Digital Customer Engagement

Wendy Moe

University of Maryland*

September 2023

** Wendy Moe holds concurrent appointments as the Dean's Professor of Marketing at the University of Maryland's Smith School of Business and as an Amazon Scholar.* This paper/publication describes work performed at the University of Maryland and is not associated with Amazon.

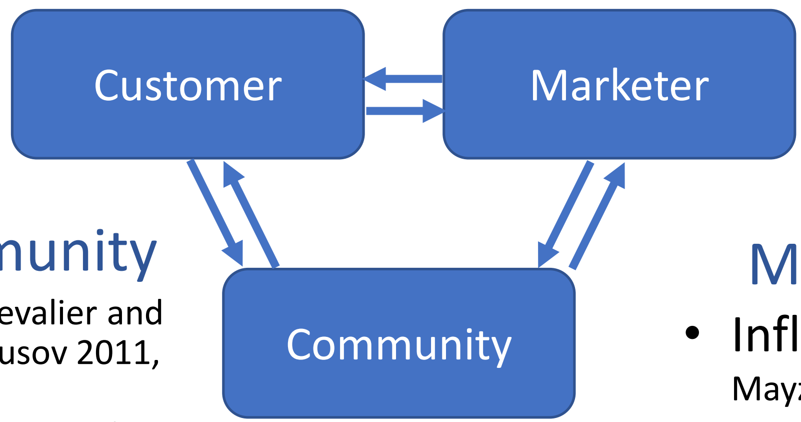
Agenda

- Overview of digital customer engagement
    - … and how is it different from traditional customer engagement
- Evolution of engagement metrics
- Research Article
    - Berger, Jonah, Wendy W. Moe, and David A. Schweidel (2023), "What Holds Attention? Linguistic Drivers of Engagement," Journal of Marketing.

Overview of Digital Customer Engagement Research

Marketer-Customer

- Targeted advertising (Goldfarb and Tucker 2011, Moe 2006)
- Complaints (Ma, Sun and Kekre 2015)
- Customer care (Packard, Moore McFerran 2018, Packard and Berger 2021)



Customer-Community

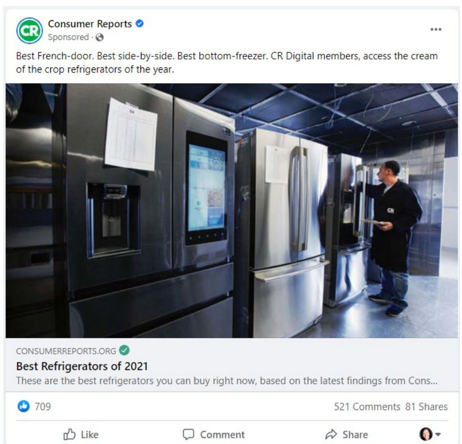
- Product reviews (Chevalier and Mayzlin, 2006, Moe and Trusov 2011, Sun 2012)
- Content sharing (Berger and Milkman 2012; Zhang, Moe and Schweidel (2017)
- Social dynamics (Moe and Schweidel 2014)

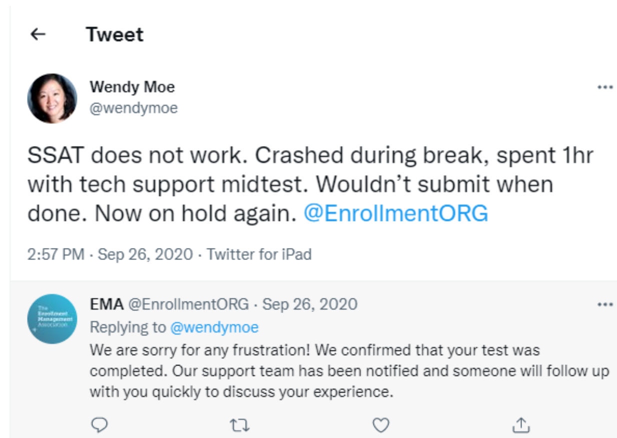
Marketer-Community

- Influence/diffusion (Godes and Mayzlin 2009, Liu-Thompkins 2012)
- Measurement (Schweidel and Moe 2014, Zhang and Moe 2021)
- Feedback and crowdsourcing (Bayus 2013)

Marketer-Customer Engagement

- General engagement with the Brand
  - Established research has focused on individual customer level purchasing and customer care
  - Platform/channel agnostic (e.g., Yelp!, Facebook, Twitter/X, etc.)

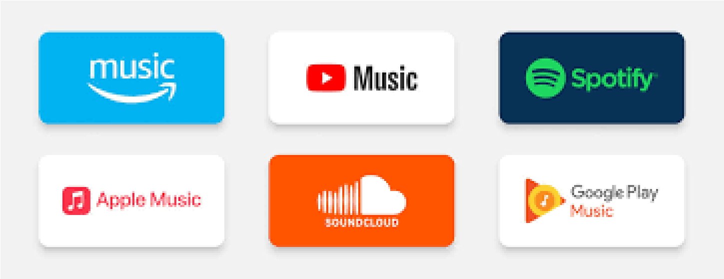




- Basically, we translated traditional advertising/direct marketing and customer service hotlines to the online environment.

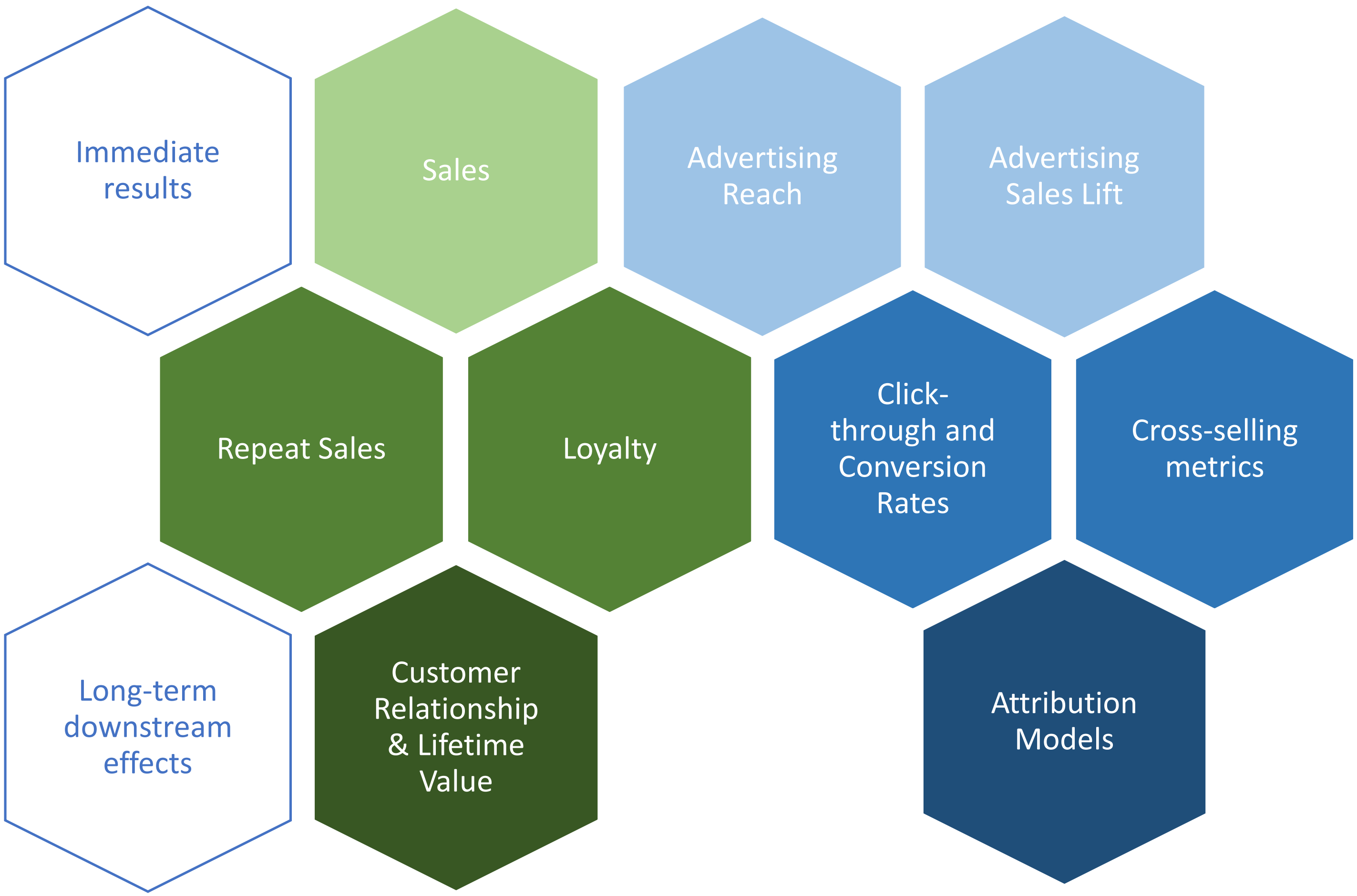
Engagement with Specific Content/Service

- New technologies
  - Streaming services
  - AI devices



- How do customers engage with these new technologies?
  - How do marketers increase engagement?
  - Implications for content design?
  - Implications for algorithms?

Evolution of Engagement Metrics

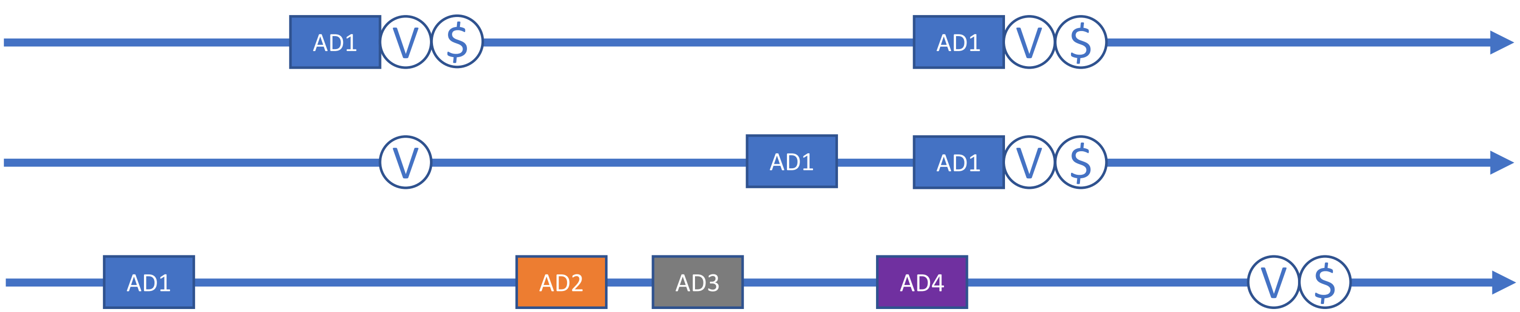


Modeling customer interactions over time

- Focus on purchasing - RFM and CLV models

- Internet clickstream models

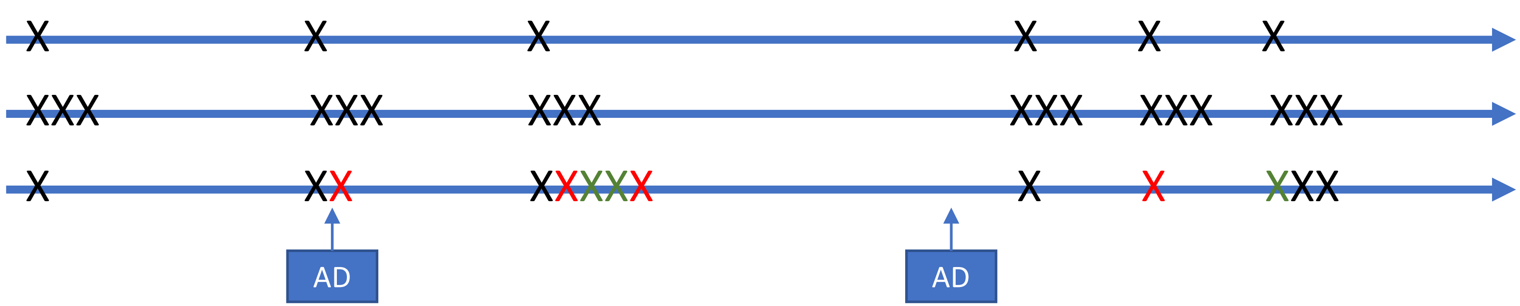
- Incorporating ads



Drilling down on in-session behavior

- Modeling goal-directed vs. exploratory search behavior within a visit

- Moving from commerce to digital content consumption



What Holds Attention?

Linguistic Drivers of Engagement

Jonah Berger (University of Pennsylvania, Wharton)

Wendy Moe (University of Maryland, Smith)

David Schweidel (Emory University, Goizueta)

Journal of Marketing

Types of Content Engagement

Attracting Attention

- Ad content and design (Lohtia, Donthu and Hershberger 2003)
- Product features (Moe 2006a)
- Search keywords (Rutz, Trusov and Bucklin 2011)

Sustained Attention

- State of flow (Hoffman, Novak and Yung 2000)
- Website browsing (Moe 2006b)
- Binge viewing (Schweidel and Moe 2016)
- Movie clips/trailers (Liu, Shi, Texixeira and Wedel 2018)

Interaction with Content

- Likes and comments of brand posts (de Vries, Gensler and Leeflang 2012)
- Sharing news articles (Berger and Milkman 2012)

Research objective

- Focus on sustained attention to content
- Role of content features
  - Emotional language
  - Processing ease
- Implications
  - Content creation
  - Effectiveness of content marketing
  - Algorithm design and outcomes

Multi-method approach

Large-scale field data:

Natural Language Processing of Over 35,000 Pieces of Content

Controlled experiments:

Experimentally manipulate emotion

Simulation:

Agent-based simulation of users' engagement response to recommender algorithms

Study 1: Large-scale field data

35,448 articles from 9 content providers

Range of topics from news, sports, business, lifestyle, etc.

Fixed layout sites

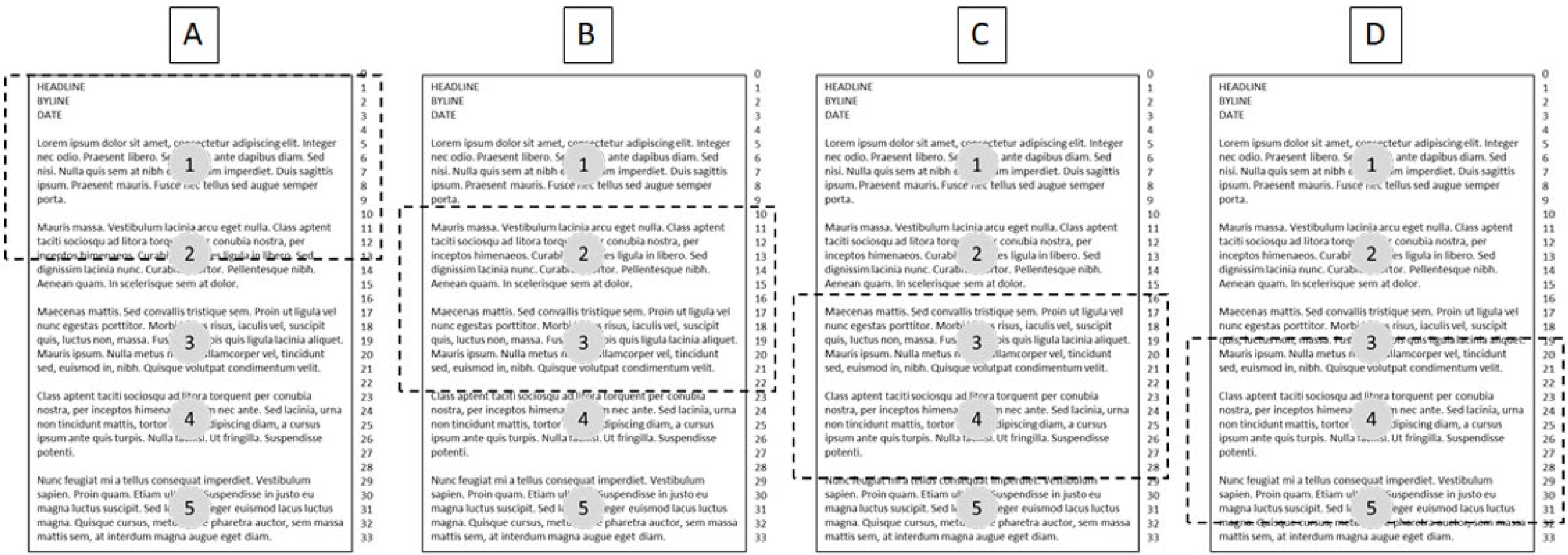
649,129 consumption events over a 2 week period

Desktop, mobile, or tablet

Data includes textual content, day/time of reading, and depth of reading

From the data, we infer the last full paragraph consumed (assumption: must fully scroll past to be considered read)

Data Collection (single article)



Note: The dotted line boxes indicate what is displayed in the browser window, the line numbers on the right indicate pixel positions, and the circled numbers indicate the paragraph number.

Coding the text

- Topic
  - Article level
  - Topic modeling using LDA
  - 25 topic solution to control for topics, not to interpret

- Emotion
  - Simple emotionality using Linguistic Inquiry and Word Count (LIWC, Pennebaker et al. 2015)
  - Emotional valence (LIWC)
  - Specific negative emotions of anger, anxiety and sadness (Keltner and Lerner 2001)

- Ease of Processing
  - Reading level (i.e., word and sentence length, Kincaid 1975)
  - Syntactic complexity (i.e., parse trees, Chomsky 1957)
  - Familiar language (i.e., more frequently heard, seen, or used, Paetzold and Specia 2016)
  - Concrete language (Paetzold and Specia 2016)

Modeling reading depth

- Paragraph-by-paragraph model where y represents whether the reader continues or ends reading session.

$Y_{ij} \sim Bernoulli(p_{ij})$ where

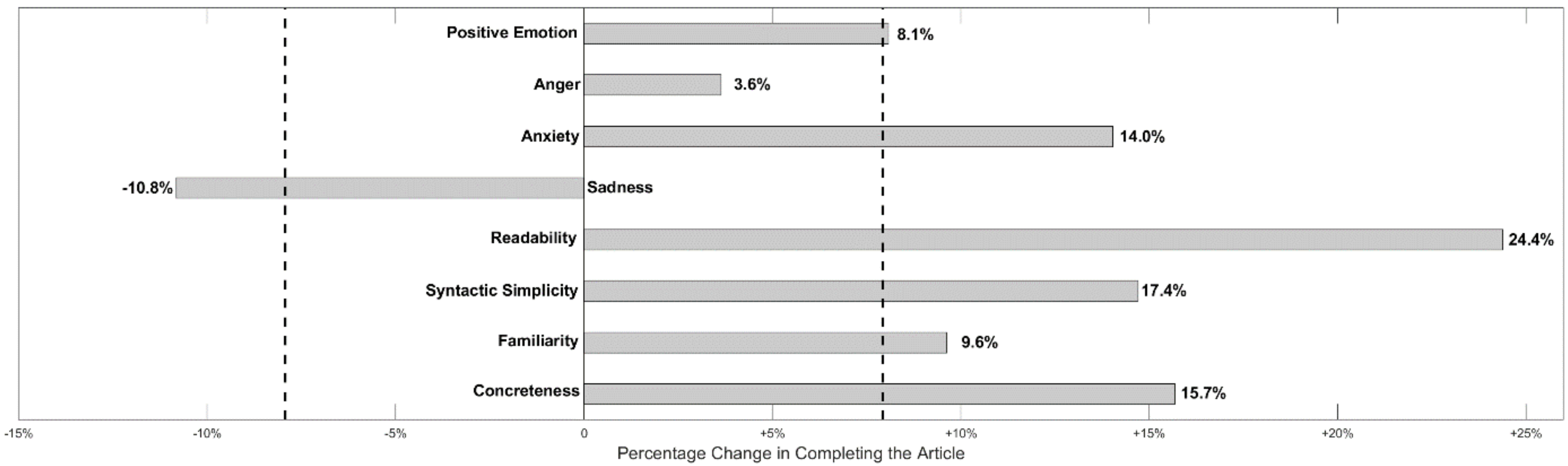
$$logit(p_{ij}) = \beta_0 + \sum_k \beta_k \cdot X_{ijk} + \sum_c \gamma_c \cdot Z_{ijc}$$

- Paragraph (j) specific variables (X) include
  - emotional content
  - ease of processing variables
- Reading event (i) specific variables (Z) which can also vary by paragraph (j) control for:
  - Article specific: device, site/publisher, article topic and word count
  - Paragraph specific: paragraph word count, position of paragraph in article
  - Session specific: % of article consumed, time/day of consumption

Results (Study 1)

		Emotionality	Valence	Specific Emotions
Emotion	Emotionality	0.0072***		
		0.0005		
	Positive Emotion		0.023***	0.025***
			0.0015	0.0015
	Negative Emotion		0.0060***	
			0.0005	
	Anger			0.011***
				0.0013
	Anxiety			0.042***
				0.0013
	Sadness			-0.036***
				0.0013
Processing Ease	Readability	0.065***	0.066***	0.070***
		0.0014	0.0014	0.0014
	Syntactic Simplicity	0.051***	0.050***	0.051***
		0.0013	0.0013	0.0013
	Familiarity	0.028***	0.028***	0.029***
		0.0014	0.0014	0.0014
	Concreteness	0.048***	0.051***	0.046***
		0.0015	0.0015	0.0015
Controls	Device dummies	Yes	Yes	Yes
	Publisher dummies	Yes	Yes	Yes
	Temporal controls	Yes	Yes	Yes
	Paragraph word count	Yes	Yes	Yes
	Reading progress	Yes	Yes	Yes
	Additional LIWC features	Yes	Yes	Yes
	Headline content	Yes	Yes	Yes
	Article popularity	Yes	Yes	Yes
	User heterogeneity	Yes	Yes	Yes
Model Metrics	Observations	6,994,372	6,994,372	6,994,372
	LL	-1969437	-1969377	-1969152
	AIC	3939088	3938971	3938524

How textual features shape continued engagement



Note: Bars represent effect of a standard deviation increase in each textual feature on continued consumption, relative to "baseline" article (i.e., Wall Street Journal article consumed on desktop with average posterior probabilities for each topic, and average emotion and control measures). Dashed vertical lines reflect average impact of the article's topical content. To derive this, we calculate the absolute value of each topic's impact by increasing the posterior topic probability by one standard deviation, reducing the topic probabilities of the remaining 24 topics by 1/24 of this amount, and average across the 25 topics to arrive at the average impact of topics.

Study 2: Experimental studies

- Manipulated emotional language:

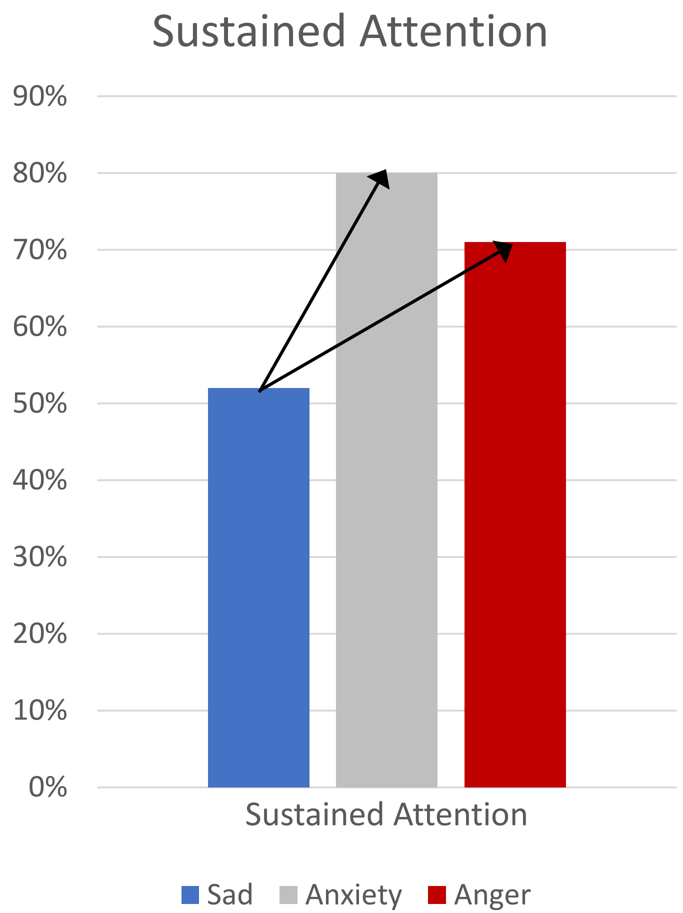
"Recent stock market performance has made investors really [sad, anxious, angry]. Most markets are down over 25%, the average American has lost tens of thousands of dollars, and many have [helplessly, nervously, furiously] watched as their retirement savings have dwindled. "I'm [heartbroken, worried, frustrated], said one New Jersey man, "my family is really [devastated, confused, bitter]."

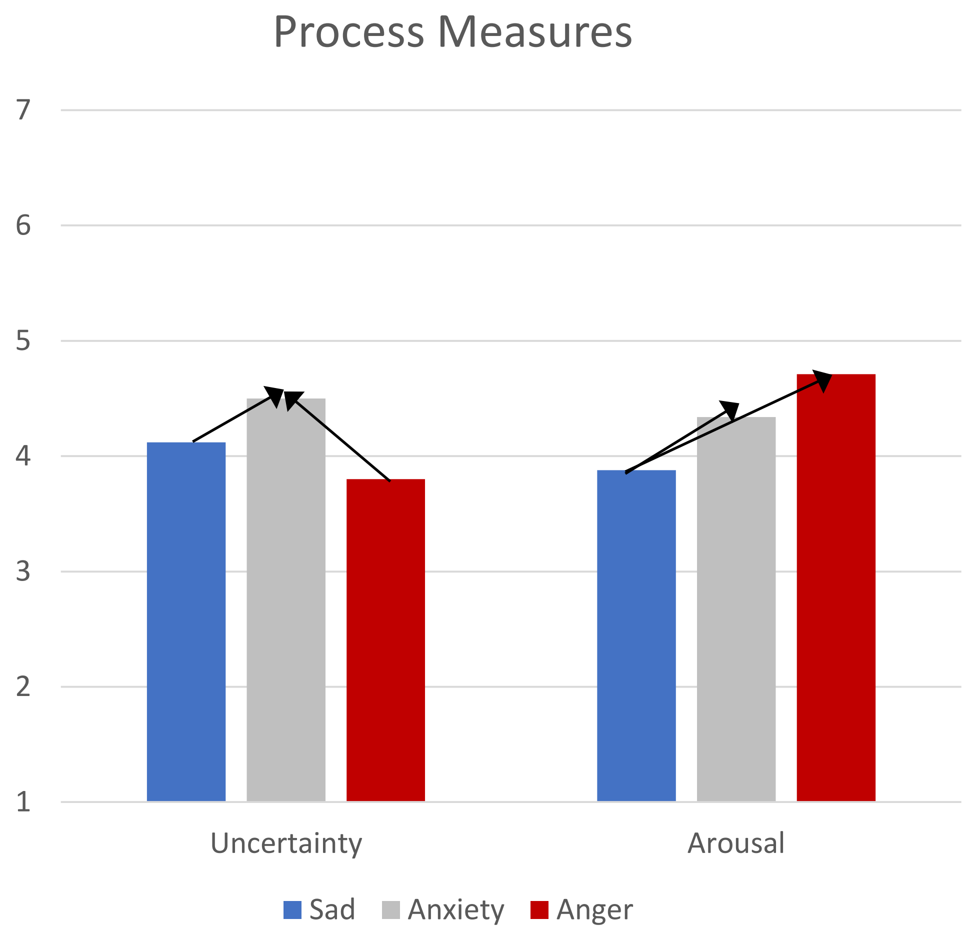
  - Manipulation checks
  - Pretest to confirm no differences between conditions on a variety of other measures (i.e., personal relevance, concreteness, extremity, or evoking hope).

- 278 MTurk respondents asked if they want to continue reading or switch to something else.

- Measured: How does this article make you feel?
  - Uncertainty: unsure/sure, hesitant/determined, don't feel confident/feel confident
  - Arousal: very low energy/very high energy, very passive/very active, very mellow/very fired up

Results (Study 2)

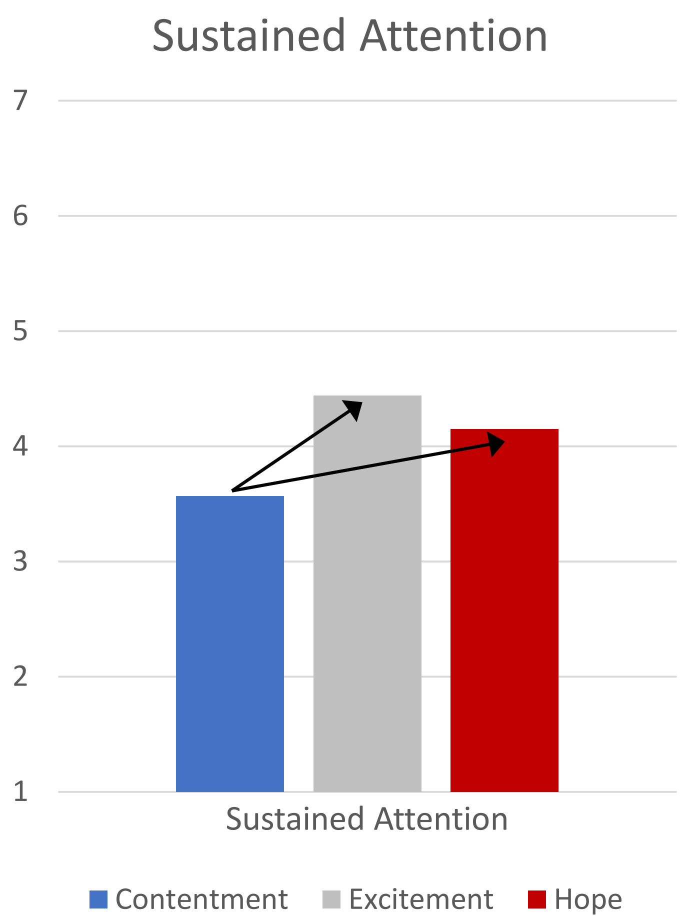


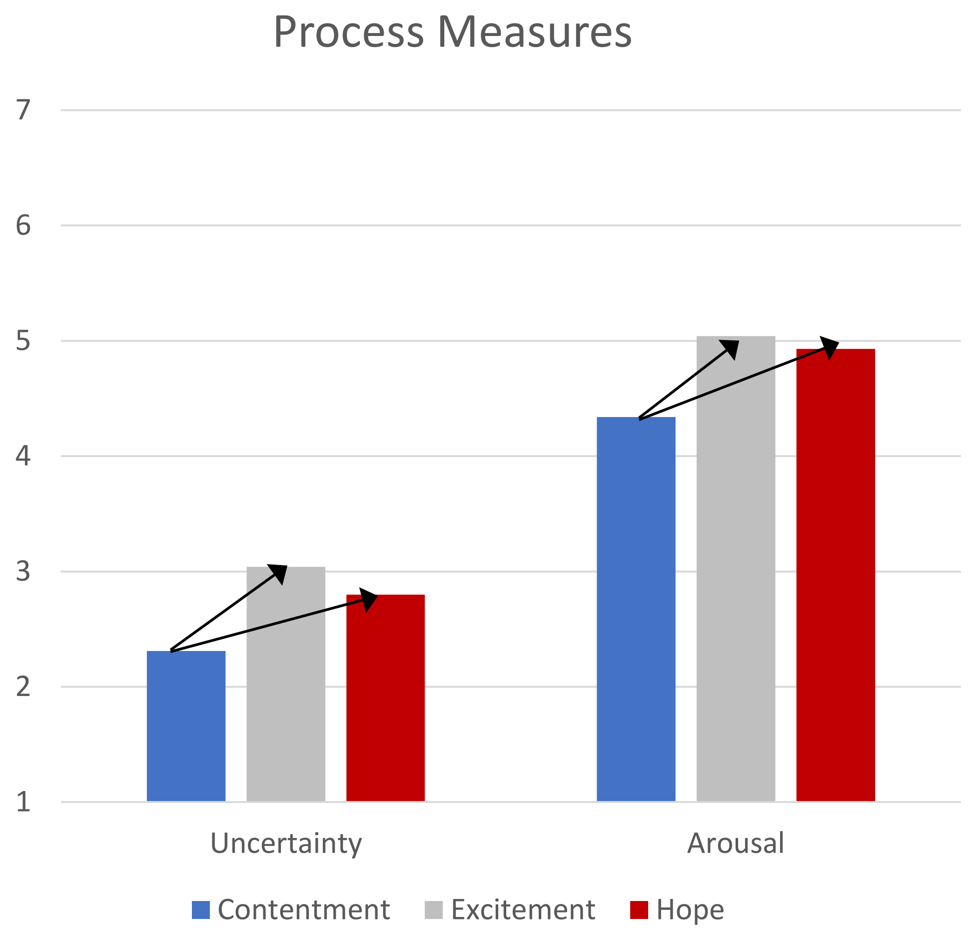


Study 3: Positive emotions

- 248 Prolific participants
- Experiment
  - Focused on positive emotions
  - Manipulated specific emotion by asking participants to describe something that made them feel excited/content/hopeful
  - Measured uncertainty and arousal
  - Read 1st paragraph from NYT article re: wireless charging
  - Measured how likely the subject was to read more

Results (Study 3)





Simulation and implications for algorithmic design

- Simulated 10,000 users

$$p_{ij} = logit(b_{0i} + b_{1i}TOPIC_j + b_{2i}ANXIETY_j)$$

  - Scenario 1 (baseline): $b_{0i}, b_{1i}, b_{2i} \sim \mathrm{N}(0,1)$
  - Scenario 2: $b_{0i}, b_{1i} \sim \mathrm{N}(0,1)$ and $b_{2i} \sim \mathrm{N}(1,1)$
  - Engagement ~ Bernoulli draw of p_{ij}

- In each of 10 rounds, we deployed 2 different algorithms. (Initial content is randomly generated in terms of TOPIC and ANXIETY)
  1. Match topic of last round only if user engages. Anxiety is randomly generated.
  2. Match topic and anxiety of last round if user engages

Simulation Results

		Engagement Rate		Average Topic		Average Emotionality	
Scenario	Algorithm	Round 1	Round 10	Round 1	Round 10	Round 1	Round 10
Topic and emotions preferences randomly distributed N(0,1)	Topic focused	50%	52%	0.50	0.52	0.50	0.50
	Engagement focused	50%	54%	0.50	0.52	0.50	0.52
Topic preference distributed N(0,1) and emotionality preference distributed N(1,1)	Engagement focused	50%	64%	0.50	0.51	0.50	0.63

- Easily extendable to include multiple topics, emotions, or other linguistic features
- Stylized simulation because of simplified user heterogeneity and targeting algorithm

Conclusions & Discussion

- Emotional language affects continued reading/engagement more than topic does
  - Generally, more emotionality increases reading
  - Negative emotions increases continued engagement more so than positive emotions
  - Anxiety and anger increase continued engagements whereas sadness decreases it
  - Mechanism is via uncertainty and arousal
- Roadmap for content creators/marketers?
  - Short term vs. long term impact
  - Branding and brand associations
- Impact of algorithmic design
  - Recommendation/newsfeed algorithms monitor engagement
  - If the target is to increase engagement, how will algorithms respond and how will newsfeeds adapt to these emotionality effects?
  - Implications for FB/Instagram/TikTok impact on emotional well-being of users (in addition to the filter bubble effects)
  - Impact on recommendation diversity
  - Alternate metrics to optimize?

Investigation: How TikTok's Algorithm Figures Out Your Deepest Desires

The Wall Street Journal created dozens of automated accounts that watched hundreds of thousands of videos to reveal how the social network knows you so well