glaven7, and metal glaven7 (C); wood glaven8, glass glaven8, stone glaven8, and metal glaven8 (D).

The four materials were selected from the assets of BlenderKit, an open extension of Blender that provides assets for models, materials, scenes, etc. Also, for the glass material, a forest lane is used as an environmental map from the high dynamic range images (HDRs) of Blenderkit. The glavens were chosen from the Glaven Set provided by Philips on GitHub (2004), which were BigGlaven1, BigGlaven4, BigGlaven7, and BigGlaven8. The rotation of glaven1 was (54.8°, -9.7°, 22.6°); the rotation of the galven2, glaven7, and glaven8 were (37.2°, 3.1°, 106.9°) on the XYZ plane.

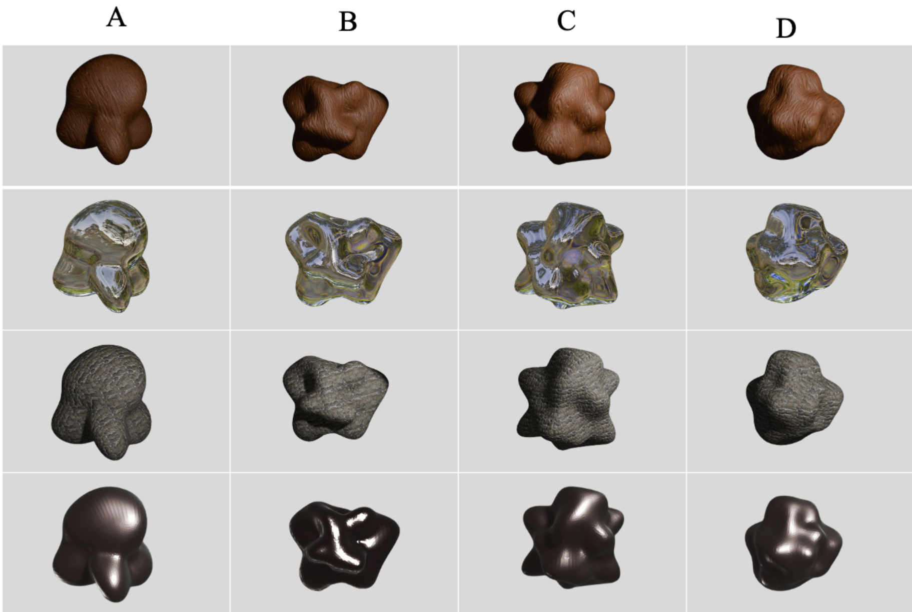

Figure 3. 3. The new unstudied experimental stimuli of Experiment 2 that did not appear on the study list and were only shown in the test list. Four unfamiliar objects rendered with four materials: wood glaven1, glass glaven1, stone glaven1, and metal glaven1 (A); wood glaven4, glass glaven4, stone glaven4, and metal glaven4 (B); wood glaven7, glass glaven7, stone glaven7, and metal glaven7 (C); wood glaven8, glass glaven8, stone glaven8, and metal glaven8 (D).

The luminance properties used when rendering the four materials were selected and modeled by the eye to portray the reflectance, transparency, translucency, and texture characteristics of each material optimally. For the glass renderings, the rectangle area light engine had a 200000- 500000 W power interval; for the wood and stone renderings, the point light engine had a 200-700 W power interval; for the metal renderings, the sunlight engine had a 50-200 W power interval (no shadow option was used). The camera viewed the objects from the front and slightly from above with the perspective camera type and a 50 mm focal length. The objects with glass, wood, and stone materials were rendered with the EEVEE render engine with a sampling level of 16 and 64 samples per pixel. The objects with metal material were rendered with the Workbench render engine with eight samples and specular reflections.

The images of unfamiliar objects were listed as pairs in an associative recognition task. There were four item conditions: in the material-congruent item condition (MC, Figure 3.4A), paired items were the images of either the same or different glavens made of the same material. In the shape-congruent item condition (SC, Figure 3.4B), paired items were images of the same glavens rendered with either identical or different materials. In material-incongruent item condition (MI, Figure 3.4C), paired items were images of either the same or different glavens made of different materials. Lastly, in shape-incongruent item condition (SI, Figure 3.4D), paired items were the images of glavens made of either the same or different material with different glaven categories.

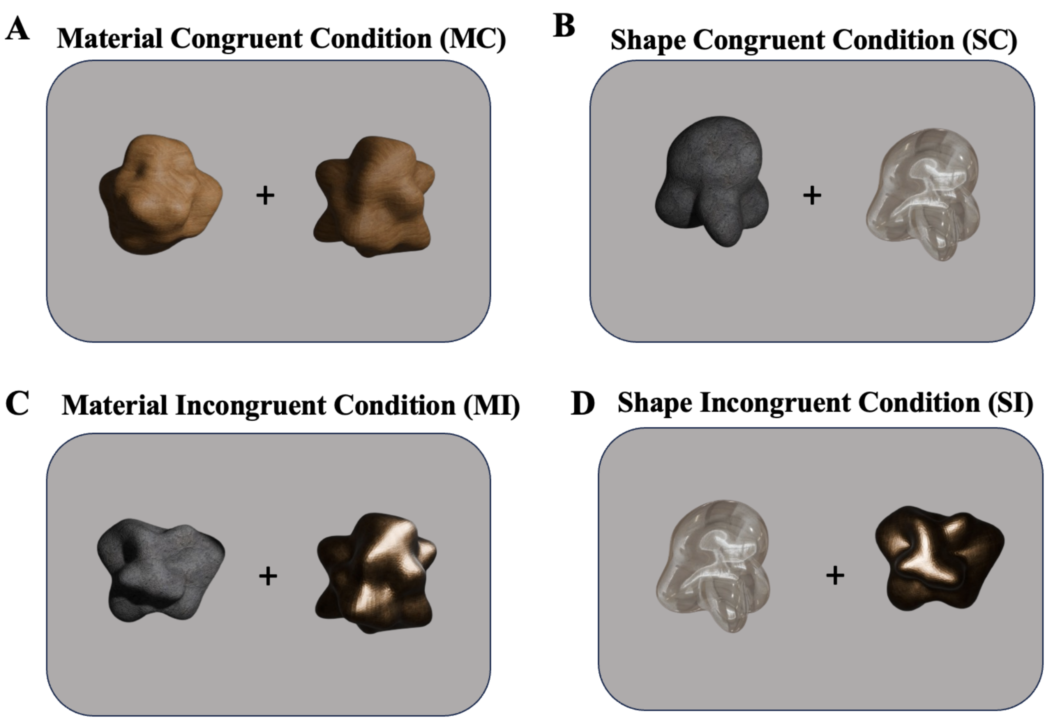

Figure 3. 4. This figure illustrates examples from the four conditions of Experiment 2 in the associative recognition task.

3.2.5. Procedure

Experiment 2 followed an identical procedure to the first experiment (Figure 3.5).

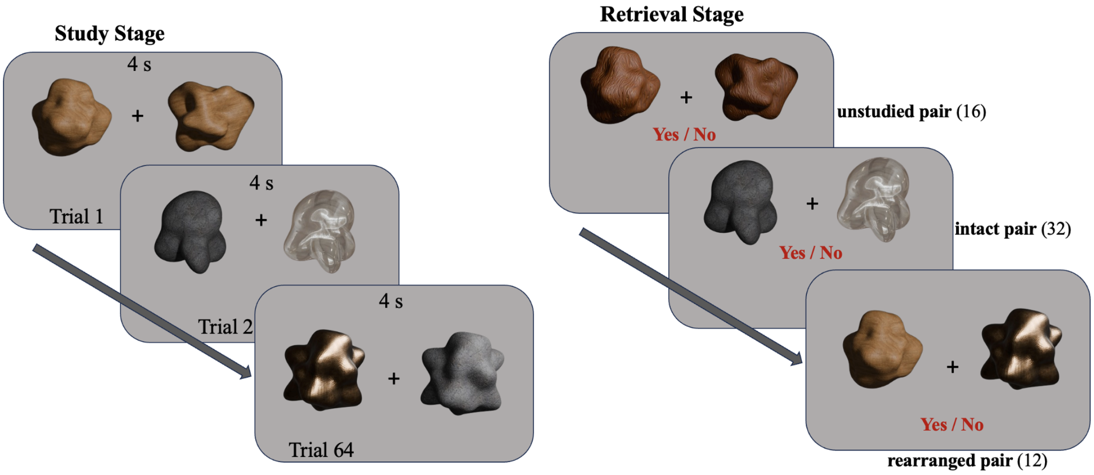

Figure 3. 5. The experimental procedure of the study stage and the retrieval stage of Experiment 2.

3.2.6. Results

A Phyton code was written to organize the data (Visual Studio Code version 1.91, 2024) using the SciPy package. Each participant's hit rate for intact pairs in every four conditions (MC, SC, MI, SI) and false alarm rate for rearranged and new pairs in every four conditions (MC, SC, MI, SI) were calculated. Hence, the sensitivity *d′* scores of every four conditions (MC, SC, MI, SI) for each participant were computed by subtracting z-scores of the false alarm rate from the hit rate (MacMillan & Creeman, 1991). Inferential statistics were run in JASP (JASP Team, 2024) and figures were drawn in R (R Core Team, 2021).

A one-sample t-test was conducted to examine the response bias of participants on associative recognition of unfamiliar objects. The normality assumption was not violated; the Shapiro-Wilk test indicated that differences between participants were normally distributed, $W(57)= 0.98$, $p= 0.32$. The findings revealed a significant main effect of response bias (M=-0.36, SD=0.35) between participants, $t(56)= -7.8$, $p< 0.001$, $d= -1.03$, which means that participants had a liberal bias in Experiment 2.

A two-way 2 (congruency) x 2 (object feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and object feature (material, shape) on the d-prime scores. The findings revealed a significant main congruency effect on associative recognition memory of unfamiliar objects, $F(1, 56) = 70.7, p < 0.001, \eta^2 p = 0.55$ (Table 3.1). There was a significant main effect of the object feature on associative recognition of unfamiliar objects, $F(1, 56) = 6.36, p = 0.01, \eta^2 p = 0.1$, mean difference = -0.024, standard error = 0.009, 95% *CI* [0.005, 0.4], $p = 0.015$. Post hoc analysis with a Bonferroni adjustment revealed the sensitivity *d'* score of the material feature (M=1.25, SE=0.06) was ever so slightly but significantly higher than the shape feature (M=1.23, SE=0.06), which might mean that the material feature of unfamiliar objects affects the associative recognition memory more significantly than the shape. There was no significant interaction effect between congruency and object feature on recognition sensitivity scores of unfamiliar objects, $F(1, 56) = 1.92, p = 0.2, \eta^2 p = 0.2$. This means that the effect of congruency was similar for the material and the shape of the object (Figure 3.7).

Table 3. 1. Repeated Measures ANOVA for Experiment 2

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object feature	0.0319	1	0.03190	6.36	0.015	0.102
Residual	0.2807	56	0.00501			
Congruency	18.0022	1	18.00218	70.77	< .001	0.558
Residual	14.2445	56	0.25437			
Surface feature ∗ Congruency	0.3470	1	0.34700	1.62	0.209	0.028
Residual	12.0203	56	0.21465			

Table 3. 2. Mean of Hit Rates, False Alarm Rates and Sensitivity d' Scores of Conditions in Experiment 2

	MC	MI	SC	SI
HR	0.85	0.75	0.88	0.73

Table 3.2. (continued)

FAR-unstudied	0.12	0.15	0.21	0.06
FAR-rearranged	0.78	0.76	0.80	0.75
FAR-total	0.34	0.45	0.40	0.40
Sensitivity d’	1.57	0.93	1.47	0.99

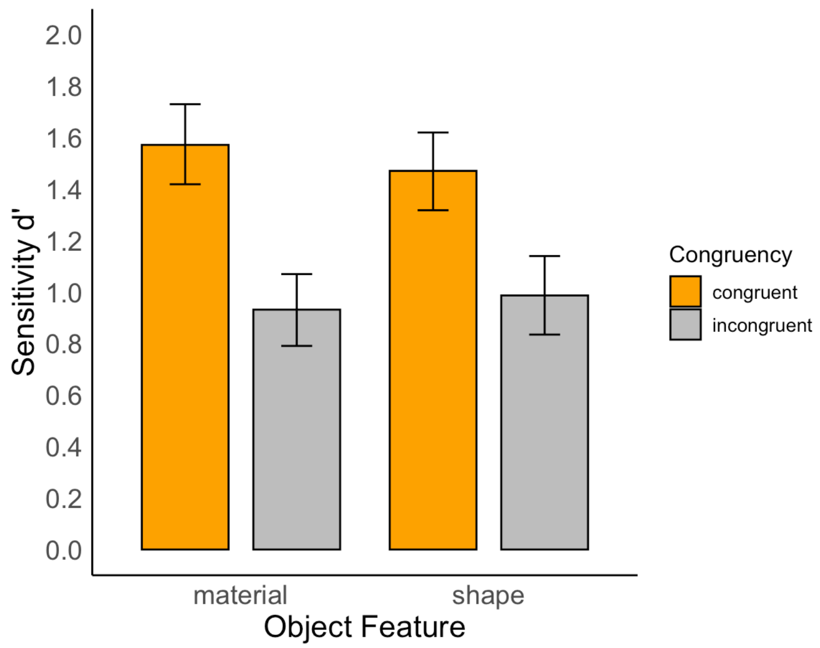

Figure 3. 6. The recognition sensitivity of four conditions (MC, SC, MI, SI) with unfamiliar objects. The X-axis represents object features, the Y-axis represents the sensitivity d’ scores. The yellow bars display congruent and the gray bars display incongruent conditions, and the error bars represent standard errors of the mean.

Post hoc analysis with a Bonferroni adjustment revealed the recognition sensitivity d' score of material congruent condition (M=1.57, SD=0.58) was higher than the material incongruent condition (M=0.93, SD=0.53), mean difference = 0.64, standard error = 0.08, 95% CI [0.39, 0.88], $p < .001$. And the recognition sensitivity d' score of the shape congruent (M=1.47, SD=0.57) condition was higher than the shape incongruent (M=0.98, SD=0.57) condition, mean difference = 0.48, standard error = 0.09, 95% CI [0.23, 0.73], $p < .001$. This means that both the material and shape congruent pairs were better recognized than incongruent pairs in the associative recognition of unfamiliar objects, mean difference = 0.2, standard error = 0.009, 95% *CI* [0.005, 0.042], $p < .001$ (Figure 3.6).

To further examine the effect of material of unfamiliar objects on associative recognition memory in more detail, a one-way repeated measures ANOVA with four levels for material (wood, stone, glass, metal) was performed as a post hoc test. The sphericity assumption was not violated, $\chi 2(5) = 4.3$, $p = 0.5$. The findings revealed a significant material effect on associative recognition of unfamiliar objects, $F(3, 56) = 12.7$, $p < 0.001$, $\eta^2 p = 0.18$. A post hoc analysis with a Bonferroni adjustment revealed that the material congruent pairs rendered as glass material (M=1.49, SD=0.54) were better recognized than the metal (M=1.14, SD=0.61, mean difference = 0.35, standard error = 0.01, 95% *CI* [0.09, 0.61], $p < 0.004$), the stone (M=0.94, SD=0.58, mean difference = 0.54, standard error = 0.01, 95% *CI* [0.28, 0.81], $p < 0.001$), and the wood (M=1.02, SD=0.63, mean difference = 0.47, standard error = 0.09, 95% *CI* [0.23, 0.72], $p < 0.001$) materials (Figure 3.8). Differences between the remaining materials remained below the significance threshold.

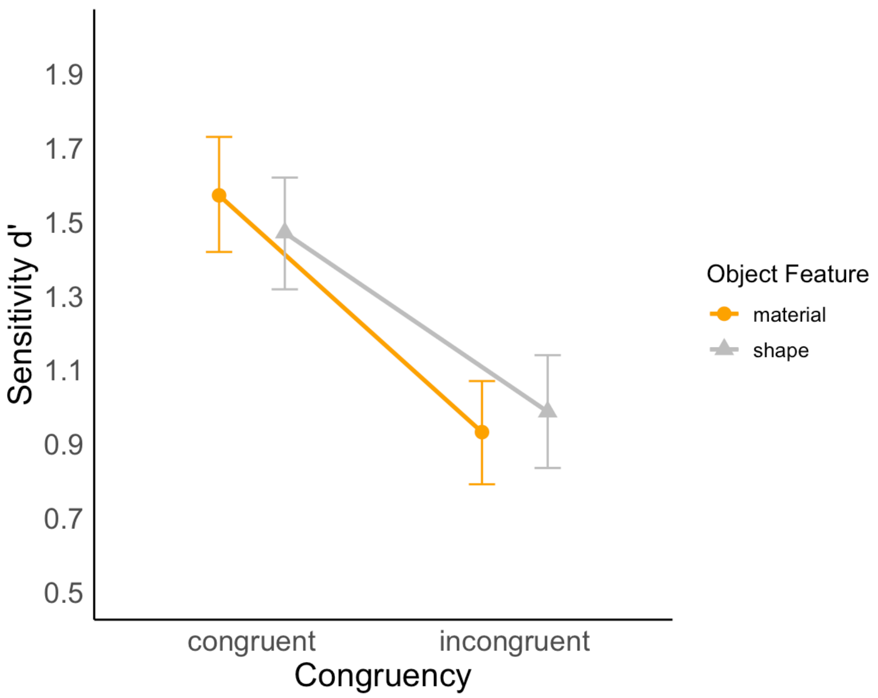

Figure 3. 7. The recognition sensitivity of four conditions (MC, SC, MI, SI) of unfamiliar objects. The X-axis represents congruency, the Y-axis represents the

sensitivity d’ scores. The yellow line displays material and the gray line displays shape conditions, and the error bars represent standard errors of the mean.

Experiments 1 and 2 were identical, except that instead of using familiar objects in Experiment 1, unfamiliar objects were used in Experiment 2. And by this experimental manipulation, *d′* sensitivity score of the material congruent condition improved from 0.70 to 1.57 in Experiment 2. The *d*' sensitivity score of the shape congruent condition enhanced from 0.79 to 1.47. The *d*' sensitivity score of the material incongruent condition increased from 0.59 to 0.93. The *d*' sensitivity score of the shape incongruent condition increased from 0.50 to 0.99 in Experiment 2 (Table 3.3). Hence, while there was no significant difference between the material and shape features on associative object recognition in Experiment 1, the material feature of objects was better recognized than the shape in Experiment 2. Indicating a material superiority effect on the associative recognition of unfamiliar objects (Figure 3.9).

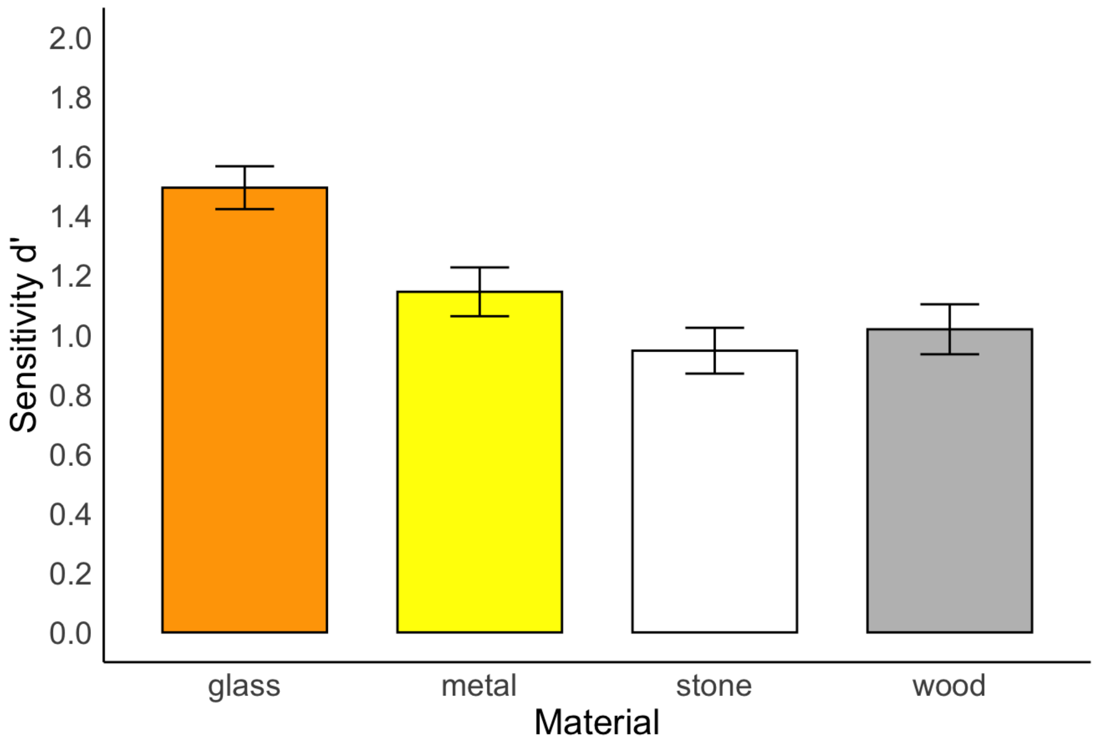

Figure 3. 8. The recognition sensitivity of material congruent pairs with glass, metal, stone, and wood materials. The X-axis represents the four materials, the Y-axis represents the sensitivity d’ scores, and the error bars represent standard errors of the mean.

Table 3. 3. Mean Sensitivity d' Scores of Conditions in Experiment 1 and 2

	MC	MI	SC	SI
Sensitivity d' Experiment 1	0.70	0.59	0.79	0.50
Sensitivity d' Experiment 2	1.57	0.93	1.47	0.99

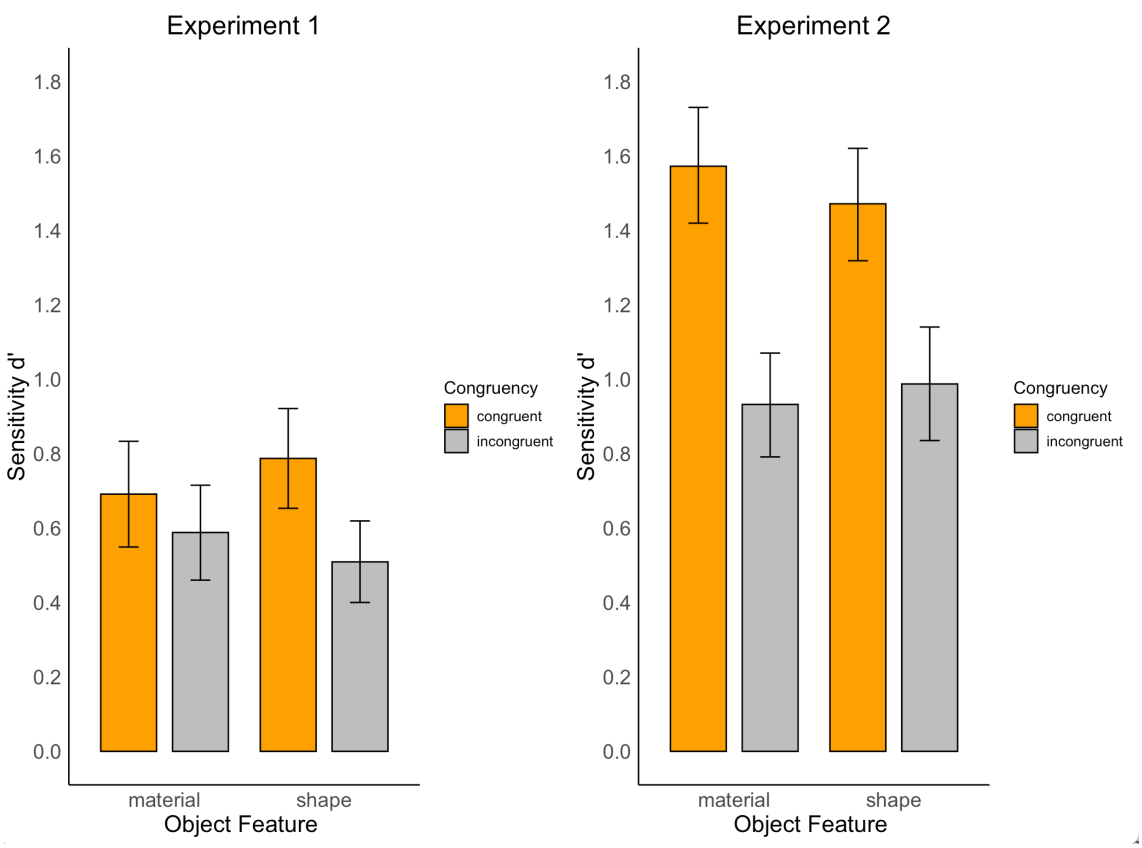

Figure 3. 9. Sensitivity scores of four conditions (MC, SC, MI, SI) of Experiment 1 and 2. The X-axis represents object features, the Y-axis represents the sensitivity d' scores. The yellow bars display congruent and the gray bars display incongruent conditions, and the error bars represent standard errors of the mean.

A two-way 2 (congruency) x 2 (object feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and object feature (material, shape) on the hit rates of unfamiliar objects. The findings revealed a significant main congruency effect on the hit rates of unfamiliar objects, $F(1, 56) = 32$, $p < 0.001$, $\eta^2 p = 0.36$ (Table E.1). There was no significant main effect of the object feature on the hit rates of unfamiliar objects, $F(1, 56) = -2.835 \times 10\text{-}14$, $p = 1$, $\eta^2 p = -5.063 \times 10\text{-}16$. Meaning that both the material and the shape features of unfamiliar objects affect the hit rates equally. There was no significant interaction effect between congruency and object feature on the hit rates of unfamiliar objects, $F(1, 56) = 1.45$, $p = 0.23$, $\eta^2 p = 0.02$. This means that the effect of congruency on hit rates was similar for the material and the shape of the object (Figure 3.10). Post hoc analysis with a Bonferroni adjustment revealed the hit rate of congruent conditions (M=0.86, SE=0.01) were higher than the incongruent conditions (M=0.74, SE=0.03), mean difference = 0.11, standard error = 0.02, $p < .001$ (Table E.2).

A two-way 2 (congruency) x 2 (object feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and object feature (material, shape) on the false alarm rates of unfamiliar objects. The findings revealed a significant main congruency effect on the false alarm rates of unfamiliar objects, $F(1, 56) = 13.65$, $p < 0.001$, $\eta^2 p = 0.2$ (Table E.3). Post hoc analysis with a Bonferroni adjustment revealed the false alarm rate of incongruent conditions (M=0.43, SE=0.014) were higher than the congruent conditions (M=0.37, SE=0.016), mean difference = 0.06, standard error = 0.01, $p < .001$ (Table E.5). There was a significant main effect of the object feature on the false alarm rates of unfamiliar objects, $F(1, 56) = 15.36$, $p < 0.001$, $\eta^2 p = 0.21$. Post hoc analysis with a Bonferroni adjustment revealed the false alarm rate of shape conditions (M=0.41, SE=0.013) was higher than the material conditions (M=0.40, SE=0.013), mean difference = 0.007, standard error = 0.002, $p < .001$ (Table E.4). There was a significant interaction effect between congruency and object feature on the false alarm rates of unfamiliar objects, $F(1, 56) = 15.36$, $p < 0.001$, $\eta^2 p = 0.21$. The false alarm rate of the material incongruent (M=0.45, SE=0.014) condition was higher than the material congruent condition (M=0.34, SE=0.018), mean difference = 0.11, standard error = 0.02, $p < .001$. The false alarm rate of the shape congruent (M=0.40, SE=0.018) condition was higher than the material congruent condition (M=0.34, SE=0.018), mean difference = 0.06, standard error = 0.015, $p = .001$. The false alarm rate of the material incongruent (M=0.45, SE=0.014) condition was higher than the shape incongruent condition (M=0.41, SE=0.015), mean difference = 0.04, standard error = 0.011, p = .001 (Figure 3.10).

Furthermore, a two-way 2 (congruency) x 2 (object feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and object feature (material, shape) on the false alarm rates of rearranged pairs. The findings revealed a significant main congruency effect on the false alarm rates of rearranged pairs, $F(1, 56) = 4.04$, $p = 0.049$, $\eta^2 p = 0.07$ (Table E.9). Post hoc analysis with a Bonferroni adjustment revealed the false alarm rate of rearranged pairs in congruent conditions (M=0.79, SE=0.024) were higher than in the incongruent conditions (M=0.75, SE=0.026), mean difference = 0.03, standard error = 0.016, p = 0.049 (Table E.10).

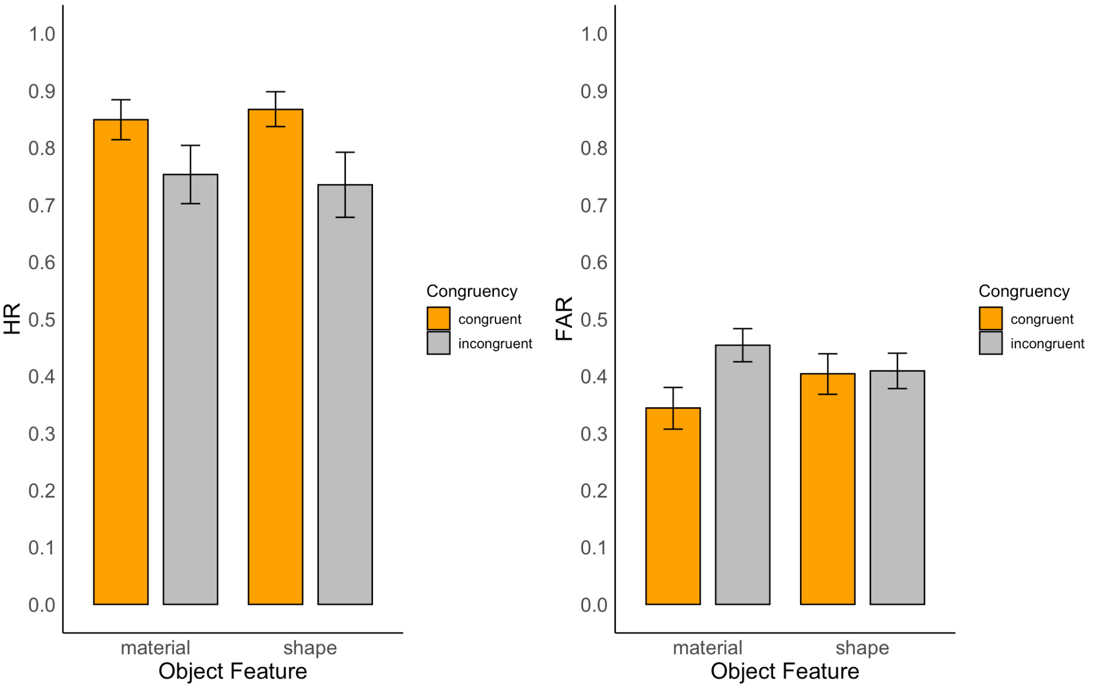

Figure 3. 10. The hit rates (HR) and false alarm rates (FAR) of four conditions (MC, SC, MI, SI) of unfamiliar objects. The X-axis represents object features, the Y-axis represents the HRs and FARs. The yellow bars display congruent and the gray bars display incongruent conditions, and the error bars represent standard errors of the mean.

CHAPTER 4

EXPERIMENT 3

4.1. Experiment 3: Texture vs. Material of Unfamiliar Objects

The findings of the second experiment revealed that the material feature was as effective as the shape in facilitating unfamiliar object memory. When the objects were unfamiliar and evoked no prior knowledge, the material of objects was more reliable than the shape. Also, the glass material was remembered better than all other materials in Experiment 2. The salient material attributes of the glass, such as glossiness and texture, could have improved its memory. Therefore, I added three more material texture classes (copper, plastic, jelly) and manipulated their reflectance characteristics (matte, glossy) in the next experiment. In Experiment 3, by keeping the geometry of objects constant across all conditions, I eliminated shape-based object recognition with a goal to isolate the role of material in object memory under varying surface reflectance conditions.

4.1.1. Metod

In the third experiment, the same procedure was used with a single unfamiliar shape and with seven texture and two reflectance categories. Participants completed an associative recognition task where they studied paired images of unfamiliar objects under different surface features (texture, reflectance) in congruent and incongruent conditions to investigate which conditions would have higher recognition rates.

4.1.2. Participants

The study was approved by the Human Studies Ethical Committee of Middle East Technical University. A priori G Power calculation was conducted to determine the sample size. For the experiment to have 0.95 power, 0.25 effect size, and .05 alpha level for two-way Repeated Measures ANOVA within factors, the estimated sample size was 54 (Faul et al., 2009). Fifty-seven participants (44 females, 12 males, 1 non-binary) aged between 19-29 (*M*= 22.5, *SD*= 2.17) from Middle East Technical University took part in this experiment in exchange for course credit or voluntarily. Participants were native Turkish speakers with normal or corrected vision. All participants gave written informed consent after a brief outline of the study's nature, methods, and ensuring the privacy of the participants' responses before participating.

4.1.3. Experimental Setup

The experimental setup was the same as Experiment 1 and 2.

4.1.4. Materials

The experimental stimuli in this study consisted of 28 images of one unfamiliar object based on the glaven models provided by Philips (2004) under two surface reflectance categories (glossy, matte) and seven material texture categories (wood, metal, glass, stone, plastic, copper, jelly). In other words, there were 2 images of one unfamiliar object rendered with seven different materials and two different reflectance features that were generated using Blender 4.1.1, an open-source 3D computer graphics application (Blender, 2024; Figure 4.1).

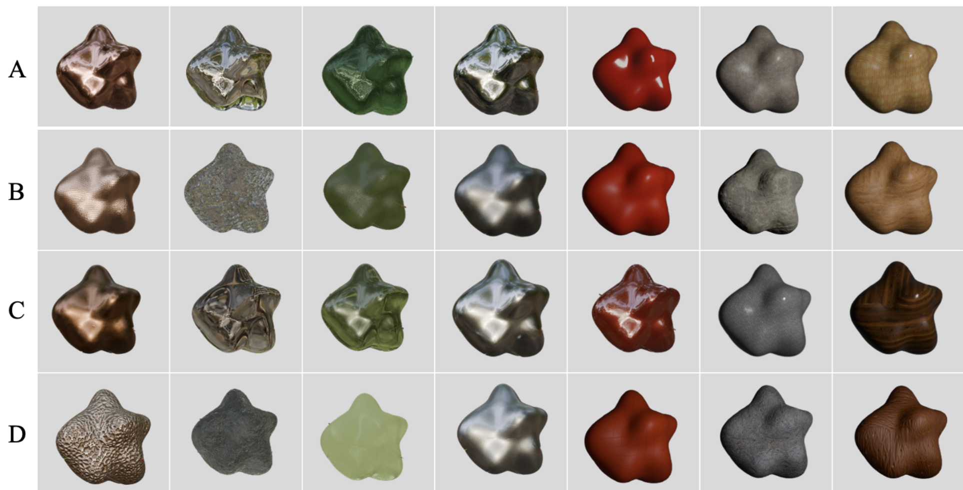

Figure 4. 1. The stimuli of Experiment 3, one unfamiliar object rendered with seven texture categories, and two reflectance features. The glossy-copper, glossy-glass,

glossy-jelly, glossy-metal, glossy-plastic, glossy-stone, glossy-wood glaven3 (A, C); matte-copper, matte-glass, matte-jelly, matte-metal, matte-plastic, matte-stone, matte-wood glaven3 (B, D). The study list stimuli (A, B), and the new unstudied stimuli that did not appear on the study list and was only shown in the test list (C, D) are displayed.

The seven material textures with glossy and matte reflectance features were selected from the assets of BlenderKit, an open extension of Blender that provides assets for models, materials, scenes, etc. Also, for the glossy glass, metal, and copper materials, a forest lane is used as an environmental map from the HDRs of Blenderkit. The selected glaven was chosen from the Glaven Set provided by Philips on GitHub (2004), which was the BigGlaven3. The rotation of glaven3 was (1.4°, -4.8°, -589.4°), and the location of glaven3 was (5.4m, 0.2m, 22.6m) on the XYZ plane. The luminance properties used when rendering the four materials were selected and modeled by the eye to portray the reflectance, transparency, translucency, and texture characteristics of each material most optimally. For the glass and jelly renderings, the rectangle area light engine had a 200000- 500000 W power interval; for the wood, stone, and plastic renderings, the point light engine had a 200-700 W power interval; for the metal and copper renderings, the sun light engine had a 50-200 W power interval (no shadow option was used). The camera viewed the objects from the front and slightly from above with the perspective camera type and a 50 mm focal length. The objects with glass, jelly, wood, plastic, and stone materials were rendered with the EEVEE render engine with a sampling level of 16 and 64 samples per pixel. The objects with metal and copper material were rendered with the Workbench render engine with eight samples and specular reflections.

The images of unfamiliar objects were listed as pairs in an associative recognition task. There was a total of four item conditions: in the texture congruent item condition (TC, Figure 4.2A), paired items were the images of glaven3 either with the same or different reflectance but made of the same texture category. In the reflectance congruent item condition (RC, Figure 4.2B), paired items were the images of glaven3 either with the same or different textures but made of the same reflectance category. In texture incongruent item condition (TI, Figure 4.2C), paired items were the images of glaven3 either with the same or different reflectance but made of different textures. Lastly, in reflectance incongruent item condition (RI, Figure 4.2D), paired items were the images of glaven3 made of either the same or different textures but with different reflectance categories.

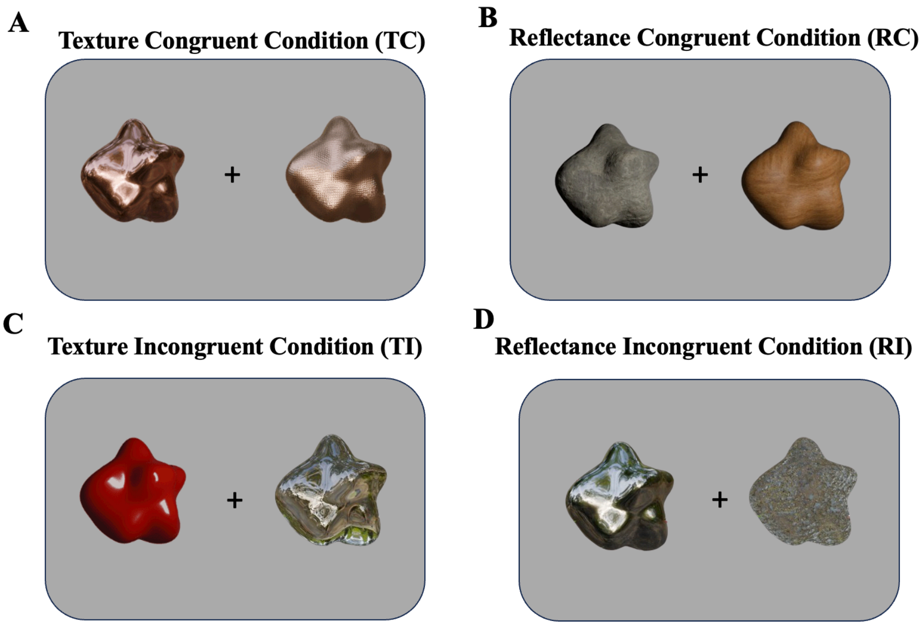

Figure 4. 2. This figure illustrates examples from the four conditions of Experiment 3 in the associative recognition task.

4.1.5. Procedure

Before the experiment started, the experimenter instructed the participants about the experiment, explaining every stage in the study in detail using instruction slides with visuals. After the instructions, the experimenter left the room, and the experiment started. Instructions were also provided on screen for the participants to read between each stage during the experiment.

In the study stage of Experiment 3, participants were shown a study list containing 7 pairs for every four conditions (TC, RC, TI, RI). A total of 28 pairs were randomly presented for 4 seconds and a four-second inter-stimulus interval prior to the presentation of the next pair. Participants were instructed to study these pairs in the study list for a later memory test. The study stage was followed by the distraction stage, which included a distractor task in which participants completed addition and subtraction calculations in a random order for two minutes. Immediately after the distractor stage, the retrieval stage took place with an associative recognition task, where participants were shown a test list containing pairs for every four conditions (TC, RC, TI, RI). A total of 55 pairs were shown, containing 28 intact pairs that were in the study list and 19 new, unstudied pairs that were not in the study list (Figure 4.1). Material and shape combinations of the objects in the unstudied pairs were shown for the first time in the retreival stage. Also, there were 8 rearranged pairs consisting of objects that were in the study list but belonged to different pairs and were rearranged in the retrieval stage. Participants were required to press the key "e" on the keyboard if they had recognized the pair from the study list or "h" if they had not recognized the pair from the study list with no time limit. This study used a within-subject design with an associative recognition task, and all responses were collected using a keyboard (Figure 4.3).

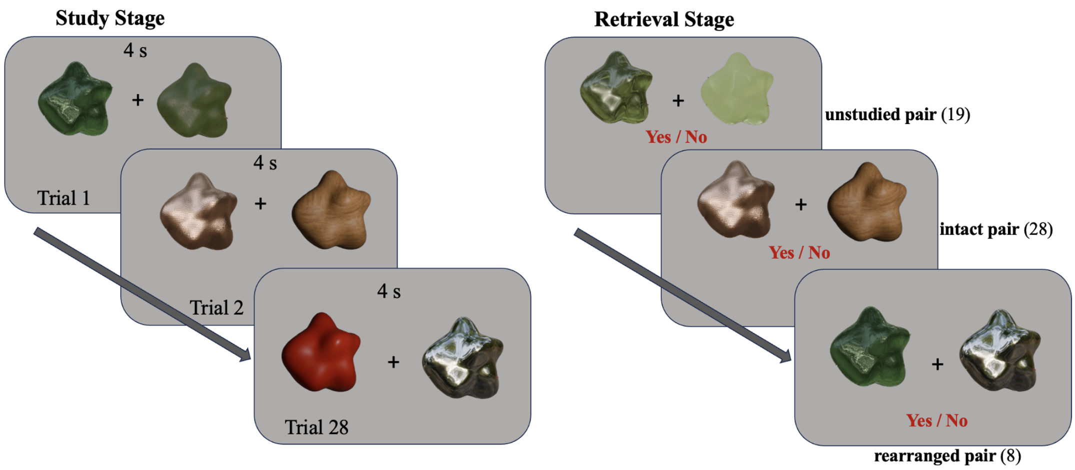

Figure 4. 3. The experimental procedure of the study stage and the retrieval stage of Experiment 3.

4.1.6. Results

A Phyton code was written to organize the data (Visual Studio Code version 1.91, 2024) using the SciPy package. Each participant's hit rate for intact pairs in every four conditions (TC, RC, TI, RI) and false alarm rate for rearranged and new pairs in every four conditions (TC, RC, TI, RI) were calculated. Hence, the sensitivity d' scores of every four conditions (TC, RC, TI, RI) for each participant were computed by subtracting z-scores of false alarm rate from the hit rate (MacMillan & Creeman, 1991). Inferential statistics were run in JASP (JASP Team, 2024) and figures were drawn in R (R Core Team, 2021).

A one-sample t-test was conducted to examine the response bias of participants on associative recognition of unfamiliar objects. The normality assumption was not violated; the Shapiro-Wilk test indicated that differences between participants were normally distributed, $W(57)= 0.96$, $p= 0.07$. The findings revealed a significant main effect of response bias (M=-0.3, SD=0.3) between participants, $t(56)= -7.05$, $p< 0.001$, $d= -0.93$, which means that participants had a liberal bias in Experiment 3.

A two-way 2 (congruency) x 2 (surface feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and surface feature (texture, reflectance) on the d-prime scores. The findings revealed a significant main congruency effect on associative recognition memory of unfamiliar objects, $F(1, 56) = 62.7$, $p < 0.001$, $\eta^2 p = 0.52$ (Table 4.1). Post hoc analysis with a Bonferroni adjustment revealed the recognition sensitivity d' score of texture congruent condition (M=1.66, SD=0.6) was higher than the texture incongruent condition (M=1.02, SD=0.45), mean difference = 0.64, standard error = 0.09, 95% *CI* [0.39, 0.89], $p < .001$. And the recognition sensitivity d' score of the reflectance congruent (M=1.43, SD=0.54) condition was higher than the reflectance incongruent (M=1.14, SD=0.46) condition, mean difference = 0.3, standard error = 0.09, 95% *CI* [0.06, 0.54], $p = .007$. This means that both the texture and reflectance feature congruent pairs were better recognized than incongruent pairs in the associative recognition of unfamiliar objects, mean difference = 0.47, standard error = 0.06, 95% *CI* [0.35, 0.59], $p < .001$ (Figure 4.4).

Table 4. 1. Repeated Measures ANOVA for Experiment 3

	Sum of Squares	df	Mean Square	F	p	η^2_p
Surface feature	0.190	1	0.190	15.087	< .001	0.212
Residuals	0.706	56	0.013			
Congruency	12.591	1	12.591	62.760	< .001	0.528

Table 4.1. (continued)

Residuals	11.235	56	0.201			
Surface feature * Congruency	1.692	1	1.692	6.747	0.012	0.108
Residuals	14.045	56	0.251			

Table 4. 2. Mean of Hit Rates, False Alarm Rates and Sensitivity d' Scores of Conditions in Experiment 3

	TC	TI	RC	RI
HR	0.83	0.77	0.82	0.77
FAR-unstudied	0.29	0.21	0.23	0.28
FAR-rearrange	-	0.64	0.60	0.67
FAR-total	0.29	0.43	0.35	0.38
Sensitivity d'	1.67	1.02	1.43	1.14

There was a significant main effect of the surface feature on associative recognition of unfamiliar objects, $F(1, 56) = 15, p < 0.001, \eta^2p = 0.2$, mean difference = 0.06, standard error = 0.01, 95% *CI* [0.03, 0.09], $p < 0.001$. According to post hoc analysis with a Bonferroni adjustment, the sensitivity *d'* score of the texture feature (*M*=1.34, *SE*=0.05) was significantly higher than the reflectance feature (*M*=1.28, *SE*=0.05); the recognition sensitivity *d'* score of texture congruent condition (*M*=1.66, *SD*=0.6) was higher than the reflectance congruent condition (*M*=1.43, *SD*=0.54), mean difference = 0.23, standard error = 0.07, 95% *CI* [0.02, 0.44], $p = .02$. This means that the texture feature of unfamiliar objects effects the associative recognition memory more significantly than the reflectance feature of unfamiliar objects. There was a significant interaction effect between congruency and surface feature on associative recognition of unfamiliar objects, $F(1, 56) = 1.92, p = 0.01, \eta^2p = 0.1$. This means that the effect of congruency on associative object recognition was more effective for the material texture compared to the reflectance feature of the unfamiliar object (Figure 4.5).

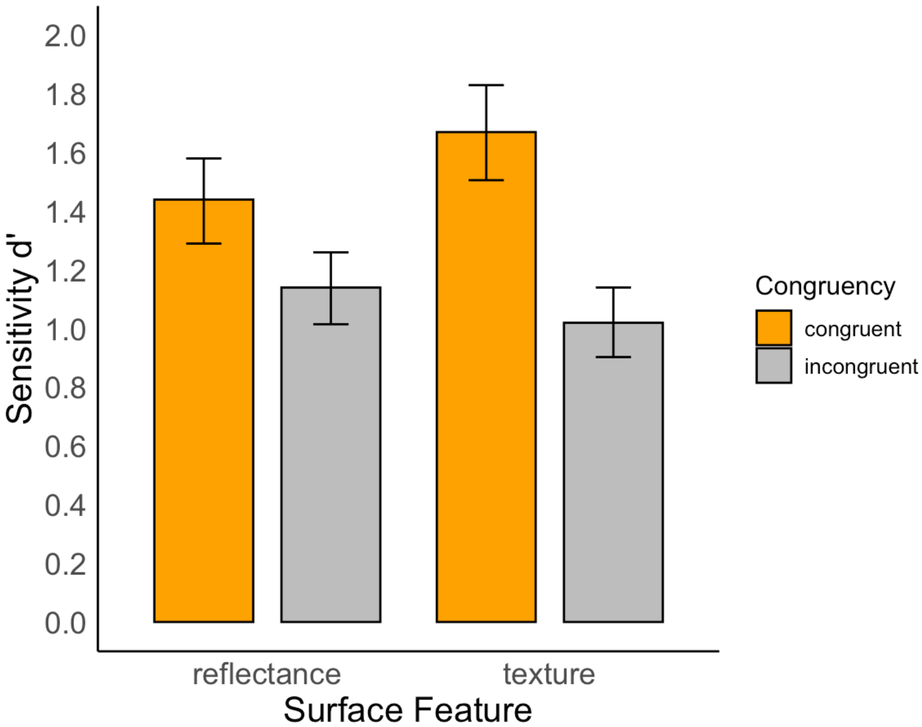

Figure 4. 4. The recognition sensitivity of four conditions (TC, RC, TI, RI) of unfamiliar objects. The X-axis represents surface features, the Y-axis represents the sensitivity d' scores. The yellow bars display congruent and the gray bars display incongruent conditions, and the error bars represent standard errors of the mean.

To further examine the effect of texture of unfamiliar objects on associative recognition memory in more detail, a one-way repeated measures ANOVA with seven levels for material texture (wood, stone, glass, metal, plastic, jelly, copper) was performed as a post-test. The sphericity assumption was violated, which was significant, $\chi 2(20) = 33$, $p = .03$; thus, the degrees of freedom were corrected using the Greenhouse-Geisser correction, $\varepsilon = 0.85$. The findings with Greenhouse-Geisser correction revealed a significant material effect on associative recognition of unfamiliar objects, $F(5, 56) = 14.7$, $p < 0.001$, $\eta^2 p = 0.2$. Post hoc analysis with a Bonferroni adjustment revealed that the congruent pairs rendered as wood (M=0.92, SD=0.52) were better recognized than the metal (M=0.53, SD=0.3, mean difference = -0.4, standard error = 0.08, 95% CI [-0.6, -0.1], $p < 0.001$), the stone (M=0.4, SD=0.4, mean difference = -0.5, standard error = 0.08, 95% CI [-0.8, -0.21], p <

0.001), the copper (*M*=0.5, *SD*=0.5, mean difference = -0.43, standard error = 0.09, 95% *CI* [-0.7, -0.2], $p < 0.001$), and the plastic (*M*=0.5, *SD*=0.3, mean difference = -0.4, standard error = 0.07, 95% *CI* [-0.6, -0.17], $p < 0.001$) material textures.

Also, the congruent pairs rendered as jelly (*M*=0.95, *SD*=0.5) were better recognized than the metal (*M*=0.53, *SD*=0.3, mean difference = -0.42, standard error = 0.07, 95% *CI* [-0.7, -0.2], $p < 0.001$), the stone (*M*=0.4, *SD*=0.4, mean difference = -0.54, standard error = 0.09, 95% *CI*[-0.8, -0.2], $p < 0.001$), the copper (*M*=0.5, *SD*=0.5, mean difference = -0.47, standard error = 0.01, 95% *CI* [-0.8, -0.2], $p < 0.001$), and the plastic (*M*=0.5, *SD*=0.3, mean difference = 0.47, standard error = 0.07, 95% *CI* [-0.7, -0.2], $p < 0.001$) textures.

Furthermore, the congruent pairs rendered as glass (*M*=0.7, *SD*=0.5) were better recognized than the stone material (*M*=0.4, *SD*=0.4, mean difference = 0.3, standard error = 0.08, 95% *CI* [0.01, 0.5], $p = 0.035$, Figure 4.6).

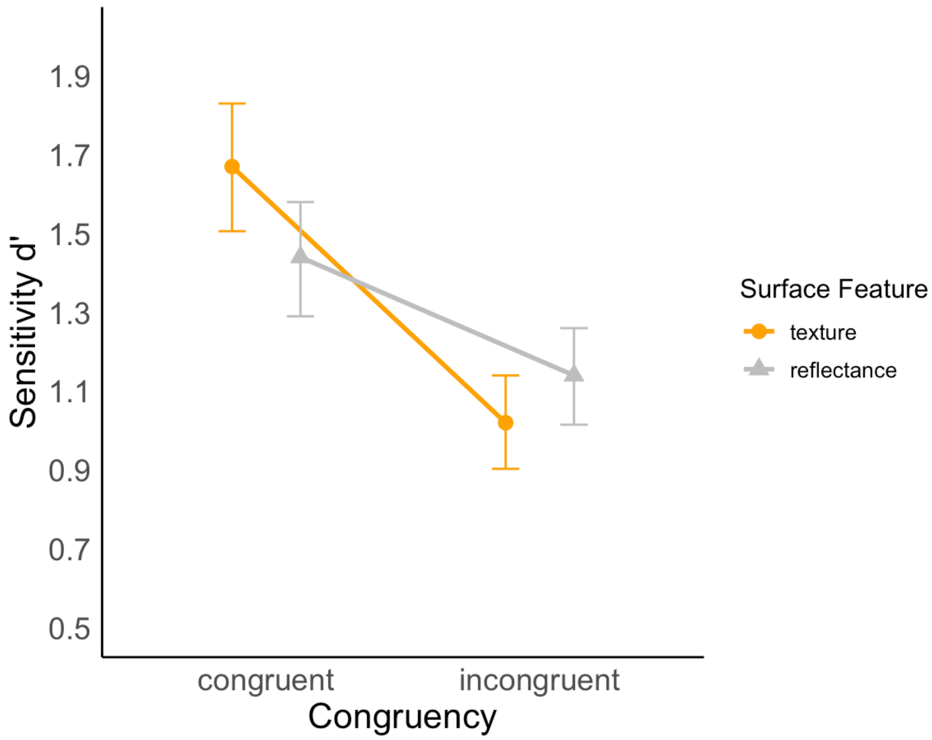

Figure 4. 5. The recognition sensitivity of four conditions (TC, RC, TI, RI) of unfamiliar objects. The X-axis represents congruency, the Y-axis represents the sensitivity d' scores. The yellow line displays texture and the gray line displays reflectance conditions, and the error bars represent standard errors of the mean.

To further examine the reflectancy effect of unfamiliar objects on associative recognition memory in more detail, a paired samples t-test with two levels (glossy, matte) was performed as a post-test. The normality assumption was not violated; the Shapiro-Wilk test indicated that differences between conditions were normally distributed, $W(57)= 0.1$, $p= 0.23$. Post t-test with a Bonferroni adjustment revealed that reflectance had a significant effect on the associative recognition of unfamiliar objects, $t(56)= 2.11$, $p= 0.039$, with a small effect size ($d= 0.28$). The sensitivity d score of the matte reflectance (M=1.5, SD=0.61) was higher than the glossy reflectance (M=1.2, SD=0.65) (Figure 4.7).

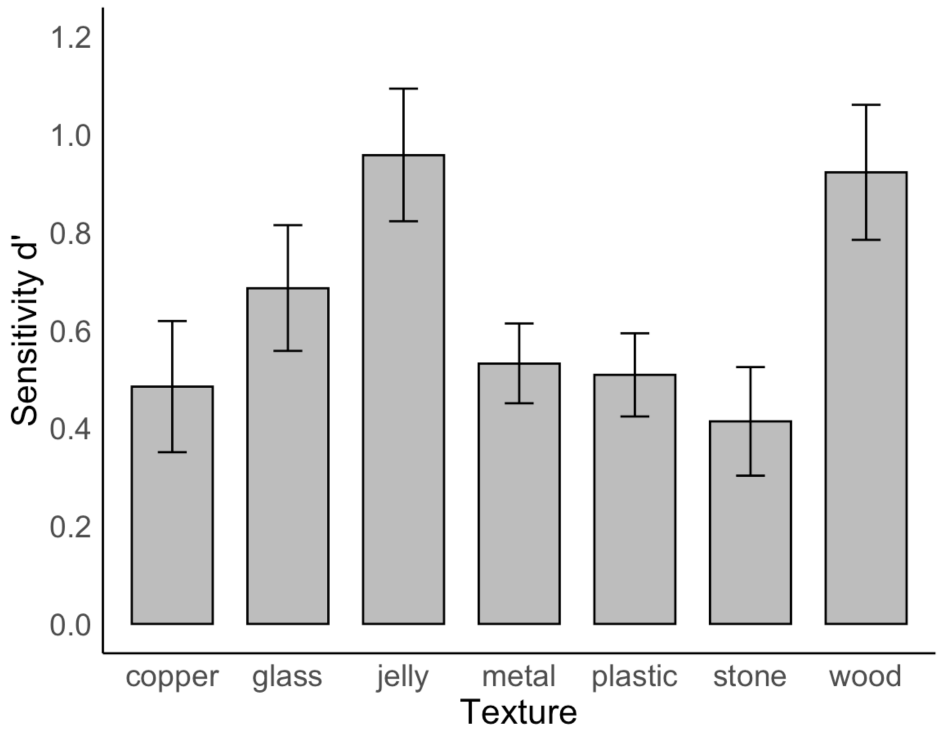

Figure 4. 6. The recognition sensitivity of texture congruent pairs with glass, jelly, metal, copper, stone, plastic, and wood material textures. The X-axis represents the seven material textures, the Y-axis represents the sensitivity d' scores, and the error bars represent standard errors of the mean.

A two-way 2 (congruency) x 2 (surface feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and surface feature (texture, reflectance) on the hit rates of unfamiliar objects. The findings revealed a significant main congruency effect on the hit rates of unfamiliar objects, $F(1, 56) = 12.29, p < 0.001$, $\eta^2 p = 0.18$ (Table F.1). Post hoc analysis with a

Bonferroni adjustment revealed the hit rate of congruent conditions (*M*=0.82, *SE*=0.016) were higher than the incongruent conditions (*M*=0.77, *SE*=0.016), mean difference = 0.05, standard error = 0.015, $p < .001$ (Table F.2). There was no significant main effect of the surface feature on the hit rates of unfamiliar objects, $F(1, 56) = -0.004$, $p = 1$, $\eta^2p = -7.901\times10\text{-}5$. Meaning that both the texture and the reflectance features of unfamiliar objects affect the hit rates equally. There was no significant interaction effect between congruency and surface feature on the hit rates of unfamiliar objects, $F(1, 56) = 0.26$, $p = 0.87$, $\eta^2p = 4.557\times10\text{-}4$. This means that the effect of congruency on hit rates was similar for the texture and the reflectance of the object (Figure 4.8).

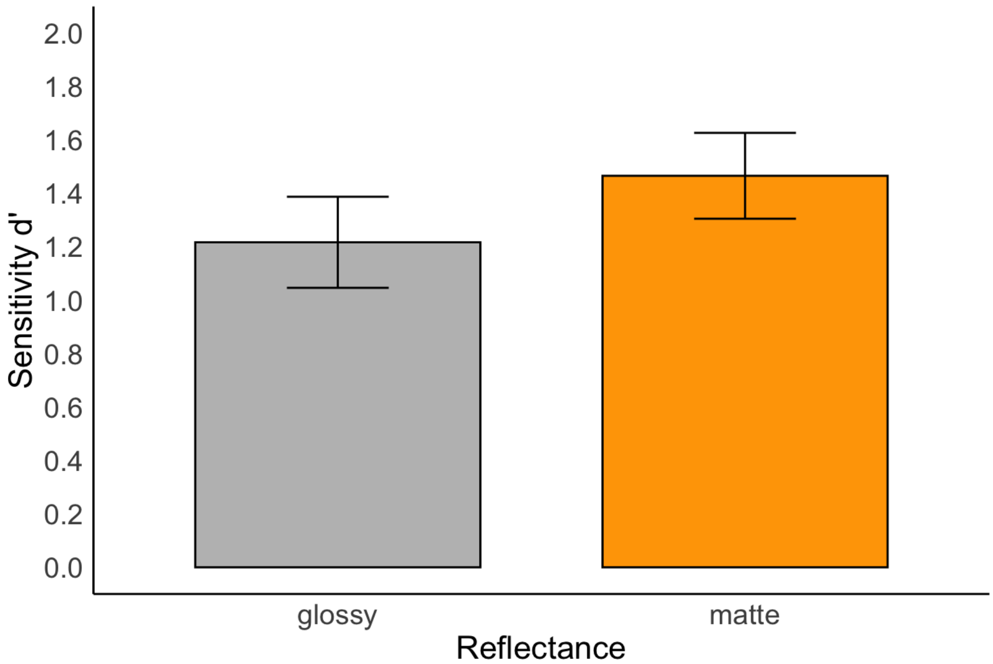

Figure 4. 7. The recognition sensitivity of reflectance congruent pairs with matte and glossy reflectance. the X-axis represents the two reflectance features, the Y-axis represents the sensitivity d' scores, and the error bars represent standard errors of the mean.

A two-way 2 (congruency) x 2 (surface feature) repeated measures ANOVA was conducted to examine the effect of congruency (congruent, incongruent) and surface feature (texture, reflectance) on the false alarm rates of unfamiliar objects. The findings revealed a significant main congruency effect on the false alarm rates of unfamiliar objects, $F(1, 56) = 32.31$, $p < 0.001$, $\eta^2p = 0.37$ (Table F.3). Post hoc analysis with a Bonferroni adjustment revealed the false alarm rate of incongruent conditions (*M*=0.41, *SE*=0.015) were higher than the congruent conditions (*M*=0.32, *SE*=0.016), mean difference = 0.08, standard error = 0.015, $p < .001$ (Table F.5). There was a significant main effect of the surface feature on the false alarm rates of unfamiliar objects, $F(1, 56) = 16.32$, $p < 0.001$, $\eta^2p = 0.23$. Post hoc analysis with a Bonferroni adjustment revealed the false alarm rate of reflectance conditions (*M*=0.37, *SE*=0.014) was higher than the texture conditions (*M*=0.36, *SE*=0.013), mean difference = 0.012, standard error = 0.003, $p < .001$ (Table F.4). There was a significant interaction effect between congruency and surface feature on the false alarm rates of unfamiliar objects, $F(1, 56) = 10.17$, $p = 0.002$, $\eta^2p = 0.15$. The false alarm rate of the texture incongruent (*M*=0.43, *SE*=0.018) condition was higher than the texture congruent condition (*M*=0.29, *SE*=0.020), mean difference = 0.14, standard error = 0.03, $p < .001$. The false alarm rate of the reflectance congruent (*M*=0.35, *SE*=0.018) condition was higher than the texture congruent condition (*M*=0.29, *SE*=0.020), mean difference = 0.07, standard error = 0.02, $p = 0.010$. The false alarm rate of the texture incongruent condition (*M*=0.43, *SE*=0.018) was higher than the reflectance incongruent condition (*M*=0.38, *SE*=0.015), mean difference = 0.045, standard error = 0.015, $p = .023$ (Figure 4.8).

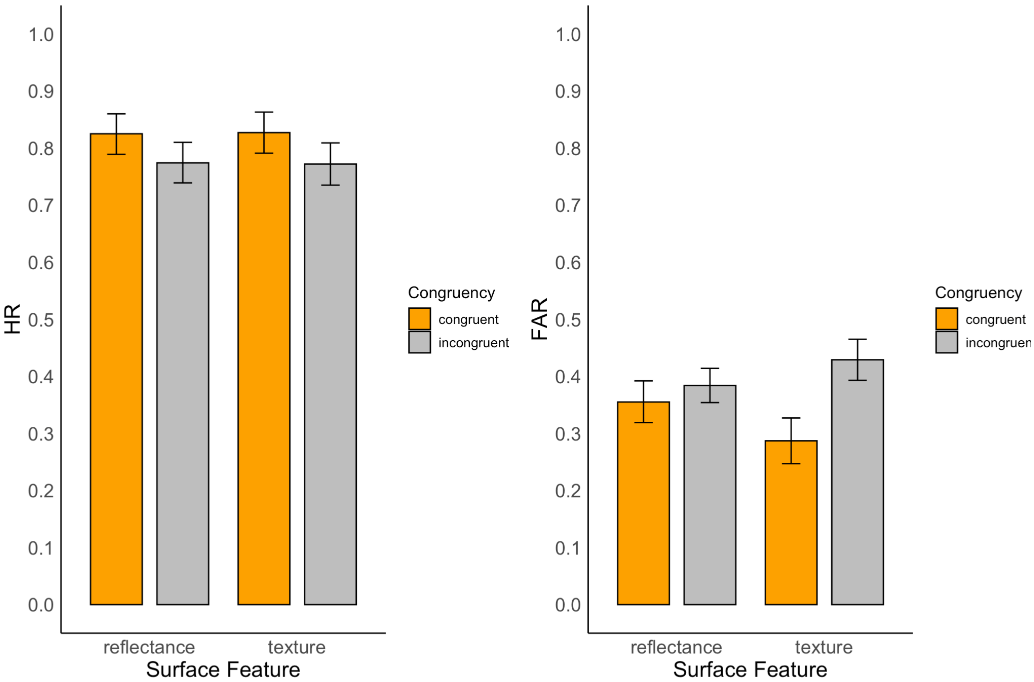

Figure 4. 8. The hit rates (HR) and false alarm rates (FAR) of four conditions (TC, RC, TI, RI) of unfamiliar objects. The X-axis represents surface features, the Y-axis

represents the HRs and FARs. The yellow bars display congruent and the gray bars display incongruent conditions, and the error bars represent standard errors of the mean.

CHAPTER 5

GENERAL DISCUSSION

In this thesis, I explore the facilitatory role of object material in associative recognition of familiar and unfamiliar shapes in three experiments and a preliminary study. The main focus was to understand how participants form associations between objects with information coming from features such as material, shape, surface reflectance, and texture.

5.1. Experiment 1

The aim of Experiment 1 was to investigate how people form associations between two familiar objects based on their shared object features like material and shape. Thus, a set of familiar objects (jug, mug, goblet, water glass) made of everyday materials (wood, stone, glass, metal) were chosen as stimuli in Experiment 1. The results of Experiment 1 revealed that participants benefitted when material and shape features were congruent in associative recognition of familiar objects, as expected.

Contrary to the hypotheses of this thesis, shape information did not affect the associative recognition more than the material information. There was no difference between the material and shape features of familiar objects in associative recognition.

Therefore, material information was found to be equally important as the shape of familiar objects in the associative recognition memory. Furthermore, it is reasonable to think that pre-experimental familiarity of object identity and object-material associations may play a role in object recognition during Experiment 1 (Sharan et al., 2009; Ngo et al., 2018).

5.2. Preliminary Study and Experiment 2

The aim of the Preliminary study was, before conducting Experiment 2, to view whether the unfamiliar glaven2 rendered with four different material categories (wood, metal, stone, glass) were perceived as the intended materials by the participants. The results revealed that participants correctly identified most of the material categories of metal, stone, and wood materials but not the glass material. Even though the same glass asset from BlenderKit was used in Experiment 1 with familiar shapes (jug, water glass, mug, goblet), participants could not recognize the glass material with the unfamiliar shape of glaven 2. So, instead of the glass rendering parameters of the Preliminary Study, I used a different glass asset from the Blenderkit in Experiment 2. In addition to that, different from Experiment 1 and the Preliminary Study, I used a forest lane as an environmental map from the HDRs of Blenderkit, which improved the glass renderings.

The aim of Experiment 2 was to investigate how people form associations between two unfamiliar objects based on their shared surface properties like material and shape. Thus, a set of four unfamiliar glavens made of the same material categories as Experiment 1 (wood, stone, glass, metal) were chosen as stimuli in Experiment 2. The reason I used unfamiliar objects like glavens, which were images varied in the underlying geometry, was to suppress any shape-based object identity or familiarity regarding these objects, which was not the case in Experiment 1. The results of Experiment 2 also revealed a congruency effect for both material and shape in associative recognition of unfamiliar objects. As expected, the material feature was found to dominate the shape feature in associative recognition memory of unfamiliar objects. It was found that when objects are not familiar, participants identified the familiar features (Schmidt et al., 2020). Hence, in Experiment 2, participants depended on the only reliable and familiar surface information when forming associations between objects, which was the material feature and not the unfamiliar shape.

Another result of Experiment 2 was the high associative recognition rate of glass material compared to other materials (metal, wood, stone) in the material congruent condition. This finding may result from the saliency of glass, which has reflective surface properties such as gloss (Okamoto et al., 2013), translucency (Xiao et al., 2014), and transparency (Fleming et al., 2011; Dövencioğlu et al., 2018). These properties have primarily visual characteristics, unlike the other materials I used, which mainly have tactile characteristics like the hardness and roughness of wood and stone (Nagai et al., 2015).

Furthermore, the shape feature of the glavens used in Experiment 2 was as discriminative as the materials (Table H.1). The associative recognition sensitivity of glaven7 was higher than the other three glavens in the shape-congruent condition (Table H.3, Figure H.1). This means that participants were able to distinguish the shape of unfamiliar glavens as well as their material. However, they were better at recognizing the material-congruent unfamiliar object pairs than shape-congruent pairs.

In Experiment 1, the two distinct routes of material perception can be observed in estimating the materials of familiar objects. The association route can be used for established material-object associations (Sharan, 2009; Schmidt et al., 2017; Alley et al., 2020). For instance, identifying the glass material of the mug, goblet, water glass, or jug can be executed based on the glass identity formed by the associations with these objects. However, with uncommon material-object combinations (e.g., stone jug), the estimation route can be used to assess material properties directly from visual image features (Van Assen & Fleming, 2016). Similarly, in Experiment 2, the association route of material estimation is not possible due to the unfamiliarity of objects and the absence of learned associations. Hence, the estimation route alone is used when identifying the materials of unfamiliar objects.

Across all three experiments, participants were more likely to falsely identify rearranged pairs as "studied" compared to completely new, unstudied pairs. This pattern reveals two important findings about memory performance. First, participants were generally good at distinguishing between pairs they had studied and completely new pairs they had never seen before. However, they had difficulty when presented with rearranged pairs that included objects they had studied but not in that particular combination. This difficulty can be explained by individual object interference (Rotello & Heit, 2000). When participants saw a rearranged pair, they recognized both individual objects from their study session (since each object was indeed studied, just in different pairs). This recognition of the individual objects sometimes led participants to mistakenly conclude they had studied these objects together as a pair when in fact, they had studied them as parts of different pairs. Hence, when both objects in a rearranged pair feel familiar (due to their presence in the study phase), participants may struggle to overcome this familiarity to accurately reject the novel pairing (Yonelinas, 2002). The higher false alarm rates for rearranged pairs demonstrate that having strong item memory (recognizing individual objects) does not necessarily translate to accurate associative memory (remembering which objects were paired together) (Humphreys, 1978; Clark et al., 1993; Cohn & Moscovitch, 2007). Hence, instead of a recall-like process, creating a compound cue is also possible in forming associations between items (Gronlund & Retcliff 1989).

Furthermore, congruency increased the interference of rearranged pairs (false alarm rates of rearranged pairs) both in Experiment 1, $F(1, 73) = 25.5, p < 0.001, \eta^2p = 0.26$ (Table D.5), and Experiment 2, $F(1, 73) = 04.4, p = 0.049, \eta^2p = 0.07$ (Table E.9). This finding could be due to the increased recognition strength of congruent pairs compared to incongruent ones. Hence, stronger item recognition could have led to higher interference and impaired the ability to discriminate specific associations in congruent conditions (Johnson et al., 2013). Especially familiar objects in Experiment 1 could have induced more substantial interference and increased susceptibility to false recognition in the congruent conditions compared to Experiment 2 (as indicated by the larger effect size: $\eta^2p = 0.26$ vs. $\eta^2p = 0.07$).

Moreover, the sensitivity *d'* scores of unfamiliar objects in Experiment 2 were higher than the sensitivity *d'* scores of familiar objects in Experiment 1. This finding can also be explained by the interference of familiar objects compared to unfamiliar ones. I found that familiar objects induced more substantial interference ($\eta^2p = 0.26$) compared to unfamiliar objects ($\eta^2p = 0.07$) in the congruent conditions, suggesting that familiarity increased susceptibility to false recognition.

Furthermore, the total false alarm rates of familiar objects were higher than those of unfamiliar objects. Thus, this drop in associative recognition sensitivity of familiar objects could be explained by the pre-existing object-material associations, which can create interference and false recognition during retrieval. For familiar objects in Experiment 1, both the association and estimation routes of material perception are active (Schmidt et al., 2017). For instance, recognizing an object's identity can lead to strong predictions about its material composition (Alley et al., 2020; Sharan et al., 2009) and these predictions could have interfered with the retrieval of the studied pairs in Experiment 1. With unfamiliar objects, only the estimation route is available, potentially leading to more focused and efficient processing based purely on visual features. Therefore, the higher sensitivity scores for unfamiliar objects may reflect a more focused perceptual processing strategy independent of pre-existing semantic associations.

5.3. Experiment 3

The aim of Experiment 3 was to investigate how people form associations between two unfamiliar objects based on their shared surface properties like texture and reflectance while holding shape constant. Thus, one unfamiliar glaven made of seven textures (glass, metal, wood, stone, plastic, copper, jelly) and two reflectance features (matte, glossy) were chosen as stimulus conditions in Experiment 3. As in Experiment 2, the reason I used one type of glaven in this experiment was to suppress any additional, shape-based object identity and familiarity regarding these objects.

The effect of object shape on reflectance perception is long known. For instance, the glossiness of a surface has been found to make curved surfaces appear more curved (Nishida & Shinya, 1998). Also, it was found that objects with identical reflectance properties were perceived as having different levels of glossiness depending on their shape (Ho et al., 2008). Also, the impact of surface texture on reflectance perception (glossiness) was shown (Ho et al., 2008). In Experiment 3, I displayed surfaces that are made of different textures but have similar reflectance properties, along with surfaces with similar reflectance patterns but made of different textures. Similar to the previous findings, the results of Experiment 3 also revealed a congruency effect for both texture and reflectance in associative recognition of unfamiliar objects, as expected. The texture feature was found to have higher sensitivity than the reflectance feature in associative recognition memory of unfamiliar objects. Although the surface reflectance property was distinctive enough to show a congruency effect, where reflectance congruent object pairs were better remembered than incongruent pairs across all textures, the surface reflectance information was still not strong enough to predominate the texture information in associative recognition of unfamiliar objects. When exposed to an unfamiliar shape that does not provide any type of information and is constant in all trials, participants relied on both texture and reflectance but focused more on the textures.

The reason surface texture showed higher sensitivity than surface reflectance in Experiment 3 is because of the higher false alarm rate of surface reflectance compared to surface texture. Similarly, the reflectance-congruent condition had a higher false alarm rate than the texture-congruent condition. Thus, participants were good at differentiating the surface texture of studied pairs from non-studied ones but poor at differentiating the surface reflectance of studied pairs from non-studied ones. One possible explanation could be that surface textures can provide distinctive surface patterns and visual cues that can make them easier to discriminate.

My findings are in line with a study conducted by Fleming et al. (2003) in which the authors used a surface reflectance matching task and found that the matching performance of surface reflectance estimation was reliable and precise. They suggest that the visual system examines the local reflectance highlights when distinguishing glossy from matte surfaces. Thus, they conclude that how a material reflects, bends, transmits, or scatters light gives us critical clues about its properties when estimating materials (Fleming et al., 2003). Hence, the light reflected by a surface holds information about the material's properties (Motoyoshi & Matoba, 2012; Kim et al., 2020). Furthermore, the Bidirectional Reflectance Distribution Function (BRDF) is a mathematical function that models how light interacts with different materials (Nishida, 2019). It emphasizes that the appearance of a material is not static but rather depends on the specific lighting and viewing conditions. Also, different material classes, such as metal, wood, and glass, exhibit different BRDFs (Xiao et al., 2012). A series of experiments investigated the relationship between the reflectance properties of a material and its perceived appearance and found that systematically changing reflectance properties also alters the perceived material (Schmid et al., 2020). For instance, the perceived gloss was found to change with material class, indicating that gloss should be viewed in the context of its material (Schmid et al., 2020). For example, the visual appearance of materials like steel and plastic can vary significantly based on their surface reflectance. Steel can appear polished, scratched, or rusted, while plastic can be smooth and glossy to rough and dull. Thus, a lack of overall matte/glossy difference in my findings might be due to the interplay between reflectance and texture.

One observation in Experiment 3 was the high associative recognition rate of the matte surfaces over the glossy surfaces in the surface congruent condition. The reason matte surfaces showed higher associative recognition sensitivity than glossy surfaces is that the glossy pairs had higher false alarm rates compared to matte pairs. This means that participants were good at differentiating the matte surfaces of studied pairs from non-studied ones but poor at differentiating the glossy surfaces of studied pairs from non-studied ones. This could be because, unlike glossy surfaces, matte surfaces do not have specular highlights (Nayar & Oren, 1995; Dana et al., 1999; Pont et al., 2015; Toscani et al., 2017; Olkkonen & Brainard, 2010). Thus, light reflects more uniformly across matte surfaces and creates stable (more discriminable) patterns compared to glossy surfaces (Nayar & Oren, 1995; Dana et al., 1999; Fleming et al., 2003; Kim et al., 2012). One possible explanation could be that matte surfaces have fewer bright reflections of light; therefore, details and textures on the surface could be simpler to distinguish between the studied pairs and non-studied ones in the associative recognition task.

Parallel to this view, glossy condition in Experiment 3 might have appeared less discriminable than the matte-textured condition since the perception of highlights on a surface is closely linked to surface geometry and perceived shape (Dövencioğlu et al 2015, 2017). Using a single geometry for all conditions in Experiment 3 might have created a very similar specular highlight pattern across all glossy materials, causing the texture information in the glossy condition to be less informative than the matte-textured condition.

Another result of Experiment 3 was the high association recognition rate of wood and jelly materials in the texture-congruent condition compared to other materials. This is consistent with the finding that wood and minerals were easiest to identify due to their distinctive surface patterns, with metal being the most difficult to recognize due to the absence of characteristic textures (Yoonessi & Zaidi, 2010; Zaidi, 2011). However, how can we explain the high associative recognition of material jelly? One explanation is especially for the jelly material; the perception of translucency may depend on image cues such as color gradients (Liao et al., 2022). Therefore, the role of color in material, reflectance, and object recognition should also be examined. The color literature on material and object recognition is somewhat convoluted. One study showed that there was no material effect in the color-matching paradigm using objects with identical colors but made of different materials and those made of the same material but with different colors (Giesel & Gegenfurtner, 2010). Likewise, another study indicated that the influence of material on color matching was minimal (Xiao & Brainard, 2008). Another study revealed that when participants were expected to make matches from three objects varying in material and color, they always selected the material match if the material was identical to the target (Radonjić et al., 2018). However, as the color difference between the matching materials increased, people were more likely to select the object with the matching color. Suggesting that as the material's color becomes more distant, it is easier for the observer to focus on color rather than material distinctions (Radonjić et al., 2018).

Furthermore, it was found that color is an important cue for identifying objects when surface details, such as texture or shadow, are not present, which is typically not the case because color is not perceived in isolation but rather in conjunction with other surface features such as texture and shading (Bramão et al., 2011), which is the case in all the three experiments. While the color of highlights and lowlights was found to provide some information about material properties, the characteristics of the gloss itself, such as contrast and sharpness, are much more critical cues (Brainard et al., 2018). Although Experiment 3 was not designed to directly investigate the role of color in object memory, these examples could account for the prominent effect of texture since I used distant colors for each texture condition (e.g., red plastic, green jelly). Further studies that control for color properties while manipulating textures are needed to fully understand the dissociation between the roles of color and texture in object memory.

What about the material-specific color information? Almost every language links color names to materials. According to research by Zaidi (2011), color is a key part of how we mentally picture what things are made of. Thus, our perception of color and material must accurately correlate to provide beneficial information about surface features (Burghouts & Geusebroek, 2009; Brainard et al., 2018). Recent work showed that we can more effectively discriminate between different objects by using both color and glossiness cues (Saarela & Olkkonen, 2017).

Interestingly, maintaining color constancy was significantly greater for glossy objects than matte objects (Granzier et al., 2014). In Experiment 3, the exact opposite finding was observed: matte surfaces were better recognized than glossier ones. This contrasting result suggests that color perception may not have been the main factor driving performance in Experiment 3. If color had been the primary basis for recognition, my findings should have aligned with Granzier et al.'s results, showing better performance with glossy surfaces. In summary, color perception and object recognition interact with each other to provide the most accurate information about the materials and objects (Witzel & Gegenfurtner, 2018). In conclusion, although color is a critical part of material and object recognition, it by itself does not define surface features such as material, and texture. Therefore, the superior material effect of glavens over the shape and reflectance found in this study cannot be reduced to color.

5.4. Memory Load in Different Conditions

The overlapping pairs between conditions in all experiments introduce memory load variations within conditions. It should be kept in mind that this could have influenced the results in ways that are difficult to separate from the main effects being studied. For instance, in the material-congruent condition (MC), when participants encountered pairs with congruent features (same material and shape, two object features), the lower memory load likely made these pairs easier to remember (Olson & Jiang, 2002; Alvarez & Cavanagh, 2004). In contrast, pairs that were congruent on one feature but incongruent on another (same material but different shapes, three object features) had a higher memory load with perceptual complexity and would have required more cognitive resources to encode and retrieve these pairs (Eng et al., 2005; Alvarez & Cavanagh, 2004).

In other words, mixing pairs with varying memory loads within conditions makes it harder to isolate the specific effects of object features on associative memory. Performance in each condition might reflect an average of two different levels of memory load rather than a pure measure of how one type of congruency affects memory. As mentioned in the method section of Experiment 1, one way to eliminate this memory load difference within conditions would be using material-congruent shape-incongruent, shape-congruent material-incongruent, material and shape congruent, and material and shape incongruent conditions. This alternative design can provide memory load distinctions between conditions and account for the specific effects of object feature congruency on associative memory.

In summary, perceptually congruent shape, material, texture, and reflectance pairs were more memorable than incongruent pairs in all three experiments. Moreover, the results of Experiment 1 showed that material information was as important as shape-based object identity in familiar object memorability.

Also, the material feature of unfamiliar objects was more memorable than the shape, and the texture of unfamiliar objects was more memorable than the surface reflectance in Experiments 2 and 3. Lastly, the material properties facilitated associative recognition of unfamiliar objects stronger than familiar objects. In conclusion, these are the first findings directly relating shape and surface properties to object memorability using familiarity as a moderator.

5.5. Limitations

The first limitation of this thesis was that there were repeating object pairs in the congruent and incongruent conditions in all three experiments. For instance, in Experiments 1 and 2, material-congruent object pairs were present in the material-congruent (MC) and shape-incongruent (SI) conditions. Material-incongruent object pairs were present in the material-incongruent (MI) and shape-congruent (SC) conditions. Similarly, shape-congruent object pairs were present in both shape-congruent (SC) and material-incongruent (MI) conditions. And shape incongruent object pairs were present in the shape-incongruent (SI) and material-congruent (MC) conditions. Although the number of these repeating pairs was controlled with equal distribution (half and half) in all conditions, the memory load of object pairs differed within the same condition. For example, in the material-congruent condition (MC), there were object pairs with both the same object shape and material, which had lower memory load than pairs with the same object material and different shapes. Therefore, the repeating pairs and the difference in memory load within experimental conditions could have partially influenced the findings of this thesis.

Another limitation was that the glass material of the unfamiliar object (glaven) was not well identified compared to other wood, metal, and stone materials in the Preliminary study. The glass material was relatively more challenging than other materials to render with glavens. For this reason, in Experiment 2, glass rendering parameters were improved by using a different "glass" asset from the Blenderkit. Therefore, the glass materials used in Experiment 2 and Experiment 1 were different from each other, and the improved recognition sensitivity of the material glass in Experiment 2 could be due to this change. Another limitation was that the study stimuli and the new-unstudied stimuli of wood and jelly materials in Experiment 3 had relatively more distinguishable color characteristics from each other compared to other materials. Therefore, because it was easier to discriminate between the studied and the unstudied pairs of these materials from each other, this could influence the associative recognition performance. Another limitation was that I referenced the dual-process theory in discussing my results, and other alternative recognition models (Dunn, 2008) should also be addressed in future studies.

The last limitation was that, in Experiment 1, lighting direction was inconsistent across the object renderings, resulting in varying shadow patterns. This inconsistency is significant because lighting and shadows (illuminance flow) provide essential information about how light interacts with objects and reveals their 3D texture structure and shape (Nishida & Shinya, 1998; Pont et al., 2015; Pont & Te Pas, 2006). Since the lighting conditions were not standardized between stimuli, this variation could have influenced how participants perceived and remembered the object material and shape, potentially affecting the study's results.

5.6. Future Research

This thesis unlocks the way for several different directions in future research. The first one is that the current data does not permit us to conclusively exclude the influence of color in associative object recognition. Color may be a valuable cue for identifying the material composition of an object, and future research should investigate the role of color in material memorability. More specifically, future research should focus on how the visual system adjusts its processing of color information to account for variations in texture, glossiness, and other material properties. Further studies are needed to examine the role of color in the perception of materials, particularly investigating whether color cues enhance our ability to perceive and remember materials in both familiar and unfamiliar objects (Yoonessi & Zaidi, 2010; Witzel & Gegenfurtner, 2018).

Second, the role of semantic features (Konkle et al., 2010; Isola et al., 2013; Shoval et al., 2023) of familiar objects and affordance attributes (Mecklinger et al., 2004; Green & Hummel, 2006; Lindemann et al., 2006) in Experiment 1 could account for the associative recognition performance. I did not control the semantic and affordance features of these familiar objects; thus, future work could investigate the role of semantic features of objects, such as their object category membership and affordance characteristics compared to perceptual object features. Third, the object properties used in this thesis (shape-base object identity, shape, material, surface reflectance) can be modeled as a simple additive process where each property influences the other to observe their interaction (Ho et al., 2008; Hansmann-Roth &

Mamassian, 2017). And lastly, future research can look into the role of illumination flow in associative object recognition.

5.7. Conclusion

Earlier studies in material perception have often explored one object property at a time (Ho et al., 2008), yet most objects exhibit several interacting properties. Here, I investigated two object features (shape-material) and surface features (reflectance-texture) and how they interact in three experiments. This thesis is the first to explore what makes familiar and unfamiliar objects memorable with different materials and investigate which material properties improve object memorability. This thesis focused on the role of material perception in associative recognition of familiar and unfamiliar objects. In the scope of this thesis, there was no difference between material and shape information in forming associations between familiar objects. However, texture information was found to predominate the shape and reflectance information in creating associations of unfamiliar objects. This thesis contributes to visual perception and memory research by highlighting the role of materials in object memorability for the first time. The findings of this thesis can also apply to real-world situations, for instance, in the industry by suggesting marketers to strategically use packaging with matte surfaces and materials like wood, glass, and jelly to be recognized better based on the results of this thesis. Also, the findings can be applied to selecting memorable materials for design choices, particularly when choosing materials for everyday items like home furnishings and tableware.

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APPENDICES

A. APPROVAL OF THE METU HUMAN SUBJECTS ETHICS COMMITTEE

UYGULAMALI ETİK ARAŞTIRMA MERKEZİ
APPLIED ETHICS RESEARCH CENTER

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06 MAYIS 2024

Konu: Değerlendirme Sonucu

Gönderen: ODTÜ İnsan Araştırmaları Etik Kurulu (İAEK)

İlgi: İnsan Araştırmaları Etik Kurulu Başvurusu

Sayın Doç. Dr. NAHİDE DİCLEDÖVENCİOĞLU

Danışmanlığını yaptığınız Öykü Göze Özdemir'in ***"Materyal Algısının Çağrısımsal Belleğe Etkisi"*** başlıklı araştırmanız İnsan Araştırmaları Etik Kurulu tarafından uygun görülerek **02321-ODTUİAEK-2024** protokol numarası ile onaylanmıştır

Bilgilerinize saygılarımla sunarım

.

Prof. Dr. Ş. Halil TURAN
Başkan

Prof. Dr. I. Semih AKÇOMAK
Üye

Doç. Dr. Ali Emre Turgut
Üye

Doç. Dr. Şerife SEVİNÇ
Üye

Doç. Dr. Murat Perit ÇAKIR
Üye

Dr. Öğretim Üyesi Süreyya ÖZCAN KABASAKAL
Üye

Dr. Öğretim Üyesi Müge GÜNDÜZ
Üye

B. THE INFORMED CONSENT

Mayıs 2024

ARAŞTIRMAYA GÖNÜLLÜ KATILIM FORMU

Bu çalışma ODTÜ Psikoloji Bölümü öğretim üyelerinden Doç. Dr. Dicle Dövencioğlu ve Doç. Dr. Aslı Kılıç danışmanlığında Öykü Göze Özdemir'in yüksek lisans tezi kapsamında yürütülmektedir. Bu form sizi araştırma koşulları hakkında bilgilendirmek için hazırlanmıştır.

Çalışmanın Amacı Nedir?

İnsanların hafızası gördükleri uyaranlara göre farklılıklar gösterebilir. Bu çalışmanın amacı gösterilen farklı uyaranların çağrışımsal bellek üzerine etkisini ölçmektir.

Bize Nasıl Yardımcı Olmanızı İsteyeceğiz?

Araştırma psikoloji bölüm laboratuarında yapılacaktır. Üniversite öğrencileri katılımcı olarak davet edilecek, katılmak isteyenler yaklaşık 20 dakikalık bir laboratuar seansına katılacaklardır. Çalışmada sizden gösterilen uyaranları hafızanızda tutmanız ve daha sonra gördüğünüzü hatırladığınız uyaranlar için "evet" hatırlamadıklarınız için "hayır" seçeneklerini işaretlemeniz istenmektedir.

Katılımınızla ilgili bilmeniz gerekenler:

Bu çalışmaya katılmak tamamen gönüllülük esasına dayalıdır. Herhangi bir yaptırıma veya cezaya maruz kalmadan çalışmaya katılmayı reddedebilir veya çalışmayı bırakabilirsiniz. Araştırma esnasında cevap vermek istemediğiniz sorular olursa boş bırakabilirsiniz.

Araştırmaya katılanlardan toplanan veriler tamamen gizli tutulacak, veriler ve kimlik bilgileri herhangi bir şekilde eşleştirilmeyecektir. Katılımcıların isimleri bağımsız bir listede toplanacaktır. Ayrıca toplanan verilere sadece araştırmacılar ulaşabilecektir. Bu araştırmanın sonuçları bilimsel ve profesyonel yayınlarda veya eğitim amaçlı kullanılabilir, fakat katılımcıların kimliği gizli tutulacaktır.

Çalışmaya katılanlar bu duyurunun yapıldığı ders için bonus puan alacaklardır. Alınacak puan dersin öğretim üyesi tarafından belirlenecektir.

Araştırmayla ilgili daha fazla bilgi almak isterseniz:

Çalışmayla ilgili soru ve yorumlarınızı araştırmacıya adresinden iletebilirsiniz.

Yukarıdaki bilgileri okudum ve bu çalışmaya tamamen gönüllü olarak katılıyorum.
(Formu doldurup imzaladıktan sonra uygulayıcıya geri veriniz).

İsim Soyad Tarih İmza

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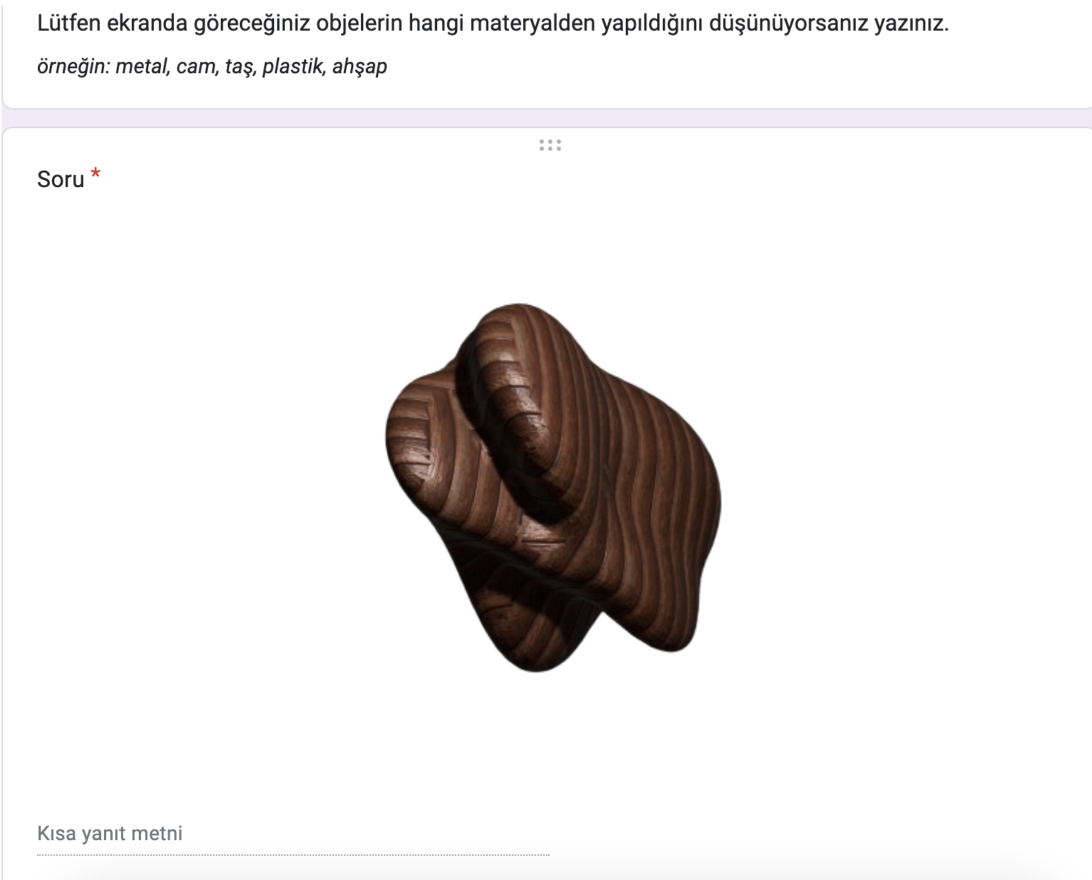
C. AN EXAMPLE SCREENSHOT FROM THE PRELIMINARY STUDY



D. HIT RATES AND FALSE ALARM RATES OF EXPERIMENT 1

Table D. 1. Repeated Measures ANOVA of HRs in Experiment 1

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object Feature	9.121×10^{-31}	1	9.121×10^{-31}	1.499×10^{-13}	1.000	2.054×10^{-15}
Residuals	4.441×10^{-16}	73	6.083×10^{-18}			
Congruency	1.906	1	1.906	83.174	< .001	0.533
Residuals	1.673	73	0.023			
Object Feature ✻ Congruency	0.014	1	0.014	0.984	0.324	0.013
Residuals	1.002	73	0.014			

Table D. 2. Post Hoc Comparison of HRs of Congruency in Experiment 1

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	0.127	0.014	9.212	< .001

Table D. 3. Repeated Measures ANOVA of FARs in Experiment 1

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object Feature	5.865×10^{-4}	1	5.865×10^{-4}	1.246	0.268	0.017
Residuals	0.034	73	4.706×10^{-4}			
Congruency	1.188	1	1.188	84.861	< .001	0.538
Residuals	1.022	73	0.014			
Object Feature ✻ Congruency	0.029	1	0.029	1.246	0.268	0.017
Residuals	1.683	73	0.023			

Table D. 4. Post Hoc Comparison of FARs of Congruency in Experiment 1

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	0.127	0.014	9.212	< .001

Table D. 5. Repeated Measures ANOVA of FAR-rearranged in Experiment 1

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object feature	0.001	1	0.001	0.173	0.679	0.002
Residuals	0.557	73	0.008			
Congruency	0.582	1	0.582	25.530	< .001	0.259
Residuals	1.664	73	0.023			
Object feature ✻ Congruency	0.012	1	0.012	0.173	0.679	0.002
Residuals	5.015	73	0.069			

Table D. 6. Post Hoc Comparison of FAR-rearranged of Congruency in Experiment 1

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	0.089	0.018	5.053	< .001

E. HIT RATES AND FALSE ALARM RATES OF EXPERIMENT 2

Table E. 1. Repeated Measures ANOVA of HRs in Experimet 2

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object Feature	1.756×10^{-31}	1	1.756×10^{-31}	-2.835×10^{-14}	1.000	-5.063×10^{-16}
Residuals	-3.469×10^{-16}	56	-6.195×10^{-18}			
Congruency	0.741	1	0.741	31.983	< .001	0.364
Residuals	1.298	56	0.023			
Object Feature ✻ Congruency	0.020	1	0.020	1.449	0.234	0.025
Residuals	0.765	56	0.014			

Table E. 2. Post Hoc Comparison of HRs of Congruency in Experimet 2

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	0.114	0.020	5.655	< .001

Table E. 3. Repeated Measures ANOVA of FARs in Experiment 2

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object Feature	0.003	1	0.003	15.362	< .001	0.215
Residuals	0.012	56	2.083×10^{-4}			
Congruency	0.191	1	0.191	13.647	< .001	0.196
Residuals	0.785	56	0.014			
Object Feature ✻ Congruency	0.157	1	0.157	15.362	< .001	0.215
Residuals	0.572	56	0.010			

Table E. 4. Post Hoc Comparison of FARs of Object Feature in Experiment 2

		Mean Difference	SE	t	p_{bonf}
material	shape	-0.007	0.002	-3.919	< .001

Table E. 5. Post Hoc Comparison of FARs of Congruency in Experiment 2

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	-0.058	0.016	-3.694	< .001

Table E. 6. Repeated Measures ANOVA of Materials HRs in Material Congruent Condition in Experiment 2

	Sum of Squares	df	Mean Square	F	p	η^2_p
HR	0.494	3	0.165	4.483	0.005	0.074
Residuals	6.177	168	0.037			

Table E. 7. Repeated Measures ANOVA of Material FARs in Material Congruent Condition in Experiment 2

	Sum of Squares	df	Mean Square	F	p	η^2_p
FAR	0.395	3	0.132	2.987	0.033	0.051
Residuals	7.410	168	0.044			

Table E. 8. Mean of Hit Rates, False Alarm Rates and Sensitivity d' Scores of Materials in Material Congruent Condition in Experiment 2

	Metal	Wood	Stone	Glass
HR	0.85	0.89	0.77	0.86
FAR-unstudied	0.17	0.18	0.09	0.40
FAR-rearranged	0.75	0.82	0.77	0.79
FAR-total	0.39	0.40	0.31	0.29
Sensitivity d'	1.14	1.01	0.95	1.49

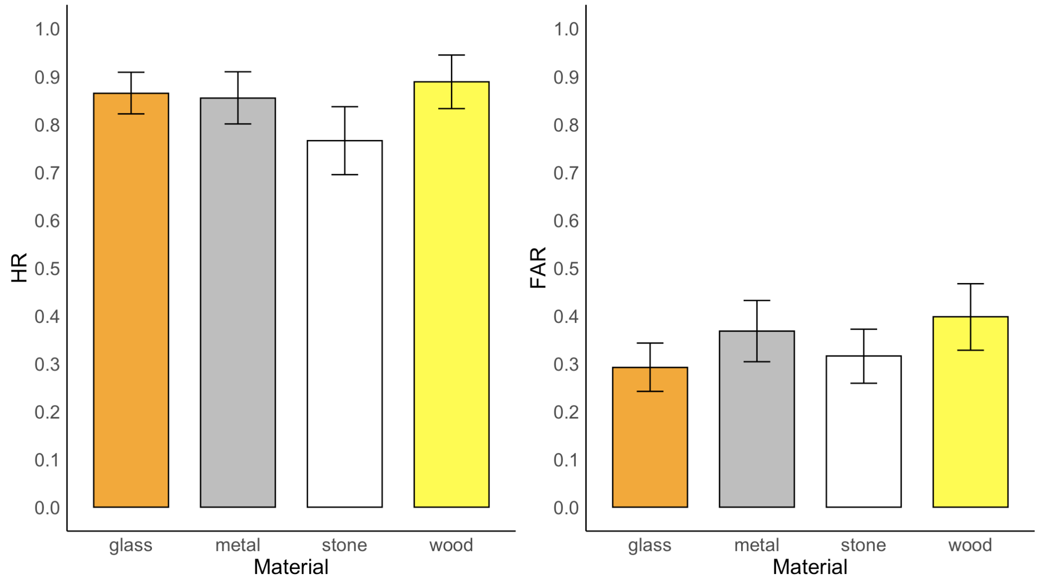


Figure E. 1. The hit rates (HR) and false alarm rates (FAR) of material congruent pairs with glass, metal, stone, and wood materials. The X-axis represents the four materials, the Y-axis represents the HRs and FARs, and the error bars represent standard errors of the mean.

Table E. 9. Repeated Measures ANOVA of FAR-rearranged in Experiment 2

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object Feature	6.853×10^{-5}	1	6.853×10^{-5}	0.015	0.904	2.618×10^{-4}
Residuals	0.262	56	0.005			
Congruency	0.058	1	0.058	4.045	0.049	0.067
Residuals	0.798	56	0.014			
Object Feature ✻ Congruency	6.168×10^{-4}	1	6.168×10^{-4}	0.015	0.904	2.618×10^{-4}
Residuals	2.355	56	0.042			

Table E. 10. Post Hoc Comparison of FAR-rearranged of Congruency in Experiment 2

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	0.032	0.016	2.011	0.049

F. HIT RATES AND FALSE ALARM RATES OF EXPERIMENT 3

Table F. 1. Repeated Measures ANOVA of HRs in Experiment 3

	Sum of Squares	df	Mean Square	F	p	η^2_p
Surface Feature	1.754×10^{-20}	1	1.754×10^{-20}	-0.004	1.000	-7.901×10^{-5}
Residuals	-2.220×10^{-16}	56	-3.965×10^{-18}			
Congruency	0.158	1	0.158	12.287	< .001	0.180
Residuals	0.720	56	0.013			
Surface Feature ✻ Congruency	3.580×10^{-4}	1	3.580×10^{-4}	0.026	0.874	4.557×10^{-4}
Residuals	0.785	56	0.014			

Table F. 2. Post Hoc Comparison of HRs of Congruency in Experimet 3

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	0.053	0.015	3.505	< .001

Table F. 3. Repeated Measures ANOVA of FARs in Experiment 3

	Sum of Squares	df	Mean Square	F	p	η^2_p
Surface Feature	0.008	1	0.008	16.318	< .001	0.226
Residuals	0.026	56	4.652×10^{-4}			
Congruency	0.412	1	0.412	32.312	< .001	0.366
Residuals	0.714	56	0.013			
Surface Feature ✻ Congruency	0.183	1	0.183	10.170	0.002	0.154
Residuals	1.007	56	0.018			

Table F. 4. Post Hoc Comparison of FARs of Surface Feature in Experimet 3

		Mean Difference	SE	t	p_{bonf}
material	reflectance	-0.012	0.003	-4.040	< .001***

Table F. 5. Post Hoc Comparison of FARs of Congruency in Experimet 3

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	-0.085	0.015	-5.684	< .001***

Table F. 6. Repeated Measures ANOVA of Texture HRs in Texture Congruent Condition in Experiment 3

	Sum of Squares	df	Mean Square	F	p	η^2_p
HR	0.585	6	0.098	1.350	0.234	0.024
Residuals	24.272	336	0.072			

Table F. 7. Repeated Measures ANOVA of Texture FARs in Texture Congruent Condition in Experiment 3

	Sphericity Correction	Sum of Squares	df	Mean Square	F	p	η^2_p
FAR	None	12.351[a]	6.000[a]	2.058[a]	15.368[a]	< .001[a]	0.215
	Greenhouse-Geisser	12.351	4.662	2.649	15.368	< .001	0.215
Residuals	None	45.006	336.000	0.134			
	Greenhouse-Geisser	45.006	261.067	0.172			

[a] Mauchly's test of sphericity indicates that the assumption of sphericity is violated (p < .05).

Table F. 8. Mean of Hit Rates, False Alarm Rates and Sensitivity d' Scores of Textures in Texture Congruent Condition in Experiment 3

	Metal	Wood	Stone	Glass	Plastic	Copper	Jelly
HR	0.90	0.80	0.80	0.79	0.88	0.80	0.81
FAR-total	0.60	0.12	0.48	0.28	0.19	0.44	0.10
Sensitivity d'	0.53	0.92	0.41	0.69	0.50	0.48	0.96

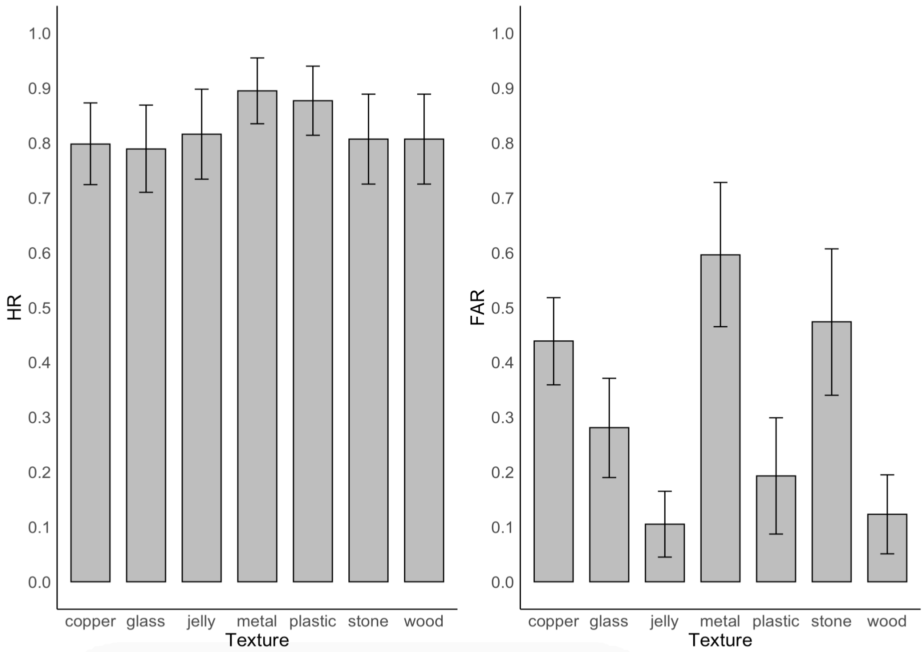


Figure F. 1. The hit rates (HR) and false alarm rates (FAR) of texture congruent pairs with glass, metal, stone, wood, plastic, copper and jelly textures. The X-axis represents the textures, the Y-axis represents the HRs and FARs, and the error bars represent standard errors of the mean.

Table F. 9. Paired Samples T-Test of Reflectance HRs in Reflectance Congruent Condition in Experiment 3

Measure 1		Measure 2	t	df	p	Cohen's d
HR_glossy	-	HR_matte	0.98	56	0.33	0.13

Table F. 10. Paired Samples T-Test of Reflectance FARs in Reflectance Congruent Condition in Experiment 3

Measure 1		Measure 2	t	df	p	Cohen's d
AR_glossy	-	FAR_matte	3.5	56	< .001	0.47

Table F. 11. *Mean of Hit Rates, False Alarm Rates and Sensitivity d' Scores of Reflectance Features in Reflectance Congruent Condition in Experiment 3*

	Matte	Glossy
HR	0.81	0.84
FAR-total	0.30	0.41
Sensitivity d'	1.47	1.22

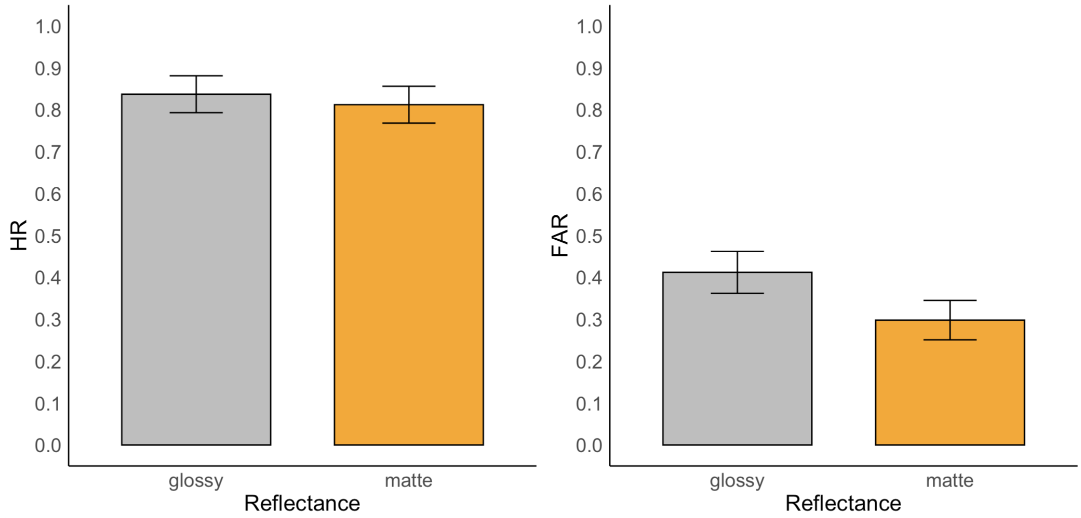


Figure F. 2. The hit rates (HR) and false alarm rates (FAR) of reflectance congruent pairs with glossy and matte reflectance features. The X-axis represents the reflectance features, the Y-axis represents the HRs and FARs, and the error bars represent standard errors of the mean.

G. THE RESPONSE BIAS IN EXPERİMENTS 1, 2 AND 3

Table G. 1. Repeated Measures ANOVA of Criterion in Experiment 1

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object Feature	0.001	1	0.001	0.276	0.601	0.004
Residuals	0.271	73	0.004			
Congruency	15.435	1	15.435	105.714	< .001	0.592
Residuals	10.659	73	0.146			
Object Feature ✻ Congruency	0.004	1	0.004	0.032	0.859	4.344×10^{-4}
Residuals	8.096	73	0.111			

Table G. 2. Post Hoc Comparison of Criterion of Congruency in Experimet 1

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	-0.457	0.044	-10.282	< .001

Table G. 3. Repeated Measures ANOVA of Criterion in Experiment 2

	Sum of Squares	df	Mean Square	F	p	η^2_p
Object Feature	0.014	1	0.014	5.960	0.018	0.095
Residuals	0.138	57	0.002			
Congruency	1.138	1	1.138	8.442	0.005	0.129
Residuals	7.685	57	0.135			
Object Feature ✻ Congruency	0.784	1	0.784	9.306	0.003	0.140
Residuals	4.805	57	0.084			

Table G. 4. Post Hoc Comparison of Criterion of Object Feature in Experimet 2

		Mean Difference	SE	t	p_{bonf}
material	shape	0.016	0.006	2.441	0.018

Table G. 5. Post Hoc Comparison of Criterion of Congruency in Experimet 2

		Mean Difference	SE	t	p_{bonf}
congruent	incongruent	-0.140	0.048	-2.905	0.005

Table G. 6. Repeated Measures ANOVA of Criterion in Experiment 3

	Sum of Squares	df	Mean Square	F	p	η^2_p
Surface Feature	0.022	1	0.022	6.861	0.011	0.109
Residuals	0.179	56	0.003			
Congruency	0.039	1	0.039	0.420	0.520	0.007
Residuals	5.231	56	0.093			
Surface Feature ✻ Congruency	0.361	1	0.361	3.283	0.075	0.055
Residuals	6.162	56	0.110			

Table G. 7. Post Hoc Comparison of Criterion of Surface Feature in Experimet 3

		Mean Difference	SE	t	p_{bonf}
texture	reflectance	0.020	0.007	2.619	0.011

Table G. 8. The Mean Criterion Values of Conditions in Experiments 1 and 2

	MC	MI	SC	SI
Criterion (*c*) Experimet 1	-0.12	-0.57	-0.13	-0.59
Criterion (*c*) Experimet 2	-0.36	-0.34	-0.50	-0.24

Table G. 9. The Criterion Values of Conditions in Experiments 3

	TC	TI	RC	RI
Criterion (*c*) Experimet 3	-0.21	-0.32	-0.31	-0.26

H. THE SHAPE DISCRIMINABILITY OF GLAVENS IN EXPERIMENT 2

Table H. 1. Repeated Measures ANOVA of Sensivity d'of Glaven Shapes in Experiment 2

Cases	Sphericity Correction	Sum of Squares	df	Mean Square	F	p	η^2_p
shape	None	23.892[a]	3.000[a]	7.964[a]	42.552[a]	< .001[a]	0.427
	Greenhouse-Geisser	23.892	2.542	9.397	42.552	< .001	0.427
Residuals	None	32.003	171.000	0.187			
	Greenhouse-Geisser	32.003	144.914	0.221			

[a] Mauchly's test of sphericity indicates that the assumption of sphericity is violated (p < .05).

Table H. 2. The Mean Sensivity d' Difference of Glaven Shapes in Experiment 2

Shape	Marginal Mean	95% CI for Mean Difference Lower	95% CI for Mean Difference Upper	SE
glaven1	1.908	1.778	2.038	0.065
glaven4	1.427	1.291	1.562	0.068
galven7	2.259	2.155	2.363	0.052
glaven8	1.576	1.439	1.712	0.068

Table H. 3. The Post Hoc Comparisons of Glaven Shapes in Experiment 2

		Mean Difference	SE	t	p_{bonf}
glaven1	glaven4	0.481	0.093	5.200	< .001
	galven7	-0.351	0.060	-5.813	< .001
	glaven8	0.332	0.080	4.176	< .001
glaven4	galven7	-0.832	0.073	-11.339	< .001
	glaven8	-0.149	0.095	-1.564	0.740
galven7	glaven8	0.684	0.076	9.038	< .001

Note. P-value adjusted for comparing a family of 6

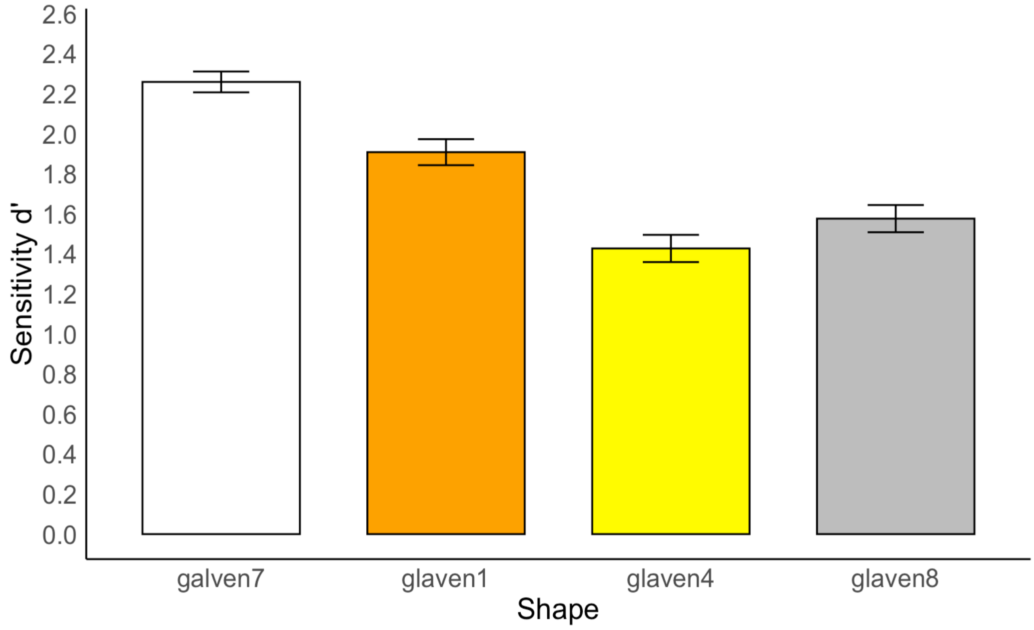


Figure H. 1. The sensitivity *d* scores of shape congruent pairs with glaven1, glaven4, glaven7, and glaven8. The X-axis represents the four shapes, the Y-axis represents the recognition sensitivity, and the error bars represent standard errors of the mean.

I. TURKISH SUMMARY / TÜRKÇE ÖZET

BÖLÜM 1

GİRİŞ

1.1. Malzeme Algısı

Günlük deneyimlerimiz, bazıları tanıdık, bazıları ise tanıdık olmayan çeşitli malzemelerden yapılmış nesnelerle etkileşimi içermektedir. Bu malzemeleri tanımlayabilir, tanıyabilir ve fiziksel özelliklerini bir bakışta çıkarabiliriz (Wiebel ve diğerleri, 2013; Sharan ve diğerleri, 2009). Bir nesnenin malzeme özellikleri, onun kimliği, kullanılabilirliği ve sağladığı olanaklar hakkında önemli ipuçları sunar, dolayısıyla nesneyle etkileşimimizi belirler. Bu nedenle, malzeme algısı çalışmaları, insanların farklı malzeme özelliklerini görsel olarak nasıl otomatik ve zahmetsiz bir şekilde algıladığını araştırır (Adelson, 2001; Buckingham ve diğerleri, 2009; Liu ve diğerleri, 2010; Fleming, 2017). Günlük hayatta karşılaştığımız malzemelerin yelpazesi geniştir: Ahşap, taş, metal ve cam gibi her malzemenin pürüzlülük, ağırlık, yansıma, yarı saydamlık ve geometri gibi benzersiz yüzey özellikleri vardır ve bunlar nesnelerle etkileşimimizi etkiler. Bu etkileşim, malzemenin özelliklerine dair algımıza dayanır ve bu algı çoğu zaman fiziksel olarak nesneye dokunmadan gerçekleşir. Böylece, nesneye dokunmadan onun nasıl hissedeceği ve günlük hayatta ne için kullanılacağı hakkında genel bir anlayışa ve beklentiye sahip oluruz (Nagai ve diğerleri, 2015).

1.1.1. Malzeme Yüzey Özellikleri

Bir malzemenin görünümü yalnızca ışığı nasıl yansıttığıyla değil, aynı zamanda üç boyutlu şekil, yansıma, çevresel aydınlatma, doku ve yüzey renginin birleşimiyle de etkilenir. Bu özellikler, malzeme kategorileri arasında ve içinde nesne hakkında değerli bilgiler sağlar (Motoyoshi ve diğerleri, 2007; Marlow ve diğerleri, 2011; Sharan ve diğerleri, 2013; Sawayama & Nishida, 2018). Özellikle bir yüzeyin şekli, ışığın nasıl yansıdığını belirleyen önemli bir faktördür ve bu, malzemenin görünümünde önemli bir rol oynar (Lagunas ve diğerleri, 2021; Serrano ve diğerleri, 2021). Dolayısıyla, malzemeleri tanıma yeteneğimiz şekil, renk ve doku gibi yüzey özelliklerine dayanır. Sonuç olarak, malzeme algısı, malzemeleri tanımak için erken seviyedeki ipuçlarını ileri seviyeli nesne bilgisiyle birleştirerek çalışır.

1.1.2. Malzeme Algısının Seviyeleri

Malzemeleri görsel olarak algılamamızın farklı seviyeleri vardır. Schmidt ve diğerleri (2017) tarafından geliştirilen modele göre, malzeme algısının iki ana yolu vardır: çağrışım yolu ve tahmin yolu (Van Assen & Fleming, 2016). Tahmin yolu, malzeme özelliklerinin doğrudan görüntü özelliklerinden tahmin edilmesiyle malzeme tanımayı sağlar. Bu süreç, açık bir malzeme kimliği belirlemeye ihtiyaç duymadan, yalnızca görsel ipuçlarının analizi yoluyla gerçekleşir ve yüzey yansıması gibi görsel ipuçlarına dayanarak malzeme özelliklerini çıkarır.

Malzemeleri tanımlamanın bir diğer yolu ise öğrenilmiş çağrışımlar kullanmaktır. Çağrışım yolu, yüzey dokusu gibi görsel ipuçlarını, yumuşak veya sert gibi malzeme özellikleriyle ilişkilendirerek, hafızadan öğrenilmiş nesne-malzeme çağrışımlarına dayalı malzeme kimliğini oluşturur. Bu nedenle, yaşam boyunca bir nesnenin görünümü ile tipik malzeme özellikleri arasında güçlü bağlantılar geliştiririz ve malzeme tanımlarken bu çağrışımlara güveniriz (Sharan, 2009; Alley ve diğerleri, 2020).

1.2. Malzeme ve Nesne Kategorisi Tanıma

Malzemelerin sınıflandırılması, algı ve anlamsal yorum arasındaki boşluğu dolduran algısal ve anlamsal niteliklerin benzerliklerine dayalı olarak oluşur (Sharan ve diğerleri, 2013). Bu durum, malzeme niteliklerinin görsel değerlendirilmesi ile farklı malzeme sınıflarının anlamsal temsili arasında güçlü bir ilişki olduğunu göstermektedir. Ancak malzemelerin oluşturduğu nesneler fiziksel formları açısından inanılmaz derecede çeşitli olabilir. Bu durum bilişsel sistemimiz için bir zorluk oluşturur. Bir malzemenin alabileceği çok sayıda şekil, yalnızca algısal veya anlamsal benzerlik temelinde malzemelerin sınıflandırması için net sınırlar oluşturmayı zorlaştırır (Fleming ve diğerleri, 2015; Caputa ve diğerleri, 2010). Dolayısıyla, malzeme tanıma konseptini nesne tanıma alanına indirgemek kolay olabilir. Nesne kimliği ile malzeme kimliği arasında istatistiksel olarak anlamlı bir ilişki olmasına rağmen, şekil temelli nesne kimliği, malzeme tanımayı açıklayamaz. Bu açıdan nesne-malzeme ilişkisinin doğrudan simetrik olmadığı vurgulanmalıdır. Aynı sınıftaki nesneler farklı malzemelerden yapılabilirken, farklı sınıflardan nesneler aynı malzeme kategorisine ait olabilir (Bileschi ve diğerleri, 2005; Sharan, 2009). Malzemeleri tanımak, nesneleri tanımanın ötesine geçen benzersiz süreçleri içerir.

Sharan ve çalışma arkadaşları (2009), günlük malzemeleri görsel olarak tanıma ve sınıflandırma yetimizin hızlı olduğunu, hatta 40 ms'lik kısa bir sunum süresiyle bile başarılı olduğunu göstermiştir. Bu nedenle, malzeme algısının nesne tanıma kadar hızlı olabileceği sonucuna varmışlardır. Buna karşılık, Wiebel ve diğerlerinin (2013) çalışması, malzeme tanımanın nesne tanımadan daha yavaş olduğunu ve malzemeleri ayırt etmenin nesnelerden daha karmaşık olduğunu ortaya koymuştur. Nagai ve çalışma arkadaşlarının (2015) bulguları, parlaklık ve saydamlık gibi özelliklerin kısa reaksiyon sürelerinde malzemeleri ayırt etme performansını artırdığını, ağırlık ve sıcaklık gibi görsel olmayan özellik derecelendirmelerinin ise daha uzun reaksiyon süreleriyle ilişkili olduğunu göstermiştir. Yazarlar, gündelik hayatta malzeme tanımada görsel yüzey özelliklerinin, görsel olmayan özelliklere kıyasla birincil kaynak olduğunu belirtmişlerdir. Örneğin, parlaklık ve saydamlığı sadece dokunsal bilgi ile görsel girdi olmadan tahmin etmek nadirdir (Okamoto ve diğerleri, 2013).

1.3. Nesne Belleği

Nesnelerle etkileşimde bulunduğumuzda, anlamsal işlev, teknik/mekanik ve sensorimotor unsurlar gibi farklı bilgi türlerini sürekli bir geri bildirim döngüsünde birleştiririz (Federico ve diğerleri, 2023). Nesne belleği araştırmaları, nesneleri kodlarken ve tanırken şekil ve rengin baskın özellikler olduğunu göstermektedir

(Schmidt ve diğerleri, 2020; Schacter ve diğerleri, 1990; Nako ve diğerleri, 2016). Şeklin (Logothetis & Sheinberg, 1996; Serrano ve diğerleri, 2021) ve rengin (Tanaka & Presnell, 1999; Redmann ve diğerleri, 2019; Reppa ve diğerleri, 2020; Nagai & Yokosawa, 2003) nesne hatırlanabilirliği üzerindeki kolaylaştırıcı rolü vurgulanmaktadır.

Renk, özellikle rengi nesne kimliği ve şekliyle güçlü bir şekilde eşleşen nesnelerin tanınmasında önemli bir rol oynar; bu durum "renk tanılayıcılığı" olarak adlandırılır. Benzer şekilde, aşinalık, tipiklik ve eşzamanlılık, nesne hatırlanabilirliği üzerinde artırıcı etkilere sahiptir (Ngo ve diğerleri, 2018; Green & Hummel, 2005, 2006; Schiffer, 2023; Kramer ve diğerleri, 2023). Ayrıca, nesnelerin anlamsal özelliklerinin görsel özelliklerinden daha iyi hatırlandığı bulunmuştur (Schiffer, 2023; Kramer ve diğerleri, 2023). Gerçek nesneler, renkli fotoğraflar veya siyah beyaz çizimlerin kullanıldığı nesne tanıma görevlerinde, gerçek nesnelerin diğer görsel uyaranlardan daha hatırlanabilir olduğu bulunmuştur (Snow ve diğerleri, 2014). Ancak, malzemenin nesne hatırlanabilirliği üzerindeki rolünü inceleyen herhangi bir çalışma bulunmamaktadır.

1.4. İlişkisel Tanıma Belleği

Çağrışım kavramı, öğrenme ve belleğin temelini oluşturur. Nesnelerin yüzey dokusu kategorisi veya malzeme kategorisi gibi duyusal uyaranlar arasında kurulan çağrışımlar, çevresel düzenlilikler hakkında bilgi sağlar ve gelecekteki duyusal girdileri tahmin etmek ve yorumlamak için bellekte depolanan anlamsal özellikleri tanımlamada kritik bir rol oynar (Albright, 2012). İlişkisel bellek, maddelerin anlamsal olarak nasıl organize edildiğinden veya gruplandığından etkilenebilir. Bu durum, aynı anlamsal gruptaki maddeleri hatırlamaya eğilim göstermemize neden olarak anlamsal çağrışımlar ağını oluşturur. İlişkisel tanıma görevi, katılımcılardan madde çiftlerini çalışmaları ve ardından sunulan çiftlerin daha önce çalışılanlarla aynı olup olmadığını belirlemelerini ister. Tanınan çiftler için “evet” ve tanınmayan çiftler için “hayır” cevabı verilir (Clark ve diğerleri, 1993; Rotello & Heit, 2000; Cohn & Moscovitch, 2007; Kahana, 2012).

1.5. Neden Tanıdık ve Tanıdık Olmayan Nesnelerin İlişkisel Tanımasında Malzeme Algısını Araştırmalıyız?

Malzemeleri tanımanın ve özelliklerini değerlendirmenin ekolojik açıdan önemi göz önüne alındığında, nesne algısı üzerine geniş bir literatür olmasına rağmen, malzeme algısının görsel nesne algısı üzerindeki etkisi son zamanlara kadar araştırmalarda büyük ölçüde göz ardı edilmiştir (Wiebel, 2014; Nagai ve diğerleri, 2015; Adelson, 2001; Fleming, 2014; Fleming ve diğerleri, 2015). Bu tezde, malzeme bilgisinin, nesne yüzey özelliklerinden şekil ve yansıma gibi diğer faktörlere kıyasla, ilişkisel nesne belleğinde nasıl saklandığı ve geri çağrıldığı incelenmiştir. Ayrıca şekil temelli tanıdıklık ve tanıdık olmama durumlarının, malzeme algısına kıyasla ilişkisel nesne belleğinde nasıl bir rol oynadığı araştırılmıştır.

Nesne tanıdıklığı, tanıdık olmama durumu, şekil, malzeme ve yansımanın ilişkisel bellek oluşumunu nasıl etkilediğini anlamak için daha fazla araştırmaya ihtiyaç vardır. Malzeme, şekil ve yansıma açısından kontrollü ve sistematik bir şekilde değişen çift örnekleri oluşturmak, bu değişkenler arasındaki ilişkiyi incelemek için faydalı olacaktır. Bunun yanında, herhangi bir tanıdıklığı veya işlevi olmayan (özellikle Glavens gibi küresel nesneler kullanarak) nesnelerle yapılan çalışmalar önceki bilgilere dayanmayı zorlaştırır (Phillips, 2004; Phillips ve diğerleri, 2009). Bu sonuçlar malzemeleri ve nesneleri algılayıp tanırken bilişsel mekanizmaların nasıl çalıştığını anlamamıza yardımcı olabilir. Gelen tanıdık ve tanıdık olmayan duyusal bilginin yüksek düzeyde beklentilerle nasıl birleştirildiğini anlamak, insan görsel sisteminin malzeme algısını ve nesne-malzeme çağrışımlarını nasıl oluşturduğunu anlamak için önemlidir (Alley ve diğerleri, 2020).

1.6. Amaç ve Hipotezler

Bu tezde, tanıdık ve tanıdık olmayan nesnelerin malzemesinin, şekil ve yansıma gibi diğer nesne özelliklerine kıyasla ilişkisel tanıma belleğindeki rolü araştırılmıştır. Bunu yapmak için, birinci deneyde günlük malzemelerden yapılmış farklı nesne kimliklerine sahip bir dizi tanıdık nesne, ikinci ve üçüncü deneyde ise aynı malzemelerden yapılmış farklı şekillere sahip tanıdık olmayan nesneler uyaran olarak kullanılmıştır.

Deney 1'in amacı, insanların tanıdık iki nesne arasında malzeme ve şekil bilgileri gibi ortak özelliklerine dayalı belleklerinde nasıl çağrışımlar kurduklarını araştırmaktır. Ana araştırma sorusu, insanların tanıdık iki nesne arasında çağrışım kurarken daha çok malzeme mi yoksa şekil bilgisine mi güvendikleridir. Hipotezler: (1) Şekil ve malzeme açısından uyumlu tanıdık nesne çiftleri, uyumsuz olanlardan daha iyi tanınacaktır (yüzey uyumu etkisi). (2) Tanıdık nesnelerle yapılan tanıma belleği görevinde şekil bilgisinin faydası, malzeme bilgisine kıyasla daha baskın olacaktır.Deney 2'nin amacı, tanıdık olmayan iki nesne arasında yüzey özelliklerine dayalı çağrışımların nasıl oluştuğunu incelemektir. Hipotezler: (1) Şekil ve malzeme açısından uyumlu tanıdık olmayan nesne çiftleri, uyumsuz olanlardan daha iyi tanınacaktır. (2) Tanıdık olmayan nesnelerle yapılan tanıma belleği görevinde malzeme bilgisinin faydası, şekil bilgisine kıyasla daha baskın olacaktır.

Deney 3'ün amacı, tanıdık olmayan nesnelerde malzeme ve yansıma bilgisine dayalı çağrışımların nasıl oluştuğunu incelemektir. Hipotezler: (1) Malzeme ve yansıma açısından uyumlu çiftler, uyumsuz olanlardan daha iyi tanınacaktır. (2) Tanıma belleği görevinde malzeme bilgisinin faydası, yansıma bilgisine kıyasla daha baskın olacaktır.

BÖLÜM 2

DENEY 1

2.1. Yöntem

İlk deneyde, katılımcılar, farklı nesne özelliklerinin (malzeme, şekil) eşleştiği ve eşleşmediği koşullarda tanıdık nesnelerin eşleştirilmiş görselleri inceledikleri bir çağrışımsal tanıma görevi tamamladılar. Bu deney, hangi koşullarda tanıma oranlarının daha yüksek olacağını araştırmak amacıyla gerçekleştirilmiştir.

2.2. Katılımcılar

Bu çalışma, Orta Doğu Teknik Üniversitesi İnsan Araştırmaları Etik Kurulu tarafından onaylanmıştır. Deneye, Orta Doğu Teknik Üniversitesi'nden 74 katılımcı

(54 kadın, 18 erkek, 2 non-binary) 19-30 yaş aralığında (M= 21.9, SD= 2.16) ders kredisi karşılığında veya gönüllü olarak katılmıştır. Katılımcılar, normal veya düzeltilmiş görme yetisine sahip ana dili Türkçe olan bireylerdi. Tüm katılımcılardan bilgilendirilmiş onay alınmıştır.

2.3. Uyaranlar

Bu çalışmadaki deneysel uyaranlar, dört şekil (sürahi, kadeh, su bardağı, kupa) ve dört malzeme kategorisi (ahşap, metal, cam, taş) altında sunulan tanıdık nesnelere ait 32 görselden oluşmaktadır. Diğer bir deyişle, her şekil ve malzeme kategorisinde, bir nesnenin dört farklı malzeme ile oluşturulmuş 4 görüntüsü, açık kaynaklı bir üç boyutlu bilgisayar grafik uygulaması olan Blender 4.1.1 programı kullanılarak üretilmiştir (Blender, 2024).

Toplam dört madde koşulu vardır: Malzeme-uyumlu koşul (MU), Malzeme-uyumsuz koşul (MUmz), Şekil-uyumlu koşul (ŞU), Şekil-uyumsuz koşul (ŞUmz).

2.5. Prosedür

Deney üç aşamadan oluşmuştur: çalışma aşaması, dikkat dağıtma aşaması ve bellekten geri çağırma aşaması. Çalışma aşamasında, katılımcılara dört koşuldan her biri için 16 çift içeren bir çalışma listesi gösterilmiştir. Toplamda 64 çift, rastgele sırayla ve her çift için dört saniye süreyle sunulmuştur.

Katılımcılardan, bu çiftleri daha sonra yapılacak bir bellek testi için öğrenmeleri istenmiştir. Dikkat dağıtma aşamasının hemen ardından, geri çağırma aşaması gerçekleştirilmiştir. Bu aşamada, katılımcılara bir çağrışımsal tanıma görevi kapsamında, her dört koşul için 15 çift içeren bir test listesi gösterilmiştir. Katılımcılardan, eğer çifti çalışma listesinden hatırlıyorlarsa klavyede “e” tuşuna, hatırlamıyorlarsa “h” tuşuna basmaları istenmiştir.

Görevde süre sınırı bulunmamaktadır. Bu çalışmada, çağrışımsal tanıma görevi ile denek içi desen (tekrarlanan ölçümler) kullanmıştır ve tüm yanıtlar bir klavye aracılığıyla toplanmıştır.

2.6. Sonuçlar

Verileri düzenlemek için SciPy paketi kullanılarak Visual Studio Code üzerinden bir Python kodu yazıldı. Duyarlılık (*d'*) ölçümlerine iki yönlü tekrarlı ölçümler varyans analizi, 2 (uyum) x 2 (yüzey özelliği), yapılarak uyumun (uyumlu, uyumsuz) ve nesne özelliklerinin (malzeme, şekil) tanıdık nesnelerin çağrışımsal tanıması üzerindeki etkisi incelenmiştir. Bulgular, uyumlu çiftlerin uyumsuz çiftlere kıyasla daha iyi tanındığını göstermiştir, $F(1, 73) = 14.3$, $p < 0.001$, $\eta^2 p = 0.16$. Şekil-uyumlu koşullarda tanıma duyarlılığı *d′* skoru uyumsuz koşullardan daha yüksek bulunmuştur. Malzeme ve şekil özellikleri arasında anlamlı bir fark gözlenmemiştir, $F(1, 73) = 0.45$, $p = 0.05$, $\eta^2_p = 0.006$. Ayrıca, uyum ve yüzey özelliği arasında anlamlı bir etkileşim bulunmamıştır ($p = 0.17$), bu da malzeme ve şeklin tanıma üzerindeki etkisinin eşit olabileceğine işaret etmektedir.

BÖLÜM 3

ÖN ÇALIŞMA VE DENEY 2

3.1. Ön Çalışma

3.1.1. Yöntem

Deney 2'yi gerçekleştirmeden önce, Google Forms kullanılarak çevrimiçi bir ön çalışma yapılmıştır. Bu ön çalışmanın amacı, tanıdık olmayan nesnelerin dört farklı malzeme kategorisi (ahşap, metal, taş, cam) ile oluşturulduğunda katılımcılar tarafından gerçekten hedeflenen malzemeler olarak algılanıp algılanmadığını incelemektir.

3.1.2. Katılımcılar

Orta Doğu Teknik Üniversitesi'nden 31 katılımcı (18 kadın, 13 erkek), 18-40 yaş aralığında (M= 23.3, SD= 4.37) gönüllü olarak veya ders kredisi karşılığında katılmıştır. Tüm katılımcılar yazılı olarak bilgilendirilmiş onay formunu doldurmuştur.

3.1.3 Uyaranlar ve Prosedür

Bu çalışmadaki deneysel uyaranlar, Philips (2004) tarafından sağlanan Glaven modellerine dayanan ve dört farklı malzeme kategorisinde (ahşap, metal, cam, taş) oluşturulmuş 19 tanıdık olmayan nesne görüntüsünden oluşmaktadır.

Uyaranlar, açık kaynaklı bir üç boyutlu bilgisayar grafik uygulaması olan Blender 4.1.1 programı kullanılarak üretilmiştir (Blender, 2024). Dört malzeme kategorisi, BlenderKit varlıklarından seçilmiştir. Kullanılan Glaven modeli, Philips tarafından GitHub'da (2004) sağlanan Glaven Seti'nden Glaven2 modelidir.

Bu çalışma, Google Forms kullanılarak çevrimiçi olarak gerçekleştirilmiştir. Görevin yönergesi, ekranın üst kısmında katılımcılara "Lütfen ekranda göreceğiniz objelerin hangi malzemeden yapıldığını düşünüyorsanız yazınız" şeklinde sunulmuştur. Katılımcılara, dört farklı malzeme kategorisine (ahşap, metal, taş, cam) ait Glaven2'nin farklı versiyonlarının 19 görseli gösterilmiş ve nesnelerin hangi malzemeden yapıldığını düşündüklerini yazmaları istenmiştir.

3.1.4. Sonuçlar

Sonuçlar, ahşap malzeme kategorisinde wood1'in yüzde 22.6, wood2'nin yüzde 32.2, wood3, wood4 ve wood5'in yüzde 61.3 ve wood6'nın yüzde 77.4 oranında doğru tanımlandığını ortaya koymuştur. Bu nedenle Deney 2'deki nesne oluşturma sürecinde ahşap malzeme kategorisi olarak wood6 ve wood4 seçilmiştir.

Taş malzeme kategorisinde stone1 ve stone2 yüzde 67.7, stone3 ve stone4 yüzde 70.9 oranında doğru tanımlanmıştır. Bu nedenle stone3 ve stone4 seçilmiştir. Metal kategorisinde metal1 yüzde 41.9, metal2 yüzde 32.2, metal3 yüzde 45.1, metal4 yüzde 77.4 ve metal5 yüzde 48.3 oranında doğru tanımlanmıştır. Bu nedenle metal4 ve metal5 seçilmiştir.

Cam malzemesinde ise glass1 yüzde 19.3, glass2 yüzde 25.8, glass3 yüzde 29 ve glass4 yüzde 6.4 oranında doğru tanımlanmıştır. Cam malzemesi için doğru tanıma oranları yetersiz kaldığından, ikinci deneyde farklı bir cam malzemesi kullanılmıştır.

3.2. Deney 2

3.2.1. Yöntem

İkinci deneyde, katılımcılar tanıdık olmayan nesnelerin eşleştirilmiş görsellerini inceledikleri bir çağrışımsal tanıma görevi tamamladılar. Bu görseller, farklı nesne özellikleri (malzeme, şekil) açısından eşleşen ve eşleşmeyen koşullarda sunuldu. Çalışmanın amacı, hangi koşulların daha yüksek tanıma oranlarına sahip olacağını araştırmaktı.

3.2.2. Katılımcılar

Çalışma, Orta Doğu Teknik Üniversitesi İnsan Araştırmaları Etik Kurulu tarafından onaylanmıştır. Örneklem büyüklüğünü belirlemek için bir G Power hesaplaması yapılmıştır. İki yönlü tekrarlı ölçümler ANOVA analizi için, 0.95 güç, 0.25 etki büyüklüğü ve 0.05 alfa düzeyine sahip olmak amacıyla tahmini örneklem büyüklüğü 54 olarak belirlenmiştir (Faul ve diğerleri, 2009). Orta Doğu Teknik Üniversitesi'nden 18-30 yaş aralığında (M= 21.1, SD= 1.93) 57 katılımcı (51 kadın, 4 erkek, 2 non-binary) bu deneye gönüllü olarak ya da ders kredisi karşılığında katılmıştır. Katılımcıların ana dili Türkçe olup, görme yetileri normal ya da düzeltilmiştir. Tüm katılımcılardan yazılı bilgilendirilmiş onay alınmıştır.

3.2.3. Uyaranlar ve Prosedür

Bu çalışmadaki deneysel uyaranlar, Philips (2004) tarafından sağlanan glaven modellerine dayanan dört nesne kategorisi (glaven1, glaven4, glaven7, glaven8) ve dört malzeme kategorisinde (ahşap, metal, cam, taş) oluşturulmuş 32 tanıdık olmayan nesne görüntüsünden oluşmaktadır. Glavenler, Philips tarafından GitHub'da (2004) sağlanan Glaven Seti'nden seçilmiş olup BigGlaven1, BigGlaven4, BigGlaven7 ve BigGlaven8 modelleridir. Toplam dört madde koşulu vardır: Malzeme-uyumlu koşul (MU), Malzeme-uyumsuz koşul (MUmz), Şekil-uyumlu koşul (ŞU), Şekil-uyumsuz koşul (ŞUmz).

Deney 2'nin prosedürü Deney 1'in aynısıdır.

3.2.4. Sonuçlar

Verileri düzenlemek için SciPy paketi kullanılarak Visual Studio Code üzerinden bir Python kodu yazıldı. Duyarlılık (*d'*) ölçümlerine iki yönlü 2 (uyum) x 2 (yüzey özelliği) tekrarlı ölçümler ANOVA analizi, uyumun (uyumlu, uyumsuz) ve nesne özelliğinin (malzeme, şekil) tanıdık olmayan nesnelerin çağrışımsal tanıma üzerindeki etkisini incelemek için yapıldı. Bulgular, tanıdık olmayan nesnelerin tanıma belleğinde anlamlı bir uyum etkisi olduğunu ortaya koydu, $F(1, 56) = 70.7$, $p < 0.001$, $\eta^2p = 0.55$.

Bonferroni düzeltmesiyle yapılan sonraki (post hoc) analiz, malzeme uyumlu koşulun duyarlılık skoru d'nin malzeme uyumsuz koşuldan daha yüksek olduğunu gösterdi. Aynı şekilde şekil uyumlu koşulun skoru da şekil uyumsuz koşuldan anlamlı derecede yüksekti. Tanıma üzerinde yüzey özelliğinin anlamlı bir ana etkisi bulundu, $F(1, 56) = 6.36$, $p = 0.01$, $\eta^2p = 1$; malzeme özelliğinin duyarlılık skoru, şekil özelliğinden daha yüksek çıktı. Ancak, uyum ve yüzey özelliği arasında anlamlı bir etkileşim gözlenmedi ($p = 0.2$). Ayrıca, malzemenin etkisini daha detaylı incelemek için tek yönlü tekrarlı ölçümler ANOVA uygulandı, $F(3, 56) = 12.7$, $p < 0.001$, $\eta^2p = 0.18$. Sonuçlar, cam malzemesinin metal, taş ve ahşap malzemelerine kıyasla daha iyi tanındığını ortaya koydu.

BÖLÜM 4

DENEY 3

3.1. Yöntem

Üçüncü deneyde, katılımcılar farklı yüzey özelliklerinin (malzeme, yansıma) eşleştiği ve eşleşmediği koşullar altında tanıdık olmayan nesnelerin eşleştirilmiş görsellerini inceledikleri bir çağrışımsal tanıma görevi tamamladılar. Bu çalışma, hangi koşulların daha yüksek tanıma oranlarına sahip olacağını araştırmak amacıyla gerçekleştirilmiştir.

3.2. Katılımcılar

Çalışma, Orta Doğu Teknik Üniversitesi İnsan Araştırmaları Etik Kurulu tarafından onaylanmıştır. Örneklem büyüklüğünü belirlemek için bir G Power hesaplaması yapılmıştır. İki yönlü tekrarlı ölçümler ANOVA analizi için, 0.95 güç, 0.25 etki büyüklüğü ve 0.05 alfa düzeyine sahip olmak amacıyla tahmini örneklem büyüklüğü 54 olarak belirlenmiştir (Faul ve diğerleri, 2009). Deneye, Orta Doğu Teknik Üniversitesi'nden 19-29 yaş aralığında ($M= 22.5$, $SD= 2.17$) 57 katılımcı (44 kadın, 12 erkek, 1 non-binary) ders kredisi karşılığında veya gönüllü olarak katılmıştır. Katılımcıların ana dili Türkçe olup, görme yetileri normal ya da düzeltilmişti. Tüm katılımcılardan yazılı bilgilendirilmiş onay alınmıştır.

3.3. Uyaranlar

Bu çalışmadaki deneysel uyaranlar, Philips (2004) tarafından sağlanan glaven modellerine dayalı, iki yüzey yansıma kategorisi (parlak, mat) ve yedi malzeme kategorisi (ahşap, metal, cam, taş, plastik, bakır, jöle) altında oluşturulan tek bir tanıdık olmayan nesneye ait 28 görüntüden oluşmaktadır. Parlak ve mat yansıma özelliklerine sahip yedi malzeme, BlenderKit'ten seçilmiştir. Seçilen glaven modeli, Philips tarafından GitHub'da (2004) sağlanan Glaven Seti'nden BigGlaven3'tür. Toplam dört madde koşulu vardır: Malzeme-uyumlu koşul (MU), Malzeme-uyumsuz koşul (MUmz), Yansıma-uyumlu koşul (YU), Yansıma-uyumsuz koşul (YUmz).

3.4. Prosedür

Üçüncü deney, birinci deneye benzer bir prosedürü takip etmiştir. Deney üç aşamadan oluşmuştur: çalışma aşaması, dikkat dağıtma aşaması ve test aşaması. Çalışma aşamasında, katılımcılara her dört madde koşulu için 7 çift içeren bir çalışma listesi gösterilmiştir. Toplamda 28 çift, her çift için dört saniye süreyle rastgele sırayla sunulmuştur. Test aşaması, çağrışımsal bir tanıma görevi kapsamında gerçekleştirilmiştir. Bu aşamada katılımcılara, her dört madde koşulu için çiftler içeren bir test listesi gösterilmiştir. Toplamda 55 çift sunulmuştur. Katılımcılardan, eğer çifti çalışma listesinden hatırlıyorlarsa klavyede e tuşuna, hatırlamıyorlarsa h tuşuna basmaları istenmiştir. Görevde süre sınırı bulunmamaktadır. Bu çalışmada, çağrışımsal tanıma görevi ile denek içi desen kullanmış ve tüm yanıtlar bir klavye aracılığıyla toplanmıştır.

3.5. Sonuçlar

Verileri düzenlemek için SciPy paketini kullanarak bir Python kodu yazılmıştır. Duyarlılık (*d'*) ölçümlerine tekrarlı ölçümler içeren iki yönlü 2 (uyum) x 2 (yüzey özelliği) ANOVA analizi, uyum (uyumlu, uyumsuz) ve yüzey özelliği (malzeme, yansıma) etkilerini incelemek için yapılmıştır. Bulgular, tanıdık olmayan nesnelerin çağrışımsal tanıma belleğinde anlamlı bir uyum etkisi olduğunu göstermiştir, $F(1, 56) = 62.7$, $p < 0.001$, $\eta^2 p = 0.52$.

Bonferroni düzeltmeli post hoc analizde, malzeme uyumlu koşulun (M=1.66, SD=0.6) tanıma duyarlılığı d' skorunun, malzeme uyumsuz koşuldan (M=1.02, SD=0.45) daha yüksek olduğu bulunmuştur (ortalama fark = 0.64, standart hata = 0.09, $p < .001$). Ayrıca, yansıma uyumlu koşulun (M=1.43, SD=0.54) tanıma duyarlılığı d' skoru, yansıma uyumsuz koşuldan (M=1.14, SD=0.46) daha yüksektir (ortalama fark = 0.3, $p = .007$).

Sonuçlar, malzeme ve yansıma özelliklerinin uyumlu eşleşmelerde daha iyi tanındığını göstermektedir. Yüzey özelliğinin tanıma üzerinde anlamlı bir ana etkisi bulunmuştur, $F(1, 56) = 15$, $p < 0.001$, $\eta^2 p = 0.2$. Malzeme özelliğinin tanıma duyarlılığı d' skoru (M=1.34), yansıma özelliğinden (M=1.28) anlamlı olarak daha yüksektir. Ayrıca, uyum etkisinin malzeme özelliğinde yansıma özelliğine kıyasla daha etkili olduğu görülmüştür.

Malzeme etkisini daha ayrıntılı incelemek için, malzeme türlerine dayalı bir yönlü tekrarlı ölçümler ANOVA analizi yapılmıştır. Bulgular, ahşap malzemesinin metal, taş, bakır ve plastikten daha iyi tanındığını göstermiştir. Ayrıca jöle malzemesinin de metal, taş, bakır ve plastikten daha iyi tanındığı gözlemlenmiştir. Yansıma etkisini değerlendirmek için yapılan çift örneklem t-testinde, mat yansıma özelliği (M=1.5) parlak yansıma özelliğinden (M=1.2) daha yüksek tanıma duyarlılığı göstermiştir ($p = 0.039$).

BÖLÜM 5

GENEL TARTIŞMA

Bu tezde, malzeme algısının tanıdık ve tanıdık olmayan nesnelerin çağrışımsal tanıma belleğinde kolaylaştırıcı rolü incelenmiştir. Bu nedenle, katılımcıların şekil, yansıma, malzeme gibi görsel özelliklerden gelen bilgileri nasıl birleştirdiği ve nesne belleğinde tanıdıklık veya tanıdık olmama durumuna bağlı olarak hangi tür bilginin daha baskın olduğunu anlamak bu tezin odak noktasını oluşturur. Bu amaçla üç deney ve bir ön çalışma gerçekleştirilmiştir.

5.1. Deney 1 Sonuçlarının Tartışması

Deney 1'in amacı, insanların tanıdık iki nesne arasındaki çağrışımsal belleği malzeme ve şekil gibi özelliklere dayalı olarak nasıl oluşturduklarını incelemekti. Aynı zamanda katılımcıların malzeme bilgisine mi yoksa şekil bilgisine mi daha fazla güvendiklerini görmek hedeflendi. Beklendiği gibi, hem malzeme hem de şekil özellikleri için bir uyum etkisi gözlenmiştir. Ancak, beklentinin aksine şekil bilgisi malzeme bilgisine kıyasla çağrışımsal tanıma performansında baskın çıkmamıştır. Tanıdık nesnelerde ne malzeme ne de şekil bilgisi tek başına baskın bir rol üstlenmiştir. Bu durum, malzeme bilgisinin tanıdık nesnelerde şekil kadar önemli olabileceğine işaret etmektedir. Ayrıca, nesnelerin önceden tanıdık olması, şeklin adlandırılabilirlik etkisine yol açmış olabilir (Walker & Cuthbert, 1998). Bu durum, deney sırasında nesne özelliklerinin nasıl algılandığını ve tanındığını etkilemiş olabilir.

5.2. Ön Çalışma ve Deney 2 Sonuçlarının Tartışması

Ön çalışmanın sonuçları, metal, taş ve ahşap malzemelerin doğru tanımlandığını ancak cam malzemesinin doğru tanımlanmadığını ortaya koydu. Bu durum, cam malzemesinin tanıdık şekillerle (sürahi, su bardağı vb.) birlikte daha doğru tanımlandığını göstermektedir. Bu bulgu, şeklin malzeme özelliklerinin algılanması üzerindeki etkisiyle tutarlıdır (Lagunas ve diğerleri, 2021; Serrano ve diğerleri, 2021).

Deney 2'nin sonuçları, malzeme ve şekil özellikleri için bir uyum etkisi olduğunu, ancak tanıdık olmayan nesnelerde malzeme bilgisinin şekil bilgisine kıyasla baskın olduğunu göstermiştir. Bu bulgu, Schmidt ve diğerlerinin (2017) araştırmasıyla tutarlıdır: Tanıdık olmayan nesnelerin algısında, malzeme özelliği değiştiğinde katılımcıların şekil ipuçlarına güvenmediği gözlemlenmiştir. Ayrıca, Deney 1 sonuçlarının aksine, Deney 2'de tanıdık olmayan nesnelerde malzeme bilgisinin baskın olması, katılımcıların güvenilir ve tanıdık yüzey bilgisine yönelmesiyle açıklanabilir. Bu bulgu, Landau ve diğerlerinin (1998) çalışmasından farklılık göstermektedir. Araştırmacılar, işlevsel bilgi sağlanmadığında hem çocukların hem de yetişkinlerin şekil bilgisine dayandığını bulmuşlardır. Bir başka önemli bulgu ise cam malzemesinin diğer malzemelere (metal, ahşap, taş) göre daha yüksek tanıma oranına sahip olmasıdır. Camın yüzey özelliklerinin (parlaklık, yarı saydamlık) görsel olarak kolay ayırt edilebilmesi bu sonucu açıklayabilir (Okamoto ve diğerleri, 2013).

5.3. Deney 3 Sonuçlarının Tartışması

Deney 3'ün amacı, şekil sabit tutularak malzeme ve yansıma özelliklerinin tanıdık olmayan nesnelerde çağrışımsal bellekte nasıl rol oynadığını incelemekti. Deney 3'ün sonuçları, malzeme ve yansıma özellikleri için bir uyum etkisi olduğunu, ancak malzeme bilgisinin yansıma bilgisinden daha baskın olduğunu göstermiştir. Yansıma özellikleri eşleşen nesne çiftleri daha iyi tanınsa da, malzeme bilgisi baskın bir rol oynamıştır. Özellikle mat yüzeylerin parlak yüzeylere kıyasla daha iyi tanınmasının nedeni, mat yüzeylerdeki dokunun parlak yüzeylerdeki ışık ve gölge oyunlarından daha fazla bilgi sağlaması olabilir (Pont ve diğerleri, 2015; Toscani ve diğerleri, 2017). Ayrıca, ahşap ve jöle malzemelerinin yüksek tanıma oranına sahip olması, yüzey dokularının belirginliğiyle açıklanabilir (Yoonessi & Zaidi, 2010). Jöle malzemesinin yarı saydamlık gibi özelliklerinin algısında renk gradyanlarının rol oynaması (Liao ve diğerleri, 2022) buradaki bulgulara da kısmen ışık tutabilir.

5.4. Sınırlılıklar

Bu çalışmanın ilk sınırlılığı, Deney 3'te kullanılan ahşap ve jöle malzemelerinin, çalışılan ve çalışılmayan çiftler arasında diğer malzemelere kıyasla renk açısından daha belirgin ayırt edilebilir özelliklere sahip olmasıdır. Bu durum, bu nesnelerin daha kolay tanınmasına ve çağrışımsal tanıma performansının etkilenmesine yol açmış olabilir. İkinci sınırlılık ise, uyaranların üç boyutlu modelleri oluşturulurken ışık kaynağının yönü tüm uyaranlarda kontrol edilmemiştir. Tezin sınırlılıkları arasında, deneylerde tekrarlayan nesne çiftleri ve koşullardaki bellek yükü farklılıkları da yer almaktadır. Ayrıca, ön çalışmada glaven nesnesinin cam materyali diğer materyaller kadar net tanımlanamamış, ikinci deneyde farklı cam görselleştirme parametreleri kullanılmıştır. Bu değişiklik, birinci ve ikinci deneylerde cam materyalinin parametrelerinin farklı olmasına neden oluşturmuştur.

5.5. Gelecek Araştırmalar

Bu çalışma, gelecekteki araştırmalar için çeşitli yönler sunmaktadır. İlk olarak, mevcut veriler, malzeme algısında rengin etkisini kesin olarak dışlamak için yeterli değildir. Gelecekteki araştırmalar, özellikle renk bilgisinin doku, parlaklık ve diğer malzeme özellikleriyle birlikte nasıl işlendiğini incelemelidir. İkinci olarak, gelecekteki araştırmalar, nesnelerin anlamsal ve kullanımsal özelliklerinin çağrışımsal nesne belleği üzerindeki rolünü, algısal özelliklerle karşılaştırmalı olarak inceleyebilir. Üçüncü olarak, bu çalışmada kullanılan nesne özellikleri (şekil, yansıma ve malzeme) birbirleriyle etkileşime girebilen eklemeli bir süreç olarak modellenebilir (Ho ve diğerleri, 2008). Ayrıca, ışık akışının malzeme ve yansıma algısındaki rolü gelecekte incelenebilir.

5.6. Sonuç

Bu tezde, malzeme algısının tanıdık ve tanıdık olmayan nesnelerin çağrışımsal belleğinde oynadığı rol araştırılmıştır. Üç deney sonucunda, tanıdık nesnelerde malzeme ve şekil bilgisinin eşit derecede önemli olabileceği, ancak tanıdık olmayan nesnelerde malzeme bilgisinin şekil ve yansıma bilgisine kıyasla baskın olduğu bulunmuştur. Bu çalışma, malzeme özelliklerinin görsel algı ve bellek araştırmalarına katkıda bulunarak, nesne tanıma süreçlerinde malzemenin önemini vurgulamaktadır. Bu bulgular, pazarlama ve endüstri gibi alanlarda pratik uygulamalar için önemli çıkarımlar sunmaktadır.

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