

MSI Webinar: The Future of Product Design: Leveraging Generative AI.

January 17, 2024 | Virtual | 12:00 pm – 12:30 pm EST

Speaker:

Alex Burnap – Assistant Professor, Yale School of Management, Yale University.

Overview:

In this MSI webinar, Alex Burnap (Yale University) examines a joint research effort with John Hauser (Massachusetts Institute of Technology) and Artem Timoshenko (Northwestern University) on the use of generative AI in marketing and product design. In this presentation, Burnap discusses a model to improve a commonly used aesthetic design process by predicting aesthetic scores and automatically generating innovative and appealing product designs by combining a probabilistic variational autoencoder (VAE) with adversarial components from generative adversarial networks (GAN) and a supervised learning component (augmentation). The research for this model is specifically applied to the automotive industry, though it could be used for a variety of product industries such as clothing design (Stitch Fix) or CPG where Heinz uses it to create labels for ketchup bottles and ads. An experiment augmenting the VAE/GAN models yielded significantly positive results, particularly in pre-screening higher potential design concepts. Additionally, the augmented model was successful in generating appealing designs which resembled designs introduced to the market in later years.

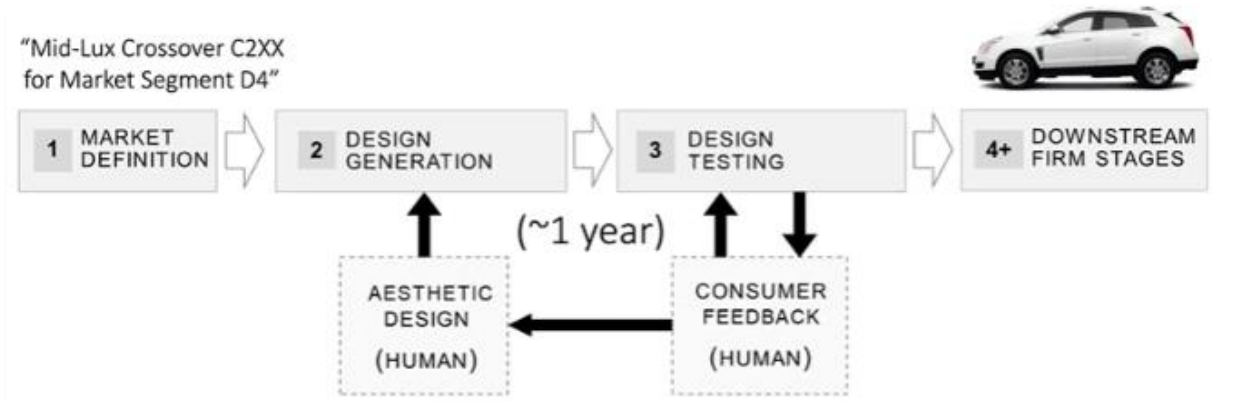
Takeaways:

The Traditional Design Process in Automotive

- **Aesthetic design plays a critical role in the automotive market**, since it is a **costly and time consuming** endeavor where failure can result in over a billion dollars in losses and success can lead to a substantial increase in MSRP.
- Traditionally, the automotive industry has taken a "funnel" approach to design aesthetics, where there are **initially many design possibilities** and those concepts are whittled down until the final product is agreed upon and sent to the market.



- **Design generation activities and design testing** requires a great deal of back and forth interaction with product designers and market research teams, which includes consumer feedback, continual testing, and can take up to a year.



- **The traditional design generation process alone considers several stages**, all of which have very intricate steps, involving different levels of refinement (e.g. sketches, sketch down selection, sketch digitization, visual images, clay models, full scale clay models, etc.), all requiring consumer feedback.
- **The design testing stage pushes the design out to consumers** (focus groups) to collect feedback in the form of product ratings (e.g. is the product appealing, innovative, etc.).

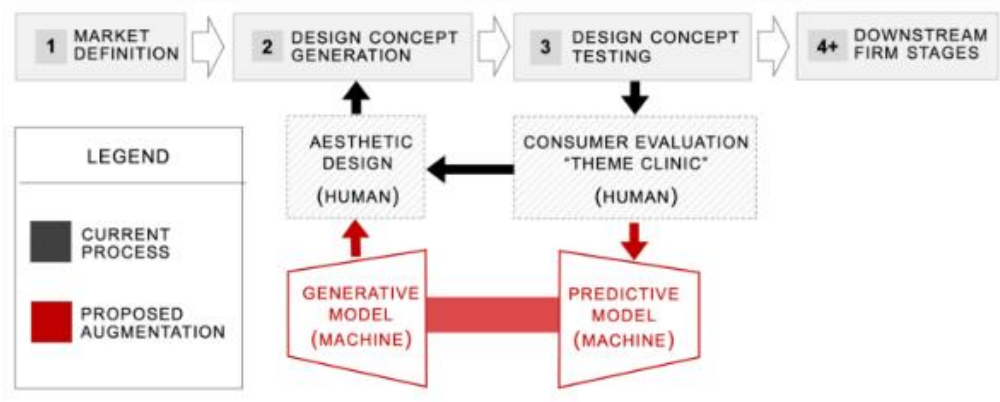
The Research—Combining VAE with GAN and Supervised Learning

- The research in conjunction with General Motors, is to **apply generative AI to predict the consumer response for marketers and generate new designs for designers.**
- To improve upon the current traditional process, the researchers considered the following research questions:

(1) Can we generate more “high-potential” aesthetic designs?

(2) Can we predict consumer response before costly Theme Clinics?

- To do this the researchers leveraged ML/AI by combining a variational autoencoder (VAE) and components from generative adversarial networks (GAN) with a supervised learning component (augmentation).
 - The researchers **augmented the ML process**, by building on what was already available using **generative AI to refine traditional design generation and design testing stages.**

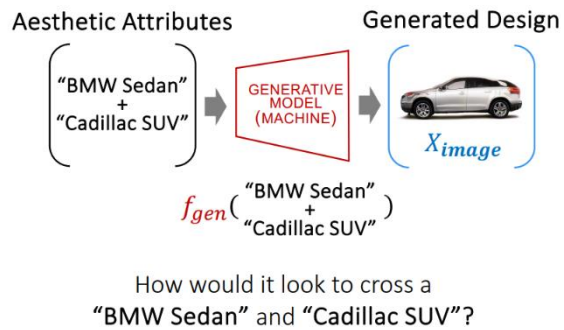


- Using **machine learning augmentation can assist designers** by inspiring and streamlining creativity, allowing them to **“morph designs,”** leading them to **generate a new product** (crossover vehicle).

MACHINE LEARNING AUGMENTATION EXPLAINED

Generative Model

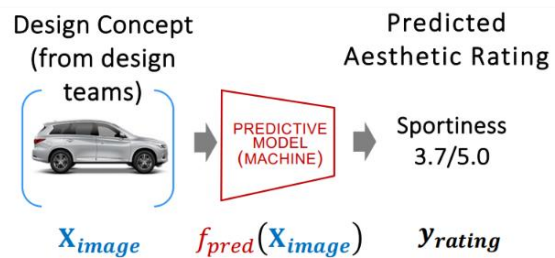
- Tool for designers to inspire creativity and to controllably morph designs.
- Control using attribute “tuning knobs”



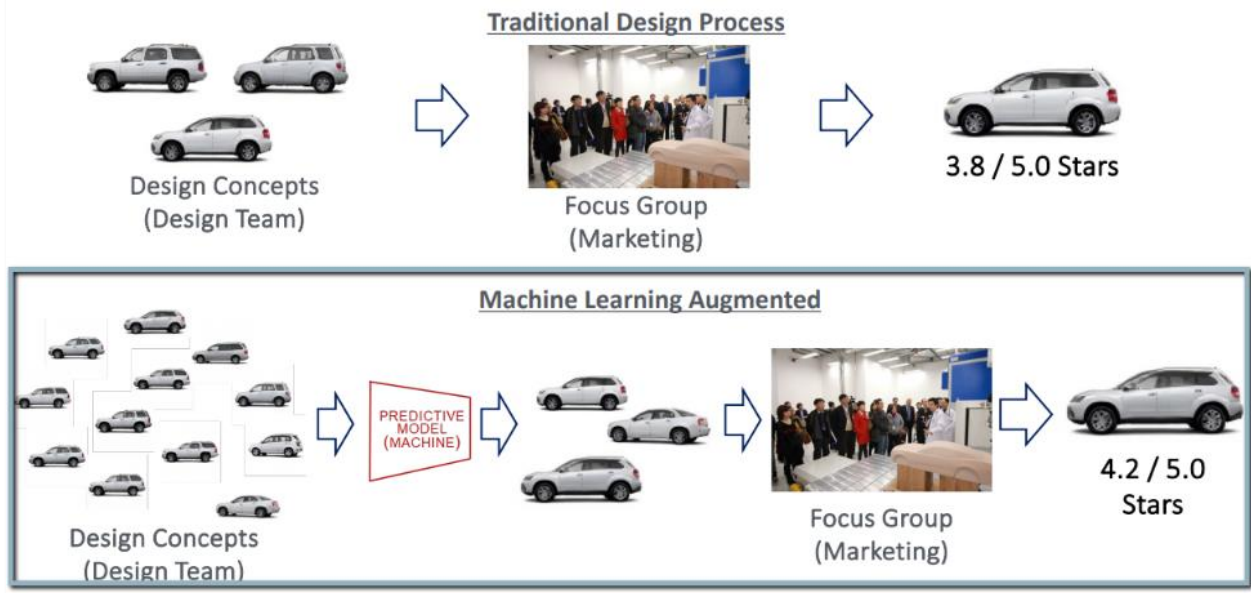
- **Machine learning augmentation as a predictive model** can be a tool for marketers by allowing them to **“pre-screen” higher potential design concepts** streamlining the process, by predicting “higher potential” designs for marketers to test in theme clinics.

Predictive Model

- Tool for marketers to “pre-screen” design concepts from design team.
- “Which ‘high-potential’ designs should Marketing test in theme clinics?”



EXAMPLE USAGE: “PRE-SCREEN” DESIGNS TO AUGMENT MARKETING



- **In an illustrative experiment** running from 2010-2014 using SUV/CUVs, the researchers goal was to address the mentioned generative and predictive research questions by augmenting models using elements of labeled data (images of prior automobiles with aesthetic ratings) combined with elements of unlabeled data (images without ratings).

EXPERIMENTAL DATA ON SUV/CUVs 2010-2014

Labeled Data

7,000 Images with Ratings
Theme Clinic

Unlabeled Data

180,000 Images without Ratings
SUVs, Cars, Trucks, etc.



- **Predictive results:**
 - Comparing the predictive performance of the proposed machine learning approach to a naïve baseline indicates that **the proposed machine learning augmentation outperforms the other methods.**
 - Additionally, it is determined that the **model predictions provide a viable alternative** for initial product screenings prior to the clinics.

- Predictive results from the experiment showed a 43.5% improvement relative to a uniform baseline and substantial improvement over conventional machine learning models.

PREDICTIVE RESULTS: AESTHETIC RATING ERROR (LOWER IS BETTER)

Prediction Model	Mean Absolute Error (std. dev.)	Improvement
Sanity Check (Training Set Median)	0.620 (0.0431)	0.0%
Conventional Machine Learning (HOG/Color/Spatial+ Random Forest)	0.446 (0.0475)	28.1%
“Transfer Learning” Deep Model (“Pre-trained”VGG16 Architecture)	0.403 (0.0430)	35.0%
Our Model (Semi-Supervised VAE with Adversarial Training)	0.348 (0.0286)	43.9%

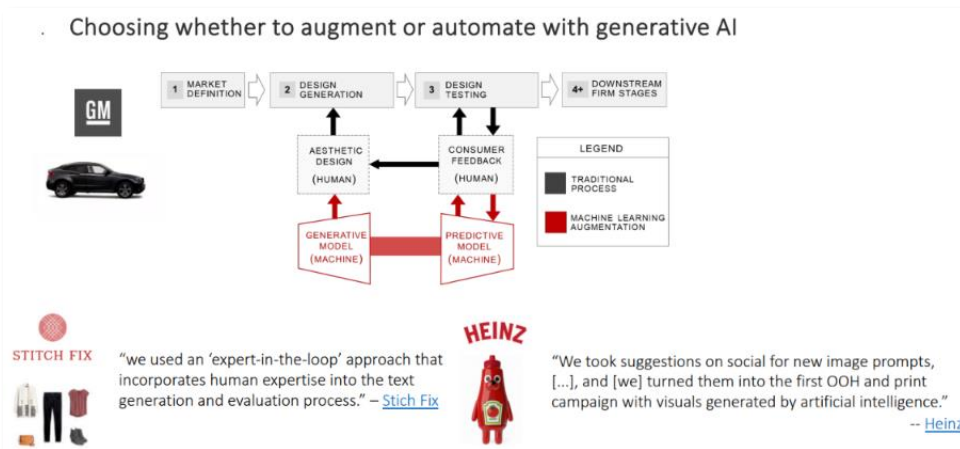
- **Generative results:**
 - It was determined that **it is feasible that the machine learning model can generate "creative designs,"** though it was noted that the quality of a generated image and **its usefulness to managers and designers is subjective.**
 - Consumer evaluations confirmed that images of products (automobiles) judged as aesthetically appealing by the predictor were seen as aesthetically appealing by consumers as well. The same was found for product images that were considered aesthetically unappealing.
 - **The generated images are realistic** and can be morphed in a controllable manner that mimics the manner in which design teams create designs.
 - Though they were not identical, the **generated images of the products (vehicles) produced results very similar to new products** introduced to the market six years after the time frame chosen for the training, validation, and test data.
 - Similar research applied to the design of dining room chairs verified that this process could be applied to other products.

**GENERATIVE RESULTS:
CAN WE CREATE “CREATIVE” DESIGNS?**



• **Challenges and takeaways:**

- Product categories vary in how challenging they are to model since some products are simpler to model than others (e.g. chairs vs. human faces).
- Although this specific research focused on automobiles, the principles and modeling decisions are applicable to other marketing/aesthetic design applications.
- The decision process needs to consider whether to augment or to automate generative models.
 - In this case, the current research suggests augmentation over automation.



- The **coordination between teams** is vital when integrating generative AI into the existing design process (e.g. designers, marketers, sub-teams). **When/how to update the AI model** with new data must also be considered.
- **Limited labeled data** can inhibit the quality of data the model outputs.
- “Off the shelf AI models do not always work with (human) marketer and designer goals and need to be fine-tuned.

Sources:**Product aesthetic design: A machine learning augmentation.**

Source: Burnap, A., Hauser, J.R., Timoshenko, A. (2023, January 24). MSI Working Paper. [MSI](#).

This working paper examines the development of a machine learning model that combines a probabilistic variational autoencoder (VAE) with adversarial components from generative adversarial networks (GAN) and supervised learning that can be used to augment human judgment for autos and other products where aesthetic design plays a major role in market acceptance.

Product aesthetic design: A machine learning augmentation

Source: Burnap, A., Hauser, J. R., & Timoshenko, A. (2023). [Market Science](#), 42(6), 1029–1185.

Aesthetics are critically important to market acceptance. In the automotive industry, an improved aesthetic design can boost sales by 30% or more. Firms invest heavily in designing and testing aesthetics. A single automotive “theme clinic” can cost over \$100,000, and hundreds are conducted annually. We propose a model to augment the commonly-used aesthetic design process by predicting aesthetic scores and generating innovative and appealing images. The model combines a probabilistic variational autoencoder (VAE), adversarial components from generative adversarial networks (GAN), and a supervised learning component. We train and evaluate the model with data from an automotive partner— images of 203 SUVs evaluated by targeted consumers and 180,000 high-quality unrated images. Our model predicts well the appeal of new aesthetic designs— 43.5% improvement relative to a baseline and substantial improvement over conventional machine learning models and pretrained deep neural networks. New automotive designs are generated in a controllable manner for use by design teams. We empirically verify that automatically generated designs are (1) appealing to consumers and (2) resemble designs which were introduced to the market five years after our data were collected. We provide an additional proof-of-concept application using open-source images of dining room chairs.

Subject Tags:

AI/ML, big data, data quality, data analytics, leveraging data, marketing experiments, modelling, research methods, predictive analytics, innovation & new product development