

Adapting Conjoint Analysis to Quantify Influential Features of Social Media Posts

Authors: Michael R. Haupt, PhD, Tim K. Mackey, MAS, PhD

Background into Project

Originally developed in the field of mathematical psychology, conjoint analysis is a methodology used often by market researchers to quantify preferences for different products or services among consumers (see the following for further details: Green et al., 2004; Green & Srinivasan, 1990). Conjoint analysis uses experimental design to mimic complex decision-making processes that require people to “consider jointly” multiple attributes and lets respondents choose, rate, or rank hypothetical product alternatives that differ by attributes and levels. In recent years, conjoint has been adapted to examine social preferences, such as ranking the most appealing features of political candidates and roommates. Researchers have also used conjoint to examine patient preferences for health products such as PreP HIV prevention medication (Shrestha et al., 2018), vaccine treatments (Sun et al., 2020), and disease modifying therapies (Wilson et al., 2014).

With the increased use of the internet and the hundreds (or thousands) of social media posts we’re exposed to each day, there is a growing need for methodologies that assess the psychological impact of social media posts and predict which posts are most likely to “go viral”, particularly in the context of patient safety challenges and their association with counterfeit health products. Existing social media research is observatory, as it collects existing posts from online platforms and uses manual content coding or machine learning/AI approaches to assess meanings and narratives across discourses. While it’s possible to identify influential posts after they’ve become popular, little work has been done to predict potential posts that are most likely to receive engagement. There are several characteristics of posts that can influence engagement: message content, post author, images used, tagging other accounts, engagement metrics (e.g., number of likes), among many others. A key advantage of conjoint analysis is that it can decompose social media posts into features (like products/services), then quantify and rank which features are most influential. As conjoint accounts for complexity in decision-making processes, it can be a powerful technique that provides insights into what aspects of social media posts are most compelling to users, impacting engagement and even purchasing intentions. Despite the promise of conjoint analysis for social media research, only recently has it been used to assess appeal of post features for public health issues, such as appeal of illicit drug sourcing (Haupt et al., 2024).

This paper will walkthrough **6 steps** on how to adapt conjoint analysis to assess influential features of social media posts for health products that are subject to counterfeiting or have known sourcing issues that can result in patient/consumer harm. The main examples will be from 3 studies that used conjoint analysis to examine features of social media posts that are most

influential on purchase intention for the following health products: GLP-1 drugs (e.g., Ozempic), cannabis, and abortion pills.

Step 1: Look at existing social media posts.

Explore social media sites to see what real posts look like for your product. What do the most engaged posts look like? What do posts from influencers or companies (both legitimate manufacturers, resellers, and grey market sellers/counterfeiters) look like? Knowing the online presence of your product will help you make realistic stimuli for your conjoint study.

Step 2: Design your conjoint experiment

Once you know what features you want to investigate, translate them into attributes (e.g., Color) and levels (e.g., Red, Blue), including those that can be suggestive of counterfeit products or sourcing from unregulated suppliers. Real social media posts should be kept in mind when designing the conjoint. Sawtooth Software (<https://sawtoothsoftware.com/>) is also a great resource for designing and implementing conjoint studies (e.g., # of sets). See **Table 1** below for example designs:

Table 1. Tested attributes and levels of social media posts advertising GLP-1, Cannabis, and Abortion Pill products.

GLP-1		Cannabis		Abortion Pills	
Attribute	Levels	Attribute	Levels	Attribute	Levels
<i>Brand Type</i>	Branded - Ozempic	<i>Brand Type</i>	Celebrity Brand	<i>Product Type</i>	Pills – Not branded
	Other Branded (ex- Wegovy)		Branded (Non-Celebrity)		Pills - Branded
	Pharmacy Brand (ex- Hers/Hims)		Unbranded - Consuming		Herbal/alt
	Branded Tirzepatide (ex- Mounjaro)		Unbranded - Plain	<i>Product Display</i>	Only product (no packaging)
<i>Seller</i>	Manufacturer (LillyDirect)	Individual - White Male	Prescription packaging		
	Online Pharmacy (Amazon Pharmacy)	Individual - Black Female	Post Author only. For Org, use graphic		
	White female in medical clothing	Store	User Non-medical (White Male)		
<i>Visual Display</i>	Drug in packaging (see Brand Status)	<i>Description</i>	Sale Promotion Only	<i>Seller</i>	User Medical (White Male)
	Picture of Seller		Sale Promotion + Endorsement		User Non-medical (White Female)
<i>Product Positioning</i>	Medical Endorsement - Diabetes		Sale Promotion + Sativa Effect		User Medical (White Female)
	Medical Endorsement - Weight Loss		Sale Promotion + Indica Effect		Organization - EmpowerHer
	Celebrity Endorse – Weight Loss	<i>Platform</i>	Instagram	<i>Post</i>	Only mentions products

	No Graphic Text		Twitter	Caption	Promotion + consultations
Caption Text	Sale promotion only	Post Engagement	Low		Promotion + legislation
	Sale promotion + Offers consultation		High	Platform	Instagram
	Sale promotion + No prescription required				TikTok

Step 3: Create mock social media posts.

When the design is complete, you need to make mock social media posts for every combination of tested levels/attributes. For example, the design for the GLP-1 study required 288 mock posts: (Brand Type (4 levels) x Seller (3 levels) x Visual Display (2 levels) x Product Positioning (4 levels) x Caption Text (3 levels) = 288). There are multiple websites that generate realistic looking social media posts, such as Zeoob.com (<https://zeoob.com/>) which has options for multiple platforms and customization. See **Figure 1** below for examples of mock social media posts for the GLP-1, cannabis, and abortion pill studies.

LEVELS DISPLAYED IN FIGURE:

GLP-1: (Left) Branded Semaglutide – Ozempic, Manufacturer (LillyDirect), Drug in packaging displayed, Medical Endorsement - Weight Loss, Sale Promotion + No prescription required (Center) Branded Semaglutide – Ozempic, White female in medical clothing, Seller displayed, Celebrity Endorsement – Weight Loss, Sale Promotion Only (Right) Pharmacy Brand Semaglutide, Online Pharmacy, Drug in packaging displayed, No Graphic Text, Sale Promotion + No prescription required.

Cannabis: (Left) Celebrity Brand, Store, Sale Promotion + Personal endorsement, Twitter, Low engagement (Center) Unbranded – Plain Display, Store, Sale Promotion + Shares experience of Indica effects, Twitter, Low engagement (Right) Branded (non-celebrity), Store, Sale Promotion Only, Instagram, High engagement.

Abortion: (Left) Pills – Not branded (Mifepristone & Misoprostol), Only product displayed (no packaging), Individual User Medical (White Female), Only mentions that products are for sale, Instagram (Center) Pills - Branded (Mifeprex & Cytotec), Post Author displayed, Organization, Product for sale + mentions restrictions in reproductive legislation, TikTok (Right) Herbal/alternative, Only product displayed (no packaging), Individual User Non-medical (White Female), Only mentions that products are for sale, TikTok.

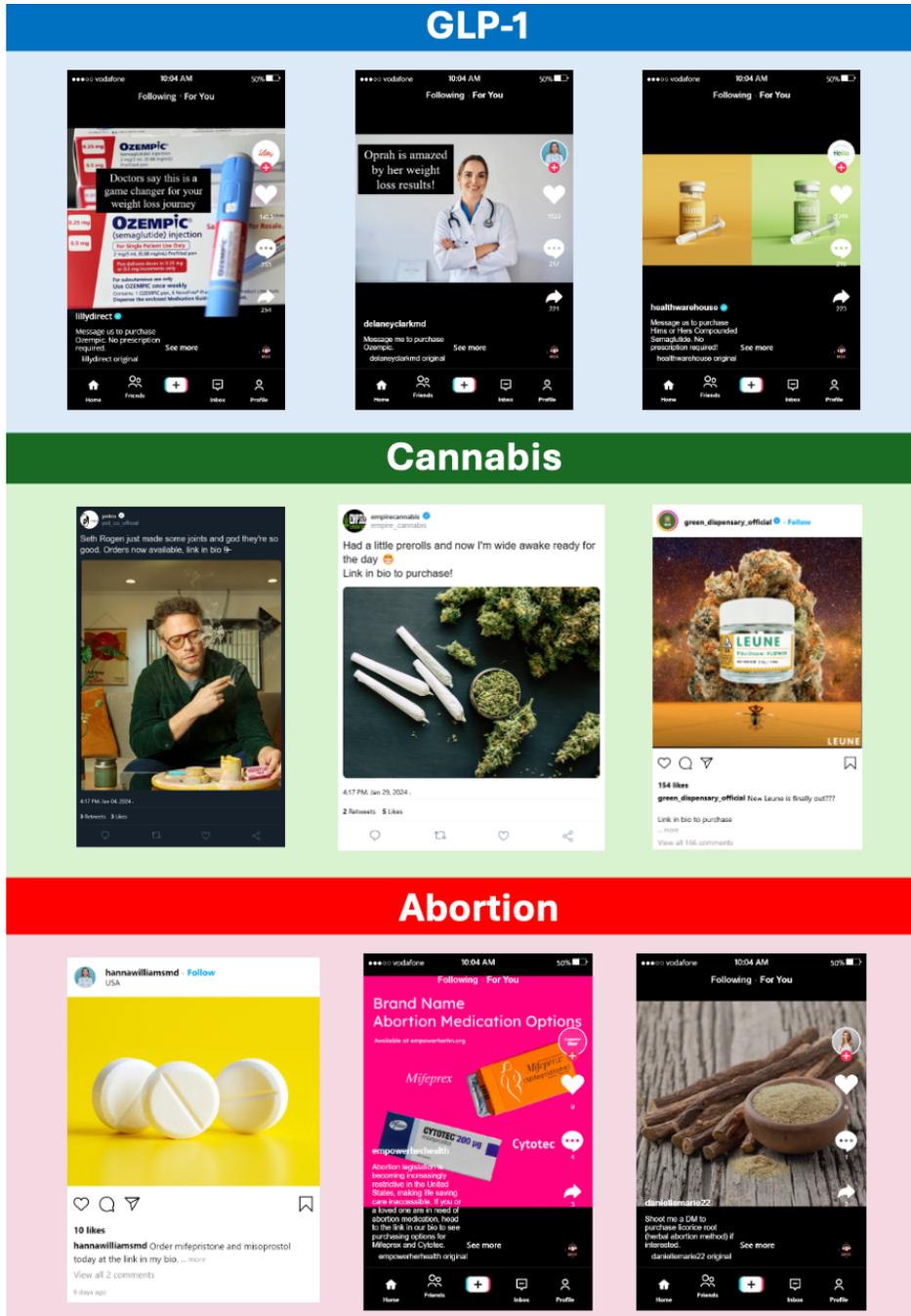
Step 4: Build your survey and integrate the conjoint exercise.

You can program the conjoint exercise and survey in Sawtooth and can integrate it with other platforms such as Qualtrics. When designing your survey, figure out what other

factors you'd like to measure to complement and validate your conjoint findings. For instance, below shows a question asked in the GLP-1 survey about brand preference, which complements findings from the Brand Attribute tested in the conjoint analysis.

“Which of the following best describes the type of GLP-1 drugs you primarily purchase? [Answer Options] 1. Branded GLP-1 injections (e.g., Ozempic, WeGovy, Mounjaro); 2. Branded GLP-1 semaglutide pills (e.g., Rybelsus); 3. Generic brand of semaglutide from a compound pharmacy or telehealth service (e.g., His/Hers); 4. I have **no preference** for branded or generic GLP-1 drugs”

Figure 1. Examples of Mock Social Media Posts for each Conjoint Study



Step 5: Analyze your conjoint results.

Use Sawtooth to analyze the conjoint data. For further detail on statistical approach, see Sawtooth's website for white papers on conjoint designs and analysis. Using Hierarchical Bayes to retrieve utility scores is the recommended option to obtain main effects. You can also assess interaction effects for combinations of levels across attributes.

Step 6. Interpret your findings.

When interpreting results from conjoint analysis, the levels with the highest average utility scores indicate higher preference. Importantly, only utility scores of levels within the same attribute can be compared, but not across attributes. While levels cannot be directly compared across attributes, it is possible to assess which attributes overall are weighted most heavily in respondent decision-making processes by using importance scores, which are computed for each attribute by taking the difference of the range in utility values and then dividing it by the sum of the differences in ranges across all attributes.

GLP-1 Results: Winning level = *Other Branded Semaglutide*, Lowest rank = *Pharmacy*

Attribute	Average Importances (Std Dev)	Levels	Average Utilities (Std Dev)
Brand Type	23.11 (9.12)	Branded Semaglutide - Ozempic	8.93 (41.54)
		Other Branded Semaglutide (ex- Wegovy)	15.38 (45.29)
		Pharmacy Branded Semaglutide (ex- Hers/Hims Compounded Semaglutide)	-15.78 (52.99)
		Branded Tirzepatide (ex- Mounjaro)	-8.53 (44.41)

Cannabis Results: Winning level = *Branded (Non-Celebrity)*, Lowest rank = *Unbranded - Consuming*

Attribute	Average Importances (Std Dev)	Levels	Average Utilities (Std Dev)
Brand Type	56.73 (15.42)	Celebrity Brand	-15.47 (97.04)
		Branded (Non-Celebrity)	91.24 (95.36)
		Unbranded - Consuming	-127.32 (66.26)
		Unbranded - Plain	51.55 (67.37)

Abortion Results: Winning level = *Pills – Not branded*, Lowest rank = *Herbal/alternative*

Attribute	Average Importances (Std Dev)	Levels	Average Utilities (Std Dev)
Product Type	29.32 (13.69)	Pills – Not branded (Mifepristone & Misoprostol)	40.29 (40.74)
		Pills - Branded (Mifeprex & Cytotec)	33.67 (33.82)
		Herbal/alternative	-73.97 (66.77)

Conclusions

Conjoint studies can elucidate insights into consumer preferences about product attributes and levels as advertised on social media, including those features that are associated with product counterfeiting. Results from this project are currently under review or are being prepared for publication and provide new insights into how consumers navigate access to a variety of health products, including a class of blockbuster chronic disease treatments (GLP-1s), a psychoactive controlled substance that is both legal and illegal depending on the state and is becoming highly commercialized (cannabis), and a women's health product that is impacted by changes in policy (abortion pills). Findings from this project can inform anti-counterfeiting strategies by informing brand holders about the specific product features and concepts that are attractive to consumers for purposes of consumer education, content moderation, enforcement action, and copyright and trademark infringement. Results can also set the foundation for a new approach in precision-based communication and consumer outreach that specifically takes into consideration the different types of consumers (e.g., demographics, age, etc.) and their receptivity to anti-counterfeiting messaging.

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