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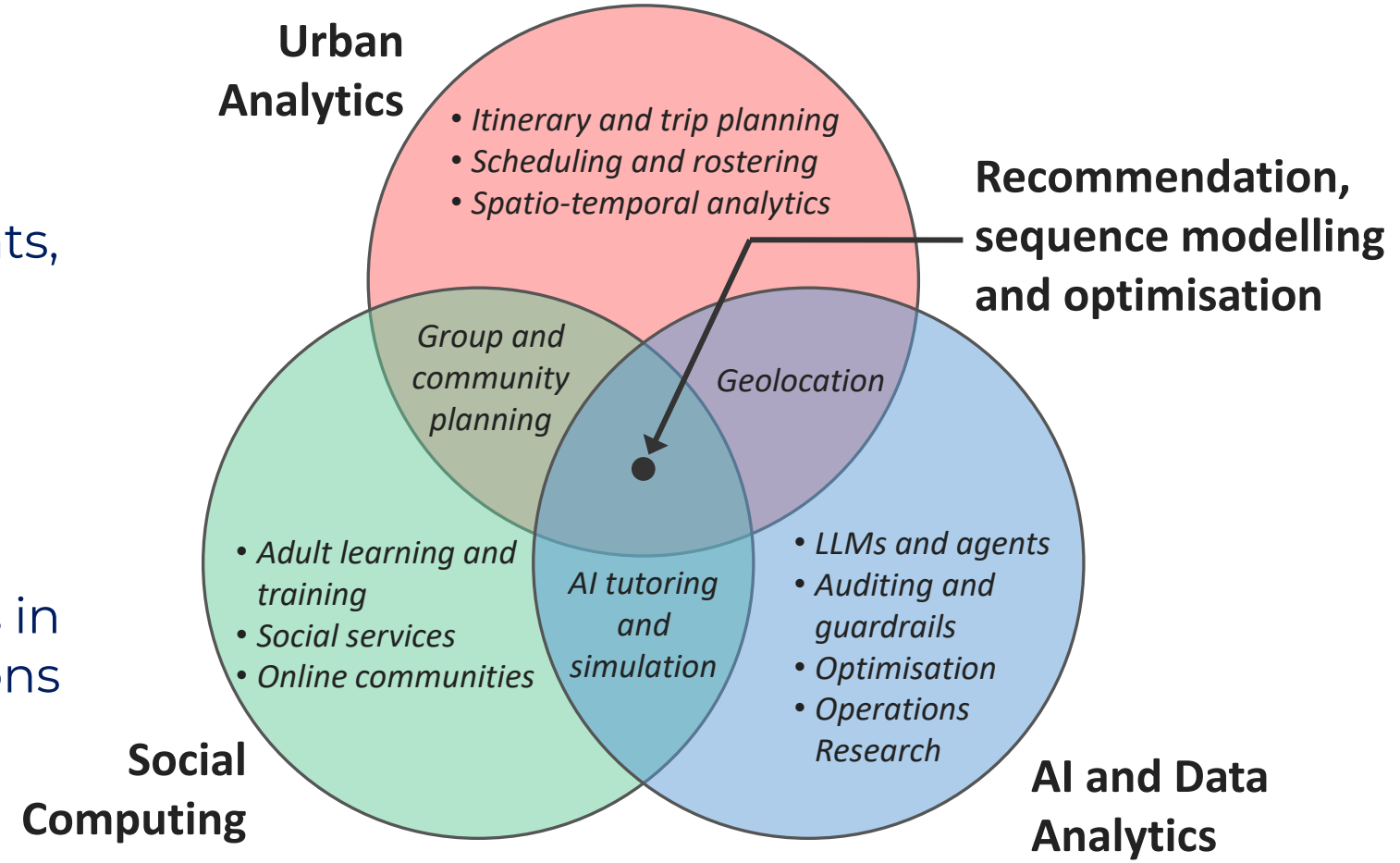
From AI Models to Public Value: Designing and Implementing AI for Society

18th Singapore Economic Policy Forum, 23 October 2026

Kwan Hui Lim
Senior Lecturer
School of Business, SUSS

AI-Driven Decision Systems for Social Good

- Understanding communities through digital traces
- Modelling preferences, constraints, and fairness
- Planning with large language model (LLM) agents and solvers
- Implementing AI with guardrails in education, services, and operations



Talk Overview

(i) **Urban wellbeing:** sentiment, amenities, and urban heat

(ii) **Mobility:** individual, group, and crowd-aware planning

(iii) **Public services:** estate operations and information tracing

(iv) **Learning:** AI support with learning scaffolds

(v) **From research to practice and public value**

Digital Traces for Decision Support

- Geo-tagged posts: where people go and the sentiment they express
- Service feedback and sensors: faults and their locations
- Learning platforms: records of learner interactions

These data inform decisions whe we account for their coverage an limitations.

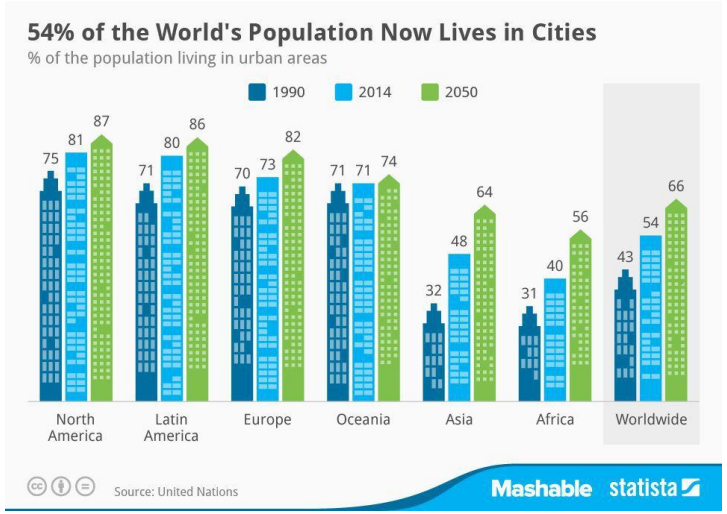
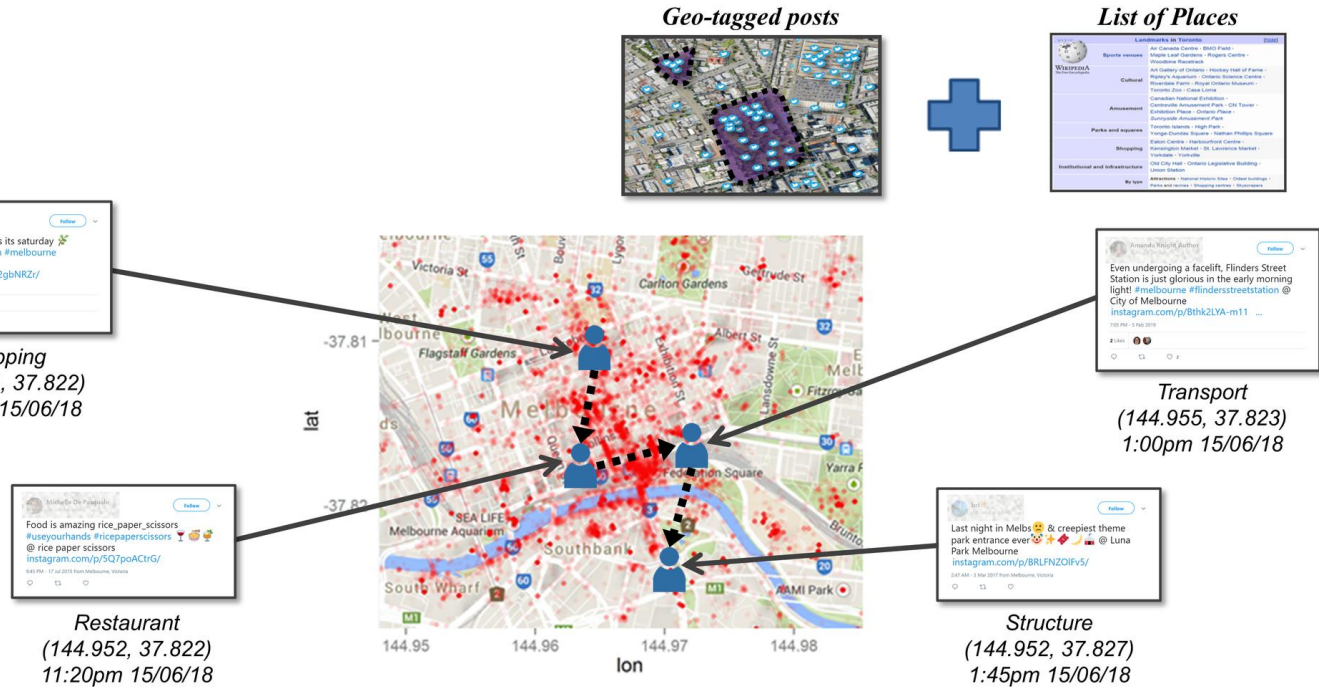


Chart: populationeducation.org



Case 1: Urban Wellbeing

Measuring sentiment across places and time

Urban Sentiment Analysis: Problem and Method

Problem: Periodic surveys of green-space use and wellbeing in Melbourne are costly and retrospective.

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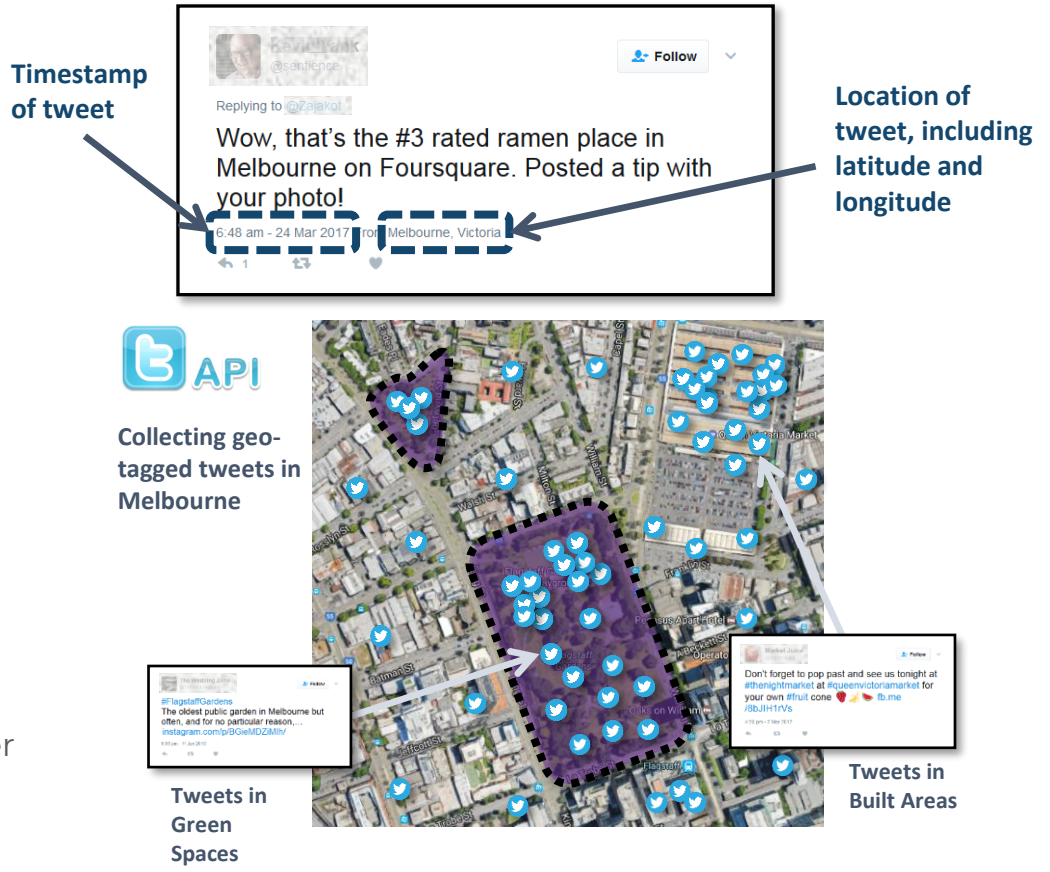
Method

(i) Collect 2.2M geo-tagged tweets from 10.5k users

(ii) Map each tweet to a green space or a built area

(iii) Score sentiment and eight emotions

(iv) Aggregate by place and time



Lim, Lee, Kendal, Rashidi, Naghizade, Winter and Vasardani. The Grass is Greener on the Other Side: Understanding the Effects of Green Spaces on Twitter User Sentiments. WWW 2018 Companion, pp. 275–282.

Sentiment across Places and Time

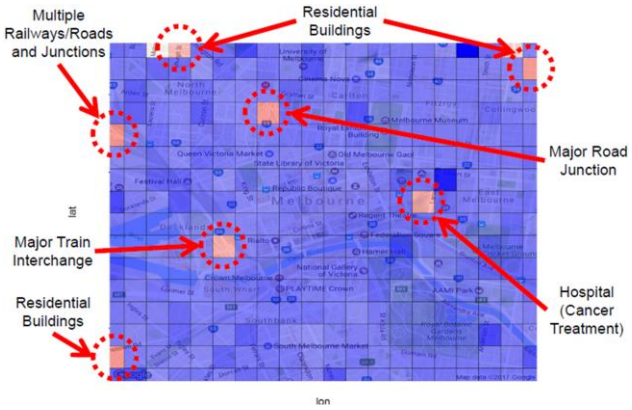
(i) Posts in green spaces are 15% more positive than posts in built areas, with more joy and trust and less anger and fear

(ii) Sentiment declines in the afternoon and increases in the evening

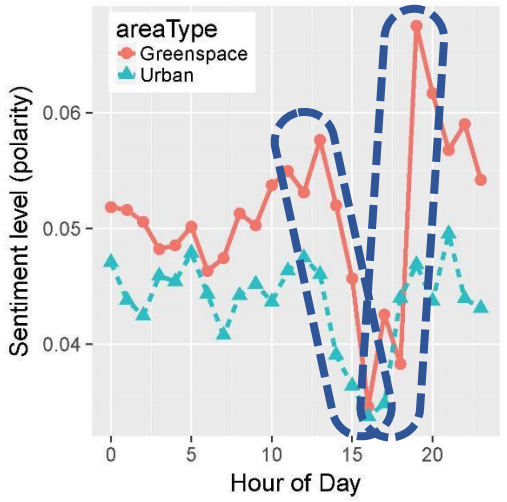
(iii) The sentiment difference between green spaces and built areas is larger in warmer months

(i)

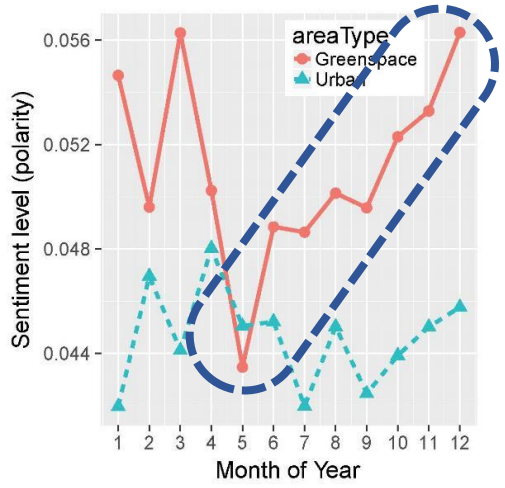
Sentiment Type	Green-space	Urban Area	Difference	p-value
anger	.0071	.0079	**-9.75%**	<.0001
anticipation	.0264	.0256	**2.95%**	<.0001
disgust	.0051	.0053	-3.13%	.05689
fear	.0085	.0095	**-10.27%**	<.0001
joy	.0300	.0271	**10.62%**	<.0001
sadness	.0093	.0092	1.39%	.24705
surprise	.0129	.0122	**5.60%**	<.0001
trust	.0252	.0236	**6.54%**	<.0001



(ii)



(iii)



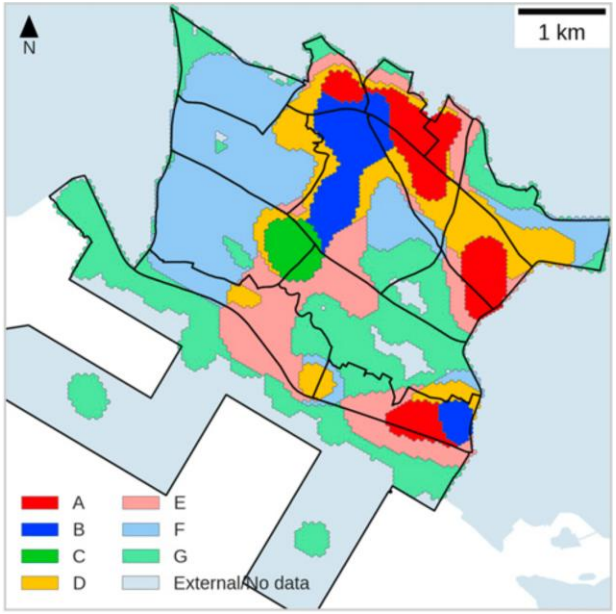
Urban Functional Zones from the Spatial Distribution of Amenities

Urban functional zones describe where people work, eat, learn, and shop.

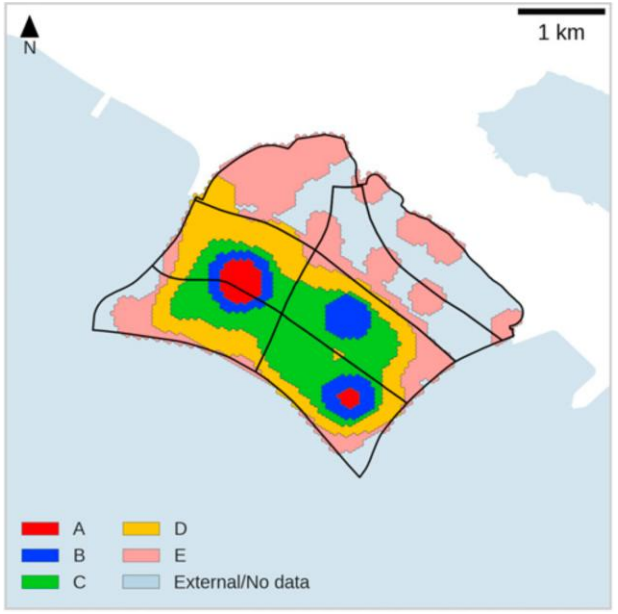
We infer zones from the locations of business, food, commercial, education, transport, outdoor, and health amenities.

Queenstown, a mature estate, and Punggol, a new town, differ in the amenity mix of their zones.

Queenstown



Punggol



Amenity distributions provide evidence for planning amenity provision.

Chin, Fu, Lim, Schroepfer and Cheah. Identifying Urban Functional Zones by Analysing the Spatial Distribution of Amenities. Environment and Planning B: Urban Analytics and City Science 51(6), pp. 1274–1289, 2024.

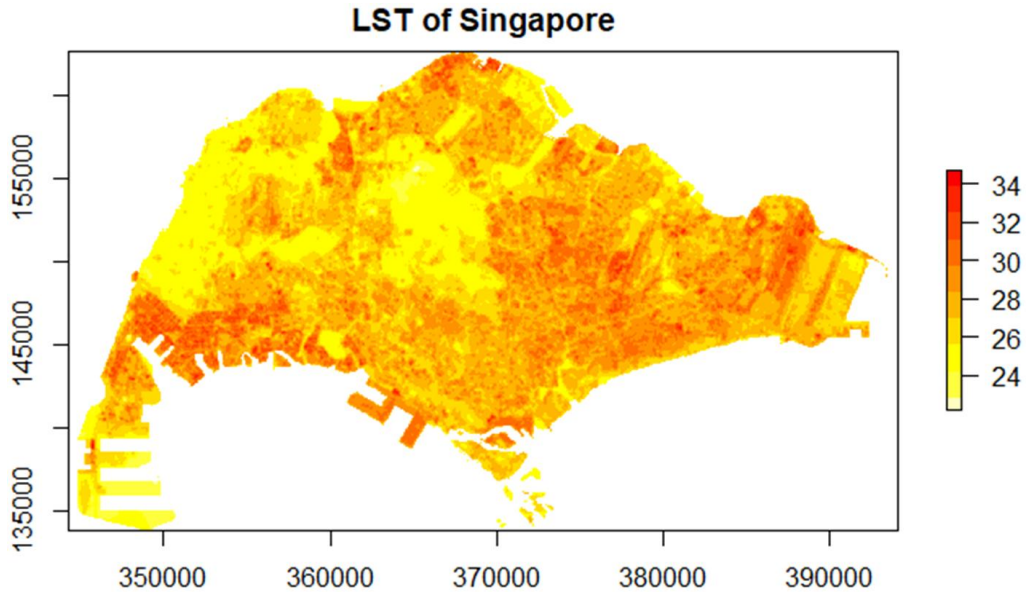
Urban Heat and the Built Environment in Singapore

Singapore is highly urbanised, with built areas warmer than their surroundings.

We combine satellite surface temperature, HDB building data (data.gov.sg), and population estimates on a hexagonal grid.

Associations with surface temperature

(i) Vegetation and water: cooler
(ii) Higher population density: warmer
(iii) More commercial facilities: warmer



Combining open data provides evidence for planning the built environment.

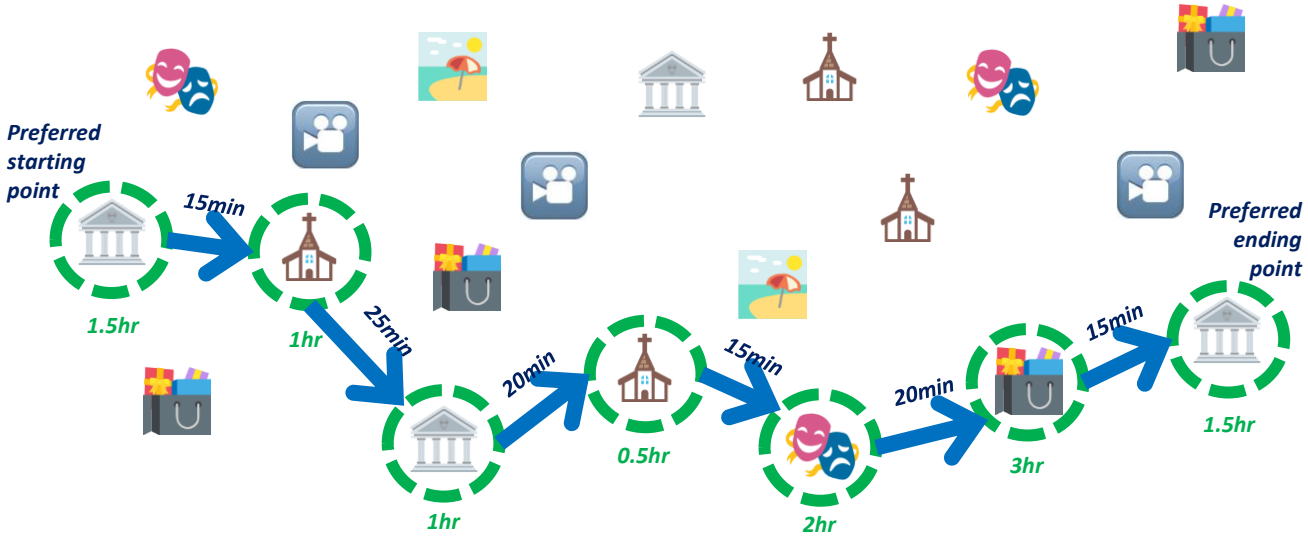
Yong and Lim. Urban Heat Islands: Beating the Heat with Multi-Modal Spatial Analysis. IEEE BigData 2020, pp. 4818–4827.

Case 2: Mobility

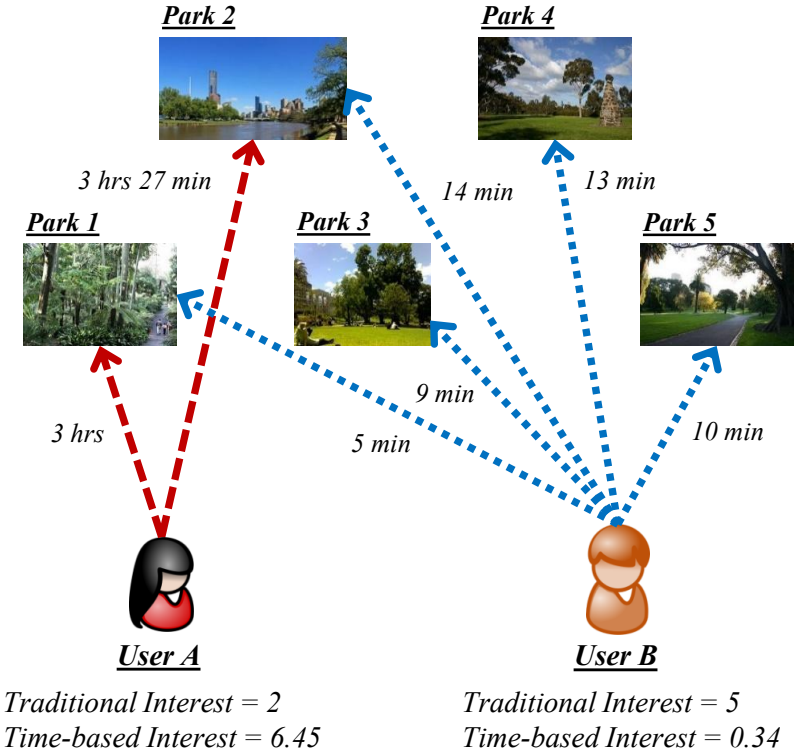
Planning for individuals, groups, and crowds: demand, capacity, and congestion

Personalised Itineraries

Recommend places that match a traveller's interests within time and travel constraints



Time spent at a place estimates interest better than visit counts



Lim, Chan, Leckie and Karunasekera. Personalized Trip Recommendation for Tourists Based on User Interests, Points of Interest Visit Durations and Visit Recency. Knowledge and Information Systems 54(2), pp. 375–406, 2018.

Group Itinerary Planning and Guide Assignment

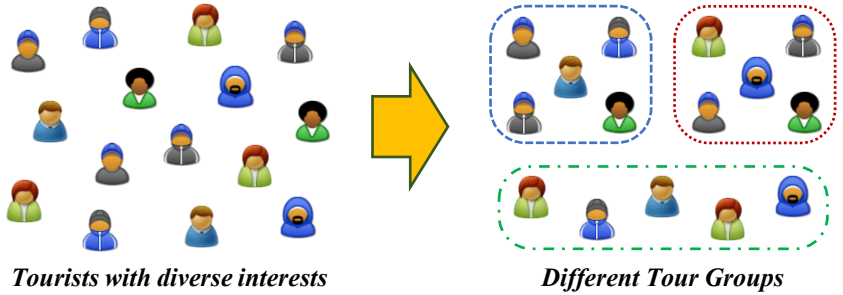
Travellers have different interests, and guides have different areas of expertise



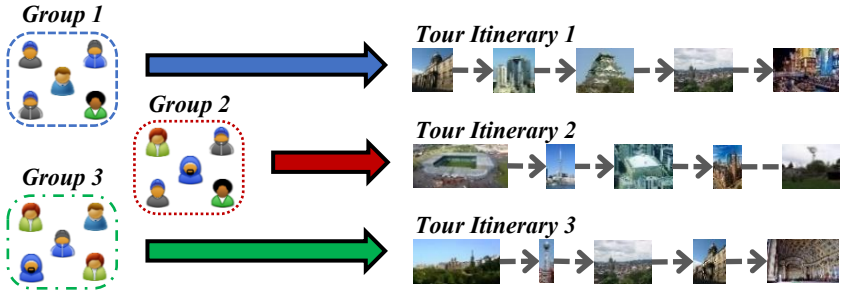
Group planning adds coordination and fairness constraints

Lim, Chan, Leckie and Karunasekera. Towards Next Generation Touring: Personalized Group Tours. ICAPS 2016, pp. 412–420.

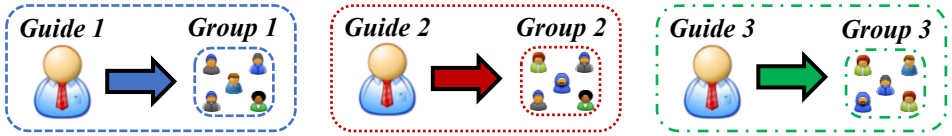
(i) Group by interest



(ii) Plan one itinerary per group

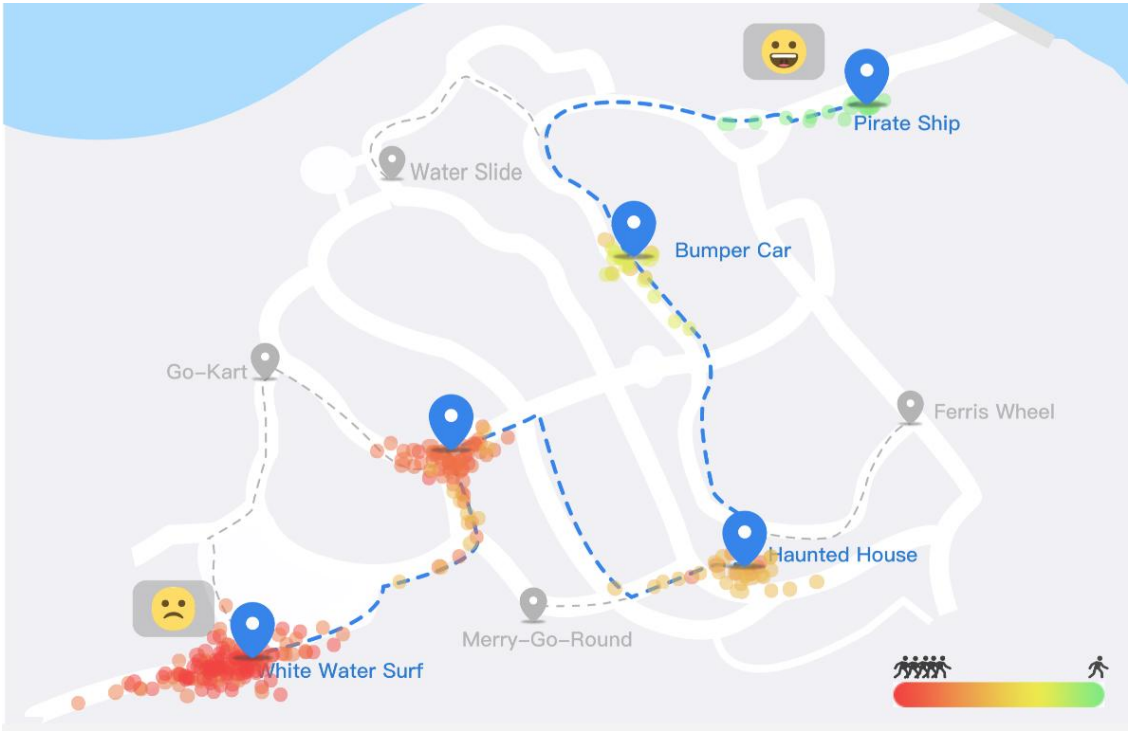


(iii) Assign guides by expertise



Crowd-Aware Itinerary Planning

- Planning itineraries independently concentrates visits at the same places and times
- Crowd-aware recommendation models capacity and queues to distribute demand
- Similar capacity considerations apply to clinics, service counters, and peak-hour transport



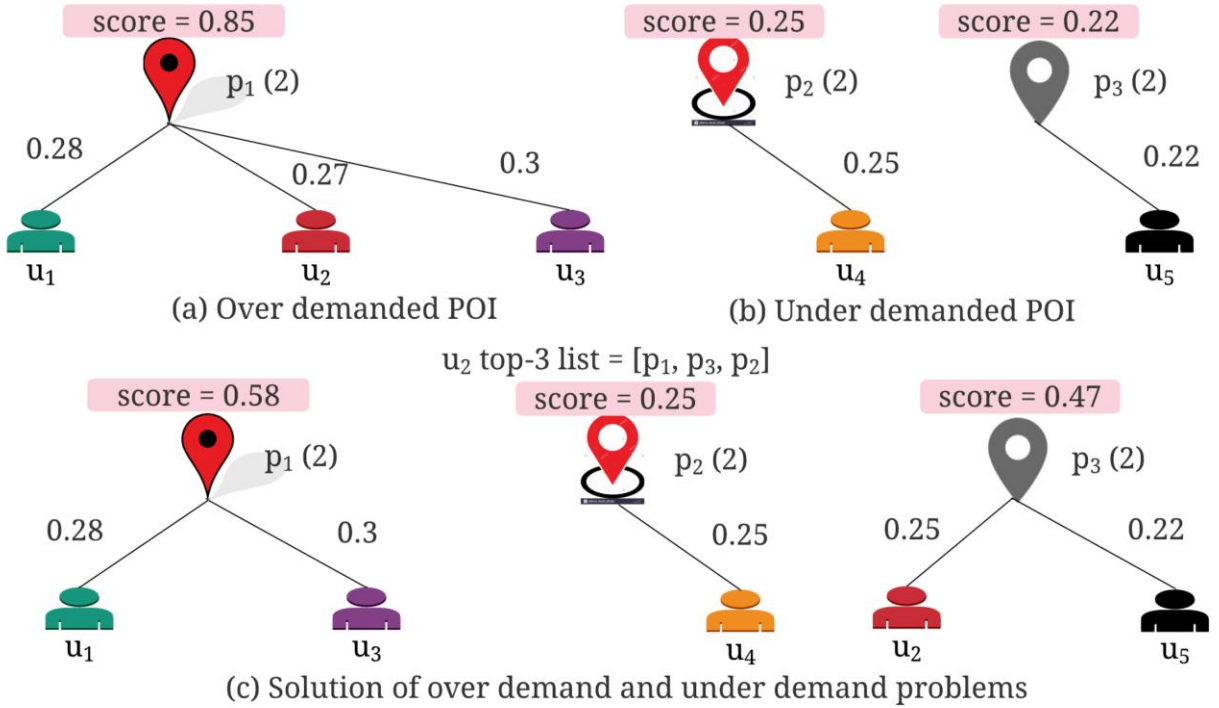
Liu, Wood and Lim. Strategic and Crowd-Aware Itinerary Recommendation. ECML-PKDD 2020.

Fair Recommendation: Spreading Visitors across Attractions

Personalised recommendation concentrates visits at a few popular places.

Capacity-aware fair recommendation balances visitor preferences with fair use of attractions.

Allocation policies address excess and insufficient demand. A transformer scores preferences, and reinforcement learning plans routes.



Fair recommendation considers how visits are distributed across attractions.

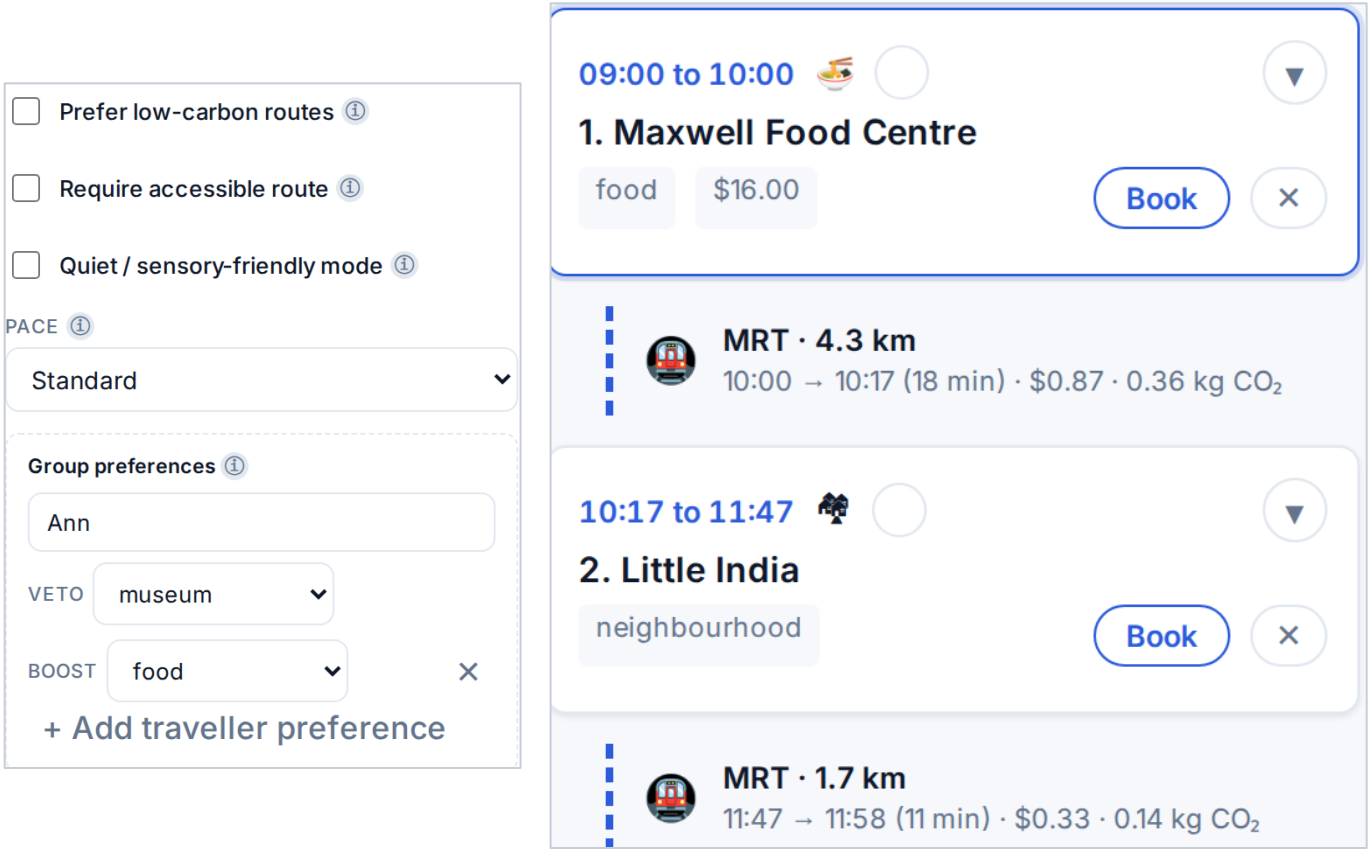
Halder, Lim, Chan and Zhang. Capacity-Aware Fair POI Recommendation Combining Transformer Neural Networks and Resource Allocation Policy. Applied Soft Computing 147, 110720, 2023.

AdaptTour: Replanning the Day with Sustainability and Group Preferences

AdaptTour updates the remaining itinerary as weather, queues, disruptions, and feedback change. Completed visits stay fixed.

Sustainability: each leg shows mode, fare, and CO2e. A low-carbon setting favours walking, cycling, and transit.

Diversity: any member can veto or boost a category, and subsequent plans reflect these preferences.



Each update checks budget, accessibility, preferences, and carbon.

Lim, Gunawan and Lee. Real-Time Adaptive Tour Recommendation with Agentic AI. CIKM 2026, demonstration track.

Case 3: Public Services

Decision support for estate operations

Estate-IQ: Identifying Estate Issues from Feedback

Problem: Find estate issues in large volumes of posts and feedback

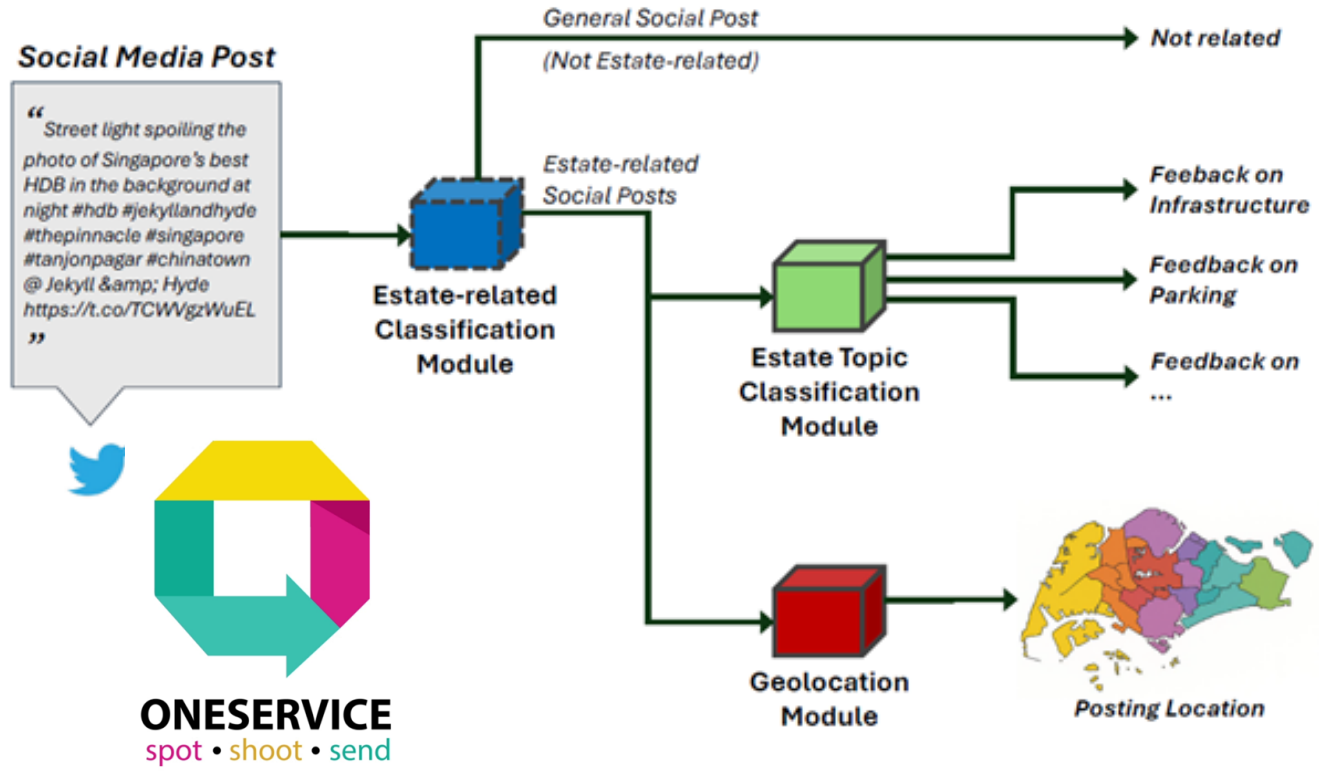
(i) Detect estate-related posts

(ii) Classify issues such as infrastructure, parking, and maintenance

(iii) Infer the block or facility associated with each issue

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data to insights

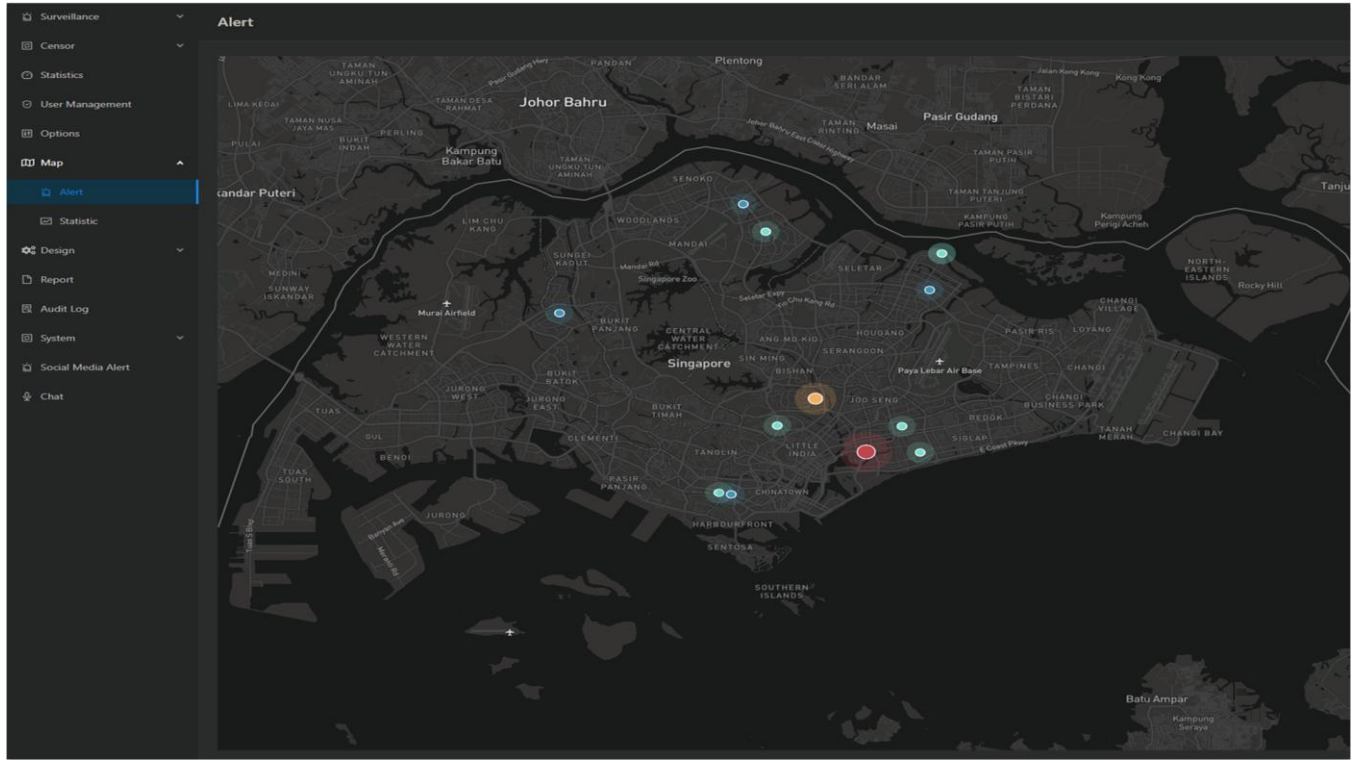


Mu, Li and Lim. A Social Data-Driven System for Identifying Estate-related Events and Topics. ASONAM 2025, demonstration track.

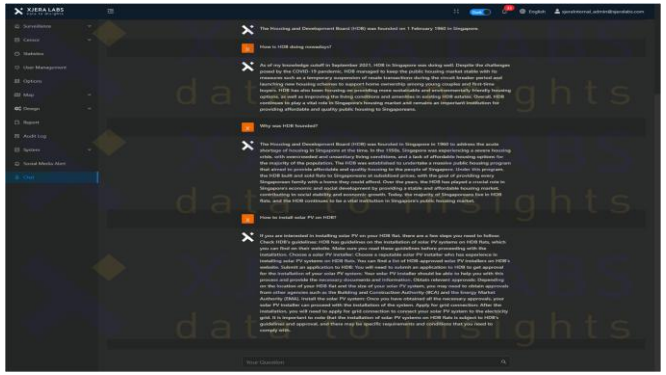
Estate-IQ: Support for Estate Operations

(i) Earlier detection of maintenance issues, (ii) prioritisation by volume and location, and (iii) reduced manual triage

The system routes feedback for analysts to review and decide on a response.





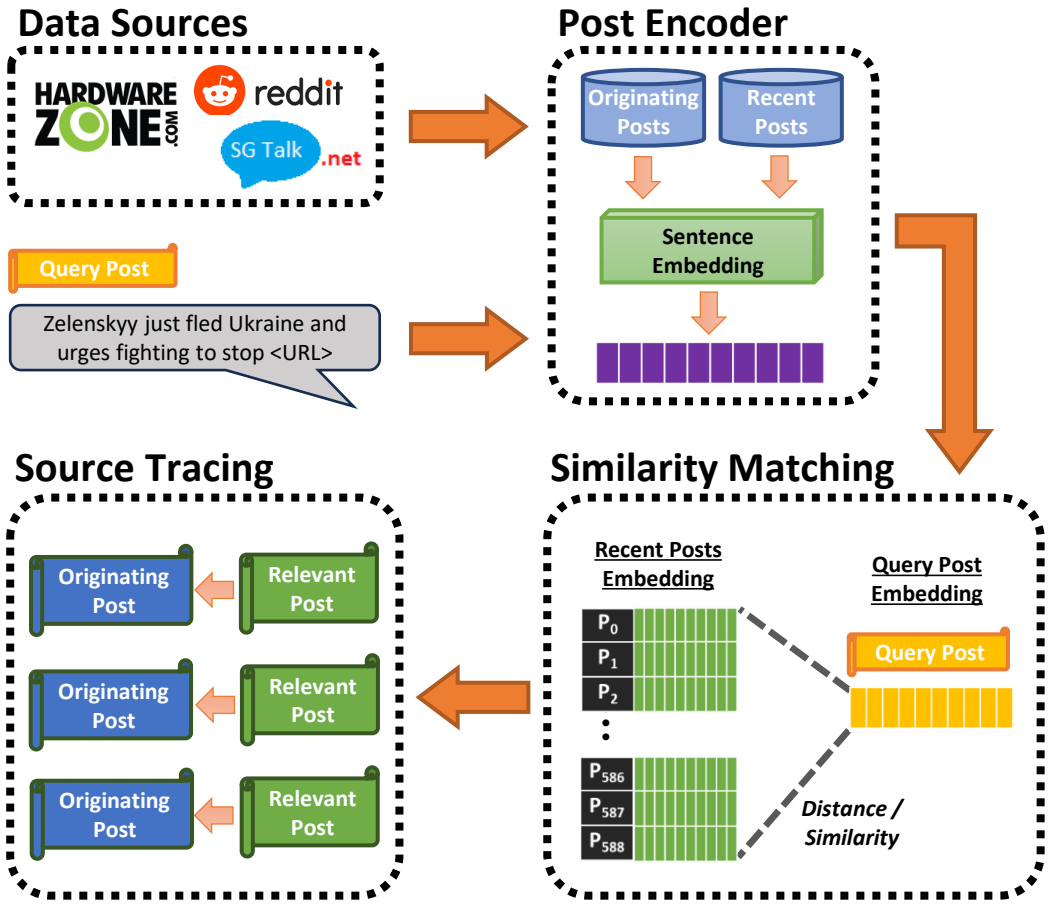


InfoTrace: Tracing Information Campaigns across Platforms

Problem: Identify the source of a post of concern and whether it belongs to a coordinated campaign.

The system collects and encodes posts across platforms, matches them by meaning and time, and traces their origins.

Communications and security teams can detect coordinated campaigns faster, with analysts responsible for assessing intent.



Cheng, Chin, Toh, Mu, Ong, Choo, Lee and Lim. InfoTrace: A System for Information Campaign Source Tracing and Analysis on Social Media. JCDL 2024, demonstration track.

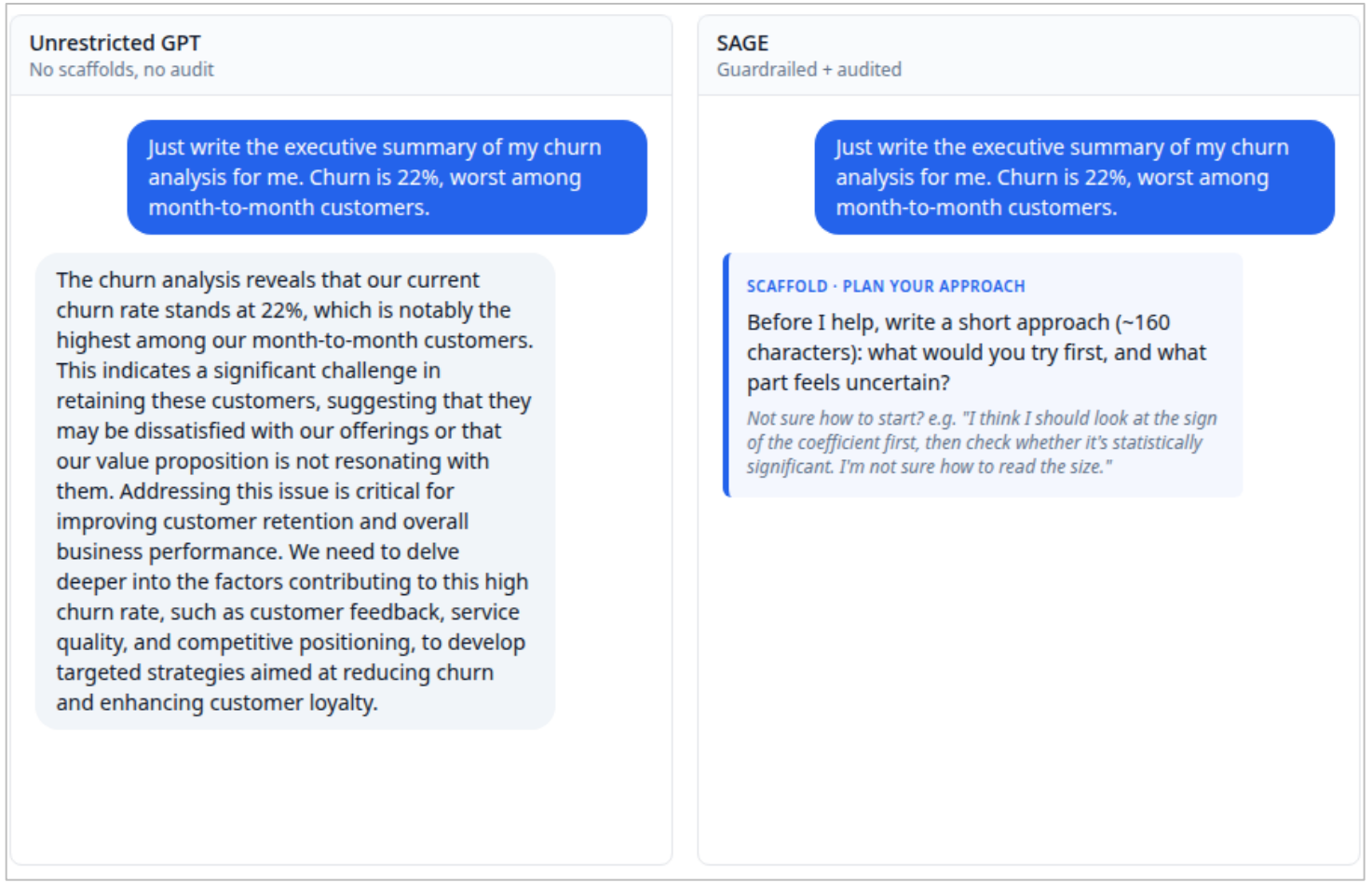
Case 4: Learning

Supporting learning with explicit scaffolds

SAGE: Learning Scaffolds for AI Tutoring

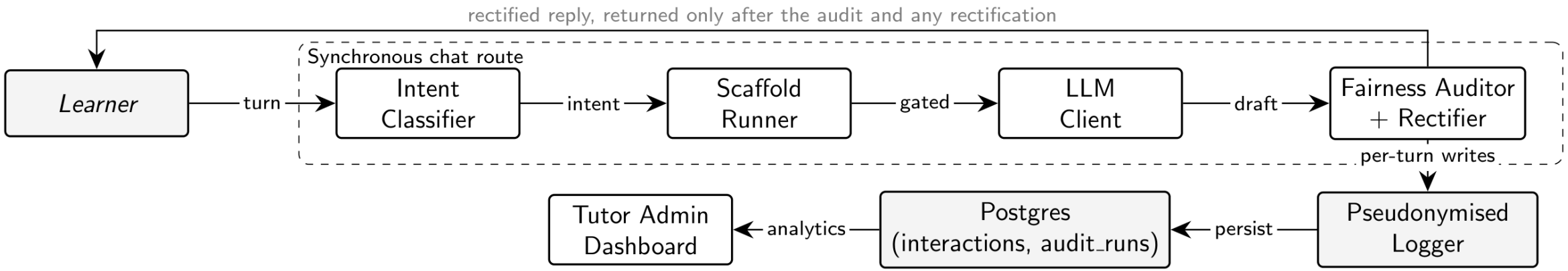
An unrestricted assistant provides a complete answer.

SAGE first asks the learner to outline an approach, paraphrase an explanation, or attempt the question.



Lim, Ren, Zhang, Chye and Wong. SAGE: A Guardrailed LLM Tutoring System with Scaffolded Self-Regulated Learning for Adult Education. CIKM 2026, demonstration track.

SAGE: Counterfactual Fairness Audit



For each question, 12 probes vary learner age, language, education, or digital fluency.

Before delivery, the audit regenerates replies when differences in explanation depth or jargon exceed a threshold.

Logs store pseudonymous metadata without learner text.

Educators set the learning scaffolds and audit thresholds.

From Research to Practice

Understand → Build → Evaluate → Translate

(i) Understand: current AI use through surveys, interviews, and logs

(ii) Build: versions with guardrails that practitioners can configure

(iii) Evaluate: learning outcomes in a randomised trial with unrestricted AI and no-AI controls

(iv) Translate: findings for policy and practice through briefs, notes, and a stakeholder workshop

Conclusion

Applications

- **Urban wellbeing:** sentiment, amenities, and heat
- **Mobility:** individual, group, and crowd-aware planning
- **Public services:** issue detection and analyst decision support
- **Learning:** scaffolding with a fairness audit

Design considerations

- Requirements of the application
- Audits and explicit trade-offs
- Practitioner oversight and responsibility

Funding agencies and partners

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Public value depends on how AI models are designed and implemented for the application.

Thank You to the Social and Urban Analytics Lab

Research staff

ZHANG Meijing (Research Fellow)

LI Menglin (Research Fellow)

Junhua LIU
(Research Fellow, alumni 2025)

Wenchuan MU
(Research Fellow, alumni 2025)

Ishan Monnappa KODIRA
(Research Assistant, alumni 2025)

Henry LIM Yu De
(Research Assistant, alumni 2024)

Yakhoub NDIAYE
(Research Fellow, alumni 2024)

PhD students

Kunrong LI

Ngai Lam HO (alumni 2024)

Menglin LI (alumni 2024)

Junhua LIU (alumni 2022)

Wenchuan MU (alumni 2022)

Sajal HALDER
(alumni 2022, RMIT)

Yan ZHANG (alumni 2020)

Masters students

TOH Hengyi Lucas

Henry LIM Yu De

Yi Ern GOH (alumni 2024)

Kelvin NG Chao Yong
(alumni 2022)

Glenn CHIA Jin Wee
(alumni 2021)

Xiang Qian ONG (alumni 2021)

Gary GOH Shing Wee
(alumni 2021)

Marcus YONG Sheng
(alumni 2020)

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THANK YOU

khlim@suss.edu.sg · sites.google.com/site/limkwanhui

Designing AI for Public Value

AI Model

- Accuracy on benchmark data
- Processing millions of records
- Training data from a specific setting

Design and implementation for the application



Data representativeness, fairness, privacy, robustness, and responsibility for decisions

Public Value

- Better evidence for decisions
- Earlier delivery of services
- Support for the learning process

Applications: urban wellbeing, mobility, public services, and learning