YouTube Video Analytics for Health Literacy and Chronic Care Management: An Augmented Intelligence Approach to Assess Content and Understandability

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Outline

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- Motivation & Background
- Research Questions
- Approach
  - Identifying Medical Information Encoded in YouTube Videos
  - Assessing Understandability of Video Content
- Evaluating Impact on Collective User Engagement
- Results & Discussion
- Conclusions

Motivation: Convergence of Three Phenomena

- Global burden of disease – “perfect storm of rising chronic diseases and public health failures fueling the COVID-19 pandemic” (Lancet 2020)
- Patient engagement and health literacy imperative for chronic disease self-care and management (McCormack 2017)
- Rise of social and mobile media producing vast amount of user generated content (UGC) on health information (Liu et al. 2020)

Chronic Disease in the US

- Chronic diseases are among the most common and costly of all health problems, many with high mortality and morbidity rates (WHO 2019)
  - Over 100 million people in the United States have been diagnosed with one or more chronic diseases, accounting for > 80% of all healthcare spending (CDC, 2019)

https://www.cdc.gov/chronicdisease/resources/infographic/chronic-diseases.htm

Chronic Care Management

- Chronic disease self-management and preventive health programs are critical for improved health outcomes and reduced costs
  - Promote informed lifestyle choices, risk factor modification, and active patient self-management (Ruppert et al. 2017).
  - Health literacy is core to the success of such programs - Relies heavily on accessible medical information and patient-centered, personalized communication practices (Hernandez-Tejada et al. 2012)

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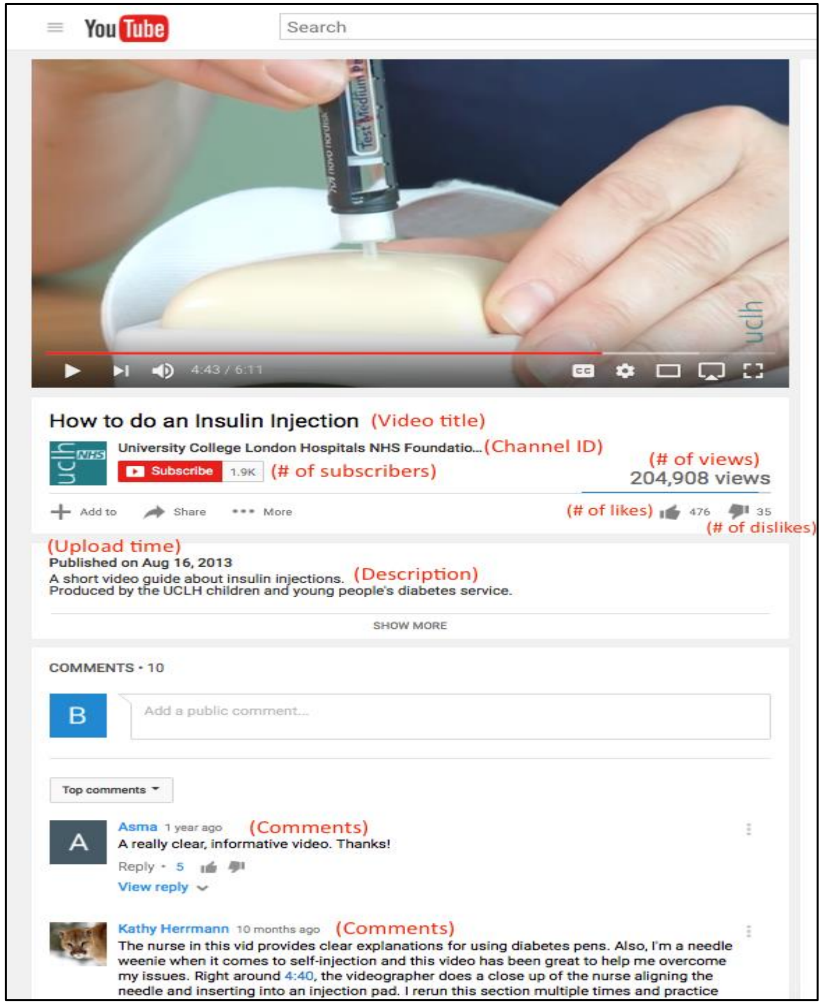
Health Literacy and Patient Engagement

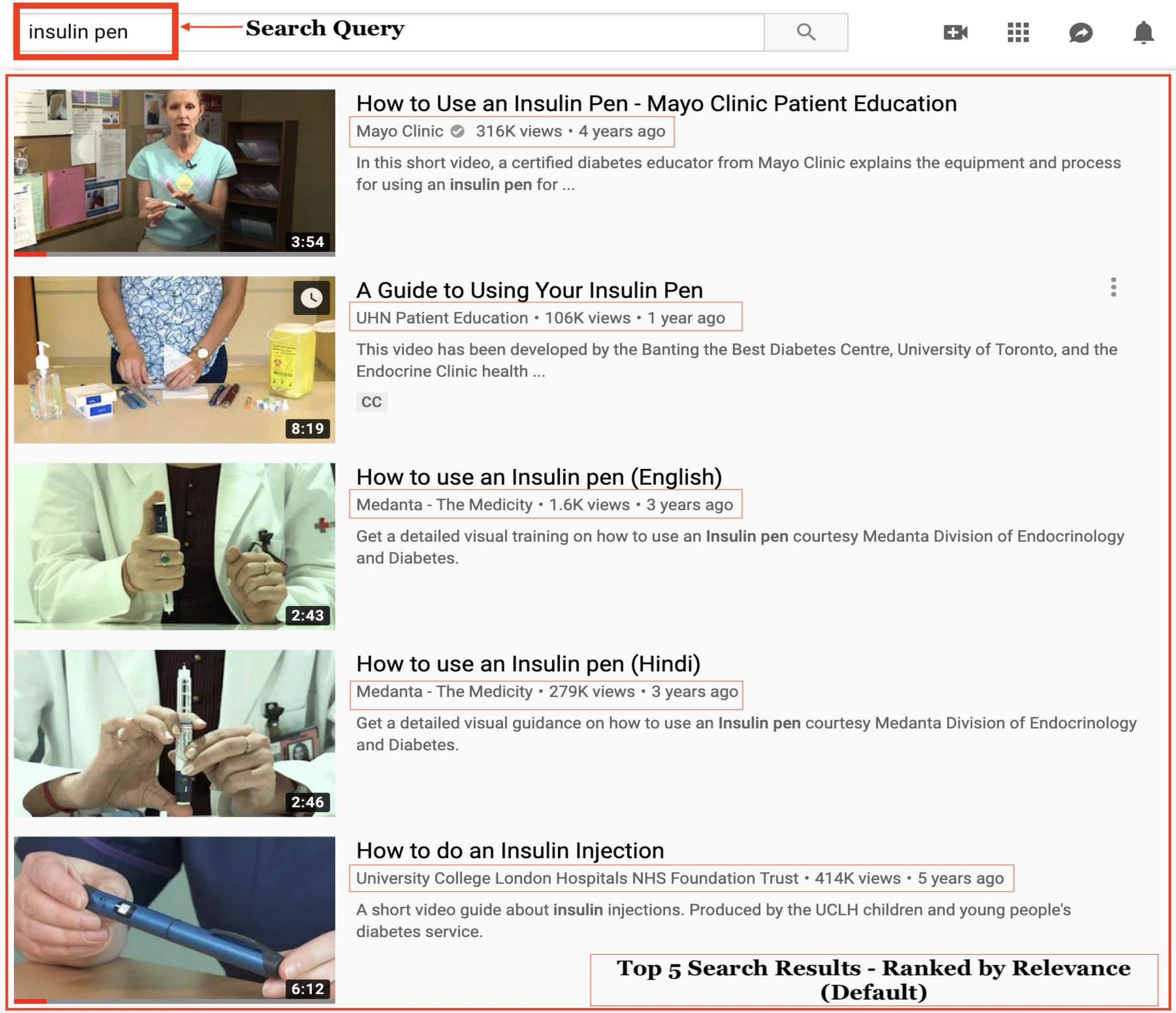
- Health literacy is defined as the degree to which individuals have "the capacity to obtain, process and understand basic medical information and services needed to make appropriate health decisions" (US National Academy of Medicine, 2004)
- Increase in health literacy has many benefits: adoption of disease prevention methods, adherence to and understanding of treatments, engagement for behavioral risk factor modification (https://www.healthliteracysolutions.org/chls/health-literacy-101/what-is-health-literacy)
  - In the US, only 12 percent of adults have Proficient health literacy, >80 million with low literacy (Kutner et al. 2006)
  - Rich literature on evidence-based strategies to address health literacy in the fields of communication, health care, public health, and adult education (HHS, 2010)
  - Most of the materials are too complex for patients to understand (Johnson et al. 2020, Rooney et al. 2020)

Rise of YouTube for Health Education

- A valuable channel for health education and communication
  - YouTube:100 million+ videos on the diagnosis, treatments, and prevention of various health conditions
  - Health promotions (Backinger et al. 2011), patient education (Sood et al. 2011; Steinberg et al. 2010), providing instructions on health procedures (Haines et al. 2010)
  - Viewers consume > 1 billion hours of video content a day (WSJ2017)
- Criticisms of visual social media use for healthcare
  - Reliability of content - includes information contradicting reference standards/guidelines (Ache et al. 2008)
  - Curation of content - lacks a clear and consistent mechanism to retrieve high quality information (Fernades-Llatas et al. 2017)



YouTube and Self Care

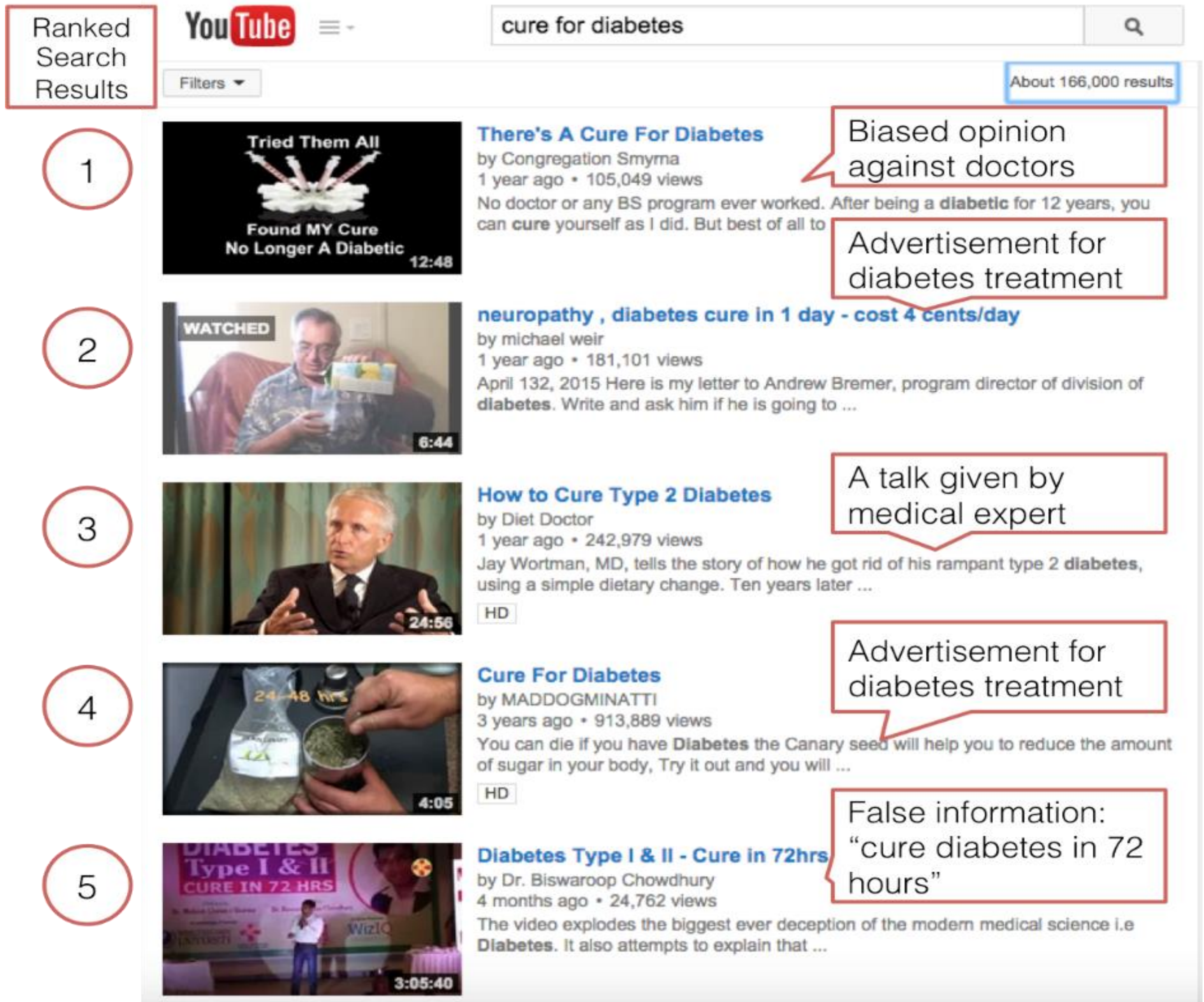


- YouTube Search Results for "Insulin Pen" ranked by relevance

- Top results are mostly from reputable health organizations such as Mayo Clinic, University College London Hospitals, etc.

- View counts range from 1.6K to 414K

Information Retrieval on YouTube: Video Search Results



- The top ranked video search results for this particular query are not very helpful for patients
- The first result contains biased opinions against doctors
- The second and fourth results are commercials of diabetes treatments
- The fifth video claims diabetes can be cured in 72 hours, which is false health information

Digital Therapeutics for Health Literacy?

- Digital therapeutics: utilizing a digital and/or online health technologies to treat medical or psychological conditions (Kvedar et al. 2016)

- Develop a scalable, replicable algorithmic solution to evaluate YouTube videos from health literacy and patient education perspectives
- Combine healthcare informatics + machine learning + social science methods
- Aid clinician decision making via ranked recommendations
- Deliver as a prescription

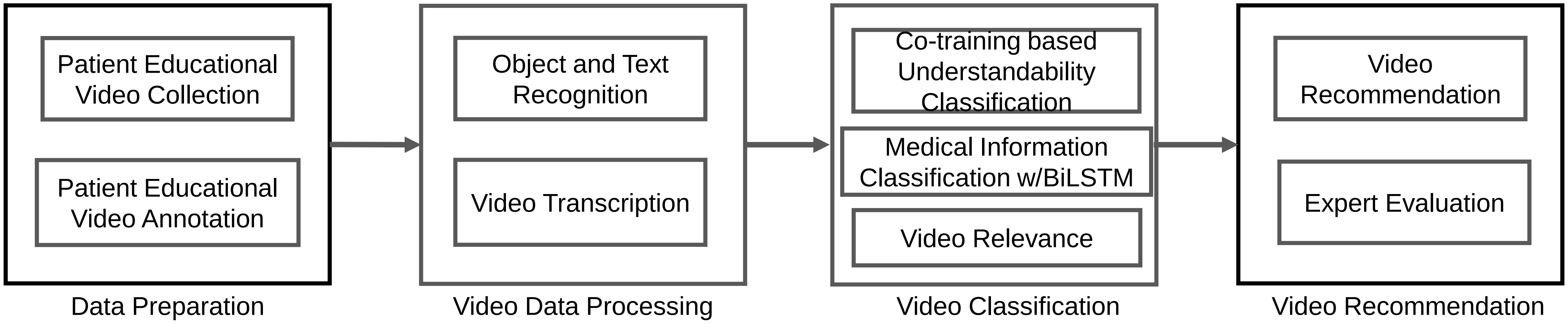
*Can we design recommendation systems to better retrieve medically-relevant, understandable, **user-generated content** for improving Health Literacy, Patient Education and Engagement?*

Research Questions

- How can we extract medical information encoded in videos on YouTube and assess their understandability?
- How do we measure collective engagement on YouTube?
  - Collective engagement: a proxy for how users understand and interact with health information on YouTube
- How does medical information encoded in YouTube videos and its understandability affect collective engagement?
- Liu et al., MISQ 2020, AMIA 2019, AIDR 2019, MLPH@NeurIPS2020

Research Approach

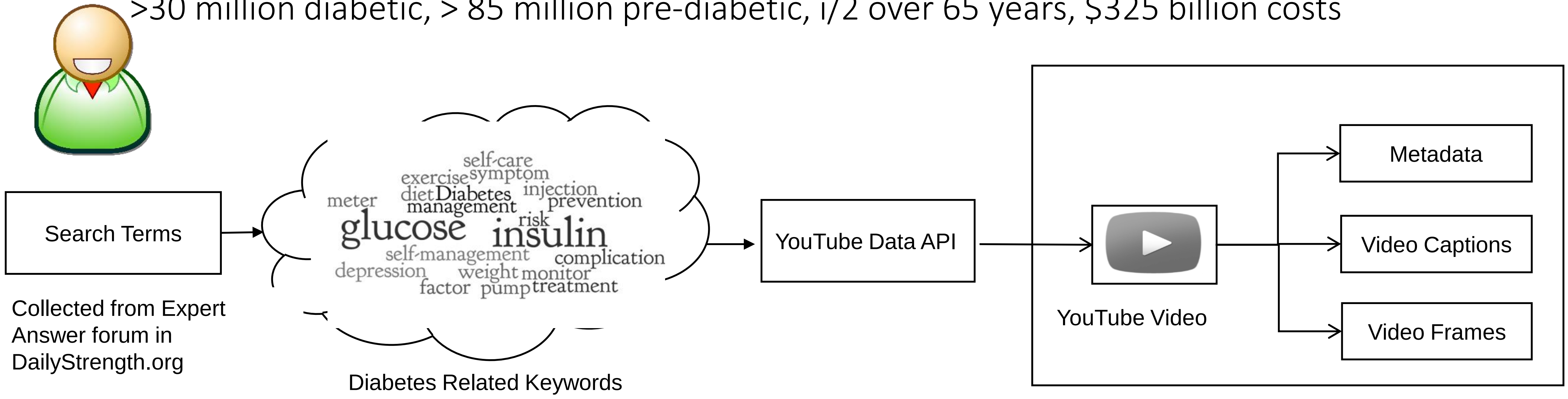
- Design a patient educational video retrieval system based on YouTube data and focus on two aspects:
  - Amount of medical information in the video
  - Understandability of the content



- Assess impact on collective user engagement

Data Collection – Diabetes Videos

>30 million diabetic, > 85 million pre-diabetic, i/2 over 65 years, $325 billion costs



- Collect search terms from questions asked in online health communities
- Categorize the search terms into different aspects of patient education
- 200 search queries about diabetes
- Top 50 videos from YouTube for each query
- Video metadata and video content

Video Data Summaries

Video engagement measures & Video level measures

Variables	Min	Q_1	Median	Mean	Q_3	Max
# of likes	0	16	62	847.8	306	14,806
# of dislikes	0	2	6	94	14	30,529
# of comments	0	1	8	436	44	80,732
# of views	0	150	2,112	2,659	6,763	1,452,723
# of words in description	0	22	64	147.5	195	1,005
Video duration (s)	1	181.2	340	677.7	711	9,716
Categorical Variables	**Categories**					
Has title	True: 9,873			False: 0		
Has tags	True: 6,325			False: 3,548		
Has caption	True: 2,357			False: 7,516		

Assessing Health Information Quality on Visual Social Media

Expert-driven measures	Popularity-driven measures	Heuristic-driven measures
• Judgment of human experts with medical knowledge (Backinger et al. 2011; Dawson et al. 2011)	• View count (Backinger et al. 2011) • Mean number of views per day (Pandey et al. 2010) • Public ratings (Backinger et al. 2011) • Viewership share (Sood et al. 2011)	• Duration of the video (Sood et al. 2011) • Titles and tags (Figueiredo et al. 2009) • Good description (Gooding et al. 2011) • Technical quality (light, sound, resolution) (Lim Fat et al. 2011) • Credentials (Gooding et al. 2011)

Human-intensive, expensive, time-consuming, limited scope – not scalable or replicable

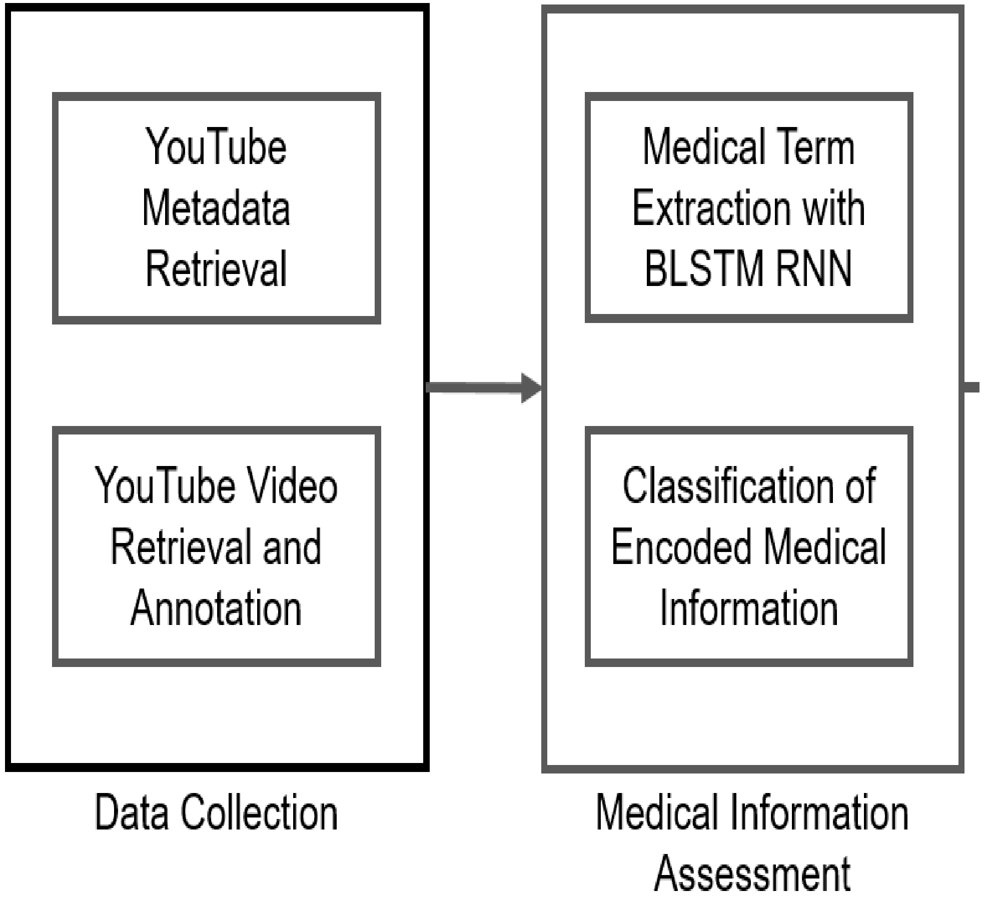
Framework to Assess Medical Information Encoded in a Video

Heuristic-driven measures

- Video duration
- Whether title is used
- Whether tags are used
- Number of words in video description
- Number of unique words in video description
- Content creator is a reputable organization
- Video definition
- Video caption

Expert-driven measures

- Number of medical terms



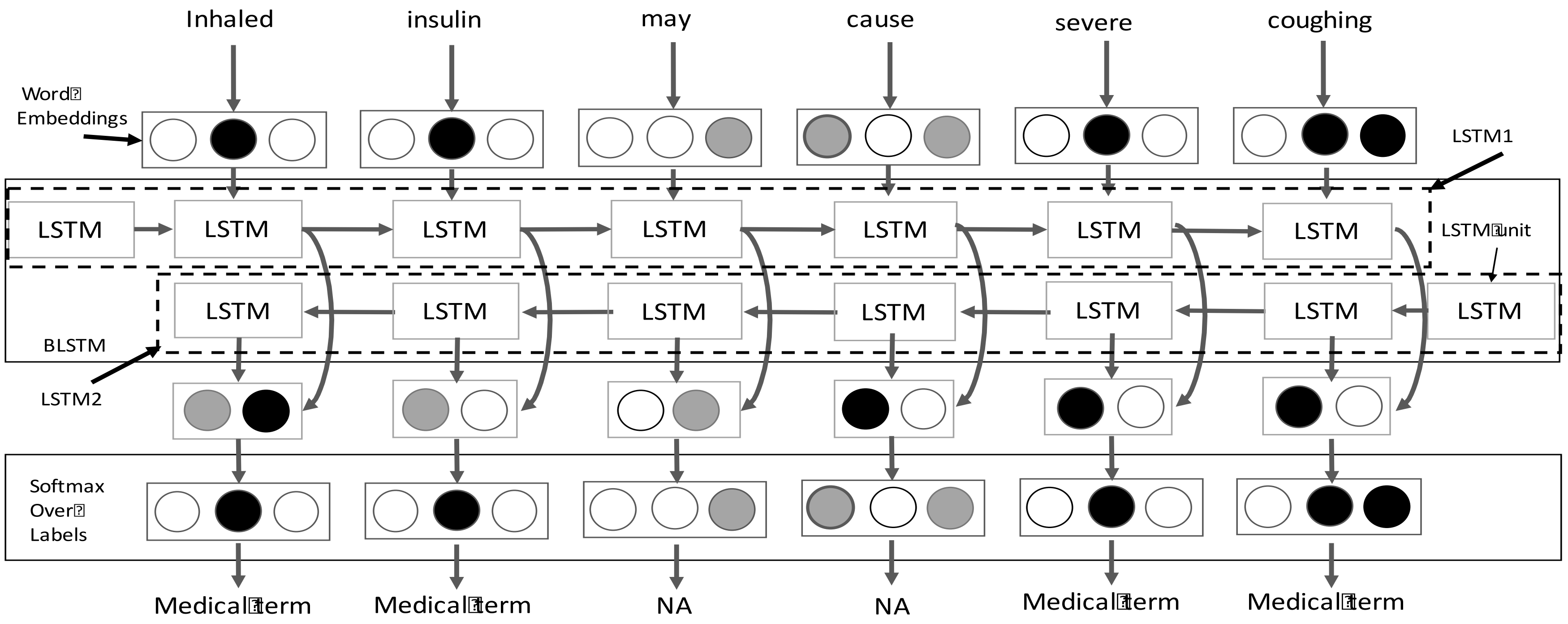
Medical Relation Identification

- **Medical information** in the video is often embedded in the video description text as **medical entities** (e.g., disease, treatment, conditions) **and semantic relations** (e.g., prevent, contraindicates, treat) between medical entities.

Key medical knowledge defined by National Library of Medicine's UMLS (https://www.nlm.nih.gov/research/umls/index.html)

Relation	Entity 1	Entity 2	UMLS Sources	Example
Treats	Disease	Treatments	May-treat, treats	[Metformin] treats [Type II Diabetes].
Prevents	Disease	Treatments	May-prevent	[Lipitor] prevents [heart disease].
Contra-indicates	Disease	Treatments	Contraindicated-drug	Patients with [kidney problems] should avoid [Actos].
Diagnosis	Disease	Test	May-diagnose	[HbA1C] test can be used to diagnose [diabetes].
Causes	Treatment	Symptoms	Causes-of	[Lantus] causes [rash].
Location-	Disease	Locations	Has-finding-site	[Bladder] [Cancer]
Symptom-of	Disease	Symptoms	Disease-has-finding	[Diabetes] causes [hypoglycemia].

Identifying Medical Terminology in YouTube Video Description



- Medical terms
  - Disease
  - Treatment
  - Symptom
  - Condition
  - Procedure
  - Component/location
- Writing styles
  - Standard medical terminology
  - Consumer health vocabulary

Model trained on 4,000 annotated sentences and 1,000 sentences for validation

Video Medical Information Classification – Features (Liu et al. 2020)

Video Features for Medical Information Classification	Description
# of words in the video description	Total number of words in the video description
# of unique words in the video description	Total number of unique words in the video description
Video duration	The total length of the video in the second
# of unique medical terms in video description	Total number of unique medical terms in video description
# of channel views	Total number of views the content contributor has
# of channel subscribers	Total number of subscribers the content contributor has
# of channel comments	Total number of comments the content contributor has
# of channel Video Count	Total number of videos the content contributor has
# of channel average video view count	Average video view count for the content contributor
Has title	Whether the video has a title
Has tags	Whether the video has tags
Has caption	Whether the content contributor submits a caption together with the video
Content creator credibility	Whether a reputable healthcare organization manages the channel
Video definition	Video resolution (HD or SD)

- Video relevance score is computed based on the cosine similarity between search query and video description

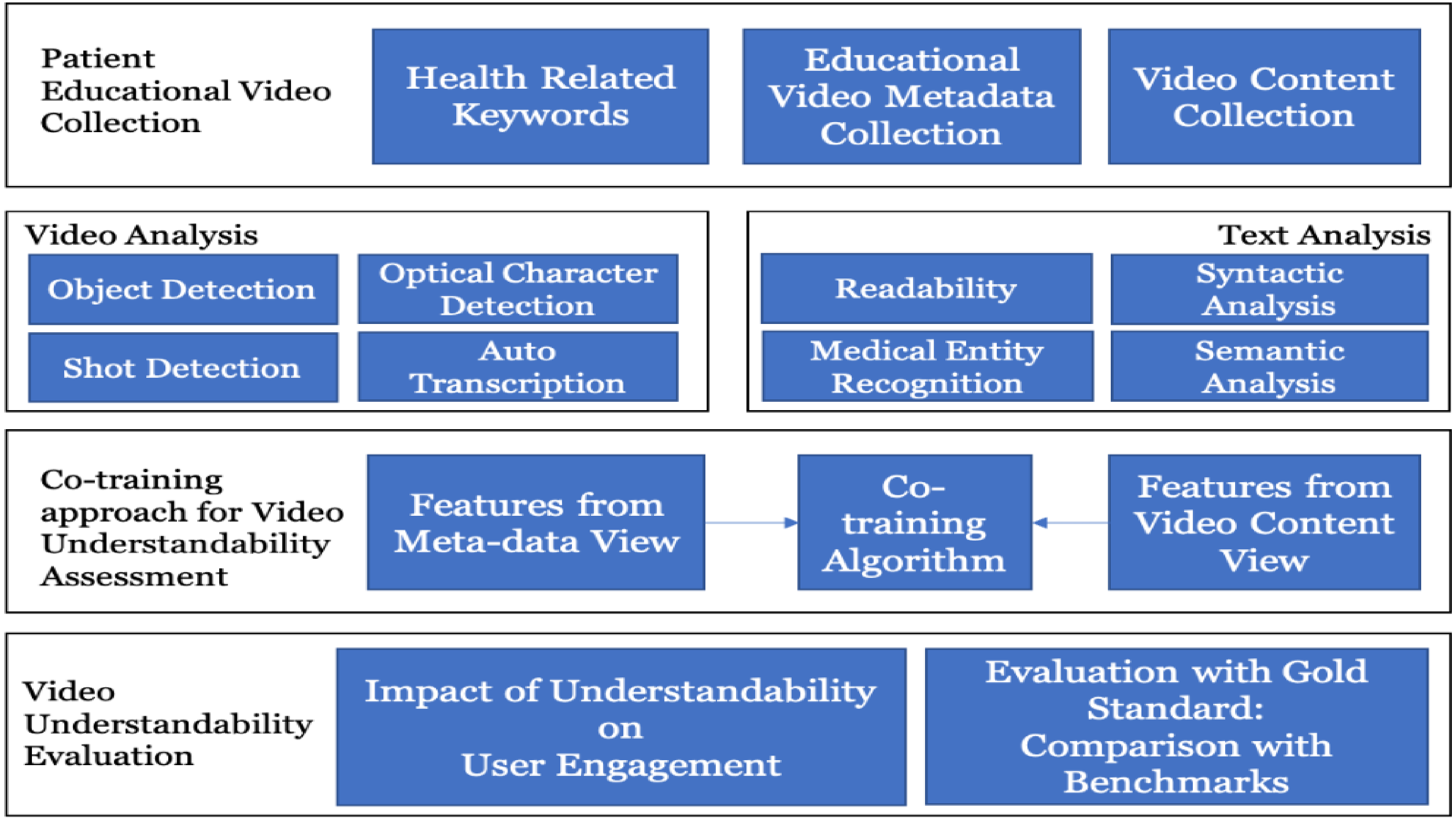
Framework to Assess Healthcare Video Understandability

A video is understandable when

- Consumers of diverse backgrounds and varying levels of health literacy can process and explain key messages

- Evaluation of patient educational videos have relied on the judgment of domain experts on several critical dimensions (Backinger et al. 2011)
  - Content understandability by end users (Ruppert et al. 2017)
  - The volume of medical information (Liu et al. 2019)
  - The complexity of medical information provided (Stellefson et al. 2014)
- Agency for Healthcare Research and Quality (AHRQ) proposed the Patient Education Materials Assessment Tool (PEMAT) (Shoemaker et al. 2014)
  - Evaluates and compares patient education materials in written, audio and video formats
  - PEMAT highlights the need to emphasize the understandability of patient educational materials

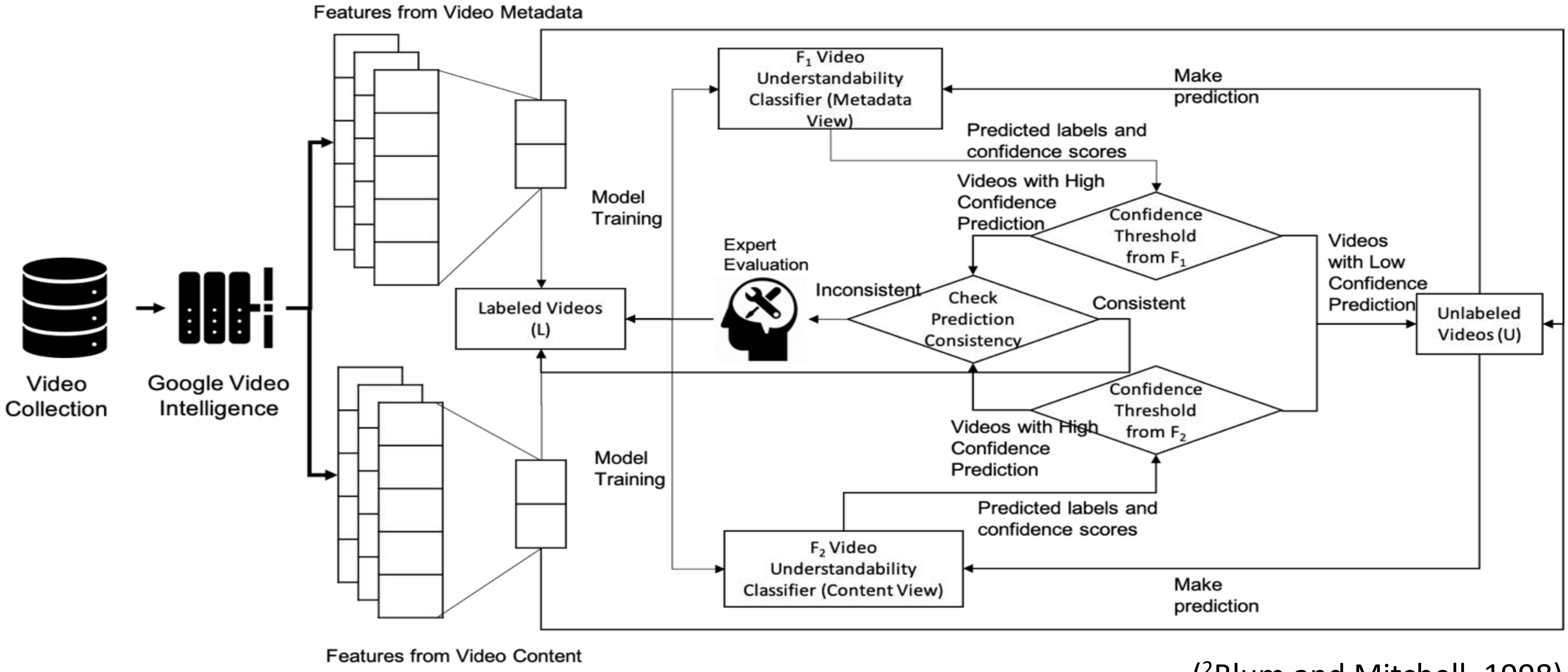
Patient Educational Materials Assessment



Patient Educational Video Annotation

- Video understandability and medical information
  - Two graduate research assistants independently evaluated 700 videos randomly selected from a collection of 9,873 videos
  - Annotation conducted according to PEMAT guideline (Shoemaker et al. 2016)
- Patient educational video recommendation
  - 500 videos generated by 20 search queries were selected for video recommendation evaluation
  - Four medical experts independently reported whether they would recommend the given video for patient education

Co-training[2] based Video Understandability Classification



([2]Blum and Mitchell, 1998)

Results

- Video Understandability Classification

	Precision	Recall	F1 score
Co-training with logistic regression	0.84	0.79	0.81
Logistic regression	0.63	0.60	0.61
Support vector machines	0.77	0.75	0.76
Random forest	0.80	0.74	0.77

- Medical Term Extraction

Medical Term Extraction		Precision	Recall	F-measure
Baseline Model 1	UMLS (Lexicon)	0.42	0.22	0.29
Baseline Model 2	CRF	0.90	0.75	0.82
Proposed Approach	BLSTM RNN	**0.94**	**0.92**	**0.93**

- Medical Information Classification

Logistic Classification	Precision	Recall	F-measure
High Medical Information Videos	0.89	0.84	0.86
Low Medical Information Videos	0.87	0.91	0.89
Overall Accuracy: 0.88			

Video Recommendation based on Relevance, Understandability and Medical Information

	Estimate	P-value
(Intercept)	-1.035	< 0.01
Video Understandability	0.508	< 0.01
Video Relevance	0.22	< 0.05
Medical Information Encoded	0.373	< 0.01

- The logistic regression classifier obtains an overall accuracy of 82.5%, weighted precision of 80.7%, weighted recall of 82.9% and F-measure of 81.8% in video recommendation
  - Relevance, video understandability, and medical information are all positively and significantly correlated with expert recommendation
  - The impact of the video understandability is the strongest among these three

How does the understandability of encoded medical information in a video impact collective engagement?

- Multiple treatment propensity score matching to construct counterfactual groups across the different conditions
- Videos classified as Medical Information: High/Low and Understandability: High/Low - Four possible treatment conditions to characterize a video
- Model the propensity of a video to contain a high/low degree of medical information that is high/low understandable
  - Treatment condition is the predicted value from classifier
- Dependent variable: Collective engagement

Key Findings

- We discover three categories of user engagement: **non-engagement**, **selective attention driven engagement** and **sustained attention driven engagement**
- The propensity score matching results confirm common assessments of the relationship between user engagement and understandability of education materials (Desai et al. 2013)
- Video understandability has a negative impact on disengagement. A video with high understandability usually attracts more views, likes, and comments, reducing user disengagement
- High understandability can help high medical information videos become more engaging. On the other hand, high medical information videos with low understandability are the least engaging
- A video with higher understandability will receive more sustained attention driven engagement
- Video understandability does not have a significant impact on selective attention driven engagement, indicating that understandable videos are not necessarily ranked highly in search results or recommended more often

Discussion and Future Directions

- How do we combine domain experts and machine learning models to further improve the patient educational video retrieval performance?
  - Add criteria such as actionability, accuracy and timeliness of content in retrieving and ranking videos
- Provide suggestions to content creators and health systems to produce relevant patient education materials
- Design and implement a patient educational video retrieval system that can scale, generalize and adapt to multiple contexts
- Conduct randomized field trials and observational studies to evaluate the automated approach

Conclusions

- This study demonstrates the use and re-use of widely available, public repository of user generated content in the form of YouTube videos to support patient education needs
- We have developed a scalable approach for identifying high content, medically relevant, understandable videos for diabetes related patient education and care management
- We combine domain experts' knowledge and machine learning models to improve the patient educational video retrieval performance
- Our method can be used to aid clinical decision-making by enabling clinicians to recommend ranked videos along with discharge instructions for patient self-care
- Insights from this research can potentially suggest best practice recommendations to content creators and healthcare practitioners to produce relevant patient education materials

Thank you!

Questions?

Acknowledgements: We sincerely thank our graduate students and clinical domain experts for their invaluable help in reviewing the videos for labeling and evaluating the final recommendations of the algorithms.