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Deep Learning Generative Models in the Product Development Process: Exploring Designers' Bias

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“Creativity is an integral part of engineering design... without creativity there is no potential for innovation”

[Howard, Culley & Dekoninck, 2008]

FORTUNE

APPLE CLOSING PRICES SINCE THE FIRST IPHONE



SOURCE: KENSHO, BLOOMBERG

GRACE DONNELLY



*fortune.com/2016/04/01/apple-favorite-products/



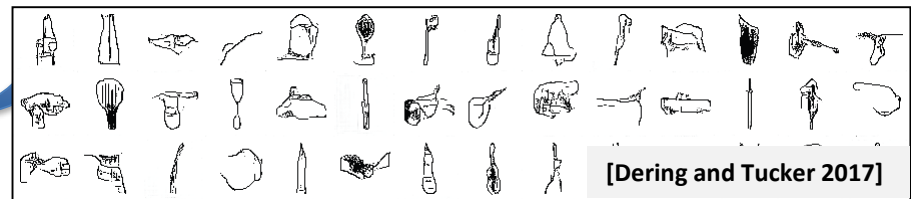
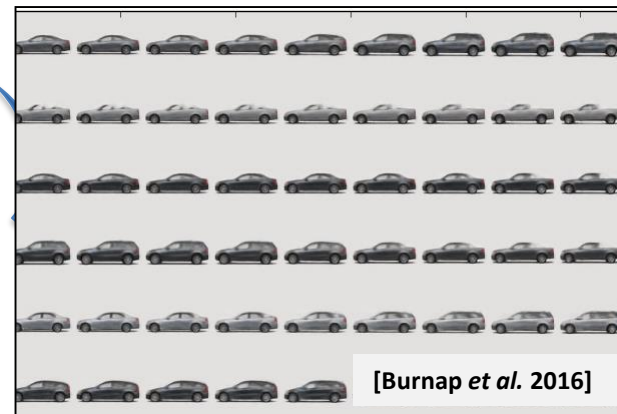
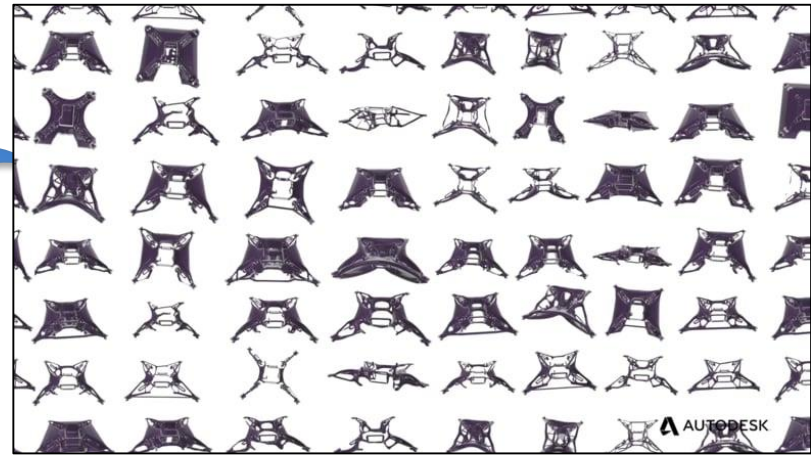
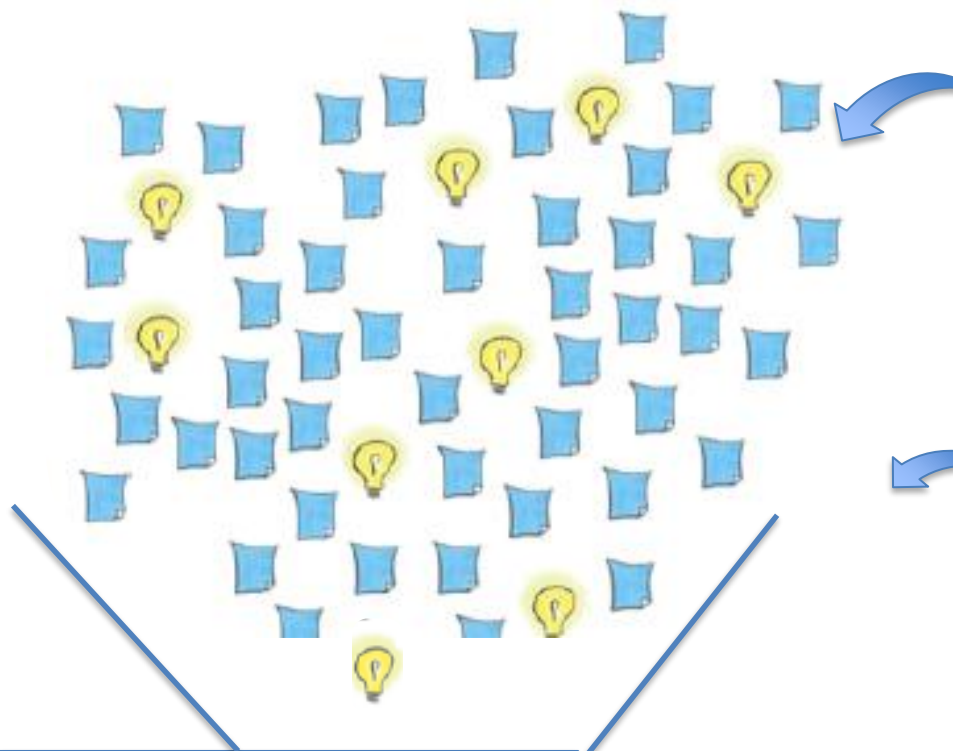
Designers are benefiting from integrating computational tools into the design process



As these computational tools become more efficient, they will foster designers' creativity. [Liapis et al., 2016]



Generative design algorithms are helping designers explore the design space



Idea Generation





Novel ideas also have to meet their intended functionality and be useful to be considered creative



Mass-Collaborative Product Development
take advantage of crowdsourcing





“... the availability of creative ideas is a necessary but insufficient condition for innovation.”

[Reitzchel *et al.*, 2006]





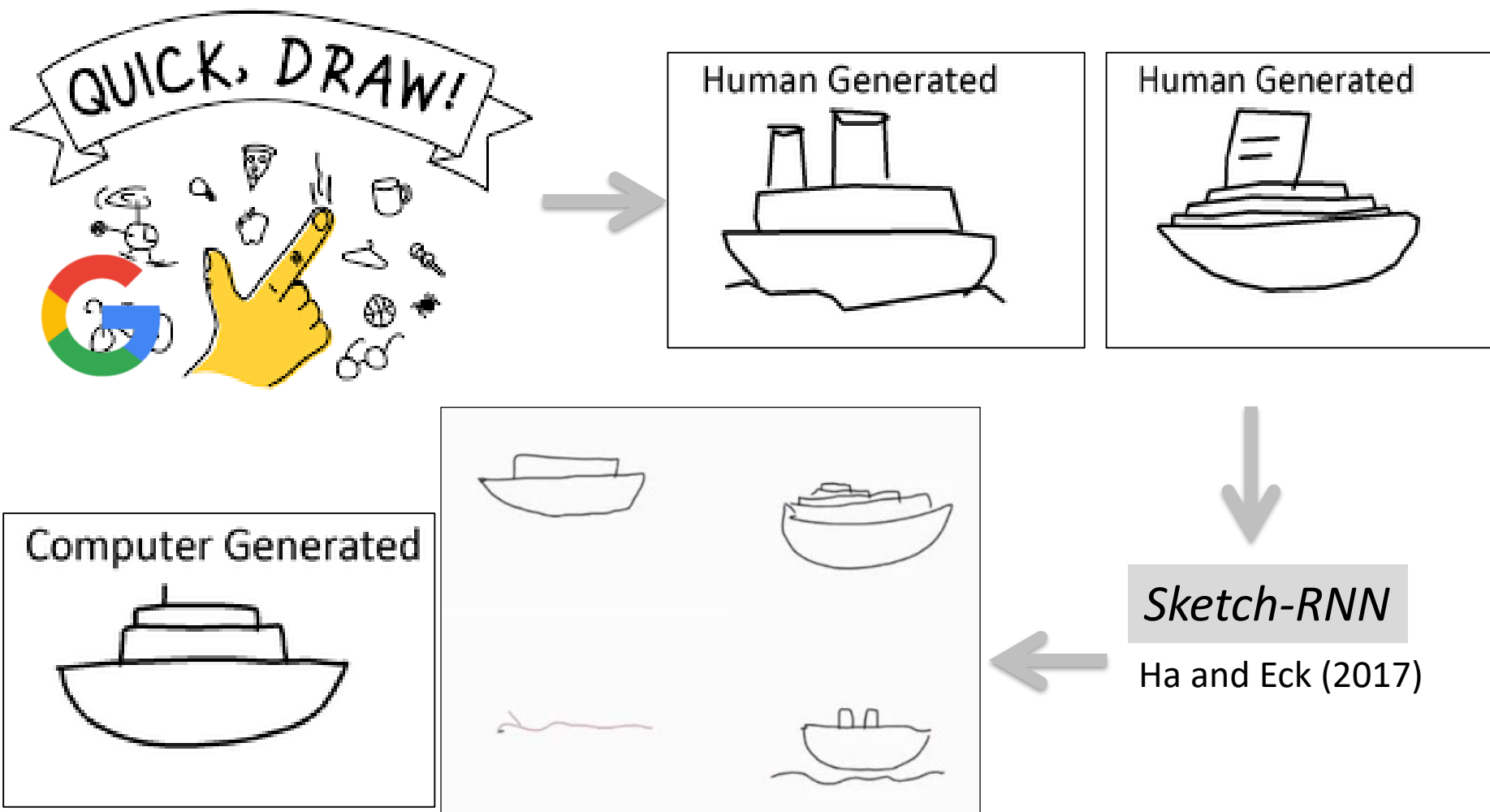
- 1) Compare the perceived functionality of human vs computer generated sketches
- 2) Explore individuals' bias towards human and computer generated sketches
- 3) Explore individuals' capability to distinguish between human and computer generated sketches
- 4) Explore the correlation between individuals' subjective and computer simulation objective functionality evaluation



Low-fidelity, rough 2D sketches are the primary communication source of ideas in early design phases

[Kazi et al. (2017)]

CASE STUDY: Boat sketches





Questionnaire and Participants



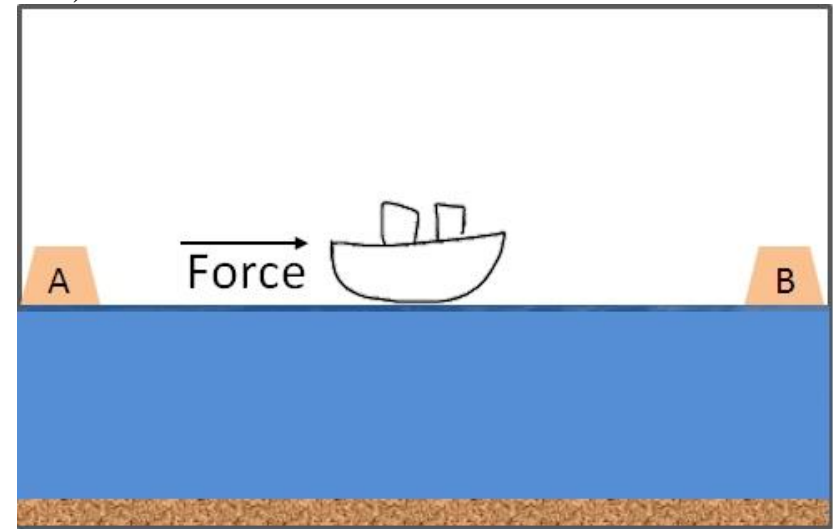
1,187 Raters

(90% satisfaction rate)

Benefits*:

- (i) Low cost
- (ii) Large rater pool access
- (iii) Large rater pool diversity

In this section, you will be shown 2D boat sketches and asked to evaluate them from 1 to 7 based on how well they will **float** in a 2D environment as the one shown below. Additionally, you will be asked to evaluate them based on how well they will **move** from point A to point B when a force is applied in the same direction, as shown below (like the force from a motor that results in a boat being propelled forward).





Questionnaire and Participants

Between-subject experiment:

- Total of 50 computer and 50 human generated sketches
- 2 sets of 4 sketches per participant

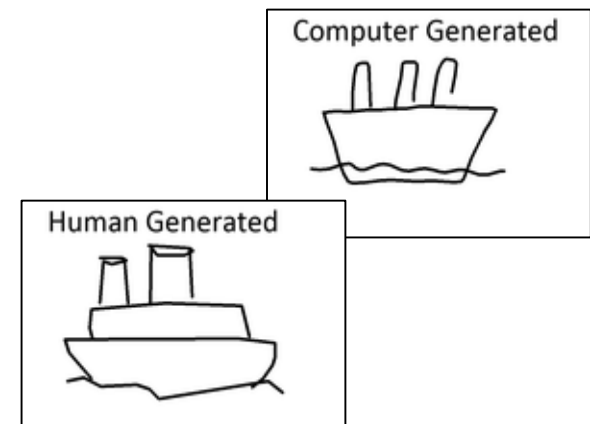
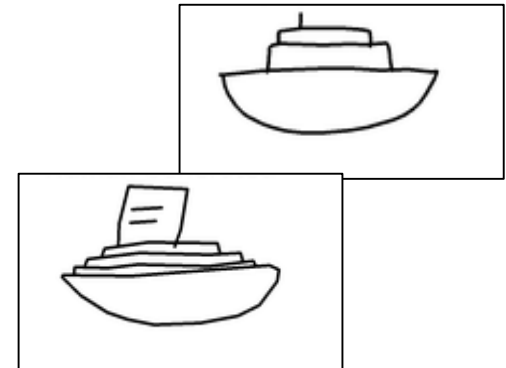
Q1: Please evaluate the following boat sketches based on how well they will **float** in the 2D environment shown below.

Q2: Please evaluate the following boat sketches based on how well they will **move** from point A (left) to point B (right) when a force is applied in the 2D environment as shown below.

Q3: Please classify the following sketches as *human-generated* (drawn by a person) or *computer-generated* (drawn by a computer).

Q4: Please evaluate the following computer and human generated boat sketches based on how well they will **float** in the 2D environment shown below.

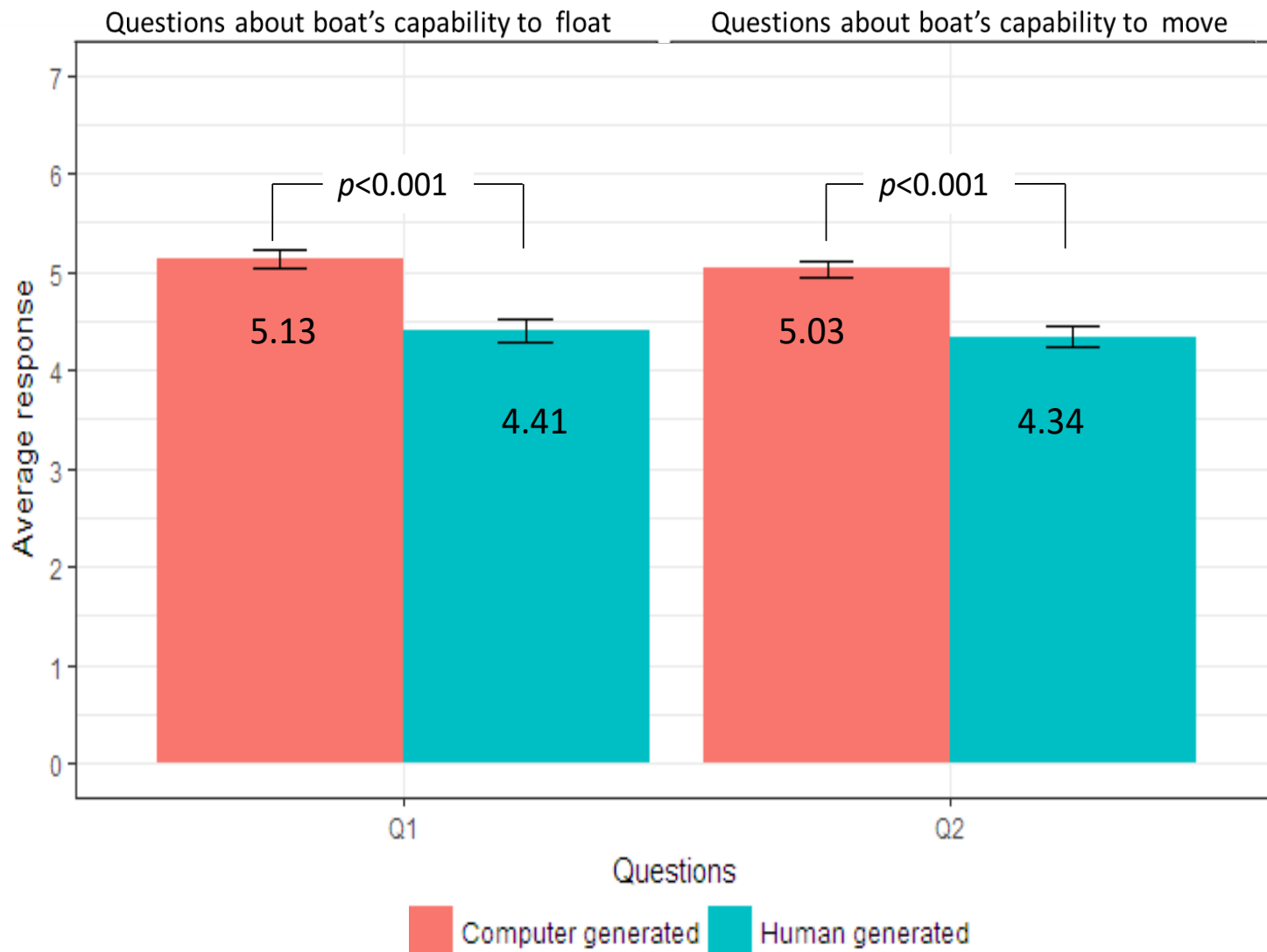
Q5: Please evaluate the following computer and human generated boat sketches based on how well they will **move** from point A (left) to point B (right) when a force is applied in the 2D environment as shown below.



7-point Likert scale

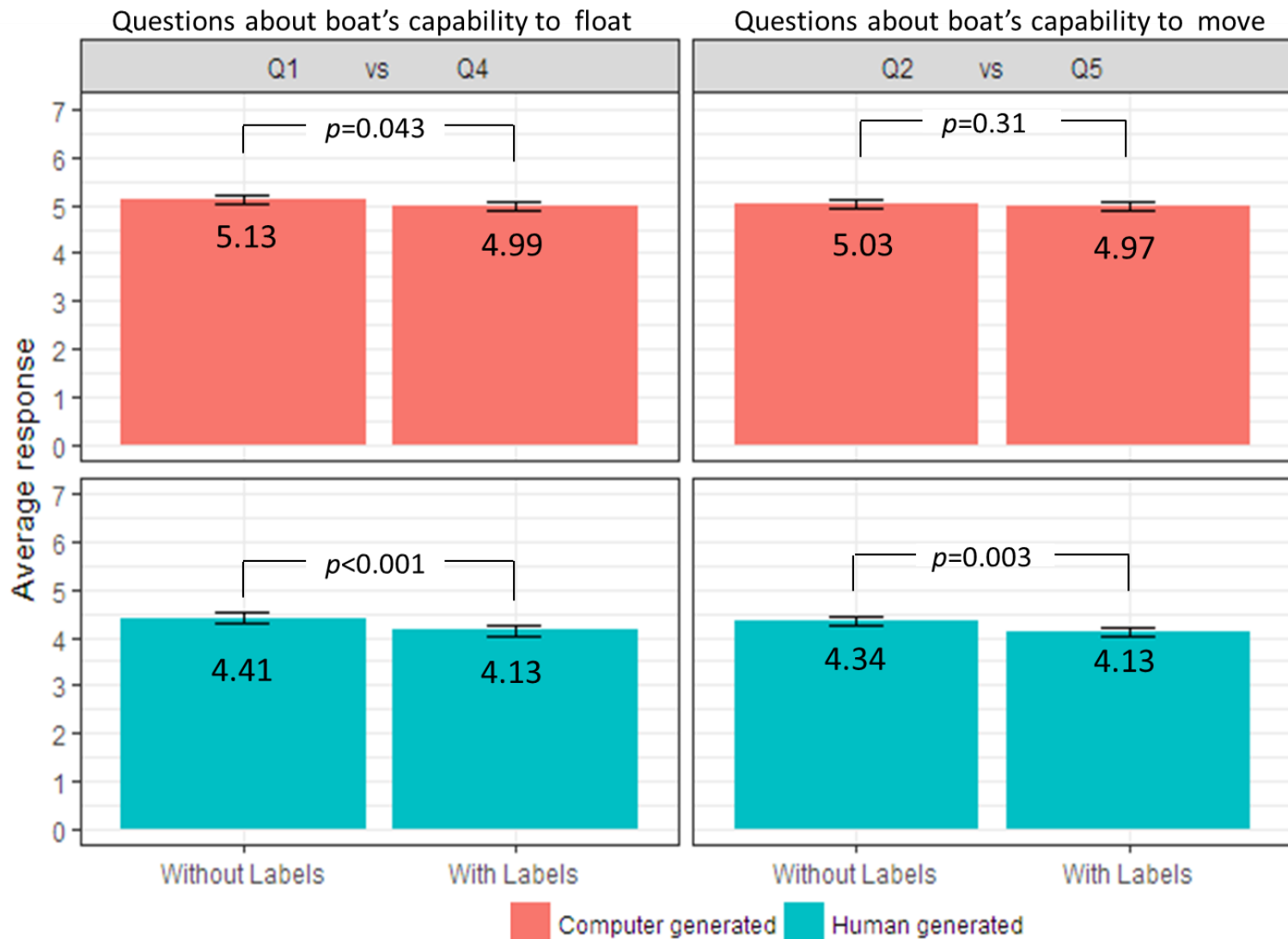


Computer generated sketches were perceived as more likely to float and move





Participants' functionality perception of human created sketches was biased





Individuals cannot accurately distinguish between human and computer generated sketches

ACCURACY

49.8%

95% CI: [47.81%-51.79%]

CONFUSION MATRIX OF SKETCHES CLASSIFICATION

Ground truth

		Ground truth		
		<i>Computer</i>	<i>Human</i>	Total
Prediction	<i>Computer</i>	264	269	533 (22%)
	<i>Human</i>	974	969	1943 (78%)
	Total	1238 (50%)	1238 (50%)	2476 (100%)

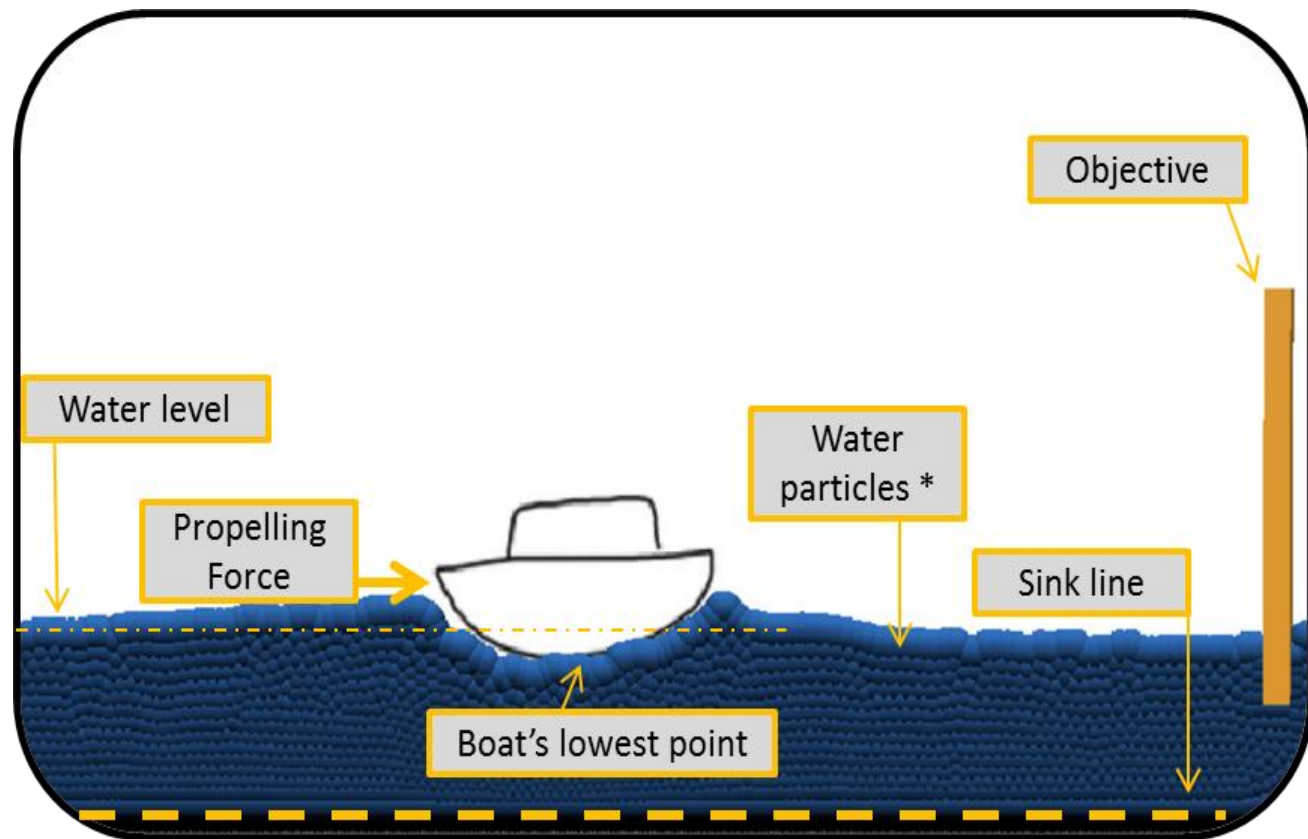


Validating raters' perceived functionality

Physics Computer Simulation

Output Scores:

- Float
- Speed

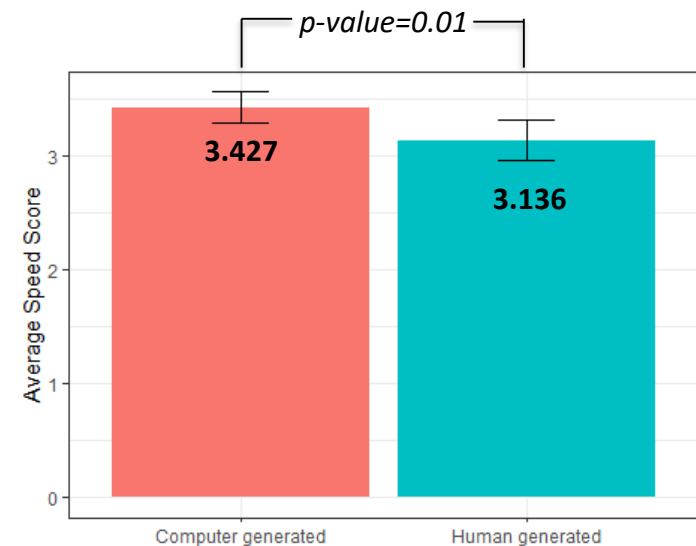
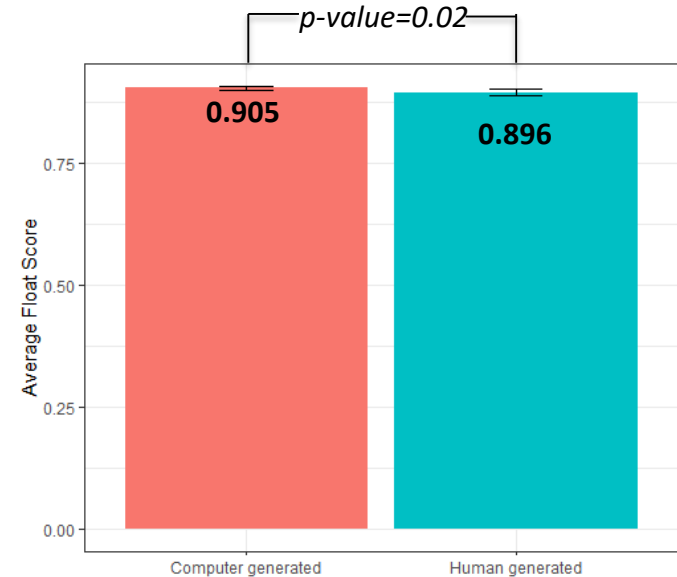




Raters' perceived functionality are in line with the Computer simulation evaluation

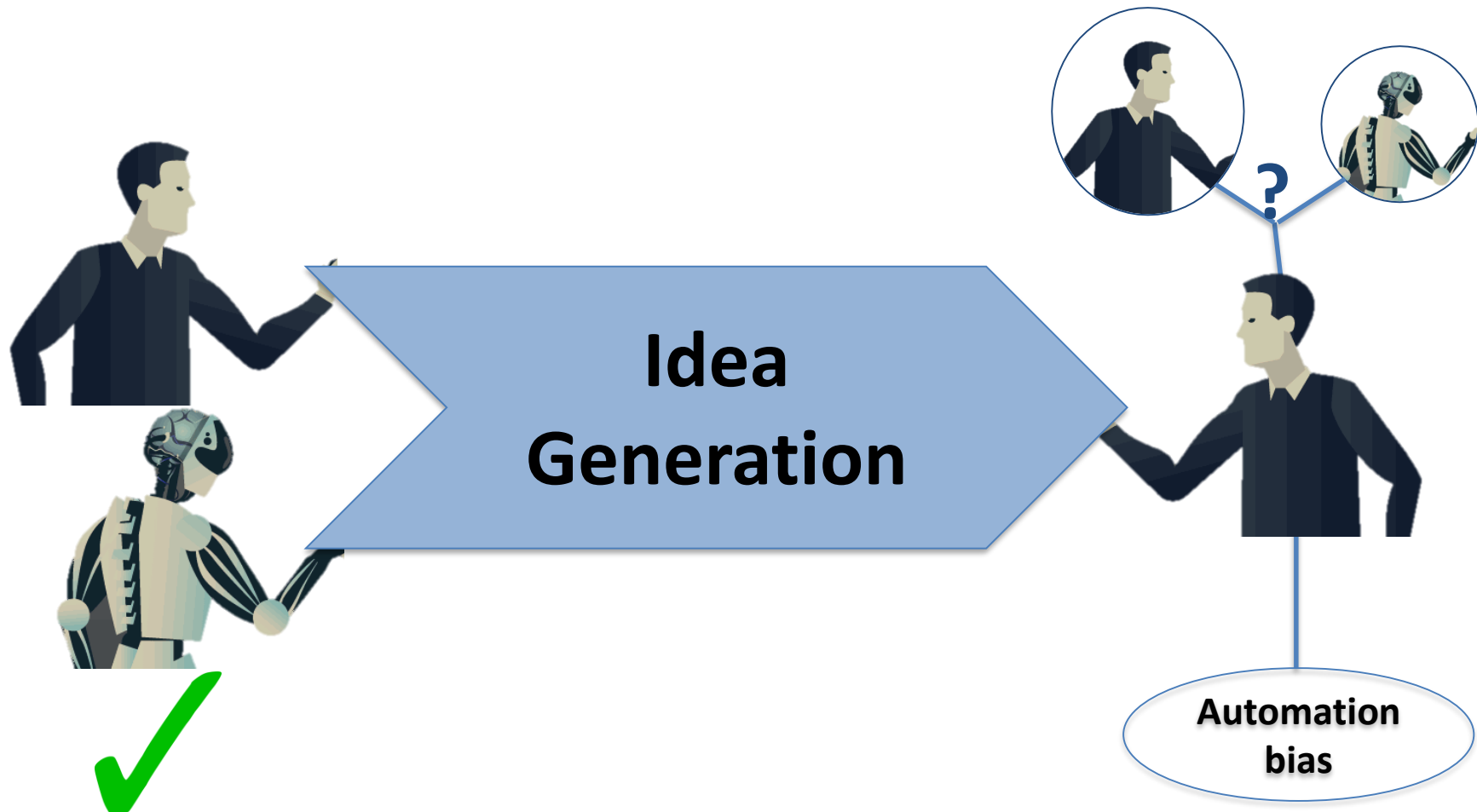
Variables		Pearson correlation (ρ)	p-value
<i>Float Score</i>	<i>Q1</i>	0.3	<0.01
<i>Speed Score</i>	<i>Q2</i>	0.5	<0.001

■ Computer generated
 ■ Human generated





Results support the capability of deep generative models to generate new functional ideas





Future works: What are the visual features of sketches that make them functional?

<i>Computer Generated</i>				<i>Human Generated</i>		
			<i>Most Likely</i>			
			<i>Less Likely</i>			

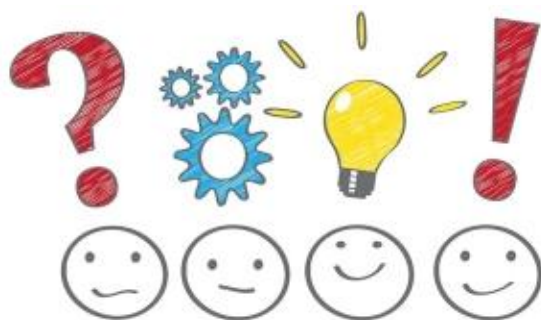


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www.engr.psu.edu/datalab

Thank you!



sites.psu.edu/clopez



[Quick, Draw!](#)



[Sketch-RNN - Magenta](#)

This research is funded in part by NSF NRI # 1527148 and DARPA HR0011-18-2-0008 Any opinions, findings, or conclusions found in this paper are those of the authors and do not necessarily reflect the National Science Foundation.

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