**Proceedings of the ASME 2025
International Design Engineering Technical Conferences and
Computers and Information in Engineering Conference
IDETC-CIE2025
August 17-20, 2025, Anaheim, CA**

DETC2025-163043

COGNITIVE DEMANDS AND INDIVIDUAL DIFFERENCES IN PRODUCT SIMILARITY JUDGEMENTS: A CONTEXT-DEPENDENT MODEL

Chukwuma M. Asuzu[1], Peiying Jian[1], Alison Olechowski[1]

[1]University of Toronto, Toronto, Canada

ABSTRACT

*Product similarity is employed as a key manipulation in design cognition experimental research. To understand user behaviour, design researchers utilize appearance or functional similarity to study far ranging concepts such as feature recognition, aesthetic preferences, and even multi-modal search. These studies rely on an implicit assumption: that product similarity is intuitive, proceeds without conscious elaboration, and is easily understood by research participants. However, this notion has not been empirically tested. In this study, we consider the cognitive demands and individual differences involved in making product similarity judgements. We devised a repeated-measures, pairwise similarity comparison experiment with pairs of products similar by appearance, function, and a baseline comparator. Our analysis of more than 7,000 similarity ratings found that appearance similarity judgements exert less cognitive demand than functional similarity judgements, however participants are more accurate when making functional similarity judgements. This phenomenon denotes the presence of a schema, which we term the **functionality context schema**, that is employed when making functional similarity judgements; applying the schema takes more cognitive effort but improves the accuracy of the judgements. We discuss the implications of our results for design research employing product similarity as a manipulation as well as for consumer behaviour studies.*

Keywords: Design cognition, Product similarity, Design of experiments, Consumer behaviour, Product design

1. INTRODUCTION

Every day, consumers make thousands of decisions about products, from choosing a new smartphone to picking a pair of shoes. These decisions often hinge on how similar one product is to another – whether in appearance, function, or both. For businesses, understanding how consumers perceive product similarity is critical for designing effective marketing strategies, improving product recommendations, and enhancing user experiences. Two modes of product similarity are commonly used: appearance similarity, which is driven by the design elements (colour, shape, texture, etc.) of a product, and functional similarity, which is driven by the use of the product. In consumer behaviour and design cognition research, product similarity is commonly employed as a manipulation to study product comparison [1, 2], decision making [3, 4], and object perception [5, 6].

Despite the widespread use of product similarity in design research, there is little understanding of the cognitive demands and individual differences involved in making these judgments. Design cognition studies assume that participants intuitively understand and process appearance and functional similarity without considering the mental effort required or the individual differences that can affect those judgements. Without a clear understanding of the cognitive processes underlying similarity judgments, researchers and practitioners risk drawing inaccurate conclusions about consumer behavior.

To address this gap, our study investigates two key research questions:

Q1: What are the cognitive demands involved in judgments of product similarity, particularly when comparing shape-based (appearance) and function-based similarity?

Q2: How do individual differences, such as age, gender, and shopping frequency, influence these judgments?

Building on the literature on product similarity and levels of processing, we devised a pairwise similarity comparison experiment to study product similarity decision-making using reaction time, demographic characteristics, and similarity ratings. Our results reveal that functional similarity judgments require significantly more cognitive effort than appearance-based judgments, as evidenced by longer reaction times. Additionally, we found that individual differences, such as online shopping frequency, influence how consumers perceive product similarity. These findings have important implications for both design cognition research and consumer behavior.

This paper proceeds as follows: first, we provide an overview of the relevant literature on product similarity and levels of processing. Next, we describe the pairwise similarity comparison experiment and our selection of stimuli. In the fourth section, we present our results. Finally, we discuss our findings and their relevance for the field.

2. BACKGROUND

In this section, we provide an overview of product similarity and levels of processing discussing relevant work from the psychology, marketing, and design research literature.

2.1 Product Similarity

In the literature, product similarity has been studied along two modes: appearance similarity and functional similarity. Driven by *low level* perception, appearance similarity encompasses representations of similar colours, shapes, and dimensions that products offer. On the other hand, functional similarity is driven by *higher level* cognition where perceived product features are analyzed in terms of functional outcomes they can provide.

In product design, appearance similarity is useful for understanding consumer preferences. Deng et al. [7] developed a similarity-based model of colour relationships using athletic shoes to understand the likelihoods of selecting different colour pairs in a mass customization use case. They found that consumers focus on hue and saturation in their colour preferences and combine colour combinations that are a close match. On the other hand, functional similarity plays a big role in consumer evaluations of product alternatives. In their research on product choice modelling, Du and Macdonald [8] focused on the commonalities across different car models and how that affects the decision-making process for consumers. Their analyses – using eye tracking and subjective ratings – showed that consumers visually fixate and consider the variants of a design in their product selection tasks.

There is also considerable literature that combines both featural and functional similarity in their methodology. For example, in their study of multi-modal search for inspirational design stimuli, Kwon et al. [9] used neural networks to provide similar parts (by function or appearance) to the research participants to understand how they searched for related part stimuli. Similarly, Ye at al. [10] used image stimuli of motorbikes to study the influences of product similarity on consumer preferences. In their case, they manipulated the stimuli in three categories: recreational bikes, folding bikes, and mountain bikes, and selected stimuli that fit either one, two, or all categories in appearance.

In the studies described above, product similarity was used as a manipulation in the study of other constructs (consumer preferences, product decision making, and multi-modal search). The underlying notion in these studies is that product similarity is easily identifiable, understood implicitly, and requires little cognition by research participants. However, we are unaware of any research that investigates this assertion. This notion needs to be tested in terms of the cognitive demands expended when considering the different modes of product similarity. In addition, individual differences have been shown to impact thematic similarity judgements in other domains, such as food products [11], we extend this analysis to design products in this paper.

2.2 Levels of Processing

To understand the complex cognitive process of product similarity, we resort to other information process theories in cognition and perception that aim to structurally understand complex cognitive processes.

The Levels of Processing (LoP) framework, first introduced by Craik and Lockhart [12] in 1972, posits that deeper cognitive engagement leads to stronger memory encoding. This theory has been widely applied in cognitive psychology and consumer research to explain how individuals perceive, process, and remember information. The LoP theory suggests that memory and recognition are influenced by the depth at which information is processed. In *shallow processing*, sensory and structural characteristics of stimuli (e.g., visual appearance, shape, color) are processed in a faster manner, while in *deep processing*, semantic and functional characteristics (e.g., meaning, use, purpose) are processed in a slower manner.

In the context of product similarity, the LoP framework provides a useful lens to understand how individuals assess similarity based on surface-level (appearance) vs. deeper (functional) features. When judging perceptual similarity, individuals judge similarity based on the design features of a product. For example, a glass tumbler and a pencil holder may be perceived as similar due to their cylindrical shape. When judging functional similarity, individuals judge similarity based on how products are used or their intended function. For example, digital and analog thermostats may be perceived as similar because both regulate temperature.

In 1977, Tversky [13] challenged traditional geometric models of similarity and propose a feature-based contrast model emphasizing the context-dependence of similarity judgments. In his study, participants were asked to compare pairs of items and rate their similarity. The study found that the context in which items are presented significantly influences similarity judgments. Therefore, people perceive product similarity beyond appearance perceptions.

Also consistent with the levels of processing theory, categorizing product function takes longer than categorizing product aesthetic values. In Lamberts' study [14], participants were required to categorize stimuli based on appearance (e.g., shape, color) and functional (e.g., purpose, usage) attributes under a time-constraint. Under increased time pressure, participants tended to rely more on perceptual features for categorization. When given more time, participants were more likely to consider functional attributes. This result indicates that functional similarity judgments require higher cognitive effort. Finally, more recent work has focused on the processing fluency of product images finding that the ease of processing is related to aesthetic preferences [15, 16], and that perceptual fluency – driven by product appearance – enhances product evaluations [17].

Applying the LoP framework, our study investigates the cognitive dimensions of product similarity tasks, comparing the reaction time undertaken to make appearance and functional similarity judgements. In addition, we analyze the relationship between individual differences (age, gender, and shopping frequency) of study participants and their product similarity ratings.

3. METHODS

To test the hypothesis, we conducted a pairwise similarity comparison experiment in PsychoPy [18] using product images. The image pairs differed in their similarity (whether by appearance or by function, we also included neutral product images) and participants rated their similarity using a Likert scale. Ethics approval was received from our institutional Research Ethics Board.

3.1 Participants

Participants were native English speakers with normal or corrected-to-normal vision who were recruited on Prolific. After applying exclusion criteria, 128 participants were included in the final analysis. Exclusions were based on failed attention checks (n = 23), multiple responses from the same participant (n = 5), and low-effort responses (n = 6).

TABLE 1: DEMOGRAPHIC TABLE OF PARTICIPANTS

	Participants	%
Gender		
Female	63	49.2%
Male	65	50.8%
Age, in years		
18-24	17	12.8%
25-34	49	36.8%
35-44	28	21.1%
45-54	13	9.8%
55-64	20	15.0%
65+	6	4.5%
Online shopping frequency		
More than once a week	29	22.7%
About once a week	19	14.8%
Several times a month	39	30.5%
About once a month	22	17.2%
Once in a few months or longer	18	14.1%
Never	1	0.7%
Country of residence		
United Kingdom	65	50.7%
Canada	27	21.1%
United States	10	7.8%
Ireland	7	5.5%
South Africa	7	5.5%
Others (Australia, France, etc.)	12	9.4%

3.2 Materials and Stimuli

The study utilized nine product images as experimental stimuli, categorized in three groups. Three of the images were selected for their similar geometric form: a toilet paper roll, a glass tumbler, and an aluminum stationery holder (see Figure 1). Another three images were selected of products that shared functionality, in this case they were images of thermostats (see Figure 2). Three additional product images served as baseline (neutral) stimuli (see Figure 3). Each image was presented against a gray background to control for visual distractions and maximize image salience. The image sources are described in the Acknowledgements.

FIGURE 1: PRODUCT STIMULI WITH THE SAME SHAPE

FIGURE 2: PRODUCT STIMULI WITH THE SAME FUNCTION

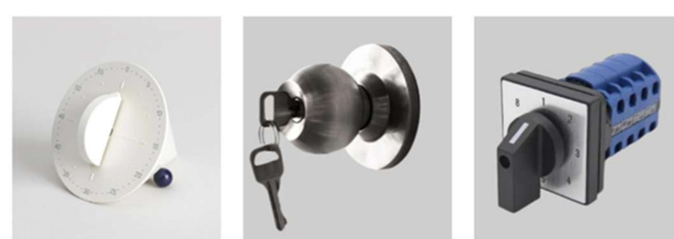

FIGURE 3: NEUTRAL STIMULI

3.3 Procedure

Participants were presented with 36 unique image pairs generated by systematically combining the nine product images. Each pair was viewed twice, with a different prompt for each similarity mode (appearance-based and function-based similarity ratings). For each image pair, participants rated the similarity using the following prompt:

> *On a scale of 1 (Not Similar) to 5 (Very Similar), to what extent are these two products similar by shape/function?*

Participants were given six seconds to provide their rating before proceeding to the next trial. The order of the pairs and position (left/right) of the stimuli pairs were randomized to minimize order effects. Prior to the main experiment, participants completed a practice session to familiarize themselves with the rating task and response scale. In this session, they rated similarity for additional product pairs that were not included in the experimental stimuli. The practice session ensured that participants understood the task instructions and response format before beginning the recorded trials.

3.4 Data Wrangling

In the main experiment, across the two similarity processes, each participant provided up to 72 ratings. In total, 8,928 similarity ratings were collected across all participants in this study. In addition, the time stamps for the start and end of each rating task were recorded, the difference between both timestamps for each task were calculated and designated as the reaction time.

To ensure data quality and accuracy, we conducted a systematic data cleaning and data treatment process before analysis. The initial dataset contained participants who provided similarity ratings for both appearance and function-based comparisons. To ensure consistency, we retained only participants who were present in both datasets (i.e., participants who provided both appearance and function similarity ratings). For the individual differences analyses, missing values were imputed using the participant's mean similarity rating. This method ensured that missing data did not introduce bias while preserving individual rating tendencies.

4. RESULTS

In this section, we present the results of the pairwise comparison experiment using the similarity ratings and the reaction time for each rating task. Apart from analyzing the full ratings, we also describe some analyses using subsets of the ratings data such as *matched pairs* (which is data from ratings where pairs with similar shape or similar function were shown to participants) and *non-matched pairs* (which is data from ratings where the pairs shown to the participants were not similar by shape/appearance or function).

Analyzing the study data within these subsets are relevant to learn more about cognitive demands and individual differences. Matched pairs provide information about the impact of image pair similarity, while non-matched pairs provide information about the influence of the shape or functional similarity prompts independent of image similarity.

4.1 Descriptive Analysis

We observed that the collected data had some missing values and first analyzed this pattern of this behaviour. On average, participants have about 1.6 missing values, with the majority (96) participants having 0 to 2 missing values; the missing ratings represent 2.3% of the data for analysis. Interestingly, the function ratings have almost 3 times the missing ratings (150) as the missing appearance ratings (52). As the experiments were timed, each pair was only shown for a maximum of 6 seconds before moving on to the next one, thus pairs that had missing ratings were likely to have caused considerable deliberation for the participant. A correlational analysis between the number of missing pairs and the average reaction time per participant revealed a moderate positive relationship with a correlation of 0.49. This anecdotally supports our hypothesis that functional similarity judgements involve more cognitive demand compared to appearance similarity judgements, as functional similarity judgements were three times as likely to be responsible for a missing rating.

Appearance similarity ratings were generally higher than function similarity ratings, a relationship that is significant ($t(8675.42) = 9.65, p < .001, d=0.21$). On average, participants' appearance similarity ratings ($M = 2.13, SD = 1.28$) were higher than their function similarity ratings ($M = 1.85, SD = 1.35$). However, as shown in Table 2, the situation is reversed when rating the matched pairs, with the functional similarity ratings much higher and less dispersed than the appearance similarity ratings.

TABLE 2: DESCRIPTIVE STATISTICS OF THE PRODUCT SIMILARITY RATINGS

Pair Ratings by Similarity Prompts	Mean	Standard Deviation
All Pairs		
Shape Similar	2.13	1.28
Function Similar	1.85	1.35
Matched Pairs		
Shape Similar	3.87	1.28
Function Similar	4.13	1.09

This finding suggests consumers have higher accuracy and are more critical in judging functional similarity than in their appearance similarity judgements. Figure 4 below shows the similarity ratings, highlighting the difference in the distribution of the global ratings and the matched pair ratings.

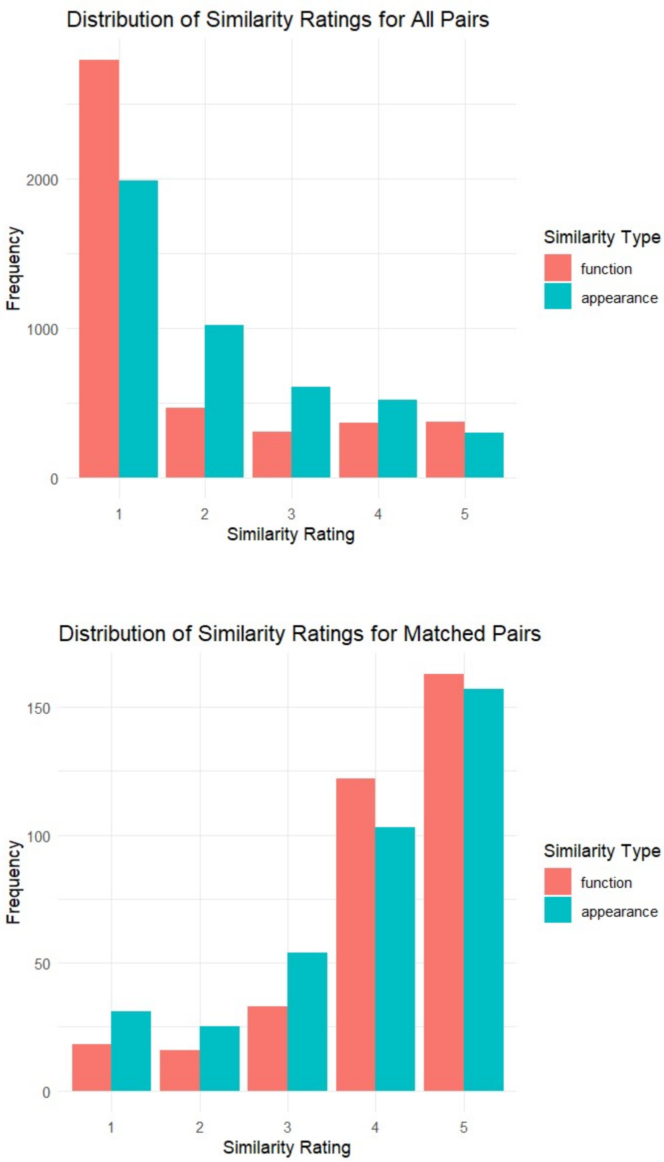

FIGURE 4: DISTRIBUTION OF PRODUCT SIMILARITY RATINGS, COMPARING THE DIFFERENCES IN RATINGS BETWEEN ALL PAIRS AND MATCHED PAIRS ACROSS BOTH RATING PROMPTS (TOP SHOWING ALL PAIRS, BOTTOM SHOWING MATCHED PAIRS).

4.2 Cognitive Demands

A linear mixed effects model was used to analyze this data to account for the effect of the image pairs and participants in the analysis of the repeated measures study. Reaction time was modelled as a function of the prompt type (appearance or function), the pair type (shape matched, function matched, or nonmatched), and the interaction between these variables. The model included random intercepts for participants and image pairs and was estimated by Restricted Maximum Likelihood (REML) and Satterthwaite degrees of freedom using the lme4 [19] and lmerTest [20] R packages.

The model showed that the prompt type has a significant effect on the reaction time ($F = 245.8902, p < 0.001$), as well as the interaction between prompt type and pair type ($F = 13.5003, p < 0.001$). On its own, the pair type did not have a significant effect on the reaction time ($F = 2.8426, p = 0.072$). As shown in Figure 5 and Table 3 below, the reaction time for the functional similarity prompt type ($M = 2.82, SD = 1.54$) is significantly higher than the reaction time for the shape similarity prompt type ($M = 2.33, SD = 1.26$) across all pair types.

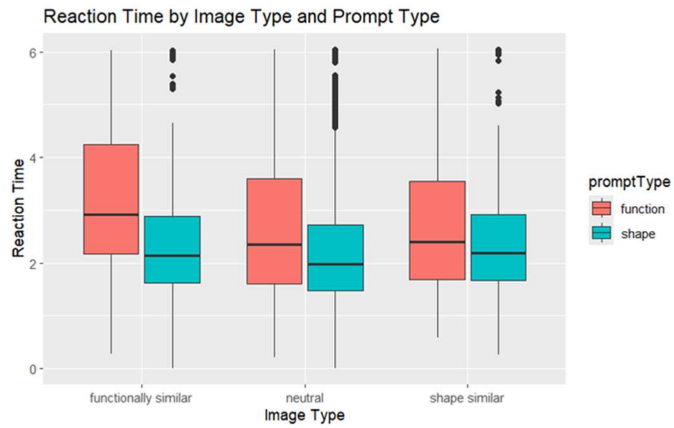

FIGURE 5: REACTION TIME VARIATION BY PROMPT TYPE AND PAIR TYPE.

TABLE 3: LINEAR MIXED-EFFECT MODEL RESULTS

Effect	Estimate	SE	t-value	p-value
Intercept	3.2714	0.1564	20.909	< 2e-16
Prompt Type: Shape	-0.8327	0.0726	-11.459	< 2e-16
Image Type: Neutral	-0.4982	0.1405	-3.545	0.0010
Image Type: Shape Similar	-0.4459	0.1894	-2.354	0.0238
Prompt Type: Shape * Image Type: Neutral	0.3702	0.0762	4.858	1.21e-06
Prompt Type: Shape * Image Type : Shape Similar	0.4766	0.1027	4.638	3.57e-06

Post-hoc pairwise comparisons (Tukey-adjusted) revealed that reaction times for function prompts on functionally similar images ($M = 3.27, SD = 1.47$) were significantly longer than for shape prompts on shape similar images ($M = 2.47, SD = 1.19$), $t(9474) = 4.23, p < 0.001, d = 0.60$, suggesting a moderate effect size. These results confirm that overall functional similarity judgements exert more cognitive demand than appearance similarity judgements. However, the interaction effects between the prompt type and pair type reveal an interesting phenomenon: when participants are asked to judge appearance similarity given products that are similar by appearance, their reaction times are slower than judging appearance similarity given a functionally similar pair.

4.3 Individual Differences

For individual differences, we were interested in demographic differences that could explain differences in the product similarity ratings. We collected the age, gender, and online shopping frequency for the participants via Prolific. For our analysis we had two considerations: the total sample of product similarity ratings as well as the subset of non-matched pair ratings. In this subsection, we present results for the total sample first, then result for the non-matched pairs.

Our analyses did not yield any significant differences in appearance and function similarity ratings by age or sex. A one-way ANOVA revealed a significant main effect of online shopping frequency on appearance similarity rating, $F(4, \sim 8675) = 4.26, p < 0.001$, but not on the functionality rating. However, a Tukey's HSD post-hoc test revealed that no specific pairwise comparisons were statistically significant after adjusting for multiple comparisons (all p-values > 0.05). This suggests that while online shopping frequency may have a small overall influence on appearance similarity perceptions, the differences between individual shopping frequency groups are not meaningful. The boxplot visualization in Figure 6 shows that mean appearance similarity ratings remain relatively stable across shopping frequency groups, with no strong deviations.

FIGURE 6: APPEARANCE SIMILARITY RATINGS ACROSS SHOPPING FREQUENCY CATEGORIES.

Finally, a multiple linear regression analysis was conducted to examine the effects of rating type (appearance vs. function) and demographic factors (age, sex, online shopping frequency) on z-normalized scores of similarity ratings for nonmatched product pairs.

The overall model was statistically significant ($F(7, 2164) = 3.048, p = .003$), but accounted for only 1% of the variance in similarity ratings ($R^2 = .010$, $Adjusted\ R^2 = .007$), suggesting a small effect size. Online shopping frequency was a significant predictor ($\beta = 0.047, SE = 0.023, t = 2.07, p = .039$), indicating that individuals who shop online more frequently tend to rate nonmatched pairs as more similar. The interaction between rating type and age was also significant ($\beta = -0.003, SE = 0.001, t = -2.64, p = .009$), suggesting that age moderates how similarity is judged when rating appearance compared to function.

As frequency shopping online is the strongest demographic predictor, we then looked at its interaction with prompt type. Through a multiple linear regression, a significant Prompt Type × Shopping Frequency interaction was found for participants who shop about once per week, $B = -0.156, SE = 0.065$, $t(8106) = -2.43, p = .015$, indicating that the effect of shopping frequency on z-scores varied by prompt type. Post-hoc comparisons revealed that frequent shoppers tend to give higher similarity ratings under function prompts compared to shape prompts.

In addition, a significant Rating Type × Shopping Frequency interaction was observed for participants who reported never shopping, $B = 0.168, SE = 0.082, t(8106) = 2.03, p = .042$. This suggests that non-shoppers relied more on shape similarity than functional similarity when making similarity judgments. However, no significant interactions were found for participants who shop more than once per week ($B = -0.025, SE = 0.072, t(8106) = -0.35, p = .725$) or several times a month ($B = -0.019, SE = 0.066, t(8106) = -0.29, p = .775$). Figure 7 below illustrates the interaction effect on shopping frequency.

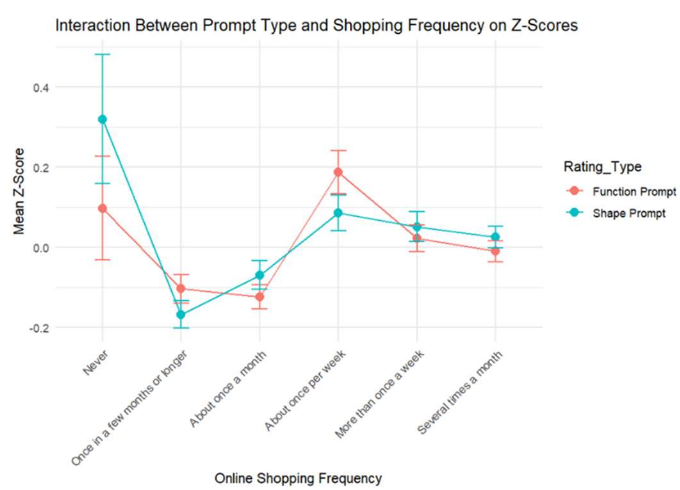

FIGURE 7: INTERACTION RELATIONSHIP BETWEEN PROMPT TYPE AND SHOPPING FREQUENCY

5. DISCUSSION

Our findings present a few phenomena worthy of discussion. In this section, we discuss the theoretical and practical implications of our results as well as the limitations of our study and directions for future research.

5.1 Cognitive Demands

Our main finding shows that consumers are more accurate in functional similarity ratings (compared to appearance similarity ratings) even though it takes more cognitive effort. Matched pair ratings are higher for functional similarity ratings compared to appearance similarity ratings, while the reverse holds for the total ratings. In our reaction time analysis, we find that participants take longer time making functional similarity judgements – a phenomenon that is consistent across all matched and non-matched pairs – compared to the time spent making appearance similarity judgements, except when they are judging functionally similar pairs. We contend that this implies a schema at work following the psychological definition [21]; while consumers expend cognition in applying this schema to determine functionality and then functional similarity, utilizing this schema improves the accuracy of their judgements. We term this the **functionality context schema**.

When considering appearance similarity, however, consumers do not apply this schema as they default to the features they can see. This finding has implications for design cognition research that employs product similarity as a manipulation as well as for product categorization and object recognition research. The results suggest that function-based categorization requires deeper semantic processing, whereas shape-based categorization relies more on perceptual processing.

As schemas require prior knowledge of the product type, category, and/or features, functional similarity may be inadequate for studying novel products as consumers have no schema to defer to. In addition, appearance similarity may be preferred for experimental conditions that have a short or limited time frame.

5.2 Individual Differences

Our results show that there are considerable individual differences in product similarity judgements. While age and gender appear to have no significant effect on the product similarity ratings, the online shopping frequency of participants influences their appearance similarity ratings. Furthermore, we find that online shopping frequency is a significant predictor in the incorrect judgement of non-matched pairs. An explanation of this finding is perhaps that consumers who shop a lot online are exposed to more products compared to the average consumer and make appearance similarity judgements by prioritizing speed over accuracy. This prioritization of speed could help the consumers select a short list of products they are interested in, which then become the alternatives for their product selection at which point they can verify their initial assessment of their features prior to purchasing the items.

Our inclusion of online shopping frequency as an individual variable was somewhat fortuitous, it is a demographic characteristic collected on Prolific by default and as our experiment ran online, we thought that viewing products in our experimental design was quite similar to the cognition required to view and purchase products online.

These findings also have some implications for research that employ similarity as a manipulation. During participant recruitment, online shopping frequency should be collected as a demographic variable as it could offer important insights into the consumer behaviour of the participants.

5.3 Limitations and Future Work

A limitation of our study is that the research participants were not asked about their knowledge of the products being shown. It is feasible that their knowledge of the products' uses and features might be a factor in their similarity ratings, particularly for functional similarity and in the analysis of non-matched pairs. We chose not to include this in our study due to the length of time for the repeated-measures design and the effective performance of the pilot test participants. Product knowledge could provide a useful variable for future work in cognitive demands and individual differences in product similarity judgements.

There are other avenues for future work in this research agenda. One avenue could explore cognitive demands and individual differences in thematic similarity judgements, i.e., similarity judgements that are cued based on the product combinations, and not explicitly prompted. Another area of research could involve quantifying the influence of personal experience or expertise on product similarity judgements.

In addition, neuroscience methods such as eye tracking could provide more information on the functionality context schema and how the schema proceeds in functional similarity judgements. As well, methods such as EEG or FMRI could highlight locations in the brain impacted during product similarity judgements and what cognitive demands of product are driven as a result.

6. CONCLUSION

Our study shows that appearance and functional product similarity, both used extensively as manipulations in design cognition studies, have non-uniform cognitive demands. While consumers expend more cognitive effort in functional similarity judgements (compared to appearance similarity judgements), their accuracy is better in functional similarity judgements. In addition, we found that individual differences in online shopping frequency influence appearance similarity judgement. These findings have implications for design cognition research as well as the consumer behaviour literature.

ACKNOWLEDGEMENTS

Four of the image stimuli (images 1, 4, 5, and 7 in the list below) used in this paper are courtesy of the Cooper Hewitt Collection, the Smithsonian Design Museum. Images from the Cooper Hewitt Collection are allowed to be used with specific citation; other images are cited based on their website sources. All images were retrieved in January 2024. Below are the citations for each of the experimental image stimuli, in order of appearance in the paper:

1. Tumbler; glass; H x diam.: 10.9 x 8.8 cm (4 5/16 x 3 7/16 in.); 1945-34-13
2. Amazon.ca; Perfectware 2 Ply Toilet Tissue
3. eBay; Black Pen Holder for Desk
4. Magic Stat Thermostat; Designed by Cousins Design; Manufactured by Honeywell, Inc. (United States); USA; plastic, electric, electronic components; in box:

4.5 x 18 x 23 cm (1 3/4 x 7 1/16 x 9 1/16 in.); Gift of Anonymous Donor; 1993-58-2

5. T-86 Round Thermostat; Designed by Henry Dreyfuss (American, 1904–1972); Office of Henry Dreyfuss Associates (United States); Manufactured by Honeywell, Inc. (United States); USA; metal, plastic; H x diam.: 4.5 x 8 cm (1 3/4 x 3 1/8 in.); Gift of Honeywell Inc.; 1994-37-1
6. Walmart; Johnson Controls GLAS Thermostat.
7. On the Dot Kitchen Timer Timer; Designed by Morison S. Cousins (American, 1934 – 2001); Manufactured by Tupperware Corporation (United States); USA; plastic, metal; 9 x 10.4 x 9 cm (3 9/16 x 4 1/8 x 3 9/16 in.); Gift of Tupperware and Morison S. Cousins; 1996-102-1
8. Patty Chan/Shutterstock.com; White Door Metal Doorknob Lock.
9. Amazon.ca; Changeover Rotary cam Switch 660V.

REFERENCES

[1] Li, B. M., and Xie, S. Q., 2013, "Product Similarity Assessment for Conceptual One-of-a-Kind Product Design: A Weight Distribution Approach," Computers in Industry, **64**(6) pp. 720–731.

[2] Schuh, G., Rudolf, S., and Riesener, M., 2014, "Similarity-Based Product Configuration," Procedia CIRP, **17**pp. 290–295.

[3] Medin, D. L., Goldstone, R. L., and Markman, A. B., 1995, "Comparison and Choice: Relations between Similarity Processes and Decision Processes," Psychonomic Bulletin & Review, **2**(1) pp. 1–19.

[4] Ramdas, K., Zhylyevskyy, O., and Moore, W. L., 2010, "A Methodology to Support Product-Differentiation Decisions," IEEE Transactions on Engineering Management, **57**(4) pp. 649–660.

[5] Perez Mata, M., Ahmed-Kristensen, S., Brockhoff, P. B., 2017, "Investigating the Influence of Product Perception and Geometric Features," Research in Engineering Design, **28**(3) pp. 357–379.

[6] Tanaka, J. W., Kantner, J., and Bartlett, M., 2012, "How Category Structure Influences the Perception of Object Similarity: The Atypicality Bias," Frontiers in Psychology, **3**pp. 147.

[7] Deng, X., Hui, S. K., and Hutchinson, J. W., 2010, "Consumer Preferences for Color Combinations: An Empirical Analysis of Similarity-Based Color Relationships," Journal of Consumer Psychology, **20**(4) pp. 476–484.

[8] Du, P., and MacDonald, E. F., 2015, "Products' Shared Visual Features do Not Cancel in Consumer Decisions," Journal of Mechanical Design (1990), **137**(7).

[9] Kwon, E., Huang, F., and Goucher-Lambert, K., 2022, "Enabling Multi-Modal Search for Inspirational Design Stimuli using Deep Learning," Ai Edam, **36**.

[10] Ye, C., Xiong, Y., Li, Y., 2020, "The Influences of Product Similarity on Consumer Preferences: A Study Based on Eye-Tracking Analysis," Cognition, Technology & Work, **22**(3) pp. 603–613.

[11] Simmons, S., and Estes, Z., 2008, "Individual Differences in the Perception of Similarity and Difference," Cognition, 108(3) pp. 781–795.

[12] Craik, F. I. M., and Lockhart, R. S., 1972, "Levels of Processing: A Framework for Memory Research," Journal of Verbal Learning and Verbal Behavior, **11**(6) pp. 671–684.

[13] Tversky, A., 1977, "Features of Similarity," Psychological Review, **84**(4) pp. 327–352.

[14] Lamberts, K., 1995, "Categorization Under Time Pressure," Journal of Experimental Psychology.General, 124(2) pp. 161–180.

[15] Willems, S., van der Linden, M., and Bastin, C., 2007, "The Contribution of Processing Fluency to Preference: A Comparison with Familiarity-Based Recognition," European Journal of Cognitive Psychology, **19**(1) pp. 119–140.

[16] Mayer, S., and Landwehr, J. R., 2018, "Quantifying Visual Aesthetics Based on Processing Fluency Theory: Four Algorithmic Measures for Antecedents of Aesthetic Preferences," Psychology of Aesthetics, Creativity, and the Arts, 12(4) pp. 399–431.

[17] Winkielman, P., Schwarz, N., and Nowak, A., 2002, "Emotional Cognition,"John Benjamins Publishing Company, pp. 111–135.

[18] Peirce, J. W., 2007, "PsychoPy—psychophysics Software in Python," Journal of Neuroscience Methods, 162(1-2) pp. 8–13.

[19] Pinheiro, J., Bates, D., DebRoy, S., 2015, "Nlme: Linear and Nonlinear Mixed Effects Models. R Package Version 3.1-122," URL Http://CRAN.R289 Project.Org/Package= Nlme, .

[20] Kuznetsova, A., Brockhoff, P. B., and Christensen, R. H. B., 2017, "lmerTest Package: Tests in Linear Mixed Effects Models," Journal of Statistical Software, **82**(13) pp. 1–26.

[21] Brewer, W.F., and Nakamura, G.V., 1984, “The Nature and Functions of Schemas. Technical Report No. 325.”