Pharma-SOS

Commercial Operations Community

Socialize – Optimize – Strategize

Community of Pharma/Biotech Operations Professionals

Using GenAI Large Language Models to Enhance Quantitative Forecasting with Qualitative Analysis

A Digital Therapeutics Case Study

Presenters

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Agenda

- Digital Therapeutics
- Primary Market Research
- Sentiment Analysis
- Large Language Models
- Putting It All Together

Digital Therapeutics

An Overview

Navigating the Digital Therapeutics Landscape

Digital Therapeutics Overview

Digital Therapeutics (DTx)

Software-based interventions for treating, managing, or preventing medical conditions

Evidence-Based Approach

Grounded in scientific research and clinical evidence, ensuring efficacy and safety

Diverse Applications

Applied across various healthcare domains, including mental health, diabetes, cardiovascular health, respiratory conditions, and substance use disorder treatment

Delivery Platforms

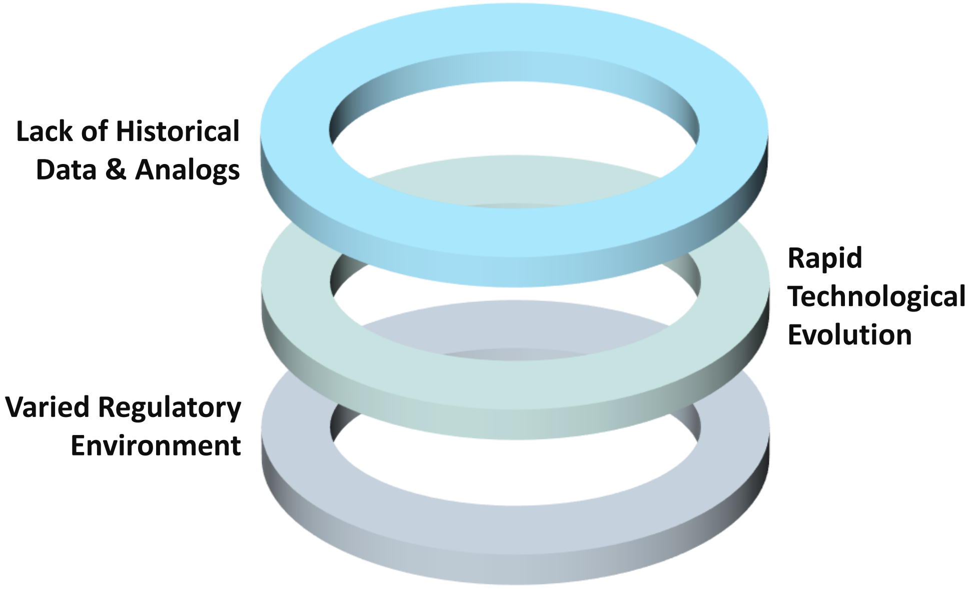
Utilized through digital platforms such as apps and websites, fostering patient interaction

Prescription or Recommendation

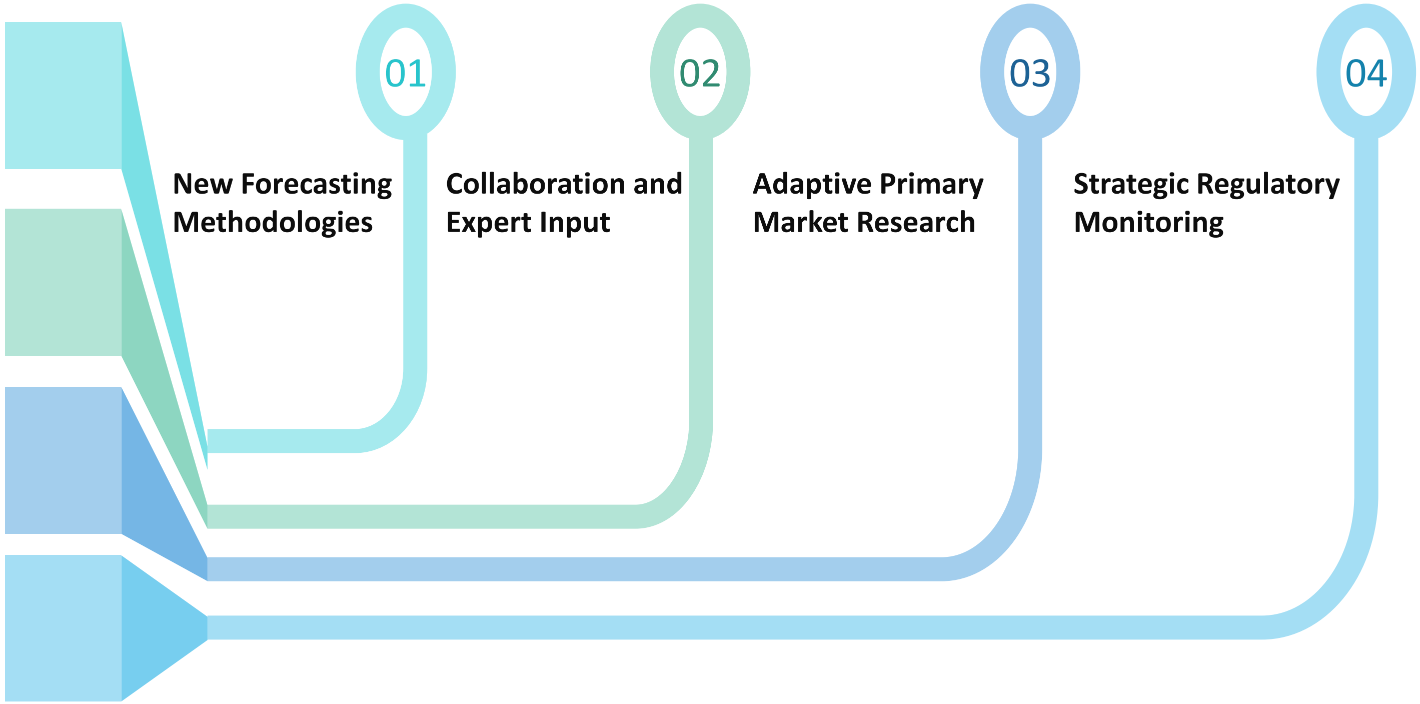
Healthcare providers integrate DTx into treatment plans, emphasizing their role in traditional healthcare

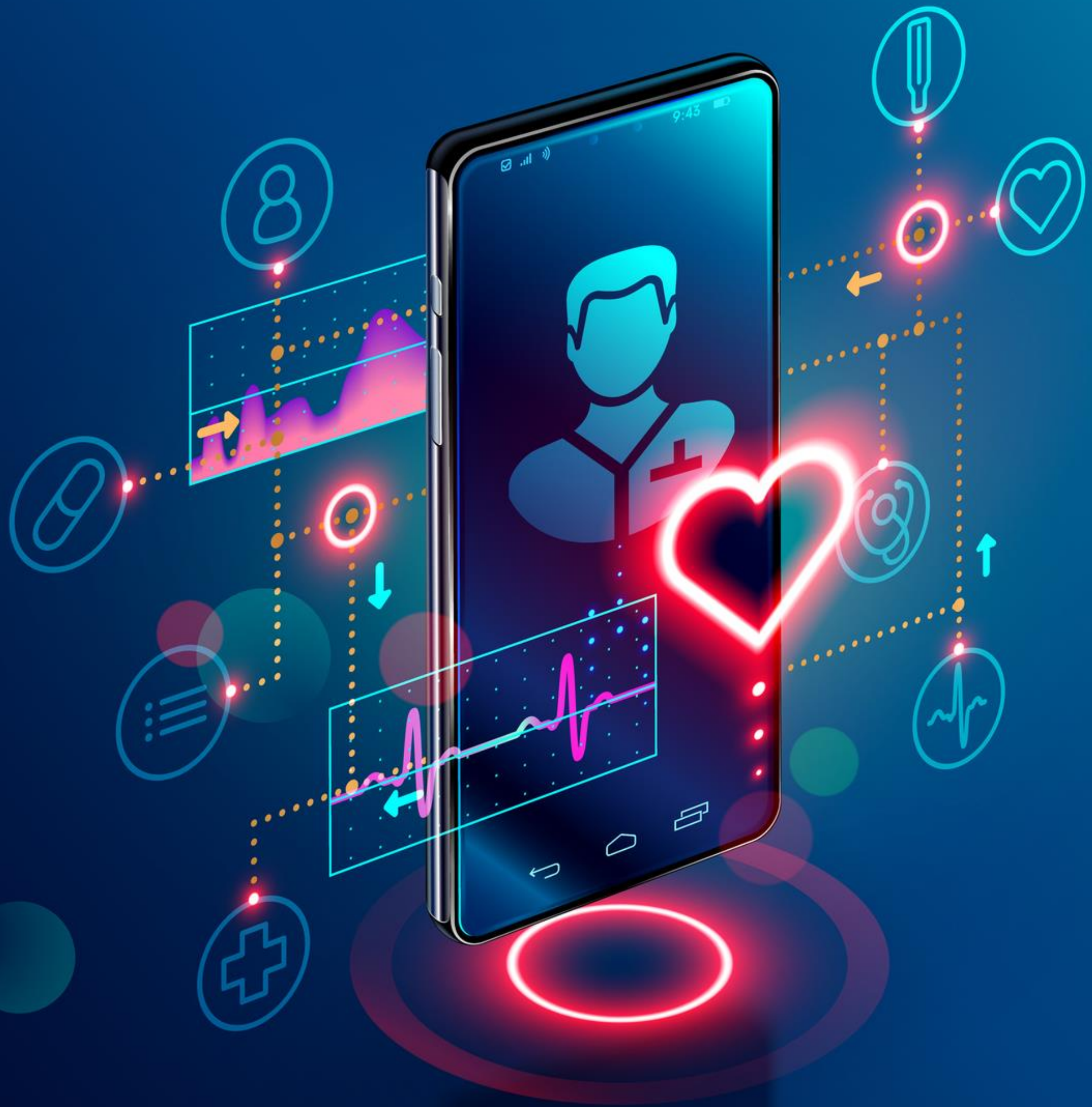
There are Numerous Considerations in Forecasting Digital Therapeutics

Challenges



Opportunities





Primary Market Research

An Overview

Significance of Primary Market Research

Gaining perspective from Primary insights

PROS

Quantitative Data

- Objectivity
- Easy to automate analysis

Qualitative Data

- Rich insights
- Contextual understanding
- Flexibility

CONS

Quantitative Data

- Lack of depth
- Limited flexibility in exploring unexpected insights

Qualitative Data

- Subjectivity
- Resource-Intensive Analysis

Using Open-ended Qualitative Responses to Further Refine Quantitative Research

GAINING PERSPECTIVE FROM OPEN-ENDED RESPONSES

OPPORTUNITIES

- Insights Generation
- The “Why”?
- Contextual Understanding/Depth
- Respondent Sentiment

CHALLENGES

- Volume and Complexity
- Time and Resource intensive
- Integration with Quantitative Data
  - Need for Analytical Frameworks
  - Sentiment Analysis

Sentiment Analysis is a Methodology to Enhance/Validate Quantitative Responses

HARNESSING TRADITIONAL SENTIMENT ANALYSIS

Overview

- Assess/evaluate sentiment of open-ended responses in quantitative research
- Can provide insights into Likert-type quantitative responses to questions relating to product satisfaction, intent-to-prescribe, etc.
- There are "Rules-based" and "Machine Learning-based" Sentiment Analysis Models
  - We investigated both in this research

Challenges

- Appropriately capturing language nuances in context/market-specific expressions
- Rules-based Models: Reliance on predefined lexicons that may be too general
- Lack of publicly available pharmaceutical (life science) industry-specific models

Large Language Models

An Overview

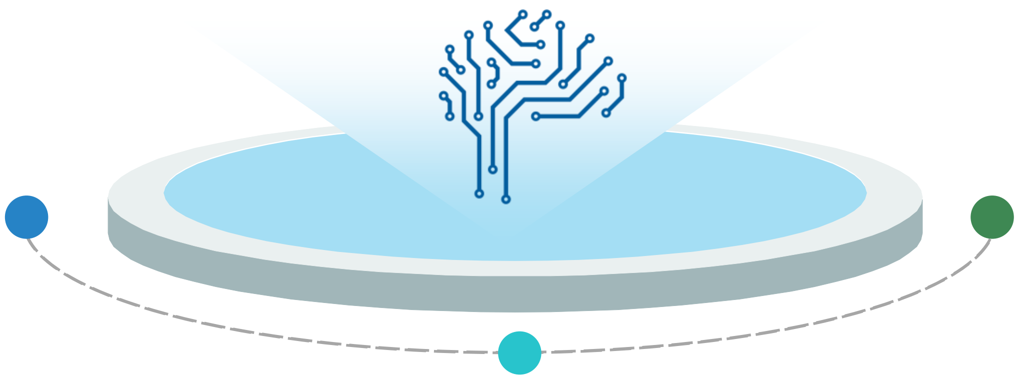
Introducing Large Language Models

The Power of Large Language Models

Large language models (LLMs) are advanced artificial intelligence systems trained on vast corpus of text

Significance

They demonstrate an understanding of context and nuances in language



Applications

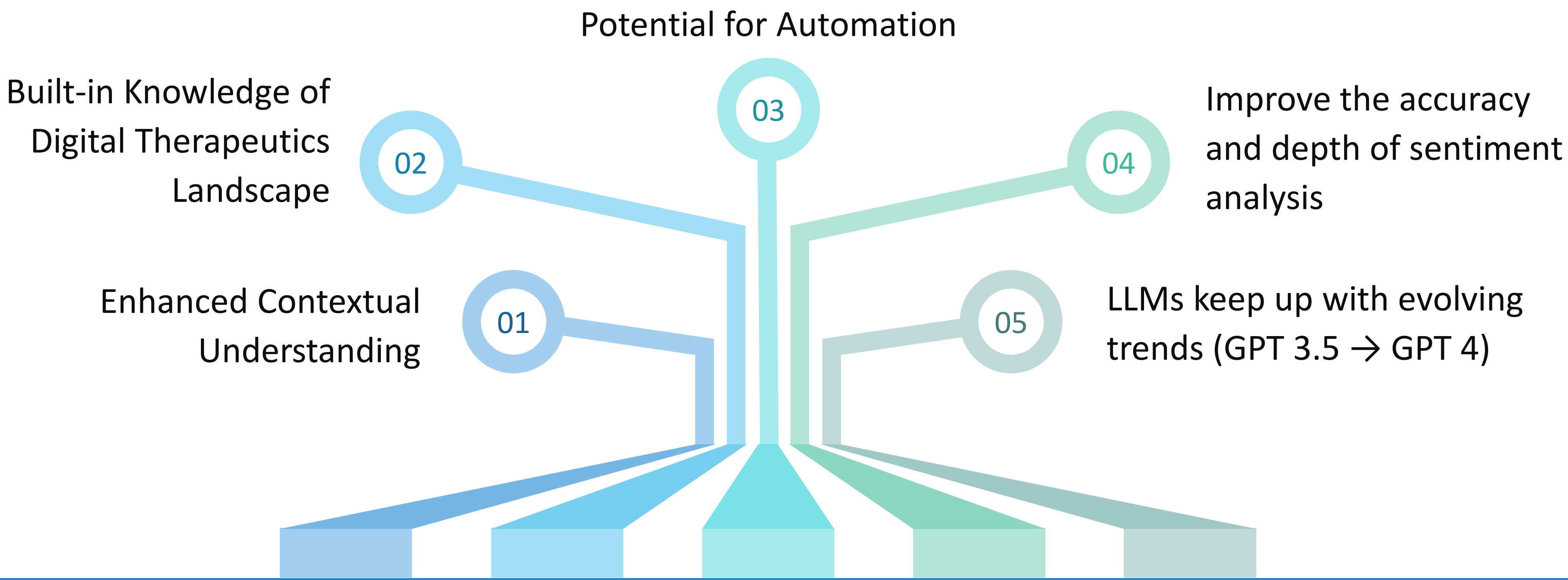
Used in natural language processing (NLP) tasks such as question answering, text completion, summarization, and many more

Examples ChatGPT, Microsoft Copilot, Mistral AI-Mixtral8x7B

OPPORTUNITY: *Use LLMs to analyze open-ended responses?*

Leveraging Large Language Models

Benefits of Using LLMs on Open-Ended Responses



Leveraging Sentiment Analysis for Actionable Insights

Transforming Results in Strategic Decisions

- Objective: Understand True Underlying Sentiment of Product
- Approach: Developed New Multi-Step Framework
- Framework Incorporates Derived Sentiments
- Output: Preference Share Overstatement

Forecasting an Unreleased DTx

A Case Study

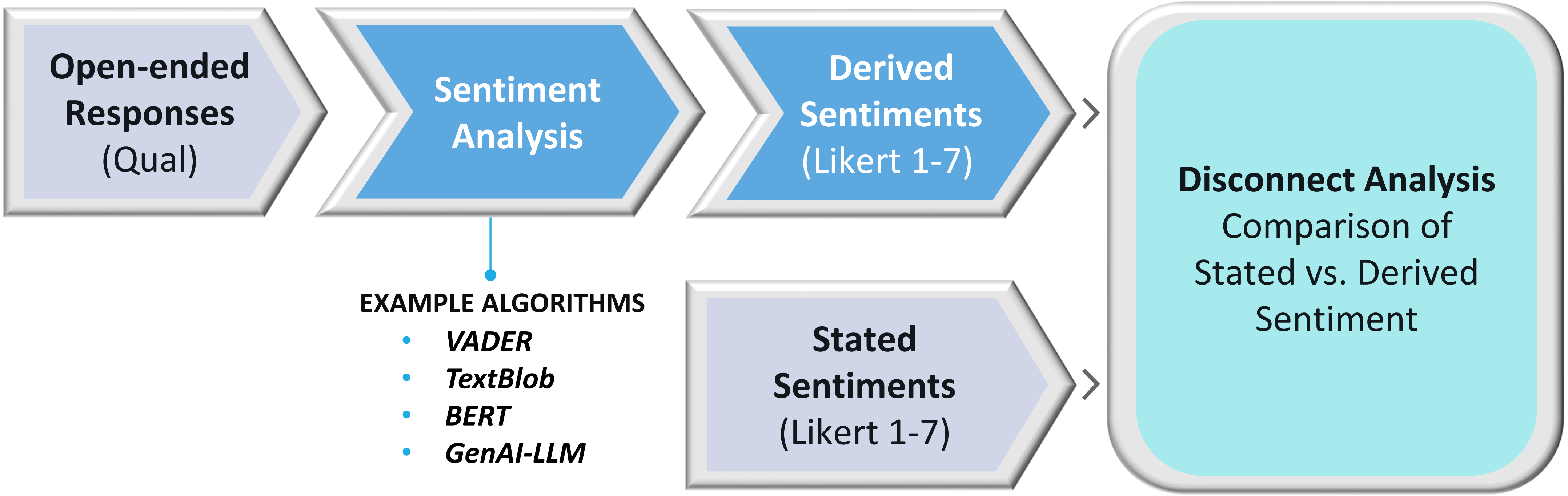
Case Study Using a Digital Therapeutic

Case study Background & key objective

Key Question	Forecast anticipated sales of the product as a digital therapeutic within the United States
Sample Size	Collected both QUAL and QUANT data from 257 prescribing health care professionals in the US
Data Points	Preference share of new digital therapeutic, as well as stated likelihood to prescribe on Likert scale (1 to 7) and rationale in an open-ended text response
Study Objective	Leverage GenAI-LLM to enhance the forecasting methodology, addressing a market research challenge: the adjustment from **preference share** to **market share**

Case Study Methodology

Navigating the Data Analysis Pipeline



The Research Explored Numerous Sentiment Analysis Methods: GenAI-LLM Was Superior

Sentiment Analysis Algorithms

VADER

- Lexicon-based
- Limited Context Understanding
- Open-source

TextBlob

- Machine learning-based
- Limited Context Understanding
- Customizable to domain-specific datasets
- Open-source

BERT

- Transformer-based
- Contextual Understanding
- Customizable to domain-specific datasets
- Open-source

GenAI-LLM

- Transformer-based
- Language Understanding
- Customizable to specific domains with fine-tuning or prompt engineering
- Some proprietary, some open-source

Case Study Sentiment Analysis Results

Stated vs Derived Sentiment: Frequency Distributions by Model

		Derived Sentiment Rating			
Responses (Likert 1-7)	**Stated Rating**	GenAI-LLM	BERT	TextBlob	VADER
1	10%	4%	0%	0%	0%
2	8%	36%	18%	1%	2%
3	9%	7%	25%	14%	11%
4	14%	13%	24%	46%	52%
5	25%	7%	16%	22%	22%
6	21%	28%	16%	16%	11%
7	12%	5%	1%	1%	1%
	100%	100%	100%	100%	100%

Difficult to determine which distribution reflects true sentiment

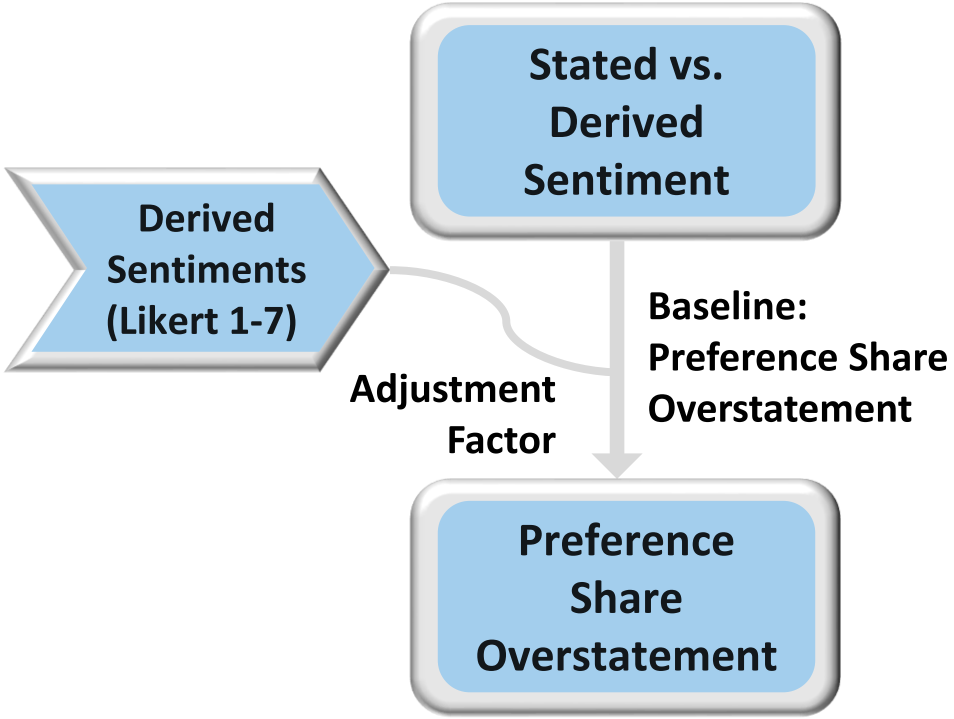
"Sentiment Analysis Results Suggest That GenAI-LLM Provide Superior Results That Are In Line With Expected Responses and Correct for Quantitative Overstatement"

STATED VS DERIVED SENTIMENT: SAMPLE OPEN-ENDED RESPONSES

	Text	Stated Rating	Derived Sentiment Rating				Expected Sentiment
			GenAI-LLM	BERT	TextBlob	VADER	
1	"Six-week program, check in regularly, activities and low cost."	6	6	6	4	3	Positive
2	"No clinically significant benefit to justify the cost."	1	2	3	5	5	Negative
3	"Everybody can scrap together 50 bucks."	7	7	4	4	4	Positive
4	"Not covered by insurance – access may be challenging for patients."	5	2	2	4	4	Negative

Potential Stated vs. Derived Sentiment Framework

ANALYZING DERIVED SENTIMENT TO DRIVE PREFERENCE SHARE OVERSTATEMENT



Stated vs. Derived Sentiment

- Measure of sentiment deviation [Derived – Stated Sentiment]
- Define an association between sentiment deviation and preference share overstatement
- Greater deviation between stated and derived sentiments leads to higher preference share overstatement
- Sets the baseline preference share overstatement

Derived Sentiment

- Measure of Absolute Sentiment
- Increased adjustment factor applied to baseline preference share overstatement in the case of neutral sentiments
- Recognizes potential risks associated with a lack of clear product sentiment

Potential Stated vs. Derived Sentiment Framework

Results and Outputs

	PMR Adjustment	
Respondent Segment	**Baseline**	**Post-Adj.**
Segment #1	63%	69%
Segment #2	66%	72%
Segment #3	61%	66%
Segment #4	63%	69%
Overall	**63%**	**69%**

Stated vs. Derived Sentiment:
Baseline Preference Share Overstatement

- Baseline preference share overstatement set at a higher minimum base (e.g. 40%, due to the newness of DTx) if there is no difference between stated and derived sentiment. Our recommendation for more established markets is minimum 25%
- Greater disparity between stated vs derived sentiment increases the baseline preference share overstatement

Derived Sentiment:
Post-Adjusted Preference Share Overstatement

- Adjustment Factor Range: +5% to +15%

Researchers Can Use LLM Sentiment Analysis to Refine Quantitative Intent-to-Prescribe Responses

ACHIEVEMENTS

- Integrated sentiment analysis which results into a quantifiable metric for preference share overstatement, driven by 2 factors: derived sentiment deviation and absolute sentiment
- Utilized state-of-the-art natural language processing techniques to enhance accuracy of market share assessments
- Developed a framework capable of discerning deviation between stated and derived sentiments
- Employed a novel approach for calculating preference share overstatement
- Successfully applied the framework to evaluate market share estimate in forecasting digital therapeutics

This Research Has Identified a Method To *Account for and Correct* the "Disconnect" Between Quantified "Intent-to-Rx" Responses and the Qualitative Explanations of the Rating

THIS PROVIDES A "PARTIAL" METHOD FOR ADJUSTING PREFERENCE SHARE

Project Conclusions

- Based on the analysis of open-ended responses that we believe are more thoughtful, and thus more representative of truer feelings, we derive a methodology to *account for and correct* the "disconnect" between the Stated Quantitative Rating (Likelihood to Prescribe) and the results of the GenAI-LLM Sentiment Analysis that also provides a Quantitative Measure Likert-type response of 1-7
- In our opinion, this addresses only that aspect of the "required overstatement"
- Other factors that are not addressed, and must be further addressed are specific external intermediating variables such as managed care impacts, competition, etc
- Future research, using LLM methodologies need to address these additional considerations to develop a model for the purpose of providing a complete assessment of Preference Share to Market Share Adjustments

There is Still Much To Do ...

Next Steps

Versatility Across Product Types

- Assess the applicability of the methodology to provide a more complete preference share adjustment
- Explore applications beyond digital therapeutics

Machine Learning Applications

- Enhance sentiment analysis by fine-tuning GenAI-LLM with labeled data
- Develop a supervised machine learning model simulating preference share overstatement, integrating other features collected from market research (ex: demographics, product characteristics)

QUESTIONS?

Thank you

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