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MARKETING SCIENCE INSTITUTE

MSI Webinar:

Watching People Watch TV: How Viewer Tuning, Presence, and Attention Respond to Ad Content and Predict Brand Search Lift

April 4, 2023 | Virtual | 12:00 pm – 12:30 pm EDT

Speakers:

Jura Liaukonte – *Associate Professor, SC Johnson College of Business at Cornell University.*
Matthew McGranaghan – *Assistant Professor of Marketing, University of Delaware's Alfred Lerner College of Business and Economics.*

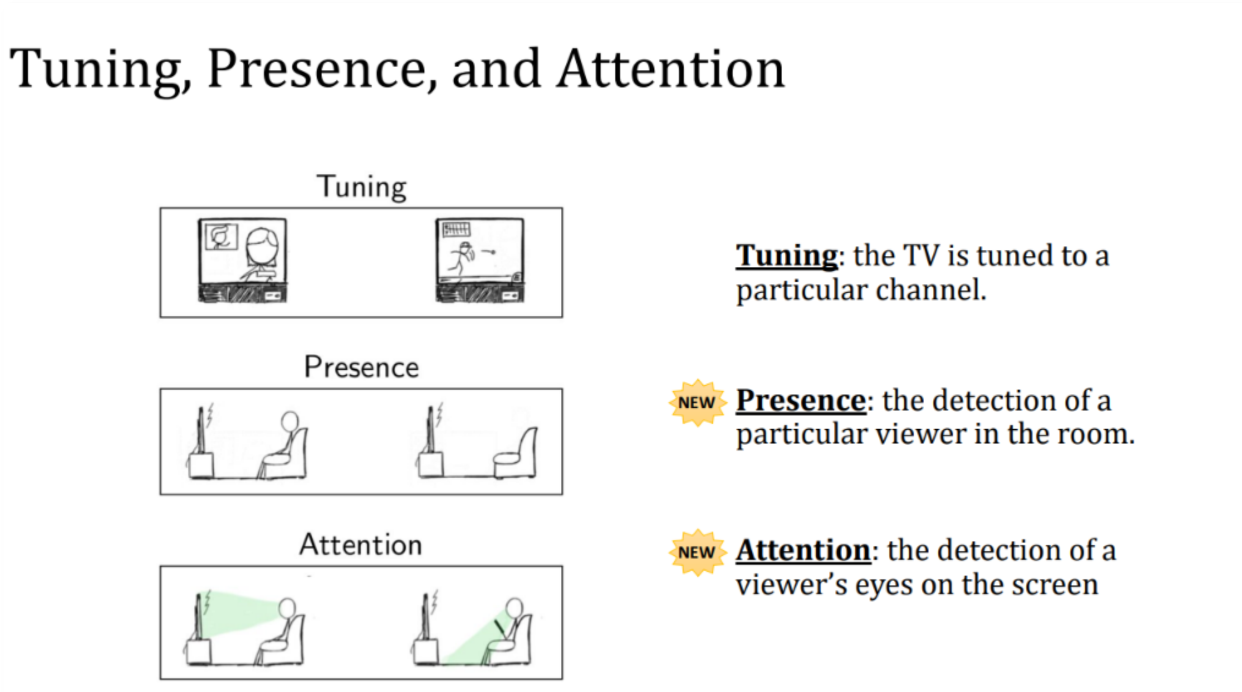
Overview:

In this MSI Webinar, presenters Jura Liaukonte (Cornell University) and Matthew McGranaghan (University of Delaware) presented research regarding TV viewership habits. Specifically, they wanted to understand how many TV ads aired to empty rooms and what types of ads capture consumer attention. In her opening, Liaukonte discussed the three-sided model of the Attention Economy, in which content providers create content to attract viewers, who in turn attract advertisers interested in reaching a specific audience. In this model, the more attention a piece of content or ad receives, the more valuable it becomes to advertisers and content providers. Liaukonte pointed out a specific flaw in this model noting that "there is no explicit contract between one side of the market, which is viewers, and the other two sides of the market." She further expanded that viewers are not forced to pay attention to advertising content, therefor ads priced in this model are based on "expected attention" (the number of TVs tuned into a specific program) and that is a rarity that actual attention is observed. To address the flaws in the Attention Economy model Liaukonte and McGranaghan explored a novel dataset from Boston company TVision, which collects viewership data via a camera placed in the TV room of the household. Using this method more accurately depicts ad attention from viewers. Liaukonte provided a detailed overview demonstrating TVision's attention-collecting process and McGranaghan provided more specific feedback on the results from the metrics gleaned from this study.

Takeaways

- **TVision captures data that better reflects attention to an ad through the use of a camera placed in the TV room of viewers.** Data includes whether the viewer is present and whether they are actually paying attention to the screen.

- This "sophisticated technology uses facial recognition, among other features, and is placed in households with consent, much like Nielsen households.
- Metrics are based on things like **tuning** in to a specific channel (currently done), **viewer presence** and whether they are **actually paying attention** (eyes on screen). In this newer method attention is measured passively, so it is not interrupting the actual viewer's behavior.



An Overview of the Study

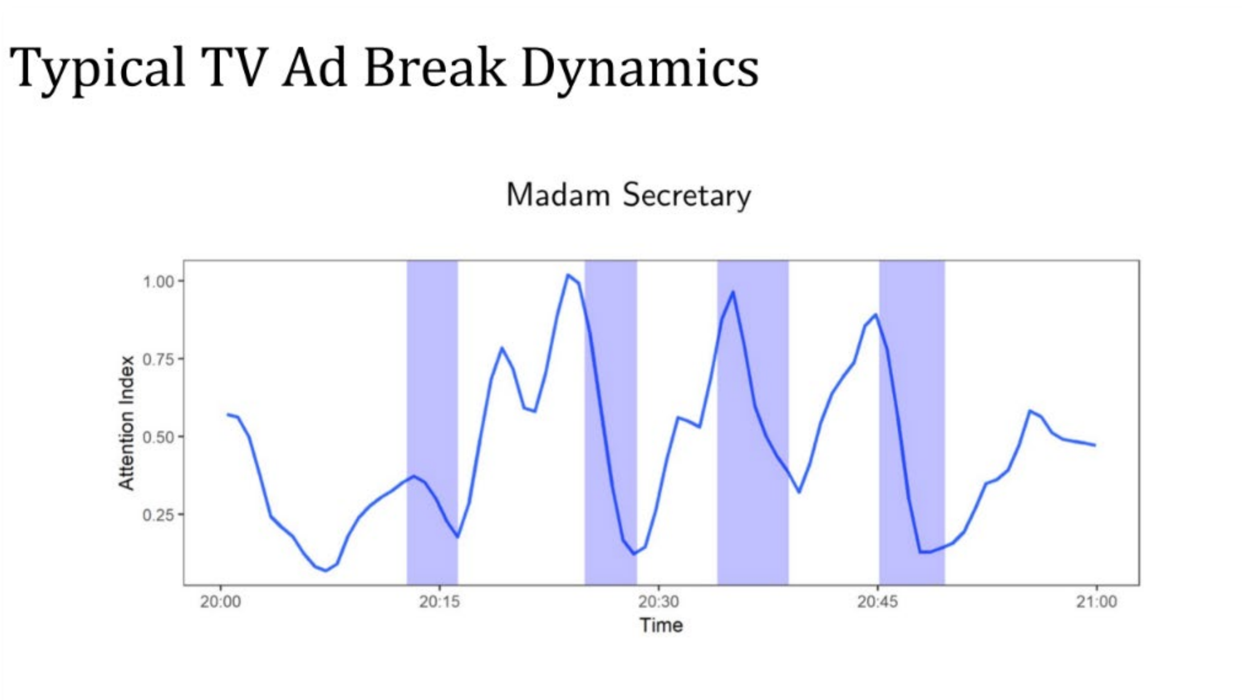
- **The research questions for this study are as follows:**
  - Do novel measures of viewer in-room presence and attention correlate with traditional TV viewership metrics?
    - **The answer to this question is no.** This is due to "meaningful differences in the levels and dynamics between traditional measures and new measures."
  - What type of ads retains the attention of the viewer the most?
    - **Ads that demonstrate recreation, movie ads, and entertainment** work best. Prescription pharmaceutical ads performed the worst.
  - Do novel measures do a better job of predicting the consumer behaviors that advertisers care about?
    - Compared to their **traditional counterparts which measure only tune-in metrics, new metrics do a better job of predicting**

online search behavior. This can be seen through the ebbs and flows depicted in television ad breaks.

- **An example from the research during the show Madam Secretary indicated a variety of attention ebbs and flows throughout the hour show**, which might reflect suspense and other reactions from the show, but **also reflect attention levels during the four ad breaks.**
    - One common factor indicated during the four ad breaks was the depreciation of attention over the course of the ad break. However, **the steepness of the depreciation depicted (the gradient) varied during each ad break, providing specific attention behaviors for each ad.**

Specific Results from the Study

- McGranaghan provided more specific feedback from the study focused on **results from the ad windows** (depicted in blue by the graphics). **In terms of ad exposures, feedback was noted whenever a viewer was detected for at least two seconds of the ad.** Presence detection allowed distinction between ads airing in empty rooms, from the ads that were airing to actual people who were present.

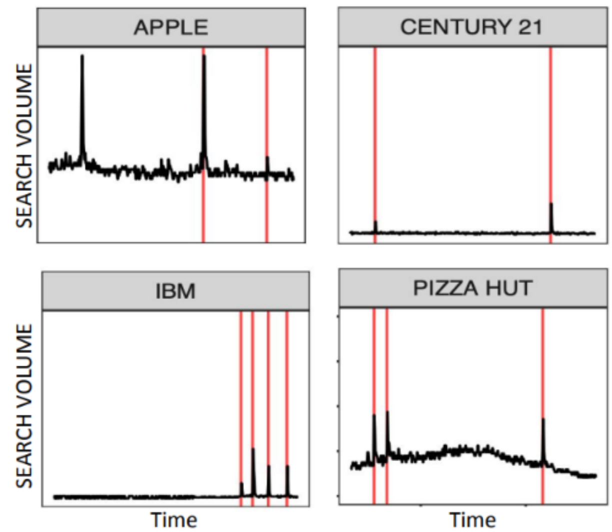


- Results using presence detection indicated that **one in three ads aired to empty rooms.**

        - Presence and attention "predictably" depreciated throughout ad breaks.
        - Conditional on a viewer being exposed to an ad, results showed that **on average people, only pay attention to 12% of ad seconds.**
            - New modes of data allow advertisers to objectively measure causal relationships from metrics (rather than intuitively).
    - **Devising a casual investigative strategy**, results from the study were able to **show which types of ads performed best.**
        - Results were based on tuning in, presence and attention and ad content such as metadata (length, pod position), product categories and machine coded-features (mood sentiment, scene elements, objects, etc.).
            - **Results indicated product categories were the strongest predictors of ad effectiveness**, while machine-coded features explained little additional variation. Ad content effects were shown to be small but some did stand out.
            - **Recreational products gained the most views** (e.g. casinos and gambling, entertainment and gaming, hunting and fishing).
            - **Ailments and medical conditions ranked lowest** in keeping attention or presence (e.g. Rx ads).
    - In terms of understanding if **presence and attention can predict behaviors that brands care about,** the study needed to isolate an external behavior that is not related to TV that is influenced by ads, relevant to brands, comparable across brands, publicly available and reliably measured.
        - To do conduct this task, **minute-by-minute data from Google Search Trends were collected,** focused on events with large national audiences (e.g. AFC and NFC Championship games). In addition, **data was collected on Google search volume pertaining to brands advertised during these larger games.**
        - Search spikes were then defined around ad timing and they investigated **which viewing behaviors best "predicted search spike intensity."**
        - **Using search spikes from ad timing in larger events allowed ample feedback** in understanding which viewing behaviors best predicted search spike intensity. This was demonstrated through a graphic comparing search spikes from a Pizza Hut ad to an ad for IBM.

Google Search Trends Data

- Focus on AFC & NFC Champ. games
- Collect Google search volume data for **all brands** that advertised during the games.
- Define **search spikes** around ad timing (red lines)
- Investigate which viewing behaviors best **predict search spike intensity**



- ➢ Results from this part of the study indicated metrics that incorporated **viewer exposures were better at predicting search lift in comparison to more traditional metrics.**
- ➢ Additionally, **attention explained the most variation in search lift.**