

How ‘real-world’ complexity impacts visual search: insights from a web-based foraging task.

Enilda M. Velazquez, University of Central Florida, enilda.velazquez@ucf.edu

Nelson A. Roque, The Pennsylvania State University, nur375@psu.edu

P.A. Hancock, University of Central Florida, peter.hancock@ucf.edu



PennState

CASCADE Lab

Background

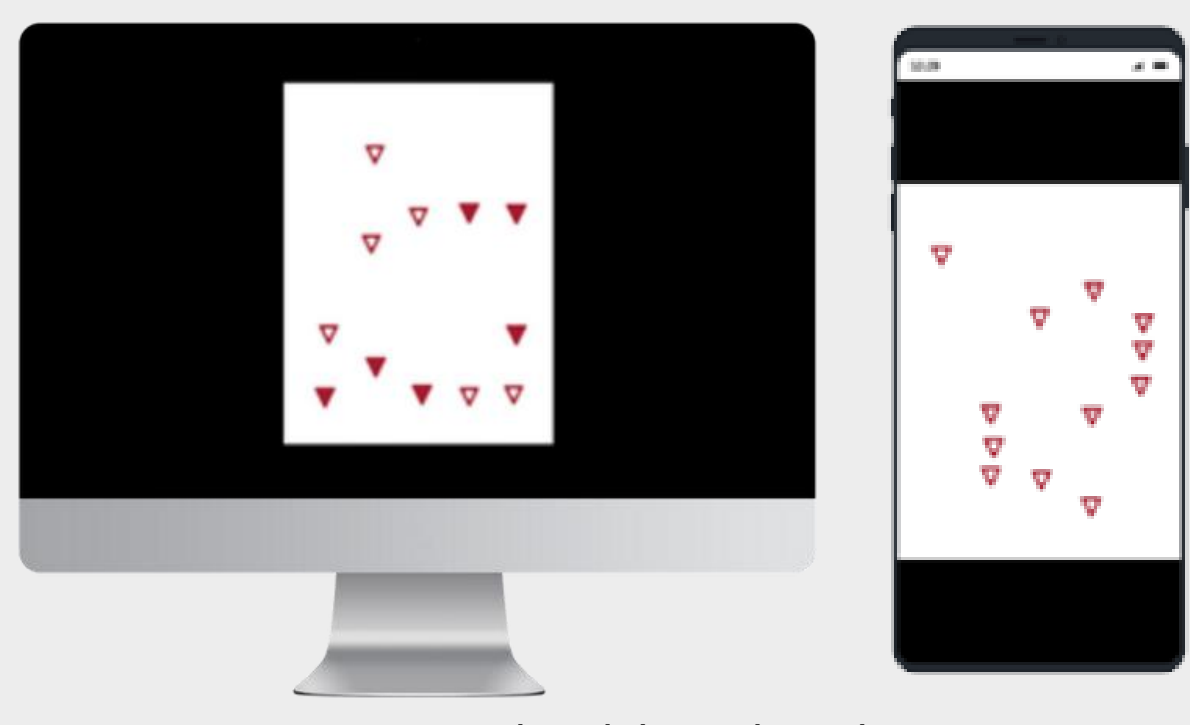
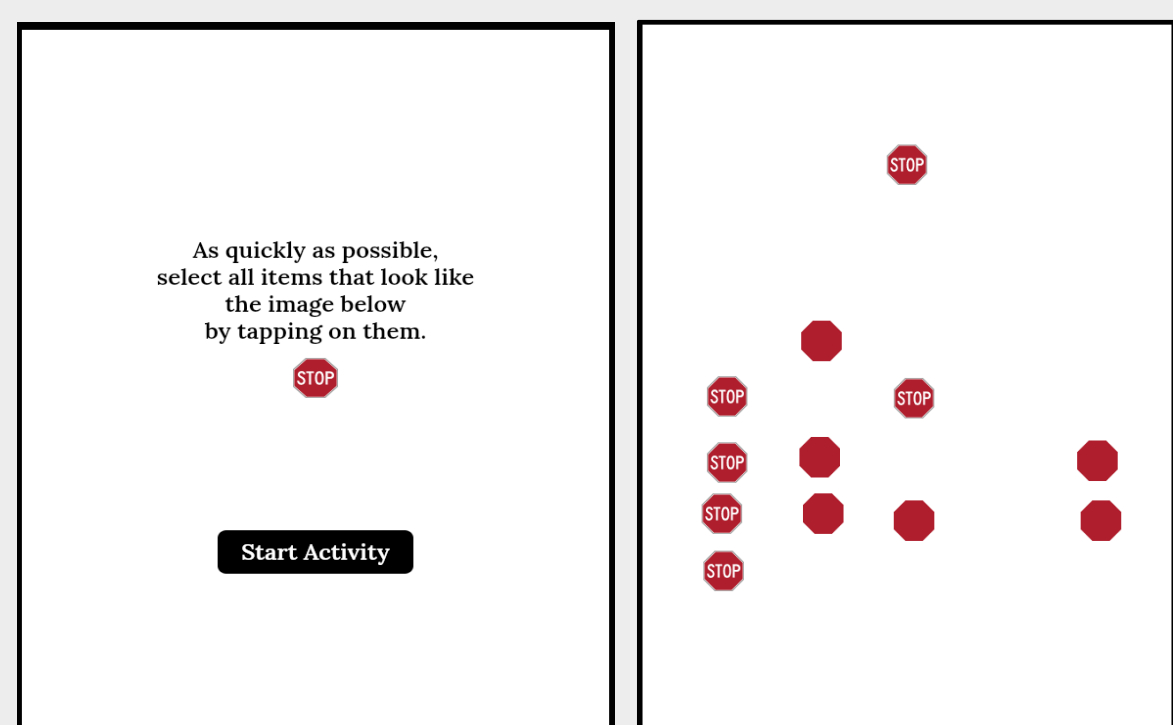
- **Single vs. Multi-target Search**
 - Single target search: looking for **one target** among many distractors.
 - Multi-target search: looking for **many targets** among many distractors.
- **Visual Foraging Task**
 - Developed to address concerns of ecological validity in single target search tasks: the **real world** is rarely comprised of single targets.
 - A multi-target search task in which observers are instructed to search for all of one kind of target among many distractors [2]
- **Information Processing → Search Strategy: Theories**
 - Optimal Foraging Theory [1]: observers maximize target acquisition for targets with maximum information and lowest energetic cost.
 - Increasing the information necessary for acquisition → increases cost to acquire target → observer changes search strategy or search slows [1, 3, 4]

Methods

- 14 block foraging task
- Conjunctive search for 2 experimental sets of stimuli and 1 control set of stimuli.
 - Experimental sets were composed of images one additional layer of features per image.
 - (1) background layer, (2) border layer, (3) writing layer



- Each block presented multiple pages of a pairwise stimuli combination.
- Each page contained 6 targets and 6 distractors.
- Participants foraged through as many pages as possible per block for 45 seconds.
- Counterbalancing of block-stimuli assignment was utilized.



Participants completed the task on their own device: task examples on non-mobile and mobile.

Research Question

How does increasing stimuli complexity affect multi-target search behavior in a foraging task?

Hypothesis

As the stimuli become more complex, mean inter-target time is expected to become larger.

Results

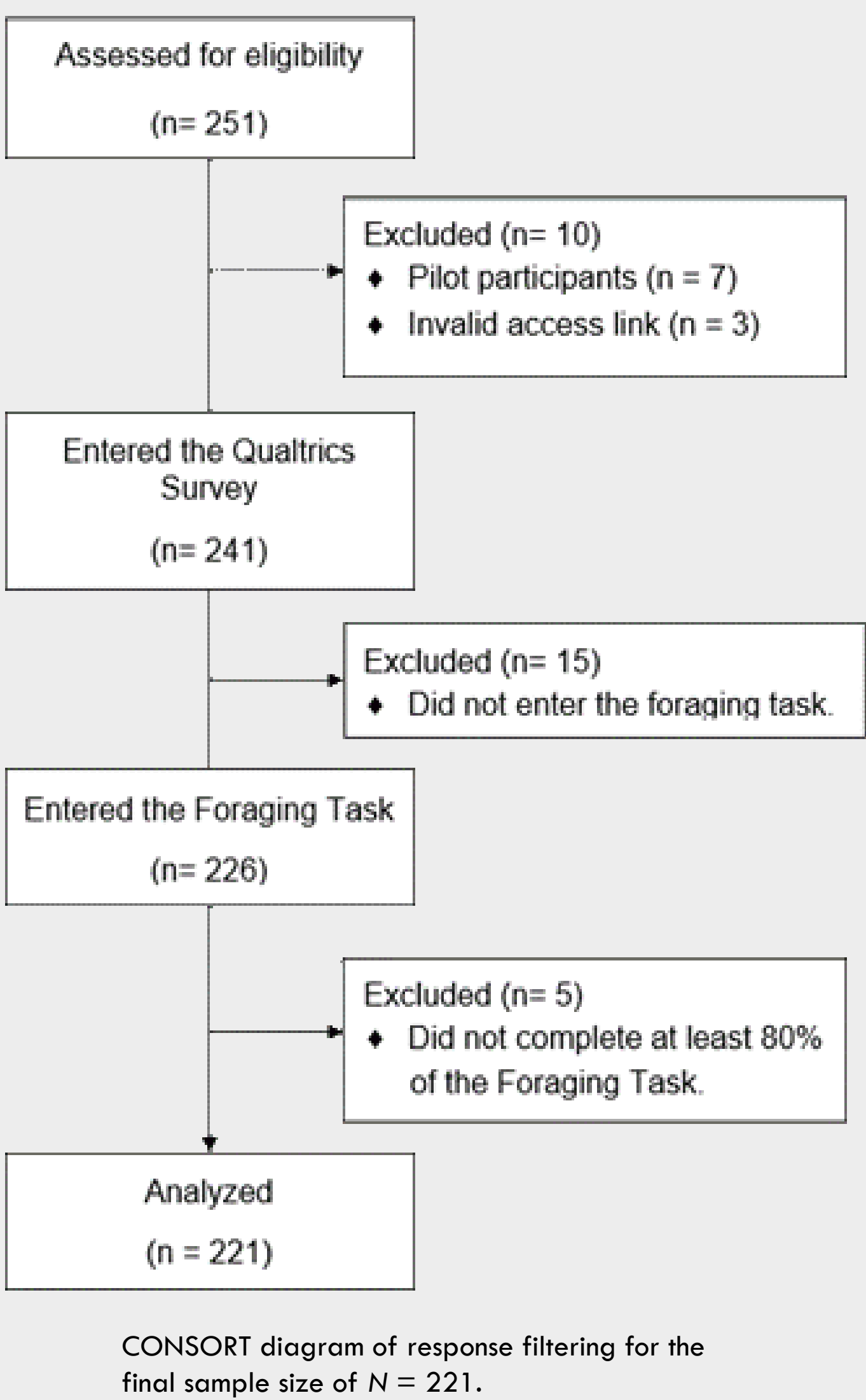
- **Finding 1:** ITT increased as the number of feature layers increased for all categories except the 3-layer stop sign condition.
- **Finding 2:** Low between-individual variation of ITT across categories.
- **Finding 3:** Performance variability was higher for the experimental categories vs the control category.
- **Exploratory Finding:** Using a mobile device for the task decreased ITT, compared to using a non-mobile device.

Yield Sign Performance					Stop Sign Performance				
Predictors	Estimates	CI	t	p	Predictors	Estimates	CI	t	p
Intercept	606.96	547.84 – 666.07	20.12	<0.001	Intercept	1433.79	1081.00 – 1786.57	7.97	<0.001
Page	-1.4	-2.09 – -0.72	-4.03	<0.001	Page	-5.55	-6.76 – -4.34	-9	<0.001
Device Type	-162.34	-258.33 – -66.34	-3.31	0.001	Device Type	-112.63	-212.25 – -13.02	-2.22	0.027
(N) Target Layers	23.6	9.24 – 37.97	3.22	0.001	(N) Target Layers	-163.68	-265.56 – -61.79	-3.15	0.002
(N) Distractor Layers	27.64	13.27 – 42.01	3.77	<0.001	(N) Distractor Layers	-153.02	-254.90 – -51.14	-2.94	0.003
Random Effects					Random Effects				
σ ²			20841.97		σ ²			59690.89	
T00 Individual			45124.02		T00 Individual			47898.32	
T00 Block			304.12		T00 Block			17598.62	
ICC			0.69		ICC			0.52	
N Block			13		N Block			13	
N Individual			215		N Individual			216	
Observations			13905		Observations			12946	
Marginal R ² / Conditional R ²	0.049 / 0.701				Marginal R ² / Conditional R ²	0.131 / 0.586			

Control Performance				
Predictors	Estimates	CI	t	p
Intercept	470.19	422.14 – 518.24	19.19	<0.001
Page	-24.53	-28.99 – -20.08	-10.8	<0.001
Device Type	-97.97	-195.55 – -0.40	-1.97	0.049
(N) Target Layers	353.42	332.51 – 374.33	33.14	<0.001
Random Effects				
σ ²			87460.45	
T00 Individual			41402.02	
ICC			0.32	
N Individual			215	
Observations			3158	
Marginal R ² / Conditional R ²	0.226 / 0.475			

Data Preparation

- All preparation done in R (v 4.2.2) and Python (v 3.11).
- Foraging task embedded into Qualtrics produced 2 databases: surveys + task.
- Event level task data → trial level aggregates by block
- Device meta-data retrieved from user-agent string and parsed.
- Qualtrics loaded and scored.
- Survey + task data joined in long format.
- Final N = 221
- Full package list available by request.



Conclusions

- **Main hypothesis supported:** as stimuli became more complex, ITT increased, except for the 3-layer stop sign condition.
- Stimuli complexity slowed foraging until the difference in complexity between target and distractor turned the search task from conjunctive search into a pop-out search.
- Low between-individual variation suggests that individuals forage at different baseline foraging rates that are consistent across categories.
- **Main Limitation:** when observers searched for the 3-layer stop sign paired with other stop signs, observer performance exhibited the performance predicted by the pop-out search effect.
 - Thus, complexity defined by number of feature layers may not fully capture how complexity impacts ‘real-world’ foraging.

References

- [1] Stephens, D. W., & Krebs, J. R. (1986). Foraging theory. In *Foraging theory*. Princeton university press. <https://doi.org/10.2307/j.ctvs32s6b>
- [2] Kristjánsson, A., Ólafsdóttir, I. M., & Kristjánsson, T. (2019). Visual Foraging Tasks Provide New Insights into the Orienting of Visual Attention: Methodological Considerations. In *Spatial Learning and Attention Guidance* (pp. 3–21). https://doi.org/10.1007/978-94-007-2019-2_1
- [3] Treisman, A., & Gelade, G. (1980). A Feature-Integration Theory of Attention. *Cognitive Psychology*. [https://doi.org/10.1016/0010-0285\(80\)90005-5](https://doi.org/10.1016/0010-0285(80)90005-5)
- [4] Wolfe, J. M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review*, 28(4), 1060–1092. <https://doi.org/10.3758/s13423-020-01859-9>