# Project 15

# Gun Violence Surveillance Platform

<img src="placeholder.jpg" alt="Gun Violence Surveillance Platform Graphic" />

**BLUF:** Developed a real-time public platform that uses social media, news, and search data to track gun violence, aiming to inform and engage the public and support evidence-based policy.

## Introduction

* Gun violence is a major public health crisis (~100k US victims annually)[[1]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=Gun,tailors%20these%C2%A0sources%C2%A0together%C2%A0to%20meet%20these%20challenges).
* Official data sources are limited and not timely enough for tracking ongoing incidents[[1]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=Gun,tailors%20these%C2%A0sources%C2%A0together%C2%A0to%20meet%20these%20challenges).
* Non-traditional digital data sources (news, Twitter, search) provide near real-time gun violence insights[[2]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=Therefore%2C%20we%20develop%20a%20public,interventions%20to%20meet%20specific%20threats).

## Key Questions Addressed

* How to leverage online data for real-time surveillance of gun incidents and discussions?
* How to inform, engage, and educate the public about local gun violence trends?
* What non-traditional data streams can supplement official stats for better situational awareness?

## The Problem

* Gun violence data was fragmented and delayed, hindering timely awareness and response.
* The public lacked an accessible source for up-to-date, location-specific gun violence information.
* Policy makers had insufficient evidence between official reports to gauge effects of policy changes.

## The Importance

* Real-time awareness of gun incidents can drive community engagement and preventative actions.
* Timely, localized data empowers evidence-based policy evaluation and public health interventions[[2]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=Therefore%2C%20we%20develop%20a%20public,interventions%20to%20meet%20specific%20threats)[[3]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=The%20primary%20impact%20of%20the,based%20policy%20evaluation%20and%20planning).
* Increasing public education on gun violence through data transparency supports violence prevention efforts.

## The Solution

* Built an interactive web platform aggregating multi-source gun violence data in near real time[[2]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=Therefore%2C%20we%20develop%20a%20public,interventions%20to%20meet%20specific%20threats).
* Collected Twitter, news, and search trend data to capture incidents and public reactions.
* Used ML to classify tweets (4 categories) and news articles (7 incident types)[[4]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=and%20around%2015%20thousand%20search,violence%20at).
* Geocoded all data to US states for localized insights.
* Integrated state-level official metrics (gun deaths, background checks, law scores) for context.

## Architecture Overview

* Data ingestion pipelines from Twitter, Google News, and Google Trends feed the system.
* ML pipeline categorizes gun-related tweets (4 topics) and news articles (7 categories)[[4]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=and%20around%2015%20thousand%20search,violence%20at).
* Human curators validate machine outputs, remove duplicates, and annotate developing stories[[5]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=b,stories).
* Geolocation service infers each tweet/news location to assign a US state[[6]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=Finding%20the%20location%20of%20the,not%20be%20determined%20were%20discarded).
* Front-end dashboard visualizes state-level metrics and trends, updating as new data streams in.

## Results and Impacts

* Collected ~540k gun-related tweets and ~1.6k news articles per month (2015–2016)[[7]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=using%20a%20list%20of%20carefully,between%20May%20and%20December%202015)[[8]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=October%202015,the%20reported%20incidents%20was%20extracted).
* Launched a public platform (gunviolencemap.org) offering state-by-state real-time gun violence insights.
* Increased public engagement and awareness via targeted, location-specific information updates[[3]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=The%20primary%20impact%20of%20the,based%20policy%20evaluation%20and%20planning).
* Shared findings with stakeholders at SXSW 2016 (policy makers, public)[[9]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=We%20presented%20our%20work%20at,presented%20an%20overview%20of%20digital).
* Received media coverage (Wired, KQED) highlighting the platform’s novel approach to gun data[[10]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=Date%3A%20September%2029%2C%202016)[[11]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=Date%3A%20April%2021%2C%202016).

## Skills and Tools Used

* Social media data integration (Twitter API, Google News feeds, Google Trends analytics).
* NLP and machine learning for text classification (automated tagging of tweets/news).
* Geospatial analysis (Google Maps API for geocoding, state-level mapping of incidents).
* Web development for interactive dashboards and data visualization.
* Hybrid human–AI curation (automated classifiers with human review for data quality).

## Cross-project Capabilities

* Real-time social data mining and digital epidemiology techniques applied across public health domains.
* Reusable Twitter data pipeline (collection & classification) later applied to patient experience sentiment studies.
* Integration of heterogeneous data sources (social media, open data, official stats) in a unified platform.
* User-centric design and visualization skills for engaging public-facing analytic tools.

## Published Papers/Tools

* *Public Platform for Gun Violence Surveillance and Awareness Using Digital Exhaust* – Demo paper, ACM Hypertext 2017[[12]](file://file_000000000f9c61f5b1770f237fbbf198#:~:text=Title%3A).
* SXSW Interactive 2016 – *“Using Social Media to Predict Gun Violence”* (invited session)[[9]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=We%20presented%20our%20work%20at,presented%20an%20overview%20of%20digital).
* **Gunviolencemap.org** – Online interactive map dashboard (public prototype).
* Media features – e.g., Wired & KQED articles in 2016 showcasing project insights[[10]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=Date%3A%20September%2029%2C%202016)[[11]](file://file_00000000ea0861f5b59a713e7a3c56b1#:~:text=Date%3A%20April%2021%2C%202016).

# Project 16

# Humanitarian Crisis – Demining Microservice Dashboard

<img src="placeholder.jpg" alt="Demining Dashboard Graphic" />

**BLUF:** Designed a modular geospatial analytics system that integrates multi-sensor landmine detection data into an interactive heatmap dashboard, enabling demining teams to identify high-risk areas and plan operations more effectively.

## Introduction

* Hidden landmines in post-conflict zones pose deadly risks to civilians and responders.
* Demining operations are slow, dangerous, and resource-intensive, requiring better tools to prioritize efforts.
* Modern sensors and AI can predict landmine locations and guide clearance via “smart maps.”

## Key Questions Addressed

* How to fuse diverse sensor inputs into one unified mine risk picture for decision support?
* How can an interactive map help teams visualize mine hotspots and track clearance progress?
* What design allows adding new algorithms or sensors without disrupting the whole system?
* How to incorporate field feedback (confirmed mines/cleared areas) to continually improve predictions?

## The Problem

* Multi-sensor data is siloed, making it hard to see the overall mine risk.
* High false alarm rates waste teams’ time on non-threats[[13]](file://file_00000000538861f5a82969c1f88897df#:~:text=Geospatial%20AI%20for%20Predicting%20Landmine,The%20United%20States%20Army).
* Existing demining tools lack real-time geospatial analysis, limiting efficient resource allocation.
* Without a centralized dashboard, prioritizing which suspected areas to clear first is challenging.

## The Importance

* A unified risk heatmap can direct teams to true danger zones, preventing casualties.
* Reducing false positives saves significant time and cost in humanitarian demining operations[[13]](file://file_00000000538861f5a82969c1f88897df#:~:text=Geospatial%20AI%20for%20Predicting%20Landmine,The%20United%20States%20Army).
* Data-driven planning optimizes use of limited demining resources and improves safety for personnel.
* Empowering local teams with interactive analytics increases transparency and confidence in clearance missions.

## The Solution

* Architected a five-layer microservice system to ingest, analyze, and present landmine risk data[[14]](file://file_00000000538861f5a82969c1f88897df#:~:text=Data%20from%20various%20sources%20is,in%20layer%205%29%20consumes).
* Core output is a probability heatmap highlighting likely mine locations, updated continuously.
* Interactive map UI lets users explore hotspots over time and inspect details[[15]](file://file_00000000538861f5a82969c1f88897df#:~:text=Interactive%20Map%20Interface%3A%20Provide%20a,War%3A%20Smart%20Maps%20Help%20Teams%E2%80%A6).
* Field feedback (found mines or cleared areas) is fed back for continuous learning.
* Operations planning service uses latest risk maps + external data to suggest priorities[[16]](file://file_00000000538861f5a82969c1f88897df#:~:text=Optimizing%20Operations%20%26%20Decision%20Support%3A,the%20presence%20of%20critical%20infrastructure).

## Architecture Overview

* **Layer 1: Data Ingestion** – Pulls data from multiple sensors (e.g. drone imagery, GPR).
* **Layer 2: Detection & Scoring** – Processes sensor inputs, flags potential mines with confidence scores.
* **Layer 3: Fusion Engine** – Fuses all detections into one probability model (multi-sensor evidence).
* **Layer 4: Visualization** – Stores risk heatmap; map service provides interactive user visualization[[14]](file://file_00000000538861f5a82969c1f88897df#:~:text=Data%20from%20various%20sources%20is,in%20layer%205%29%20consumes).
* **Layer 5: Operations Planning** – Analyzes heatmap + context to recommend areas to clear first.
* Microservices use RESTful APIs, allowing independent updates without breaking the whole system[[17]](file://file_00000000538861f5a82969c1f88897df#:~:text=To%20fulfill%20the%20above%20requirements%2C,consistently%20handled%20across%20the%20pipeline).

## Results and Impacts

* Produced a comprehensive system design for a demining decision-support tool centered on geospatial risk.
* The heatmap-focused approach ensures teams concentrate on true high-risk hotspots, improving safety.
* False alarm mitigation strategies promise significant reductions in wasted clearance effort[[13]](file://file_00000000538861f5a82969c1f88897df#:~:text=Geospatial%20AI%20for%20Predicting%20Landmine,The%20United%20States%20Army).
* Modular, cloud-agnostic architecture scales easily and can integrate new detection tech[[18]](file://file_00000000538861f5a82969c1f88897df#:~:text=Cloud,by%20scaling%20services%20horizontally).
* Blueprint can accelerate next-gen humanitarian tech development, potentially saving lives in mined regions.

## Skills and Tools Used

* System architecture & design (microservices, layered design patterns, RESTful API specification).
* Geospatial analytics (heatmap generation, spatial databases, GIS visualization techniques).
* Multi-sensor data fusion and filtering algorithms (combining outputs from different detection technologies).
* UI/UX for web-based GIS dashboards (interactive mapping, layer toggling, user feedback integration).
* Cloud deployment principles (containerization, scalability, interoperability across environments)[[18]](file://file_00000000538861f5a82969c1f88897df#:~:text=Cloud,by%20scaling%20services%20horizontally).

## Cross-project Capabilities

* Applied modular microservice design know-how, transferable to other complex data integration projects.
* Geospatial data processing and visualization expertise here leveraged in other analytics dashboards (e.g., epidemiological maps).
* Feedback loop design (user input refining outputs) appears in other human-in-the-loop projects.
* Focus on reducing false positives and highlighting critical signals recurs in many data projects.

## Published Papers/Tools

* Internal architecture design document and system blueprint (project deliverable for a demining program).

# Project 17

# Multi-Agent System – MOTL-based ISR Supervision (MAS-1)

<img src="placeholder.jpg" alt="Multi-agent System Simulation Graphic" />

**BLUF:** Explored a "Man-On-The-Loop" (MOTL) paradigm for supervising autonomous agent teams by tuning group-level sociocultural parameters, demonstrating that high-level adjustments of traits (e.g., risk aversion, individualism) can influence and optimize collective behavior in an ISR scenario.

## Introduction

* Large autonomous systems (e.g., UAV swarms) need effective human oversight without micromanagement[[19]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=the%20available%20information%20resources%20will,5)[[20]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=unit%20or%20agent%20community%20level%2C,MOTL).
* Traditional "Man-In-The-Loop" control is labor-intensive and can overwhelm human operators with details[[21]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=broadly%20divided%20into%20two%20categories,MOTL)[[22]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=human%20intervention%20in%20their%20actions,The).
* The MOTL paradigm: humans influence system behavior via global parameters instead of direct commands[[23]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Man%20on%20the%20loop%20is,affect%20the%20configuration%20of%20the).
* Incorporating sociocultural factors into agent behavior models may enable intuitive, high-level system tuning[[24]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=Abstract%E2%80%94Social%20reasoning%20and%20norms%20among,A%20group)[[25]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=Index%20Terms%E2%80%94Command%20and%20control%2C%20intelligence%2C,system%2C%20supervisory%20control%2C%20unmanned%20vehicles).

## Key Questions Addressed

* Can adjusting group "culture" parameters (e.g., uncertainty avoidance, individualism) steer agent team behavior?[[26]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=validate%20our%20methodology%2C%20we%20implemented,between%20cultural%20values%20and%20system)
* How to design a simulation to test MOTL control vs traditional MITL control?
* What is the impact of tuning sociocultural traits on ISR mission outcomes?
* Does the MOTL approach reduce cognitive load on human supervisors while achieving desired results?

## The Problem

* Supervising numerous agents individually (MITL) is impractical in time-critical, info-dense scenarios[[27]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=ments%20for%20the%20information%20sharing,5)[[28]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=of%20a%20specific%20acting%20entity,MOTL).
* Increasing autonomy demands new control methods to keep humans in charge without micromanagement[[29]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=The%20DOD%20roadmap%20for%20unmanned,level%20decision%20making%20to)[[23]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Man%20on%20the%20loop%20is,affect%20the%20configuration%20of%20the).
* No established method existed to influence autonomous group behavior indirectly through "soft" parameters.
* Ensuring coordinated group performance without direct commands was an open challenge.

## The Importance

* MOTL allows one operator to control large robot teams by adjusting a few high-level settings instead of many commands[[30]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=a%20methodology%20for%20parametrically%20adjusting,observed%20against%20parametric%20values%20for).
* This replaces many direct commands with intuitive trait "dials," simplifying control[[30]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=a%20methodology%20for%20parametrically%20adjusting,observed%20against%20parametric%20values%20for).
* Reducing the operator’s burden increases efficiency and potentially mission success in network-centric warfare[[19]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=the%20available%20information%20resources%20will,5)[[31]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=The%20level%20of%20human%20intervention,be%20broadly%20divided%20into%20two).
* Understanding cultural trait impacts on group dynamics provides insight for future autonomous systems governance.
* Paves the way for more resilient, human-aware AI systems where oversight is intuitive and scalable.

## The Solution

* Built an agent-based simulation where a user can adjust group sociocultural parameters[[26]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=validate%20our%20methodology%2C%20we%20implemented,between%20cultural%20values%20and%20system).
* Modeled two key cultural dimensions: Uncertainty Avoidance (risk aversion) and Individualism vs Collectivism[[32]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=of%20simulated%20agents%20traverses%20a,Efficacy%20and%20timely%20application)[[33]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=CLV%20Collectivism,MOTL%20Man%20on%20the%20loop).
* Implemented agent behaviors that respond to global trait values (e.g., share risk vs act independently).
* User interface allowed real-time trait slider tuning and visualization of immediate effects on agents.
* Tracked group and individual performance metrics under varying traits to correlate adjustments with mission effectiveness[[34]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=based%20simulated%20test%20bed%20for,produce%20the%20desired%20system%20utilities).

## Architecture Overview

* **Agent Society:** Simulated a team of autonomous agents on a mission in a hostile area[[35]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=based%20simulated%20test%20bed%20for,Uncertainty%20avoidance%20index%20and%20individualism).
* **Cultural Parameters:** Agents’ decisions influenced by global trait settings (e.g., UAI, IDV).
* **Supervisory Console:** Provided controls to adjust traits and see effects immediately.
* **Utility Monitoring:** Calculated individual & group performance metrics under different trait settings.
* **Norms & Rules:** Utility-based rules let agents sacrifice personal gains for group benefit (Pareto optimal)[[36]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=care%20has%20been%20given%20to,18).

## Results and Impacts

* Small adjustments in trait values led to significant changes in group behavior and mission success[[30]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=a%20methodology%20for%20parametrically%20adjusting,observed%20against%20parametric%20values%20for).
* Operator learned trait–outcome relationships and tuned traits to achieve desired system performance[[32]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=of%20simulated%20agents%20traverses%20a,Efficacy%20and%20timely%20application).
* Validated the MOTL concept: high-level parameter tuning can effectively steer a multi-agent system without direct micromanagement[[30]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=a%20methodology%20for%20parametrically%20adjusting,observed%20against%20parametric%20values%20for)[[37]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=meaning%20outside%20of%20their%20context,systems%20via%20parametric%20cultural%20adjustments).
* Showed that well-chosen sociocultural parameters (like risk tolerance) improve coordination and adaptability.
* Guided future UAV control design by proving feasibility of macro-level parametric human oversight.

## Skills and Tools Used

* Multi-agent system programming and simulation (custom testbed development).
* Application of social science models (Hofstede’s cultural dimensions) to AI agent design[[33]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=CLV%20Collectivism,MOTL%20Man%20on%20the%20loop).
* Utility theory and optimization (to evaluate and guide agent behavior).
* Experimentation and data analysis on simulation outputs to derive insights.
* Academic research writing and collaboration (work funded by USAF, published in IEEE).

## Cross-project Capabilities

* Introduced the MOTL paradigm utilized in subsequent research (concept extended in MAS-2).
* Pioneered methods for indirect control of complex systems, relevant to projects needing human-in-the-loop optimization.
* Simulation and behavior modeling skills applied here were transferable to other domains (though context differs).
* Interdisciplinary approach (combining AI with psychology) reappears in later projects involving human factors.

## Published Papers/Tools

* IEEE Trans. SMC-B, 2010 – *Influencing Agent Group Behavior by Adjusting Cultural Trait Values*[[38]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=IEEE%20TRANSACTIONS%20ON%20SYSTEMS%2C%20MAN%2C,5%2C%20OCTOBER%202010%201243).
* Prototype multi-agent simulation platform (research tool) developed under USAF-funded project.

# Project 18

# Multi-Agent System – MOTL Paradigm for Control Systems (MAS-2)

<img src="placeholder.jpg" alt="Man-on-the-Loop Paradigm Graphic" />

**BLUF:** Proposed and validated the "Man-On-The-Loop" paradigm as a novel approach for human supervision of complex multi-agent systems, using a psycho-socio-cultural model to influence large agent communities indirectly. This groundwork showed that a human can shape system-wide behavior via high-level policy changes, reducing the need for micromanagement.

## Introduction

* Controlling complex systems (e.g., defense networks, space missions) raises the question of optimal human involvement[[39]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Large%20collections%20of%20communities%20such,proposing%20for%20a%20novel%20human)[[40]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=%E2%80%98Man%20In%20The%20Loop%E2%80%99%20%28MITL%29,MOTL).
* Traditional direct control (MITL) is unsustainable for large, fast-moving systems due to cognitive overload[[41]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=to%20total%20domination%20within%20a,at%20the%20unit%20or%20agent)[[22]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=human%20intervention%20in%20their%20actions,The).
* Introduced "Man-On-The-Loop (MOTL)" as a paradigm where a human supervisor sets high-level policies that indirectly shape system behavior[[42]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=human%20cognitive%20load%20will%20enable,those%20found%20in%20natural%20systems)[[23]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Man%20on%20the%20loop%20is,affect%20the%20configuration%20of%20the).
* Developed psycho-social models to embed human-like influences (acquaintance, influence, rights/duties) into agent communities[[43]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=responsible%20society%2C%20discharging%20minimum%20sets,Jennings%20and)[[44]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=,the%20society%20contains%20other%20members).

## Key Questions Addressed

* What level of human intervention yields the best outcomes in large autonomous systems?[[45]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=A%20key%20issue%20that%20arises,are%20increasingly%20and%20technologically%20widely)[[46]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=%E2%80%98Man%20In%20The%20Loop%E2%80%99%20%28MITL%29,MOTL)
* Can a human indirectly manage agent societies by altering global rules instead of individual commands (MOTL vs MITL)?[[28]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=of%20a%20specific%20acting%20entity,MOTL)[[23]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Man%20on%20the%20loop%20is,affect%20the%20configuration%20of%20the)
* Does applying social/psychological constructs to agent control reduce operator workload and improve coordination?
* How to validate MOTL parameters and effects in a simulation, and compare them to natural human systems?

## The Problem

* Complex control systems require human oversight, but micromanaging every agent becomes infeasible as scale and speed increase[[47]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=to%20total%20domination%20within%20a,MOTL)[[48]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=problem%20with%20the%20MITL%20approach,rigorous%20monitoring%20and%20maintenance%20of).
* Operators faced information overload in network-centric warfare, limiting success of micro-management[[49]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=information%20sources%20for%20decisions%20under,5)[[19]](file://file_00000000971c61f5a6e76f7adc66cd36#:~:text=the%20available%20information%20resources%20will,5).
* Needed a framework allowing humans to guide outcomes without direct control of each component.
* Unclear if high-level social rule changes could effectively control system dynamics.

## The Importance

* MOTL offers a paradigm shift for scalable human supervision of many agents[[23]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Man%20on%20the%20loop%20is,affect%20the%20configuration%20of%20the).
* Lowering cognitive load via macro-management lets humans focus on strategy rather than low-level details[[50]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=system%20behaviours,those%20found%20in%20natural%20systems)[[42]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=human%20cognitive%20load%20will%20enable,those%20found%20in%20natural%20systems).
* Keeps critical missions under human intent while exploiting autonomous capabilities[[39]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Large%20collections%20of%20communities%20such,proposing%20for%20a%20novel%20human)[[45]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=A%20key%20issue%20that%20arises,are%20increasingly%20and%20technologically%20widely).
* Provides a blueprint for designing AI systems with built-in social mediation for easier human governance.

## The Solution

* Formulated a domain-neutral agent-based simulation with social, psychological, and cultural parameters[[50]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=system%20behaviours,those%20found%20in%20natural%20systems)[[43]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=responsible%20society%2C%20discharging%20minimum%20sets,Jennings%20and).
* Defined MOTL control variables (global policy tweaks) a human supervisor could adjust to influence all agents.
* Ensured agents recognized other members (acquaintance), could affect each other (influence), and had defined rights/duties – mirroring societal behavior[[43]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=responsible%20society%2C%20discharging%20minimum%20sets,Jennings%20and)[[51]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=,members%20can%20affect%20one%20another).
* Implemented comparative scenarios: one with direct micromanagement (MITL), another with indirect MOTL-style interventions.
* Analyzed outcomes and compared them to patterns in natural human organizations for validation.

## Architecture Overview

* **Simulation Environment:** Large-scale multi-agent community with configurable rules and objectives.
* **Human Influence Model:** Global policy parameters that emulate a human supervisor’s macro-level inputs.
* **Agent Rules:** Agents follow global norms and adapt when those norms are changed by the supervisor[[44]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=,the%20society%20contains%20other%20members).
* **Experimental Scenarios:** Evaluated performance under minimal intervention, MITL (direct control), and MOTL (indirect influence).
* **Metrics & Validation:** Monitored system efficiency and coordination, comparing MOTL scenario results to expected human organizational behaviors.

## Results and Impacts

* Validated MOTL viability: global policy tweaks by a human led to measurable changes in collective agent behavior and outcomes[[42]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=human%20cognitive%20load%20will%20enable,those%20found%20in%20natural%20systems)[[23]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Man%20on%20the%20loop%20is,affect%20the%20configuration%20of%20the).
* Showed agents can be guided en masse through high-level rules, reducing need for constant micromanagement[[23]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Man%20on%20the%20loop%20is,affect%20the%20configuration%20of%20the)[[52]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=relinquish%20the).
* Reduced human cognitive strain: supervisors in MOTL scenarios managed large systems without overload.
* Laid conceptual foundation that influenced subsequent applied research (MAS-1) and new thinking in autonomous system control.

## Skills and Tools Used

* Theoretical model development (combining AI with social science concepts).
* Agent-based simulation building and parameter-driven experimentation.
* Statistical comparison of simulation scenarios and alignment with real-world patterns (for validation).
* Thought leadership in conceptualizing new human–machine interaction paradigms.
* Academic dissemination (journal publication, peer review).

## Cross-project Capabilities

* Served as conceptual groundwork for MAS-1, which applied MOTL in a specific ISR context.
* Demonstrated interdisciplinary approach (psychology + AI), a skill later applied in healthcare social media analyses.
* Emphasized designing systems with human influence at a high level – a philosophy seen across projects.
* Simulation and modeling techniques from this project provided a template for analyzing complex networks in other domains.

## Published Papers/Tools

* **"Natural human role in supervising complex control systems"** – Published in Journal of Experimental & Theoretical AI, 2009[[53]](file://file_0000000089f8622fa3b4ab89adaaa18b#:~:text=Vol,2009%2C%2059%E2%80%9377).
* Simulation framework for MOTL vs MITL control (research prototype for experimentation).

# Project 19

# Patient Experience – US Longitudinal Study (1)

<img src="placeholder.jpg" alt="Patient Experience Sentiment Trends Graphic" />

**BLUF:** Analyzed 2.76 million patient experience tweets (2013–2017) across the United States to uncover sentiment patterns over time and geography. The study found that patient sentiments became less negative nationwide, identified daily and urban-rural differences in experience, and demonstrated Twitter as a viable tool for monitoring healthcare experiences at scale.

## Introduction

* Patient-centered care has increased the focus on measuring patient experience in healthcare[[54]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=health%20care%20system%20to%20emphasize,safety%20within%20hospitals%2C%20and%20less).
* Traditional surveys (e.g., HCAHPS) are limited by low response rates, bias, and significant lag[[55]](file://file_00000000739c61f5995718e822de48cc#:~:text=A%20major%20drawback%20with%20these,surveys%20traditionally%20have%20low%20response)[[56]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=However%2C%20commonly%20used%20assessments%20of,11%2C12).
* Social media (Twitter) provides a large, unsolicited source of patient opinions that can complement official surveys[[57]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=With%20an%20increasing%20demand%20for,could%20be%20valuable%20to%20complement).
* Understanding national patient sentiment trends can inform efforts to improve healthcare quality and access.

## Key Questions Addressed

* What are the overall patient experience sentiment levels across the US, and how do they change over time?[[58]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=Objective%3A%20The%20objective%20of%20our,year%20period)
* Do patient sentiments differ between regions or states, and between metropolitan vs non-metropolitan areas?[[59]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=tweet%20sentiments%20at%20national%20and,in%20metropolitan%20and%20nonmetropolitan%20areas)[[60]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=observed%20the%20sentiment%20of%20tweets,34%29%20at%20the%20national%20level)
* Are there temporal patterns in patient experience discussions (time of day, day of week)?[[61]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=average%20sentiment%20polarity%20shifted%20toward,negative%20sentiments%20had%20a%20medium)
* How effectively can Twitter data reflect real-world patient experience compared to traditional metrics?

## The Problem

* Documented regional disparities in healthcare experiences exist, but real-time, nationwide data to track these is lacking[[62]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=Background%3A%20There%20are%20documented%20differences,care%20across%20the%20United%20States).
* Surveys capture limited feedback and often exclude marginalized voices or granular temporal trends[[63]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=surveys%20or%20focus%20groups%2C%20have,11%2C12).
* Healthcare stakeholders need timely insights into patient satisfaction and concerns to drive improvements.
* Without alternate data sources, important shifts in patient sentiment may go unnoticed until official reports.

## The Importance

* Capturing genuine patient feedback from social media can highlight issues in care delivery that formal surveys miss[[56]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=However%2C%20commonly%20used%20assessments%20of,11%2C12).
* Timely awareness of rising negative sentiment in certain areas or times can prompt early interventions.
* Identifying urban vs rural sentiment gaps helps target resource allocation and policy for health equity.
* Demonstrates a method for continuous, large-scale patient experience surveillance to inform quality improvement.

## The Solution

* Collected 27.3 million tweets (Feb 2013 – Feb 2017) using patient experience-related keywords via Twitter’s GNIP API[[64]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=1%3B%20for%20example%2C%20care%20condition,not%20considered%20in%20the%20study)[[65]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=condition,not%20considered%20in%20the%20study).
* Built an automated pipeline with four components: a patient experience tweet classifier, a geolocation inference engine, a sentiment analyzer, and a metro/non-metro classifier[[66]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=We%20developed%20a%20set%20of,health%20care%20experience%20social%20data).
* Filtered down to ~2.76 million relevant patient experience tweets via supervised ML classification (training data labeled on MTurk)[[67]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=We%20developed%20a%20support%20vector,Other%20features%20included)[[68]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=without%20URLs%20for%20this%20study,performing%20and%20demonstrating%20excellence%20in).
* Inferred location for ~32% of these tweets (876k tweets) using user profiles and Google Maps geocoding (state-level assignment)[[69]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=experience,all%20regions%20of%20the%20United)[[70]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=We%20used%20a%20combination%20of,combined%20with%20natural%20language%20processing).
* Analyzed sentiment (positive, neutral, negative) by region and over time; examined differences between metro and rural areas and daily patterns[[71]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=approximate%20location%20of%2031.76,negative%20over%20the%20study%20period)[[60]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=observed%20the%20sentiment%20of%20tweets,34%29%20at%20the%20national%20level).

## Architecture Overview

* **Data Collection:** Continuous ingestion of tweets via keyword rules (excluding tweets with URLs to improve relevance)[[72]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=determined%20that%20tweets%20containing%20a,We%20curated%2015%2C000%20additional).
* **Classification:** SVM-based classifier filters tweets about healthcare experiences vs irrelevant content[[73]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=We%20developed%20a%20support%20vector,inverse%20document%20frequency).
* **Geolocation Module:** NLP-enhanced engine maps tweets to US states via profile text and Google Geocoding API[[70]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=We%20used%20a%20combination%20of,combined%20with%20natural%20language%20processing).
* **Sentiment Analysis:** Applied a sentiment classifier to label each relevant tweet’s polarity (positive/neutral/negative).
* **Analysis Dashboard:** Aggregated sentiment data by time and location for visualization and statistical comparison (urban vs rural, year-over-year trends).

## Results and Impacts

* Identified ~36% of patient experience tweets as negative, ~28% positive, ~36% neutral nationally[[71]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=approximate%20location%20of%2031.76,negative%20over%20the%20study%20period).
* Observed sentiment trending less negative over the 4-year period (overall patient tweets became less negative)[[74]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=were%20slight%20differences%20in%20tweet,positive%20compared%20with%20tweets%20in).
* Detected a daily pattern: tweets at night (8 pm–10 am) were more negative than daytime tweets[[61]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=average%20sentiment%20polarity%20shifted%20toward,negative%20sentiments%20had%20a%20medium).
* Found metro-area tweets had more extreme sentiment (more very negative and slightly more positive) than rural tweets; urban tweets showed higher negativity (P<.001)[[75]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=between%208%20pm%20and%2010,34%29%20at%20the%20national%20level).
* Demonstrated that Twitter can serve as a real-time barometer of patient experience, offering insights beyond traditional surveys[[76]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=Conclusions%3A%20This%20study%20presents%20methodologies,receive%20in%20the%20United%20States).

## Skills and Tools Used

* Big data handling and social media mining (collected tens of millions of tweets via GNIP).
* NLP and machine learning (tweet classification with NLTK/SVM; sentiment analysis model)[[73]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=We%20developed%20a%20support%20vector,inverse%20document%20frequency).
* Crowdsourced annotation for training data (Amazon Mechanical Turk curation of tweets)[[72]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=determined%20that%20tweets%20containing%20a,We%20curated%2015%2C000%20additional).
* Geospatial analysis (custom location inference using Google Maps API and census data)[[70]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=We%20used%20a%20combination%20of,combined%20with%20natural%20language%20processing).
* Statistical analysis and visualization (spatiotemporal sentiment trends, significance testing for group differences).

## Cross-project Capabilities

* Twitter data processing pipeline and sentiment analysis methods here were reused in subsequent patient experience studies (hospital analysis and disparities study).
* Integration of human judgment (MTurk labels) with ML is reflected in other projects (e.g., Gun Violence platform’s human+AI curation).
* Geolocation and mapping of social data parallels techniques in the Gun Violence project’s state-level mapping.
* Pioneered a digital epidemiology approach foundational to later analyses of healthcare disparities (project 21).

## Published Papers/Tools

* **"Using Twitter to Examine Web-Based Patient Experience Sentiments in the United States: Longitudinal Study"** – Published in J. Med. Internet Res. 2018[[77]](file://file_00000000f640622fbdeebd2f5b593241#:~:text=J%20Med%20Internet%20Res%202018,number%20not%20for%20citation%20purposes).
* Code suite for tweet classification, geolocation, and sentiment analysis (developed for this project).
* Data visualization of sentiment by state and over time (produced for publication figures).

# Project 20

# Patient Experience – US Hospital Sentiment via Twitter (2)

<img src="placeholder.jpg" alt="Hospital Twitter Feedback Graphic" />

**BLUF:** Investigated tweets directed at US hospitals to gauge patient-perceived quality of care. Analyzed 404,065 tweets (in one year) addressed to 2,349 hospitals, identifying ~34,700 patient experience-related tweets. Results showed that Twitter feedback covered diverse care topics and offered a real-time, albeit imperfect, supplement to traditional quality measures like HCAHPS, with weak links to lower readmission rates.

## Introduction

* Patient experience is a critical component of healthcare quality, and patient feedback is increasingly valued in care delivery[[78]](file://file_00000000739c61f5995718e822de48cc#:~:text=INTRODUCTION%20Over%20the%20past%20decade%2C,able%20to%20measure%2C%20report%20and).
* HCAHPS surveys are standard but have time lags and low response rates, limiting timely quality assessment[[79]](file://file_00000000739c61f5995718e822de48cc#:~:text=A%20major%20drawback%20with%20these,8%20raising%20concerns%20about%20potential).
* Roughly half of US hospitals have a Twitter presence, and patients often share feedback publicly in real time[[80]](file://file_00000000739c61f5995718e822de48cc#:~:text=how%20they%20use%20Twitter%20to,national%20median%20of%20Medicare%20patients).
* Leveraging social media feedback could give hospitals and stakeholders an immediate pulse on patient sentiment.

## Key Questions Addressed

* Can tweets directed at hospitals serve as a reliable indicator of patient-perceived care quality?[[81]](file://file_00000000739c61f5995718e822de48cc#:~:text=Background%20Patients%20routinely%20use%20Twitter,care%20in%20US%20hospitals%20and)
* What proportion of tweets to hospitals relate to patient experience, and what topics do they cover?[[82]](file://file_00000000739c61f5995718e822de48cc#:~:text=language%20processing,to%20patient%20experience%20and%20covered)
* Do hospitals with more Twitter engagement differ in characteristics (size, patient mix, staffing) or quality metrics?
* How does Twitter sentiment correlate with established quality measures (HCAHPS scores, readmission rates)?[[83]](file://file_00000000739c61f5995718e822de48cc#:~:text=hospital%20characteristics%2C%20we%20found%20that,cover%20a%20wide%20range%20of)

## The Problem

* Official patient surveys are released only after months, delaying awareness of emerging issues[[55]](file://file_00000000739c61f5995718e822de48cc#:~:text=A%20major%20drawback%20with%20these,surveys%20traditionally%20have%20low%20response).
* Survey biases and low participation mean many patient voices (especially younger, online-active ones) aren’t heard[[84]](file://file_00000000739c61f5995718e822de48cc#:~:text=the%20significant%20time%20lag%E2%80%94often%20several,selection%20bias%20in%20the%20results).
* Hospitals lacked immediate, unfiltered feedback outside formal complaint channels.
* Unclear if social media feedback could complement traditional quality indicators or just noise.

## The Importance

* Real-time social feedback allows hospitals to address service issues faster than waiting for quarterly surveys.
* Public tweets can highlight specific incidents or aspects of care (staff courtesy, wait times) that surveys might miss.
* Understanding the link (or lack thereof) between online sentiment and outcomes can guide hospitals in using social media as a quality tool.
* If positive Twitter sentiment aligns with better outcomes (e.g., lower readmissions), it validates social engagement as beneficial.

## The Solution

* Collected 404,065 tweets (2012) mentioning 2,349 U.S. hospitals’ Twitter accounts over one year[[85]](file://file_00000000739c61f5995718e822de48cc#:~:text=established%20quality%20measures,Finally%2C%20hospitals%20with%20%E2%89%A550%20patient).
* Used an ML classifier to identify ~34,725 tweets (9.4%) related to patient experience topics[[86]](file://file_00000000739c61f5995718e822de48cc#:~:text=hospitals%20over%20a%201,Twitter%20to%20interact%20with%20patients)[[87]](file://file_00000000739c61f5995718e822de48cc#:~:text=US%20have%20a%20presence%20on,and%20to%20be%20a%20non).
* Performed sentiment analysis on these patient experience tweets to gauge positive vs negative tone.
* Manually categorized 11,602 tweets into patient experience topics (e.g., staff, wait time, billing) for deeper insight[[88]](file://file_00000000739c61f5995718e822de48cc#:~:text=machine%20learning%20approach,Of%20the%20tweets).
* Surveyed hospitals with ≥50 experience tweets and analyzed hospital attributes (Medicare patient %, nurse ratio, profit status) and quality metrics (HCAHPS scores, 30-day readmission) in relation to Twitter feedback[[89]](file://file_00000000739c61f5995718e822de48cc#:~:text=%E2%89%A550%20patient%20experience%20tweets%20revealed,Consumer%20Assessment%20of%20Healthcare%20Providers)[[83]](file://file_00000000739c61f5995718e822de48cc#:~:text=hospital%20characteristics%2C%20we%20found%20that,cover%20a%20wide%20range%20of).

## Architecture Overview

* **Data Source:** Aggregated all tweets directed (@mentions) to official hospital Twitter accounts.
* **Tweet Classification:** Machine-learned model filtered patient experience-related tweets from general mentions.
* **Sentiment & Topic Tagging:** NLP tools scored tweet sentiment; manual review categorized sample tweets by topic.
* **Hospital Data Integration:** Merged Twitter findings with hospital datasets (e.g., CMS’s HCAHPS and readmission data).
* **Analysis:** Statistical comparison of hospitals’ social media engagement and sentiment against their performance metrics.

## Results and Impacts

* ~50% of US hospitals were on Twitter, but only 9.4% of tweets at them were about patient experience[[80]](file://file_00000000739c61f5995718e822de48cc#:~:text=how%20they%20use%20Twitter%20to,national%20median%20of%20Medicare%20patients)[[82]](file://file_00000000739c61f5995718e822de48cc#:~:text=language%20processing,to%20patient%20experience%20and%20covered).
* Those ~34.7k patient experience tweets covered diverse aspects of care, showing Twitter feedback is multifaceted.
* Hospitals with high Twitter feedback (≥50 experience tweets) tended to have fewer Medicare patients (younger clientele), better nurse staffing, and were often nonprofits[[89]](file://file_00000000739c61f5995718e822de48cc#:~:text=%E2%89%A550%20patient%20experience%20tweets%20revealed,Consumer%20Assessment%20of%20Healthcare%20Providers).
* Twitter sentiment did **not** strongly correlate with HCAHPS satisfaction scores (online sentiment often diverged from survey results), though hospitals active on Twitter tended to have higher HCAHPS[[83]](file://file_00000000739c61f5995718e822de48cc#:~:text=hospital%20characteristics%2C%20we%20found%20that,cover%20a%20wide%20range%20of).
* A weak but significant link: more positive Twitter sentiment was associated with slightly lower 30-day readmission rates (p=0.003)[[90]](file://file_00000000739c61f5995718e822de48cc#:~:text=Consumer%20Assessment%20of%20Healthcare%20Providers,and%20can%20be%20identified%20using).
* Conclusion: tweets are an “untapped indicator” of quality – not a replacement for surveys but a real-time supplement for patients, researchers, and administrators[[91]](file://file_00000000739c61f5995718e822de48cc#:~:text=rates%20%28p%3D0,These%20tweets%20represent).

## Skills and Tools Used

* Social media data mining (captured tweets directed at specific hospital handles).
* Machine learning text classification to isolate patient experience discussions.
* Sentiment analysis and content coding (NLP and manual qualitative analysis combined).
* Data integration of social media metrics with healthcare quality data (survey scores, clinical outcomes).
* Statistical analysis (group comparisons, correlation/regression between Twitter data and hospital metrics).

## Cross-project Capabilities

* Reinforced methods of combining social media and traditional data, as used in the longitudinal and disparities studies.
* Tweet classification and sentiment techniques here informed the approach for the racial disparities analysis (project 21).
* Engaging stakeholders (hospitals) with social data is analogous to engaging policymakers in the Gun Violence project – demonstrating versatile communication of data insights.
* Showcased handling of sensitive health data (patient feedback) ethically and effectively, applicable across health informatics projects.

## Published Papers/Tools

* **"Measuring patient-perceived quality of care in US hospitals using Twitter"** – Published in BMJ Quality & Safety 2016[[92]](file://file_00000000739c61f5995718e822de48cc#:~:text=To%20cite%3A%20Hawkins%20JB%2C%20Brownstein,BMJ%20Qual%20Saf%202016%3B25%3A%20404%E2%80%93413).
* Dataset of tweets directed at hospitals (compiled for research purposes).
* Survey instrument for hospital social media usage (developed to gather context on hospitals’ Twitter practices).

# Project 21

# Patient Experience – Racial Disparities in Experience Sentiment (3)

<img src="placeholder.jpg" alt="Patient Experience Racial Disparities Graphic" />

**BLUF:** Leveraged Twitter to examine patient experience sentiments among racial and ethnic groups (2013–2016) and assess changes following the Affordable Care Act (ACA). The study found that Twitter's racial/ethnic user distribution mirrors the US population (enabling robust analysis), and revealed that all groups’ sentiments improved over time, with Hispanic/Latino patients showing the greatest sentiment gain and Black patients experiencing the most significant improvement post-ACA implementation.

## Introduction

* Racial and ethnic minorities in the US often face worse healthcare experiences and outcomes than White patients[[93]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Background%3A%20Racial%20and%20ethnic%20minority,in%20traditional%20health%20care%20surveys)[[94]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=In%20the%20United%20States%2C%20racial,fears%2C%20and%20lack%20of%20access).
* Traditional patient experience research underrepresents minorities due to mistrust, lower participation, and survey bias[[95]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=patient%20experience%20can%20be%20difficult,5)[[96]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=due%20to%20high%20risks%20of,17).
* The ACA (2010) mandated measuring patient experience of care, but evaluating its impact on minority groups via surveys has been difficult.
* Social media provides a new way to capture minority patient voices at scale, bypassing biases of traditional surveys[[97]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Objective%3A%20This%20study%20aims%20to,States%20from%202013%20to%202016).

## Key Questions Addressed

* Can Twitter data identify disparities in patient experience sentiment among different racial/ethnic groups?[[93]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Background%3A%20Racial%20and%20ethnic%20minority,in%20traditional%20health%20care%20surveys)[[98]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Results%3A%20Racial%20and%20ethnic%20distribution,population%20estimates%20from%20the%20United)
* How did patient sentiment trends differ by race from 2013 to 2016, and what changes occurred after ACA implementation in 2014?[[99]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=was%20highest%20for%20White%20patients%2C,2016%29%20compared%20with)[[100]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=increase%20%28P,users%20who%20identified%20as%20White)
* Is the racial/ethnic makeup of Twitter users discussing healthcare representative of the actual population (for valid analysis)?[[98]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Results%3A%20Racial%20and%20ethnic%20distribution,population%20estimates%20from%20the%20United)[[101]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=correlated%20with%20population%20estimates%20from,the%20United)
* Which groups saw the greatest improvement in patient experience sentiment over the study period?

## The Problem

* Minority patients’ true experiences are hard to capture; fears and historical mistrust often suppress honest feedback in surveys[[102]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=patient%20experience%20can%20be%20difficult,5)[[103]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=is%20responsible%20for%20respondents%E2%80%99%20care,patients%20are%20more%20likely%20to).
* Surveys often overrepresent satisfied White patients and underrepresent minorities, masking disparities in feedback[[96]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=due%20to%20high%20risks%20of,17)[[104]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=and%20care%20,17).
* Without inclusive data, health systems struggle to identify and address patient experience gaps in minority communities.
* Policymakers lacked timely tools to evaluate if reforms like the ACA reduced disparities in care experiences.

## The Importance

* Exposing racial/ethnic disparities in patient experience is crucial for targeting improvements and achieving health equity[[93]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Background%3A%20Racial%20and%20ethnic%20minority,in%20traditional%20health%20care%20surveys).
* Continuous monitoring of minority patient sentiment ensures policy changes (e.g., ACA) are benefiting all groups.
* If ACA improved minority patients’ experiences, highlighting that trend validates policy impact and guides future initiatives.
* Identifying which groups still lag in sentiment helps focus interventions (cultural competency, community outreach) where needed most.

## The Solution

* Analyzed ~851,973 patient experience tweets from 2013–2016 that were geolocated in the US and had identifiable racial/ethnic context[[105]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Methods%3A%20In%20total%2C%20851%2C973%20patient,Protection%20and%20Affordable%20Care%20Act).
* Verified representativeness: Twitter user racial distribution highly correlated with 2016 Census data (r²=0.99)[[98]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Results%3A%20Racial%20and%20ethnic%20distribution,population%20estimates%20from%20the%20United).
* Classified tweets by inferred user race/ethnicity (White, Black, Hispanic/Latino, Asian/PI, American Indian/AN) via profile analysis and content cues.
* Computed average sentiment for each group by year (2013, 2014, 2015, 2016) to observe trends.
* Used regression models to quantify sentiment changes over time and differences pre- vs post-ACA (pre-2014 vs 2014–2016) for each group[[106]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=patient%20experience%20sentiment%20and%20racial,ACA%29%20in%202014)[[107]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Twitter%20users%20who%20identified%20as,users%20who%20identified%20as%20White).

## Architecture Overview

* **Data Filtering:** From the full tweet dataset, extracted tweets whose users could be categorized by race/ethnicity and located in the US.
* **Demographic Inference:** Employed algorithms to assign each user a racial/ethnic group based on profile information; validated distribution against Census[[98]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Results%3A%20Racial%20and%20ethnic%20distribution,population%20estimates%20from%20the%20United).
* **Sentiment Analysis:** Each tweet carried a sentiment label (positive/neutral/negative) from the earlier classifier.
* **Trend Analysis:** Calculated sentiment averages per group per year; applied regression to detect significant changes and group-by-time interactions[[108]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=care%20received%20in%20a%20hospital%2C,ACA%29%20in%202014).
* **Policy Impact Modeling:** Included ACA implementation as a variable to measure differences in sentiment trend slopes before vs after 2014[[100]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=increase%20%28P,users%20who%20identified%20as%20White).

## Results and Impacts

* Twitter’s racial/ethnic user distribution closely matched the US population, confirming data validity for disparity analysis[[98]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Results%3A%20Racial%20and%20ethnic%20distribution,population%20estimates%20from%20the%20United).
* White patients’ tweets had the highest average sentiment (most positive), followed by Asian/PI, then Hispanic/Latino; American Indian/AN were lowest[[109]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=States%20Census%20Bureau%E2%80%99s%205,Twitter%20users%20who).
* All groups’ sentiment improved (became less negative) from 2013 to 2016, indicating broad positive trends[[99]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=was%20highest%20for%20White%20patients%2C,2016%29%20compared%20with).
* Hispanic/Latino users’ sentiment improved the most over time – their increase was 1.5× greater than White users’ increase (P<.001)[[110]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=A%20reduction%20in%20negative%20patient,Twitter%20users%20who%20identified%20as).
* Post-ACA (2014–2016), Black patients’ sentiment rose significantly more than White patients’ – a 2.2× greater improvement (P<.001)[[107]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Twitter%20users%20who%20identified%20as,users%20who%20identified%20as%20White).
* These findings suggest the ACA era coincided with improved experiences for minority groups and demonstrate Twitter as a feasible tool to monitor patient experience equity[[111]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=Conclusions%3A%20The%20ACA%20mandated%20the,health%20policies%20like%20the%20ACA).

## Skills and Tools Used

* Advanced data filtering and demographic inference on social media (assigning race/ethnicity to Twitter users at scale).
* Statistical regression analysis to measure sentiment differences and policy-related changes.
* Public health and policy knowledge integration (interpreting ACA impact through data).
* Large-scale data analysis (nearly 1M tweets) with multiple attributes (sentiment, demographics, time).
* Interdisciplinary collaboration (with epidemiologists, social scientists) and publication in a high-impact journal.

## Cross-project Capabilities

* Built directly on the pipeline from the earlier patient experience study, showing scalability to demographic-focused questions.
* Combining social data with demographic inference to evaluate policy impacts is a model that can apply to other domains (e.g., tracking policy effects on social disparities).
* Emphasized equity-focused analytics, aligning with the humanitarian ethos in other projects (like targeting vulnerable populations in Gun Violence and demining projects).
* Enhanced the digital epidemiology toolkit by adding demographic lenses, a skill transferable to analyzing disparities in other fields.

## Published Papers/Tools

* **"Racial and Ethnic Disparities in Patient Experiences in the United States: 4-Year Content Analysis of Twitter"** – Published in J. Med. Internet Res. 2020[[112]](file://file_000000009b4861f5aacfe566d4c2aef8#:~:text=,2196%2F17048).
* Analytical framework for social media-based health disparity research (methodology developed in this project).
* Findings shared with public health stakeholders to inform evaluation of ACA’s impact on patient experience equity.