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The U.S.-Asia Center for Tourism and Hospitality Research

FOX Ph.D. Research Workshop

Machine Learning and Artificial Intelligence Research in Tourism and Hospitality

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ML and AI matter

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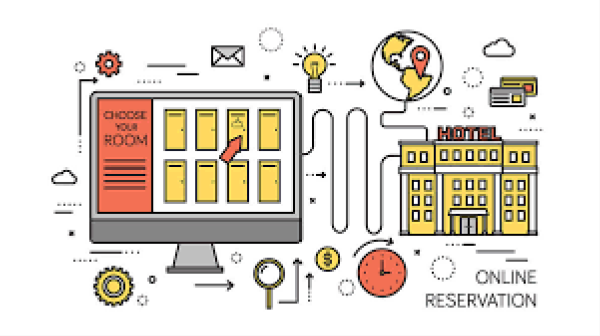
About 12% of other travel and tourism businesses (e.g. hospitality and entertainment) have embraced AI at scale with an annual growth rate of 6.5% (Huang, et. Al., 2021).



AI technologies can offer various advantages for both suppliers (e.g. improved productivity, efficiency and profitability) and consumers (e.g. convenient and personalized tourist experiences) (Samara et al., 2020).

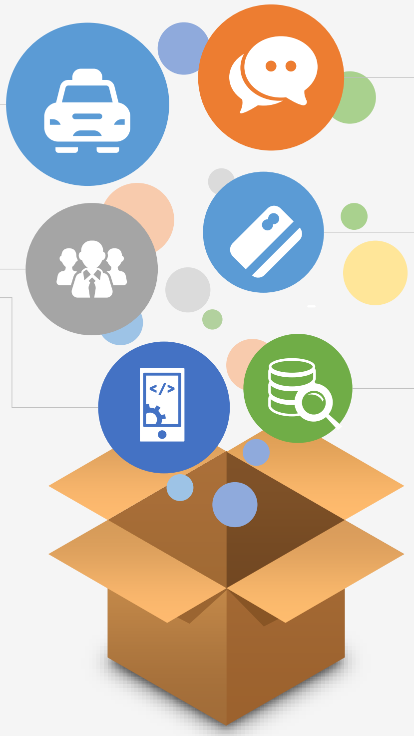
ML and AI matter - data

Various types of big data available

GPS track of vehicles

Social media

Cell phone roaming



User Generate Content

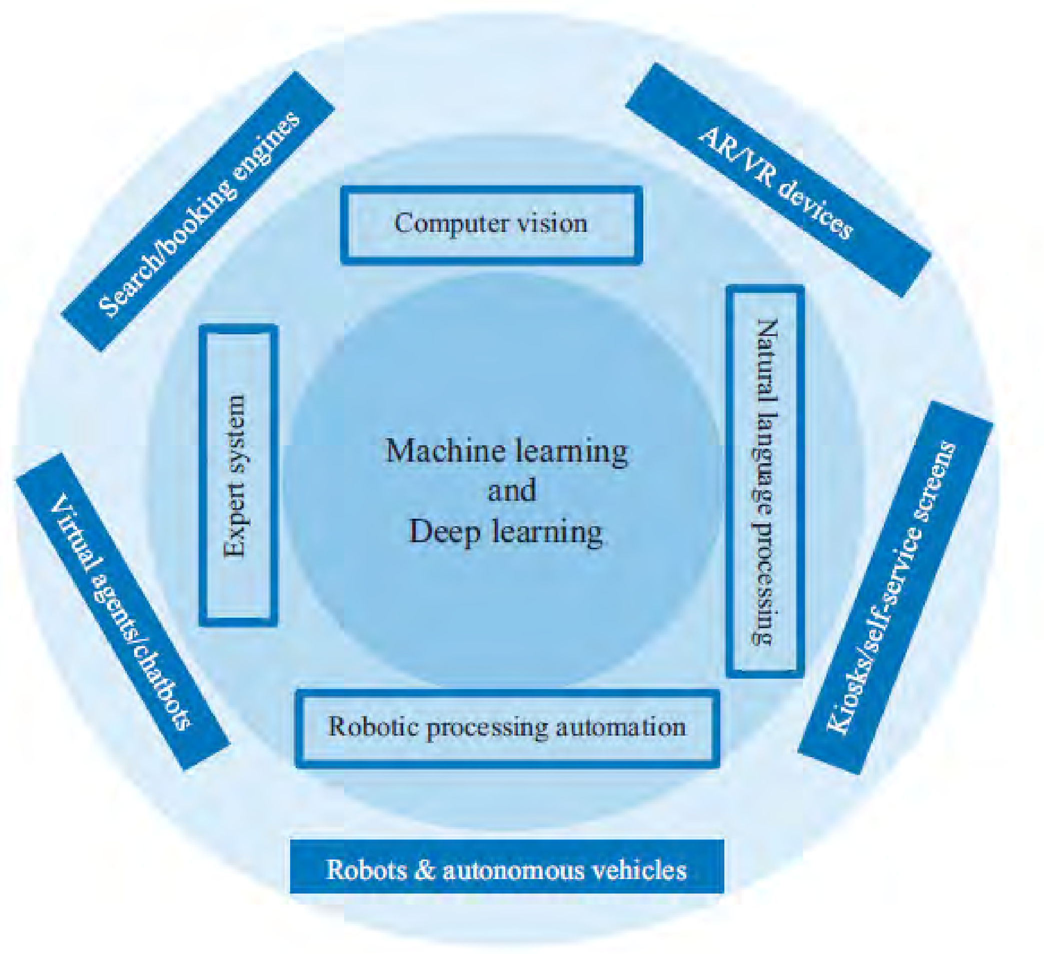
Credit card transaction

Search engine query/ web traffic

Text analytics became particularly popular to explore text data, and popular methods include sentiment analysis, topic mining, and document classification (Zhang, Qiao, Yang, & Zhang, 2020).

Also, sophisticated artificial intelligence methods have been introduced to analyze big data in tourism (Zhang, et al., 2019).

ML and AI matter



Huang, et.al. (2021)

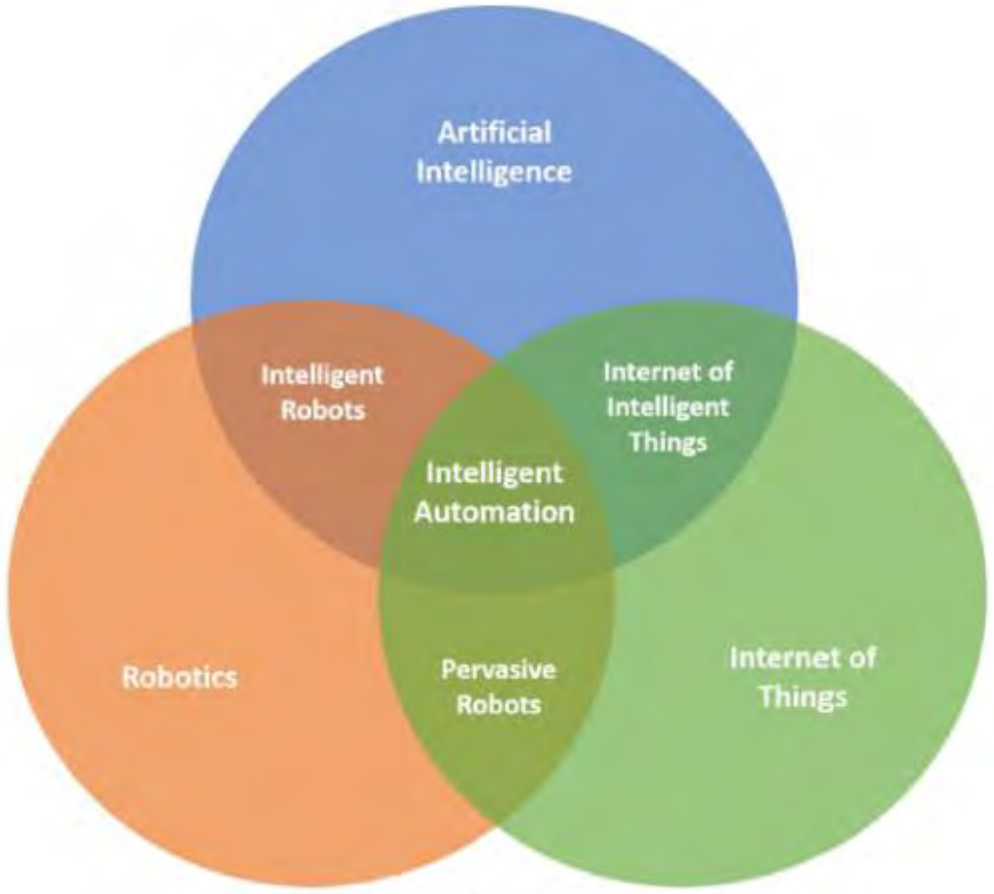


Fig. 1. Technological Framework of Intelligent Automation in Tourism.

Iis (2020)

Research examples

1. Machine learning and GIS system: hotel location selection tool
2. Text-mining: sleep quality study
3. CNN: air quality study
4. Image analytics: avatar and review usefulness
5. Video analytics: Facebook videos on destination marketing
6. Experiment study: robotic involvement

1. Machine learning and GIS system

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journal homepage: www.elsevier.com/locate/ijhosman

Hotel location evaluation: A combination of machine learning tools and web GIS

Yang Yang[a,1], Jingyin Tang[b,2], Hao Luo[c,*], Rob Law[d,3]

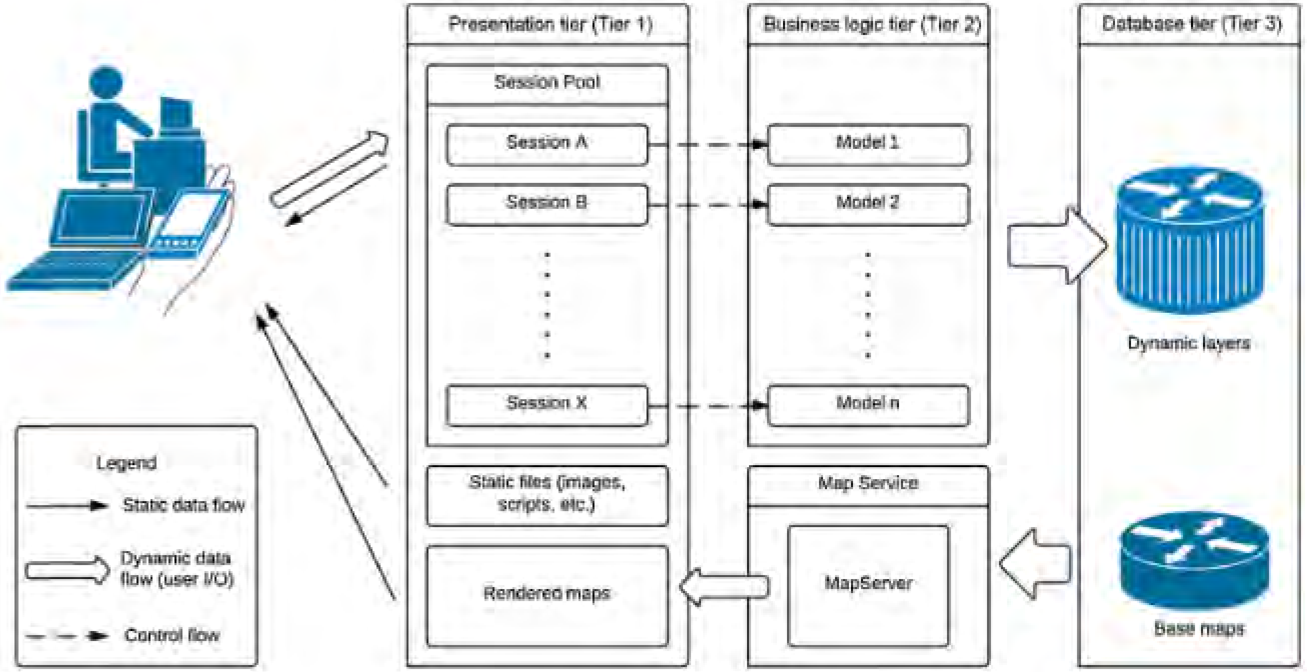

Fig. 1. Three-tier architecture of HoLSAT.

1. Machine learning and GIS system

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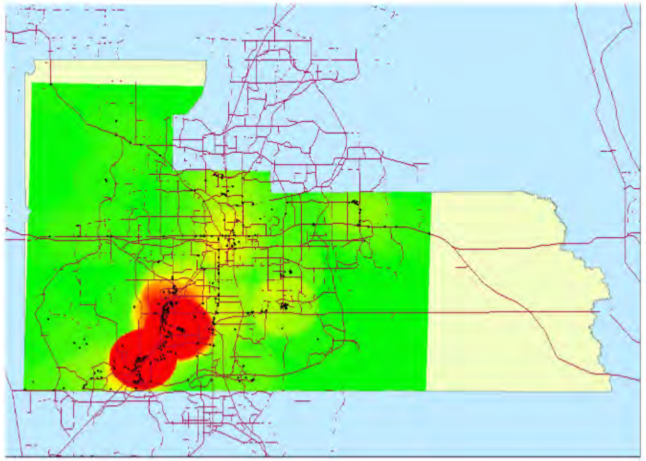
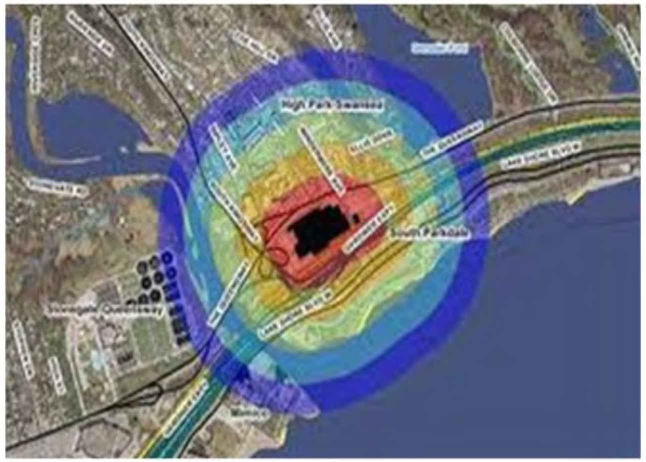
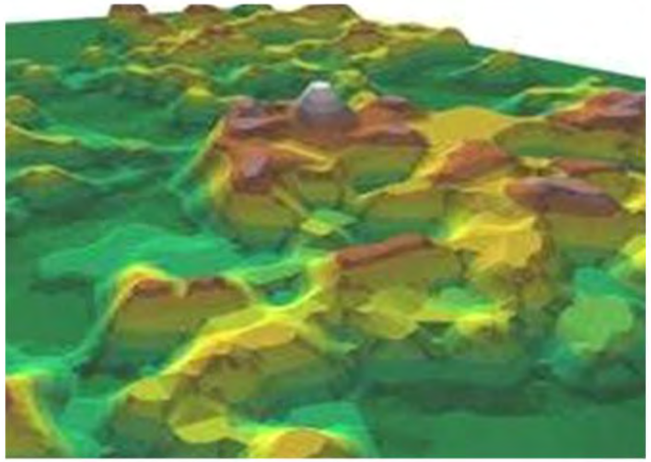
- Visualize, question, analyze, interpret, and understand data to reveal relationships, patterns, and trends



Hot-spot of hotel demand



Accessibility measure



Hotel pricing surface

1. Machine learning and GIS system

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Geo-database
A better way to store geo-referenced hotel business data

Spatial info.
Facilitate the understanding of various spatial factors

Location analysis
Feasibility analysis of potential sites for new hotels

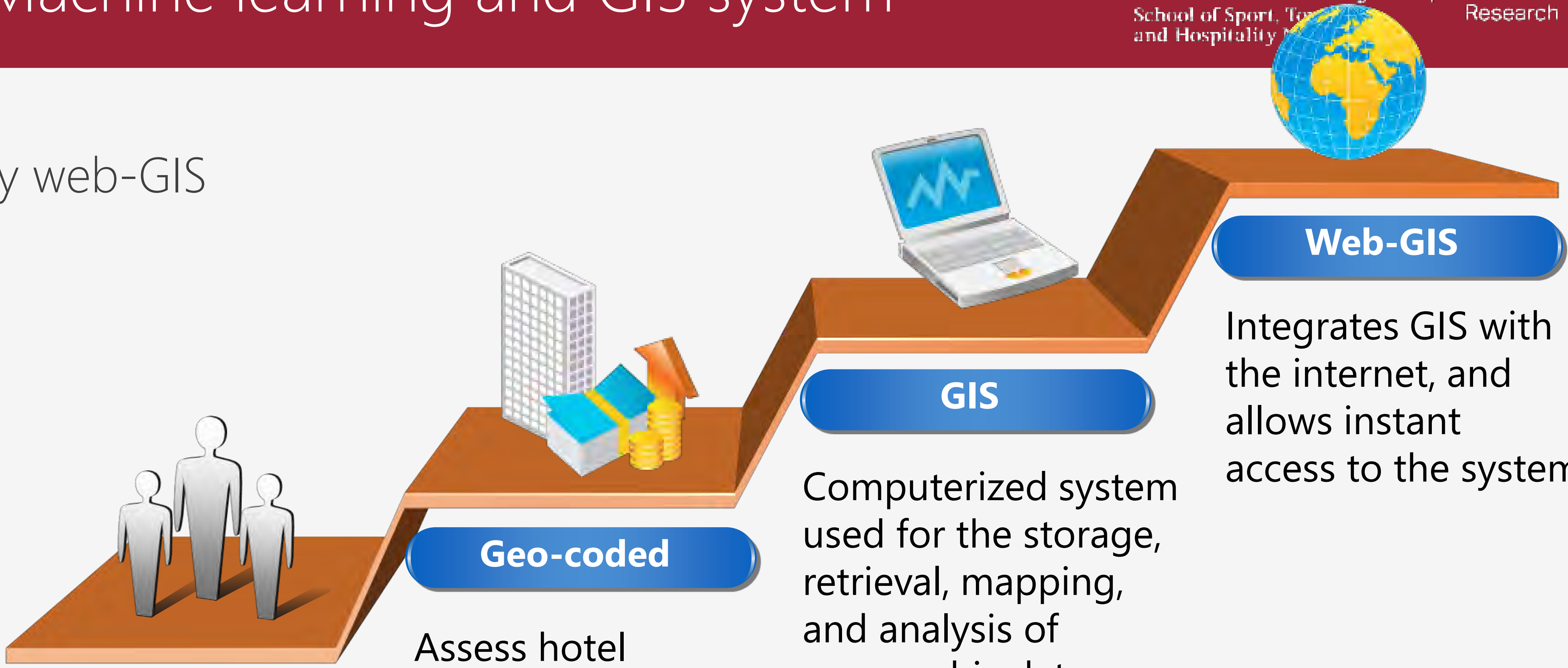
Web-GIS
GIS application integrated with internet

Geo-visualization
Mapping is a better way to understand the pattern

Geo-simulation
Prediction based on various spatial factors

1. Machine learning and GIS system

Why web-GIS



Easy

Easy to operate map algebra

Geo-coded

Assess hotel location factors, and identifying the potential location

GIS

Computerized system used for the storage, retrieval, mapping, and analysis of geographic data.

Web-GIS

Integrates GIS with the internet, and allows instant access to the system

1. Machine learning and GIS system

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Neural Network

1. Inspired by animal nervous systems
2. Identify patterns or structures in data
3. Approximate complex function relationships

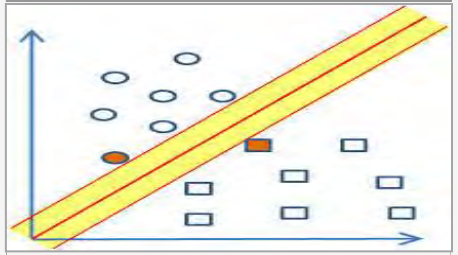
$$y = f\left(\beta_0 + \sum_{j=1}^{r} \beta_j \cdot f\left(\beta_{0j} + \boldsymbol{\beta}_j'\mathbf{x}\right)\right)$$

Projection Pursuit

1. Capture the non-linear relationship
2. Alleviates the multi-collinearity
3. Provides an ideal solution for over-fitting

$$y = \beta_0 + \sum_{j=1}^{r} f_j\left(\boldsymbol{\beta}_j'\mathbf{x}\right) + \varepsilon$$

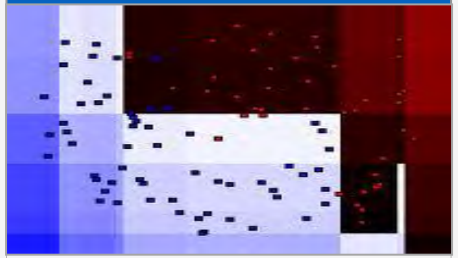
Support Vector



1. Robust and distribution-free
2. Solid statistical theory background
3. Capture non-linear relationship

$$y = \beta_0 + \left(\mathbf{w}' \cdot \Phi\left(\mathbf{x}\right)\right)$$

Boosting Reg.



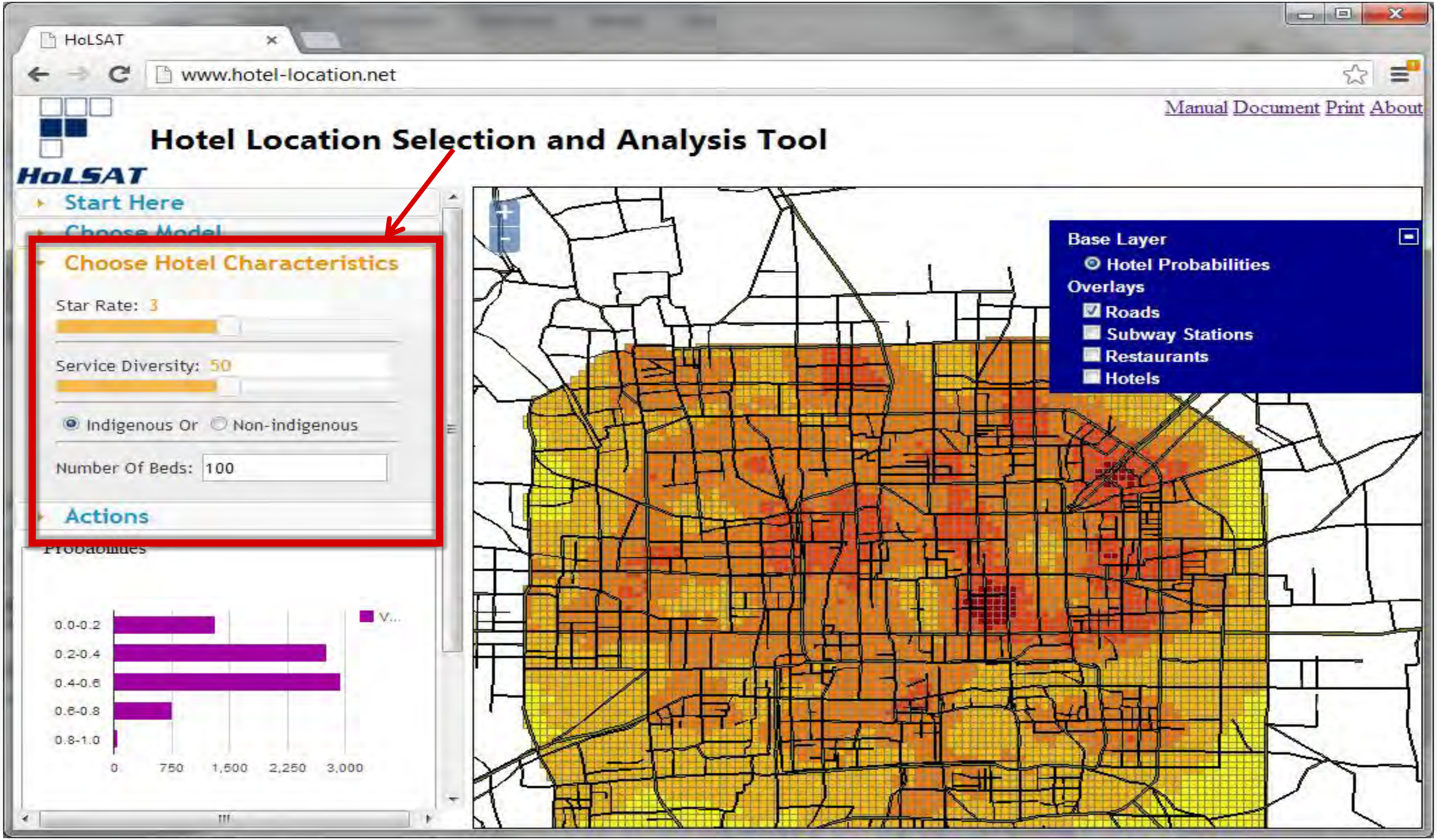
1. Free of a pre-specified functional relationship
2. Owns inherent advantages in predictive accuracy

$$y = F_0\left(\mathbf{x}\right) + \sum_{m=1}^{M} \nu \rho_m B_m\left(\mathbf{x}\right)$$

1. Machine learning and GIS system

Table 3
Results of models with alternative business success indicators.

	Linear regression	Projection pursuit regression	Neural network	Support vector regression	Boosted regression
Labor productivity					
Pseudo-R^2	0.157	0.181	0.146	0.184	0.107
MAE (CV)	6.784	6.178	6.879	6.323	6.763
MSE (CV)	246.704	224.884	251.858	247.676	280.126
Occupancy rate					
Pseudo-R^2	0.153	0.207	0.179	0.237	0.225
MAE (CV)	7.920	8.107	8.017	8.373	8.505
MSE (CV)	99.231	103.418	100.422	110.498	113.054
DEA efficiency score					
Pseudo-R^2	0.184	0.206	0.182	0.262	0.149
MAE (CV)	0.0852	0.0891	0.0892	0.0922	0.1276
MSE (CV)	0.0119	0.0131	0.0131	0.0132	0.0239


HoLSAT
www.hotel-location.net
Manual Document Print About
Hotel Location Selection and Analysis Tool
HoLSAT
Start Here
Choose Model
Choose Hotel Characteristics
Star Rate: 3
Service Diversity: 50
Indigenous Or Non-indigenous
Number Of Beds: 100
Actions
Probabilities
0.0-0.2
0.2-0.4
0.4-0.6
0.6-0.8
0.8-1.0
0
750
1,500
2,250
3,000
V...
Base Layer
Hotel Probabilities
Overlays
Roads
Subway Stations
Restaurants
Hotels

2. Text-mining: sleep quality study

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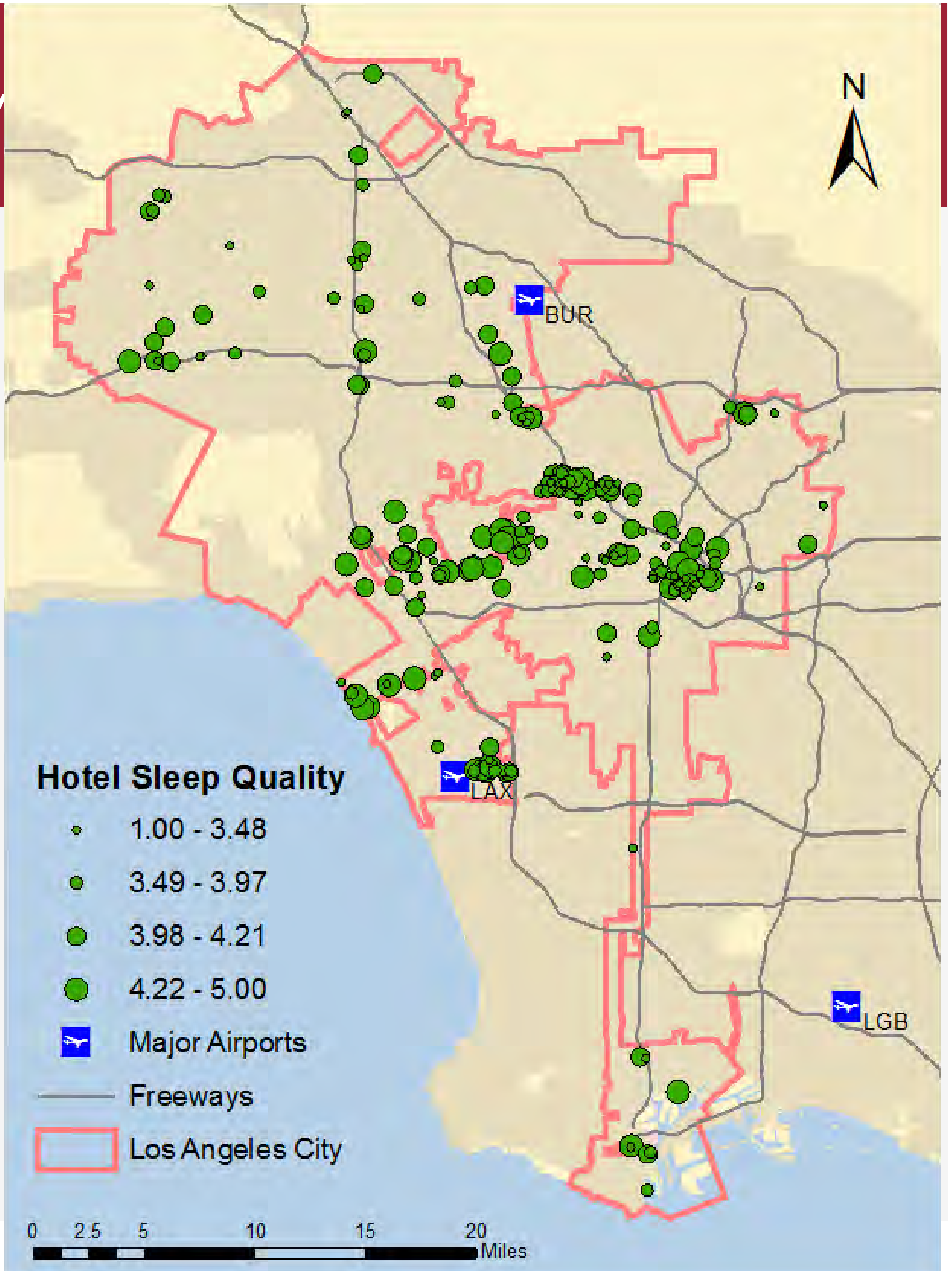
Sleepless nights in hotels? Understanding factors that influence hotel sleep quality

Zhenxing Mao[a], Yang Yang[b,*], Mingshu Wang[c]

2. Text-mining: sleep quality study

Objective: investigate how unique travel- and hotel-related factors (facilitators and barriers) contribute to subjective sleep quality for travelers who stay overnight in hotels.

Method: we collected a large corpus of TripAdvisor review data for hotels in Los Angeles to explore and unveil how different factors help influence the level of sleep quality rated by reviewers.



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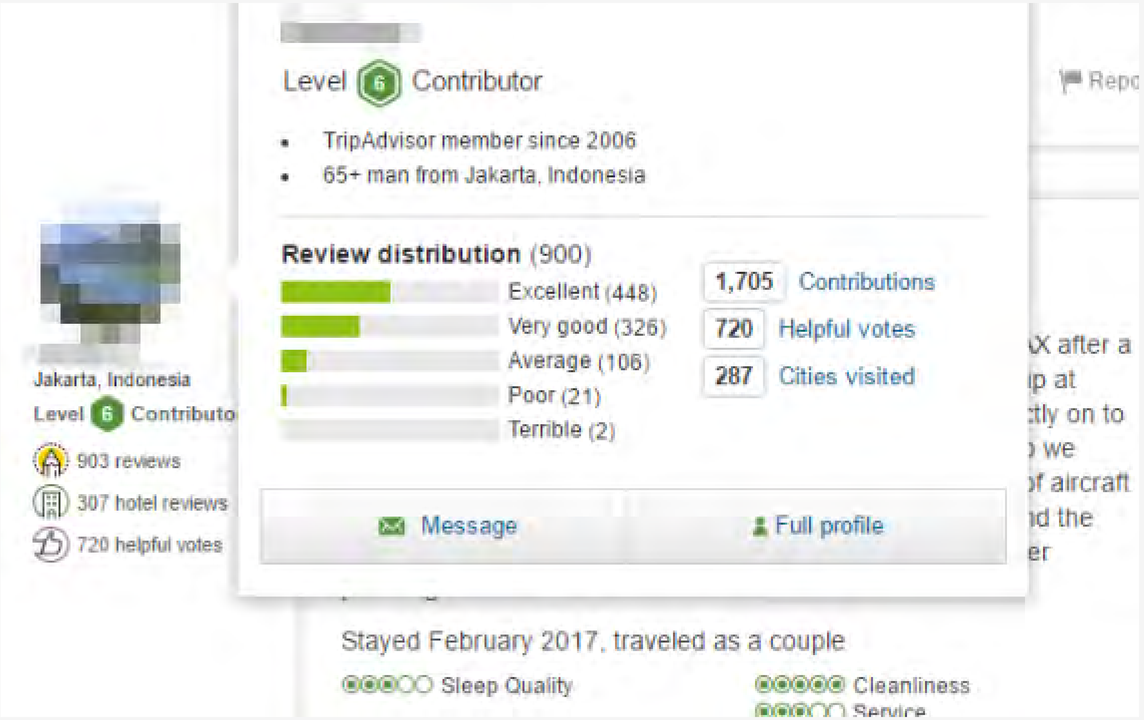

2. Text-mining: sleep quality study

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We propose a framework/typology to classify potential sleep factors among hotel guests into two meaningful domains, traveler characteristics and hotel characteristics

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Demographic characteristics	
traveler_age	Traveler age: 1 = 18–24; 2 = 25–34; 3 = 35–49; 4 = 50–64; 5 = 65 and above
traveler_gender	Traveler gender: 1 = male; 2 = female.
Tripographic characteristics	
traveler_type	Traveler type: 1 = couple travelers; 2 = business travelers; 3 = solo travelers; 4 = family travelers; 5 = travelers with friends
lncities	Log of number of different cities visited as shown in reviewer profile
lndistance	Log of geographical distance between the home city and Los Angeles (in km
longitude_dif	Difference in longitude between the home city and Los Angeles
Hotel facilities	
floors	Number of floors of the hotel's major building with guest accommodations
star	Star rating for the hotel on TripAdvisor
Hotel location	
restaurant	Number of restaurants within 1 km of the hotel
freeway	An indicator of a freeway within 200 m of the hotel
airport	An indicator of an airport within 2 km of the hotel
canopy_cover	Tree canopy cover percentage within 500 m of hotel
Control variable	
expertise	Reviewer's expertise class on TripAdvisor from 0 to 6.

2. Text-mining: sleep quality study

We searched the review content using the defined list of sleep-related keywords associated with hotel sleeping environment (Pallesen, et al., 2016).

We also manually excluded irrelevant reviews like those highlighting pool temperature and lighting problems when taking showers.

The results demonstrate the applicability and accuracy of using sentiment analysis to generate an evaluation measure of each aspect related to sleeping environment in a hotel setting.

Factor	Observations	Mean of score	Std. Dev. of score	Example
Pillow	373	0.306	0.270	“Beds and pillows are glorious :)” (score = 0.500) “The one thing I hate is tons of pillows on the bed that are all down” (score = -0.176)
Mattress	127	0.205	0.306	“Very comfortable beds with mattress cushion covers” (score = 0.560) “The comfort level of the mattress was so poor that my sleep was terrible” (score = -0.548)
Bedding	170	0.264	0.296	“Very comfortable bedding” (score = 0.523) “The carpet is dingy shag and the bedding is outdated” (score = -0.400)
Temperature	251	0.162	0.268	“Room temperature - I admittedly like my room on the cold side but it seems as though the insulation of our room was weak and by mid-afternoon it got very warm” (score = 0.041) “The temperature was impossible to control” (score = -0.483)
Noise	1337	0.146	0.233	“I expected some street noise but was surprised how good the sound proofing was” (score = 0.431) “The noise was going on all night with doors being slammed and loud talking in the corridors” (score = -0.236)
Lighting	225	0.227	0.285	“It was nice to have a dimmer so we could have the light on at night without being too intrusive” (score = 0.313) “The noise is pretty bad and also the lights from the Holiday Inn sign creates a green glow into the room” (score = -0.217)
Ventilation	39	0.095	0.242	“On the upside, the ventilation in the room was terrific” (score = 0.407) “Poor ventilation which kept the bathroom hot and steamy after showering” (score = -0.250)

2. Text-mining: sleep quali

S_mattress, S_temperature, S_noise and S_lighting—are positive and significant, suggesting that more positive evaluations of mattresses, temperature, noise and lighting are associated with a higher levels of reported sleep quality.

S_mattress has the largest coefficient, which again highlights the important role mattresses play in determining guests' sleep quality.

	Model 6	Model 7	Model 8	Model 9
I_pillow	0.161	-0.550***	0.137	-0.558***
	(0.134)	(0.192)	(0.133)	(0.191)
I_mattress	-0.991***	-1.604***	-0.993***	-1.590***
	(0.234)	(0.267)	(0.237)	(0.273)
I_bedding	0.00114	-0.233	-0.0592	-0.272
	(0.192)	(0.247)	(0.198)	(0.255)
I_temperature	-0.744***	-0.989***	-0.738***	-0.986***
	(0.128)	(0.126)	(0.128)	(0.132)
I_noise	-0.750***	-0.898***	-0.764***	-0.903***
	(0.071)	(0.081)	(0.073)	(0.082)
I_lighting	-0.211*	-0.476***	-0.229*	-0.495***
	(0.128)	(0.153)	(0.134)	(0.160)
I_vent	-0.769***	-0.725**	-0.795***	-0.749**
	(0.259)	(0.285)	(0.266)	(0.297)
S_pillow		2.473***		2.431***
		(0.461)		(0.468)
S_mattress		2.974***		2.895***
		(0.731)		(0.757)
S_bedding		0.800		0.678
		(0.557)		(0.567)
S_temperature		2.131***		2.075***
		(0.483)		(0.486)
S_noise		1.213***		1.154***
		(0.222)		(0.222)
S_lighting		1.284***		1.304***
		(0.415)		(0.436)
S_vent		-0.334		-0.391
		(0.993)		(1.154)

3. CNN: air quality study

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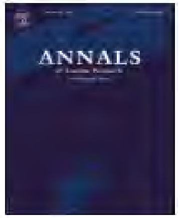


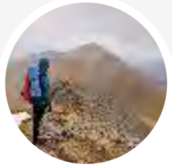
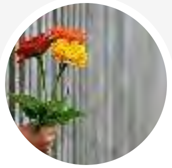
Research article

Designing tourist experiences amidst air pollution: A spatial analytical approach using social media

Xiaowei Zhang[a], Yang Yang[b,*], Yi Zhang[c], Zili Zhang[a]

Impact of Air Pollution

(Measured by PM 2.5 concentration level)

Smog Awareness	Behavioral Consequence	Emotional Consequence	Health Consequence
			
Whether the tourists are aware of the issue of air pollution, such as smog attacks	How tourists change their behavior in terms of location visited, travel scope, and duration.	How tourists' emotion and sentiment change.	The occurrence of health related issues such as illness and insomnia.

3. CNN: air quality study

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Many tourist destinations are suffering from varying levels of air pollution. The situation is particularly worse in urban destinations.


POLLUTION

Foreign Tourists Skipping Delhi over Air Quality Fears

By Niharika Lal | TNN · 12 December 2018 · TWC India

Tourists at Chandni Chowk market in Delhi (RAJESH MEHTA/ BCCL Delhi)


South China Morning Post

China

Air pollution takes toll on China's tourism

Shocking levels of air pollution have cast a pall over China's burgeoning tourism industry

AP

Published: 4:02pm, 13 Aug, 2013

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Sentiment analysis

Opinion Mining within Natural Language Processing (NLP) that builds systems that try to identify and extract opinions

Chinese text segmentation: built to be the best Python Chinese word segmentation module.

Provides solutions from automatic Chinese words segmentation to psychological analysis.

3. CNN: air quality study

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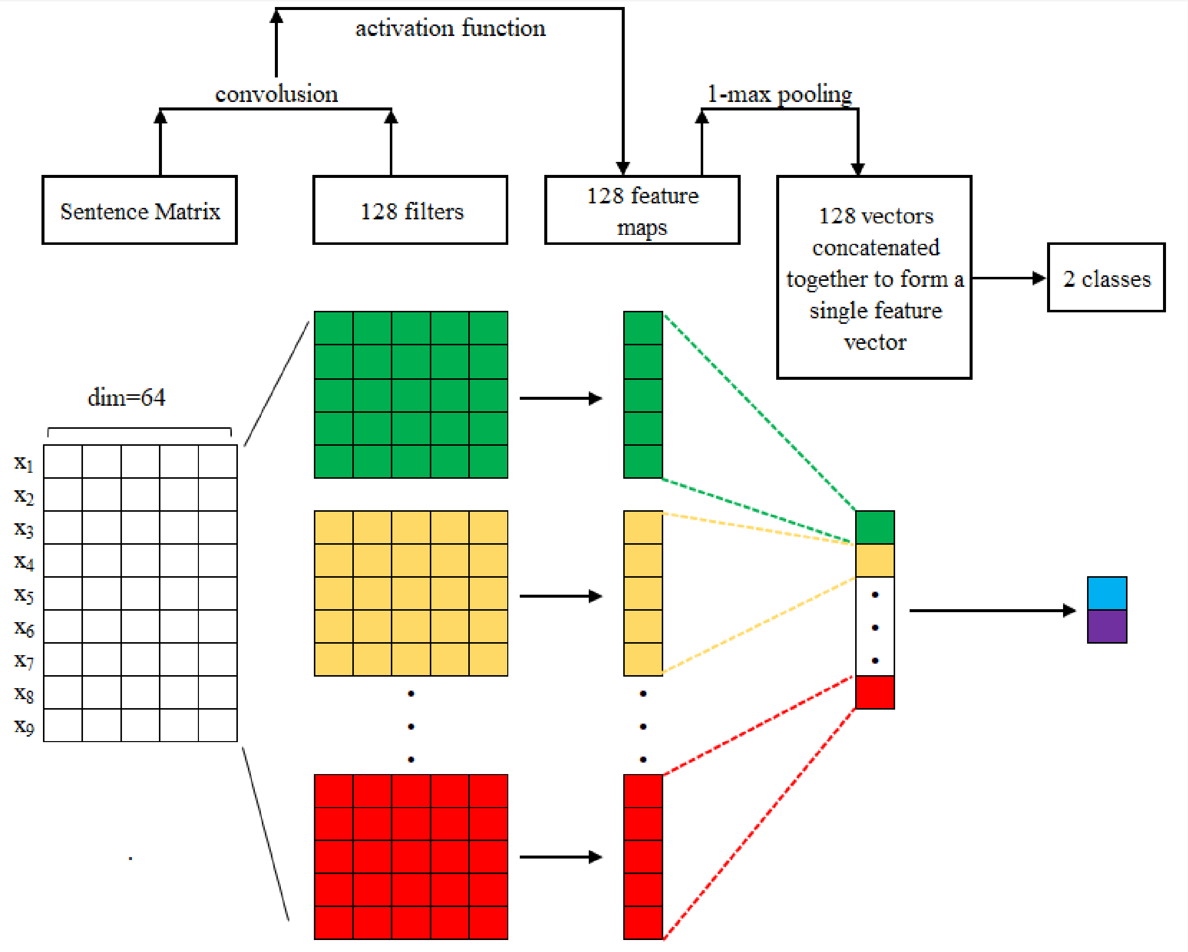
Deep learning classification

manually check 14300 Weibo for health issues

health-related keywords include coughing“咳嗽”, dizzy“头晕”, sickness“生病”, headache“头痛”, and difficulty breathing “呼吸困难”

11000 texts as the training dataset, 2200 texts as the testing dataset, and the other 1100 as the validation dataset



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Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	smog_tag	distance_TAM	radius	sentiment	health_issue	sleep_issue
pm2_5*(tourist=0)	0.00398***	-0.000508***	0.000146***	-0.000605***	0.000262***	0.000244***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pm2_5*(tourist=1)	0.00397***	-0.000103**	0.000213**	-0.000685***	0.000391***	0.000120
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tourist	0.505***	-0.182***	0.923***	-0.187***	-0.193***	-0.200***
	(0.020)	(0.007)	(0.012)	(0.011)	(0.006)	(0.017)
sunny	0.151***	0.0300***	-0.0680***	-0.0436***	0.0259***	-0.0385***
	(0.015)	(0.004)	(0.006)	(0.007)	(0.004)	(0.010)
precipitation	0.132***	0.0336***	0.0499***	-0.0950***	-0.00410	0.00614
	(0.017)	(0.004)	(0.006)	(0.007)	(0.004)	(0.010)
windy	-0.439***	-0.0317***	0.0593***	0.00185	-0.000743	-0.0120
	(0.016)	(0.004)	(0.006)	(0.007)	(0.003)	(0.010)
temp	0.0713***	0.0240***	-0.00936***	-0.0161***	0.00148***	-0.00955***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
temp2	-0.00480***	-0.000229***	0.000582***	0.000405***	-0.000159***	0.000243***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

3. CNN: air quality study

Tourists are more vulnerable than residents for health-related issues

- Tourists are less adaptive to an unfamiliar environment.

Tourists do not suffer from sleep issues due to air pollution.

- Many other factors shaping the sleep quality of tourists that may be more important than air pollution, such as travel fatigue, accommodation environment, jet lag, etc.

3. CNN: air quality study

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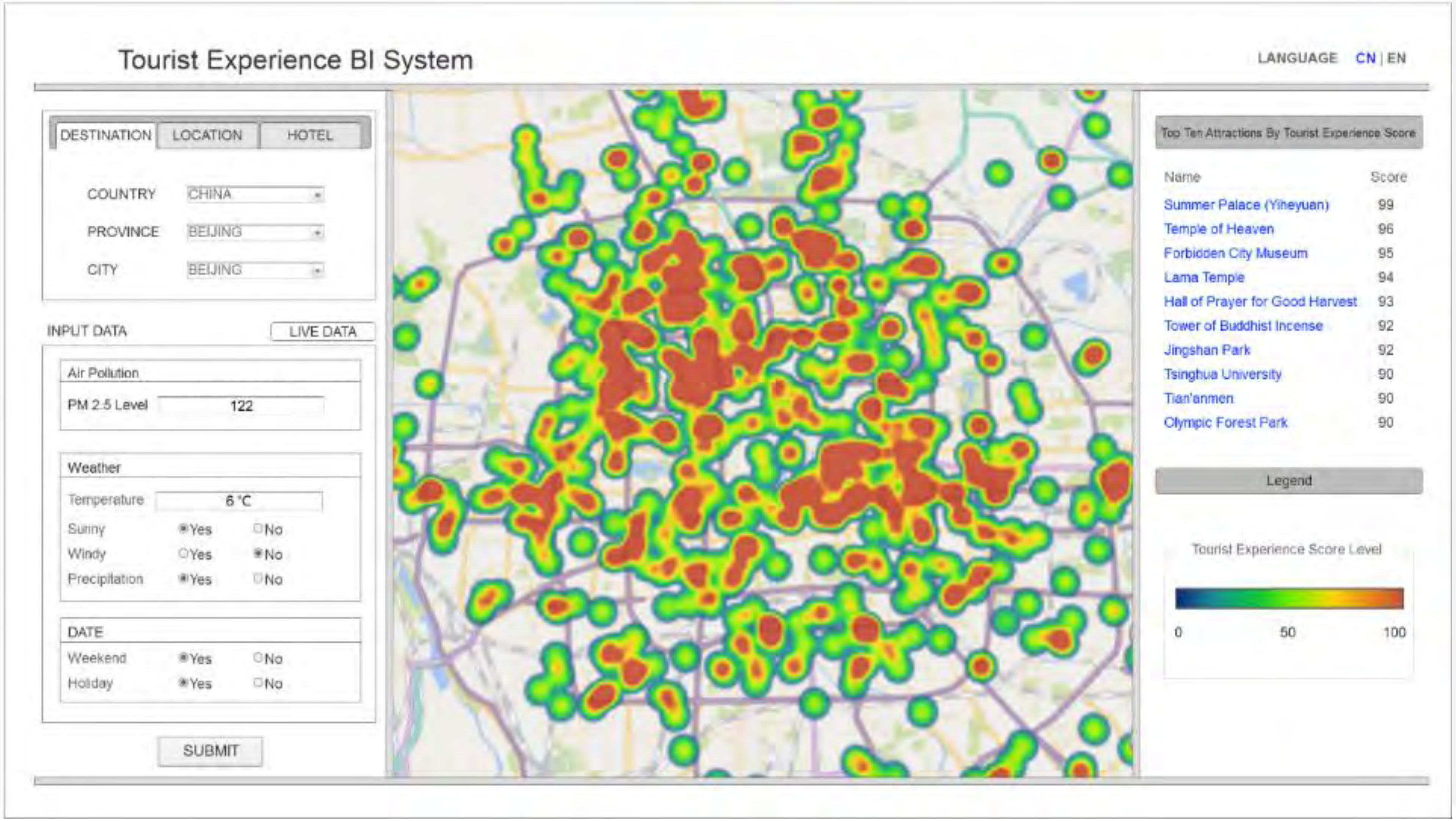

4. Image analytics: avatar and review

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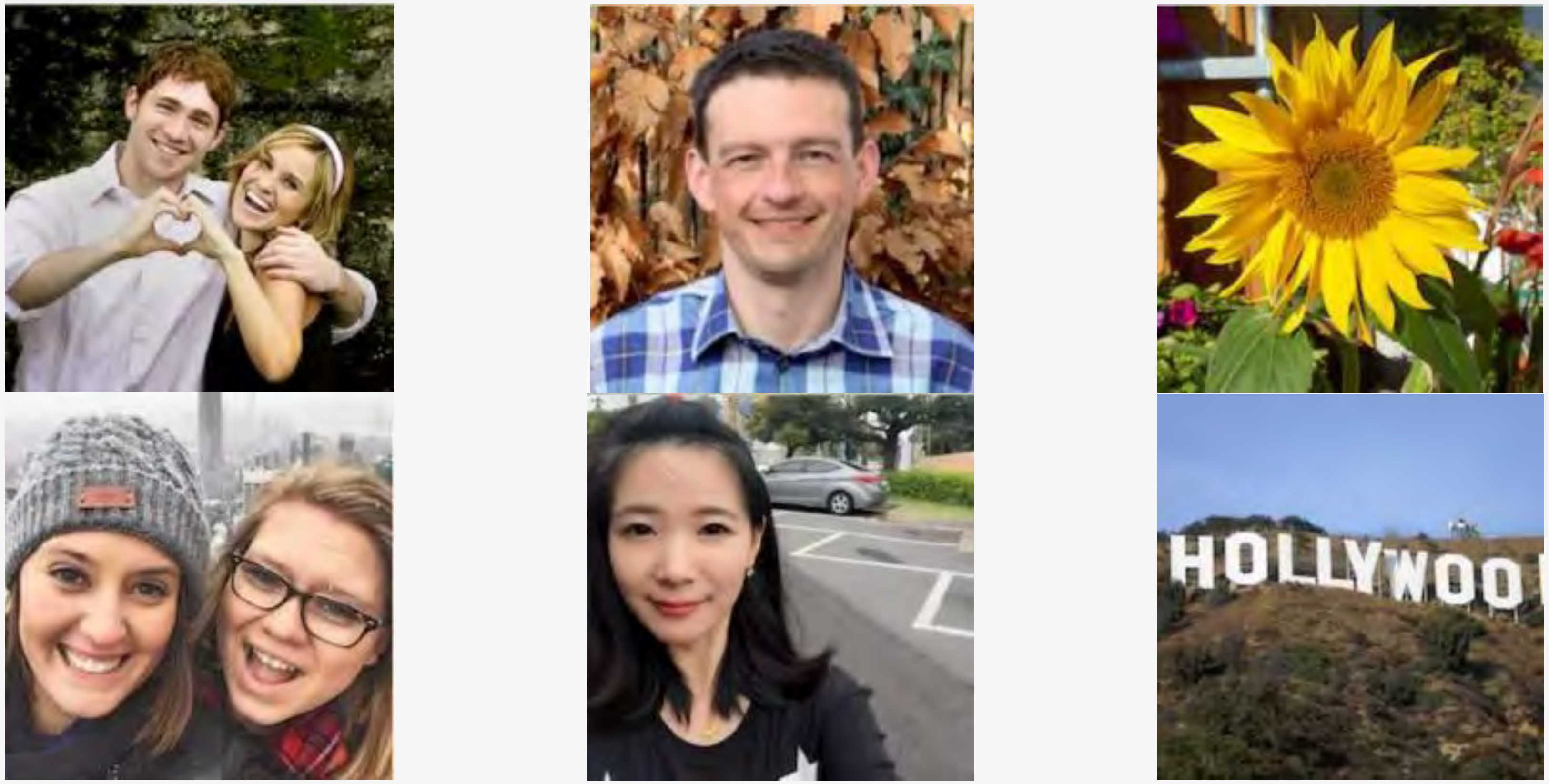
Real estate agent	Car dealer
	

4. Image analytics: avatar and review



Reviewers' profile photos (RPPs) were identified as an important indicator of reviewers' characteristics (Lee & Shin, 2014)

4. Image analytics: avatar and review

Based on supervised learning results on billions of photos

- Returns information about visual content found in an image.
- Uses tagging, descriptions, and domain-specific models to identify content and label it with confidence.
- Identifies image types and color schemes in pictures.
- Recognizes Celebrity and Landmark around the world.
- Detects faces and its gender and age.

Google Cloud Platform

amazon web services™

clarifai

Microsoft Azure

4. Image analytics: avatar and review

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	Model 2	Model 3	Model 4
	Category	Tag	Tag
green	-0.632*	-0.0174	
	(0.343)	(0.041)	
red	-0.421	0.0314	
	(0.287)	(0.040)	
yellow	0.0222	-0.00994	
	(0.173)	(0.053)	
blue	0.0428	0.0409	
	(0.228)	(0.036)	
black	0.0926	-0.0389	
	(0.301)	(0.057)	
grey	1.890***	0.567***	
	(0.529)	(0.216)	
white	-0.366	-0.0211	
	(0.240)	(0.030)	
pink	-0.110	-0.200	
	(0.569)	(0.156)	
purple	1.176	0.509	
	(1.144)	(0.391)	
colors			0.0492***
			(0.017)

	Model 5	Model 6	Model 7	Model 8	Model 9
	Category	Category	Category	Category	Tag
C_outdoor	0.0281**				
	(0.011)				
C_food		-0.227**			
		(0.113)			
C_people_portrait			0.0624**		
			(0.029)		
C_people				-0.109	
				(0.068)	
T_smiling					-0.0429
					(0.046)

4. Image analytics: avatar and review

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Ask graduate students to rank credibility and social distance (scale 1-5) of 1,500 randomly selected RPPs in TripAdvisor.

Use machine learning tools to train a model based on 1,000 rated RPPs, and use the remaining 500 as a validation set.

	Model 10	Model 11	Model 12
Social dist	0.102*		0.088
	(0.060)		(0.059)
Trustworthiness		-0.017	-0.015
		(0.013)	(0.013)

5. Video analytics: Facebook videos

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The U.S.-Asia Center for Tourism and Hospitality Research

Video analytics of Facebook videos from DMOs

5. Video analytics: Facebook videos

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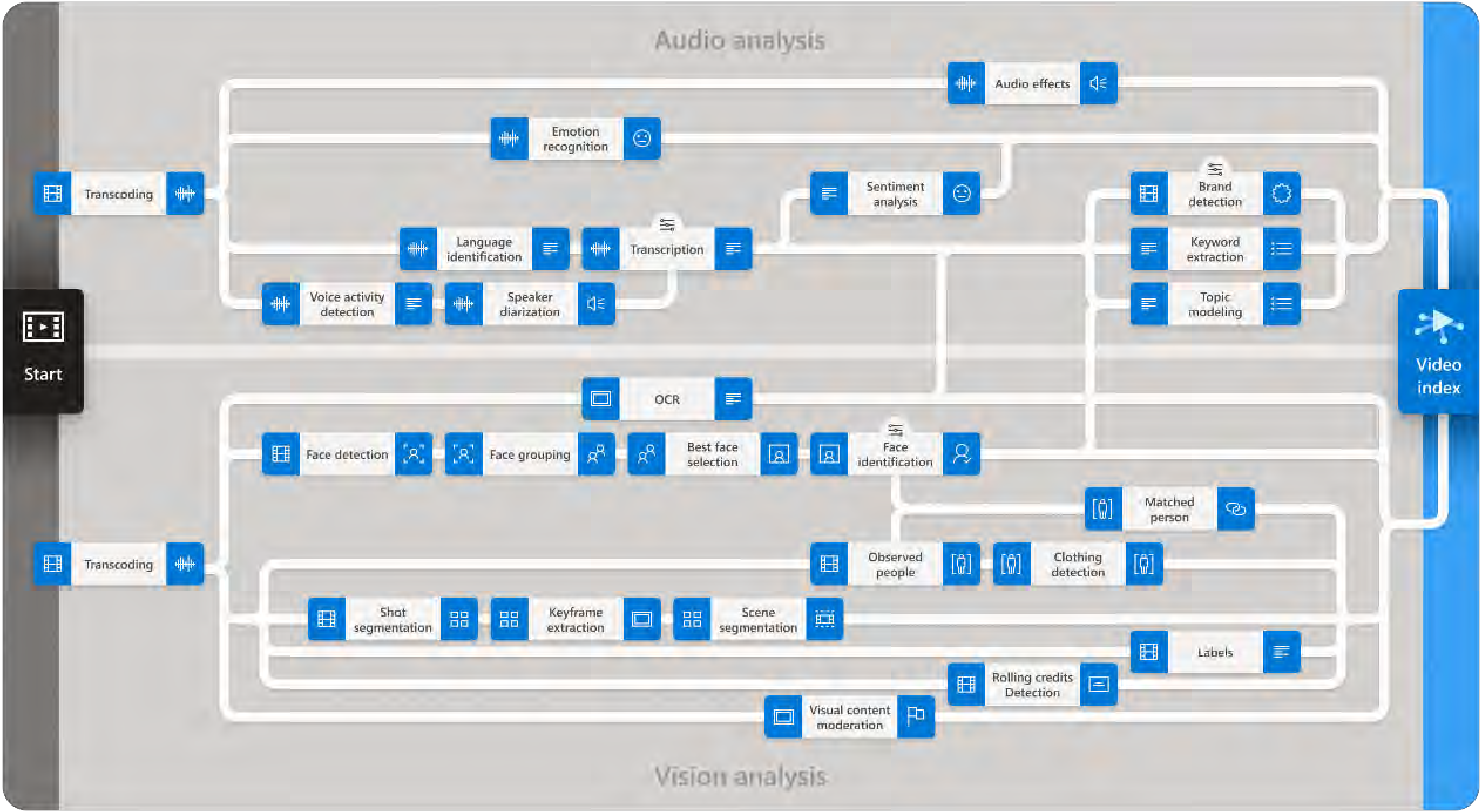
We collected the video (<10 min) from state DMOs' Facebook accounts, and conduct the video analytics in Azure Video Analyzer APIs.

More than 3,000+ videos were analyzed, and regression analysis was used to understand what video factors are associated with social media post performance indicators (i.e., number of views, number of likes, number of comments, number of likes, number of shares….)


Audio analysis
Audio effects
Emotion recognition
Transcoding
Sentiment analysis
Brand detection
Language identification
Transcription
Keyword extraction
Voice activity detection
Speaker diarization
Topic modeling
Start
Video index
OCR
Face detection
Face grouping
Best face selection
Face identification
Matched person
Transcoding
Observed people
Clothing detection
Shot segmentation
Keyframe extraction
Scene segmentation
Labels
Rolling credits Detection
Visual content moderation
Vision analysis

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	Variable definition	(1)	(2)
		lnviews	lnlikes
lntitle_len	Lenth of title in words (in log)	-0.0286	-0.109*
		(0.077)	(0.061)
lnbody_len	Lenth of body content in words (in log)	0.217***	0.278***
		(0.036)	(0.031)
lnvideo_len	Lenth of video in seconds (in log)	0.273***	0.0808
		(0.090)	(0.073)
is_hd	Whether the resolution is 720 or higher	0.418***	0.233**
		(0.130)	(0.097)
L_start	Luminance of first 30sec	-0.000252	-0.000308
		(0.001)	(0.001)
L_mid	Luminance at midpoint	0.000634	0.000562
		(0.001)	(0.001)
L_end	Luminance of last 30sec	0.000357	0.0000918
		(0.001)	(0.001)
C_start	Colorfulness of first 30sec	0.00187**	0.00174**
		(0.001)	(0.001)
C_mid	Colorfulness at midpoint	-0.000829	-0.000574
		(0.001)	(0.001)
C_end	Colurfulness of last 30sec	-0.000832	-0.000615
		(0.001)	(0.001)
luminance_var	standardar deviation between L_start L_mid, and L_end to capture the varia	-0.00157	-0.00327**
		(0.002)	(0.001)
colorfulness_var	standardar deviation between C_start, C_mid, and C_end to capture the var	-0.00152	-0.000869
		(0.002)	(0.001)
lnnumb_scenes_minute	Number of scenes per minute (in log)	0.120*	-0.0143
		(0.066)	(0.052)
lnnumb_faces_minute	Number of faces per minute (in log)	-0.0470	-0.148***
		(0.052)	(0.042)
lnnumb_locations_minute	Number of well-known locations per minute (in log)	0.115*	0.148***
		(0.062)	(0.048)
Num_Speakers	How many people are speaking	0.0453***	0.0170*
		(0.011)	(0.009)
TalkToListenRatio	How many people are speaking / How many people are listening	0.567***	-0.123
		(0.218)	(0.152)

lnword_count	Word count spoken (in log)	-0.125***	-0.0982***
		(0.038)	(0.030)
Sentiment_Neg	(Based on audio/text in the video) negative sentiment score	1.119*	0.193
		(0.577)	(0.445)
Sentiment_Pos	(Based on audio/text in the video) positive sentiment score	0.121	0.0861
		(0.139)	(0.114)
smile	Indicators of smiles in video content	0.0690	-0.0408
		(0.107)	(0.083)
laugh	Indicators of laughs in video content	1.134***	1.137***
		(0.330)	(0.259)
historic	Indicators of historical in video content	0.566*	0.211
		(0.321)	(0.223)
nature	Indicators of nature in video content	0.362***	0.419***
		(0.075)	(0.061)
plant_tree	Indicators of trees and plants in video content	0.0480	0.00238
		(0.085)	(0.068)
animal	Indicators of animals in video content	0.154**	0.171***
		(0.072)	(0.059)
people	Indicators of people in video content	-0.0117	0.0112
		(0.080)	(0.066)
_cons		6.205***	3.508***
		(0.518)	(0.424)
State-specific effects		Yes	Yes
Year-month-specific effects		Yes	Yes
Day-of-week-specific effects		Yes	Yes
Posting-hour-specific effects		Yes	Yes
N		2681	2676
AIC		9625.4	8398.2
BIC		9790.4	8563.1
ll		-4784.7	-4171.1
r2		0.585	0.643
r2_a		0.553	0.616

6. Experiment study: robotic involvement

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Tech-touch balance in the service encounter: The impact of supplementary human service on consumer responses

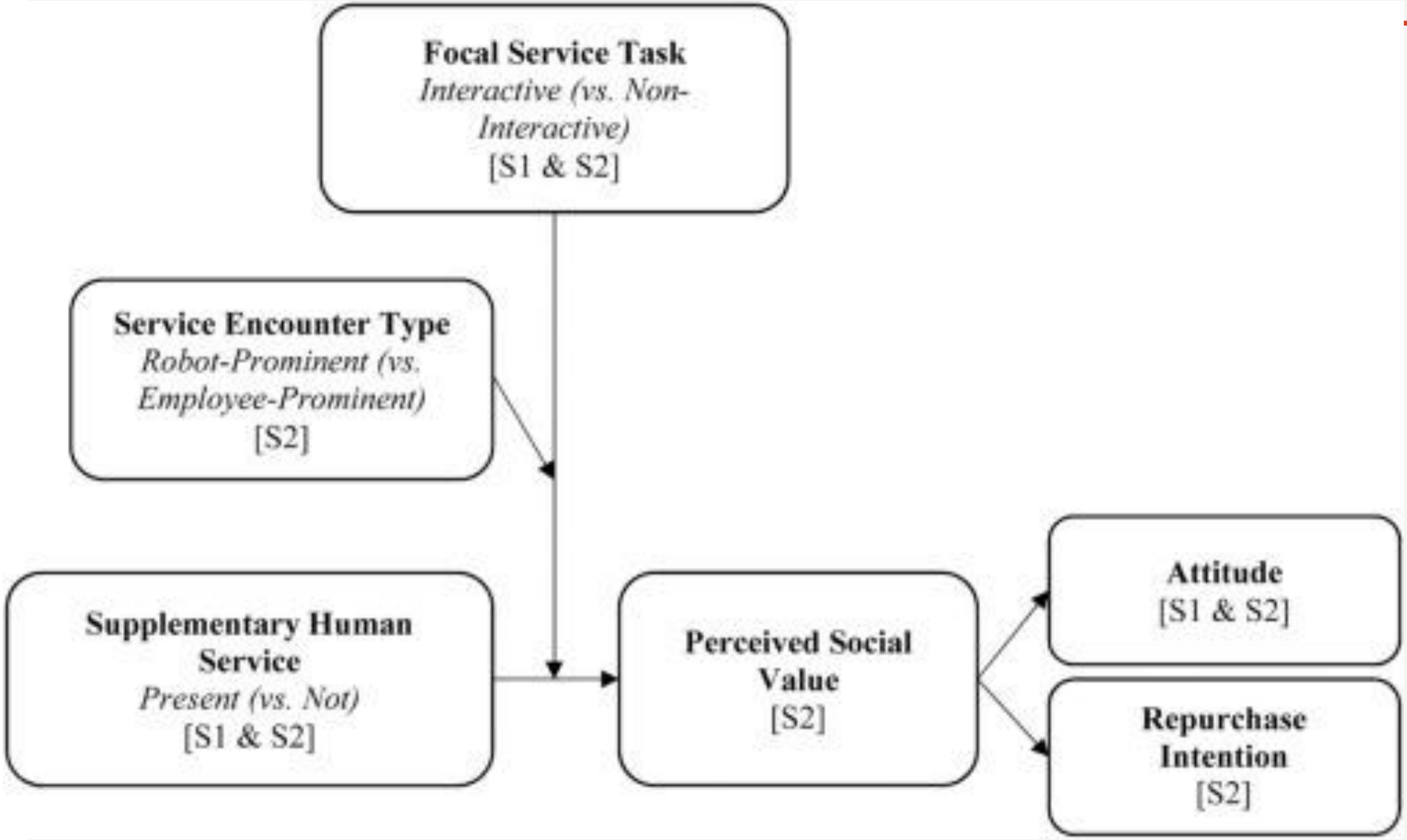
Laurie Wu [a], Alei Fan [b], Yang Yang [c], Zeya He [d,*]

6. Experiment study: robotic involvement

Trends in service innovation continue to shift service encounters from human-prominent to robot-prominent (Larivière et al., 2017, Van Doorn et al., 2017).

To date, relatively little scholarly attention has been paid to designing robot-prominent service encounters to overcome obstacles imposed by an absence of socialization (e.g., Fernandes and Oliveira, 2021; Yoganathan et al., 2021).

We draw upon the notion of "tech–touch" balance and the theoretical perspective of "Service Encounter 2.0" to address these issues (Larivière et al., 2017).



H1: In robot-prominent service encounters where robots are programmed to deliver interactive focal service tasks, supplementary human service will enhance consumers' (a) attitudes and (b) repurchase intentions towards the service business.

H2: In robot-prominent service encounters where robots are programmed to deliver non-interactive focal service tasks, supplementary human service will not influence consumers' (a) attitudes and (b) repurchase intentions towards the service business.

H3: In robot-prominent service encounters, perceived social value will mediate the focal service task–moderated effect of supplementary human service on consumers' (a) attitudes and (b) repurchase intentions towards the service business.

H4: In employee-prominent service encounters, the focal service task–moderated effect of supplementary human service on consumers' (a) attitudes and (b) repurchase intentions towards the service business will be attenuated.

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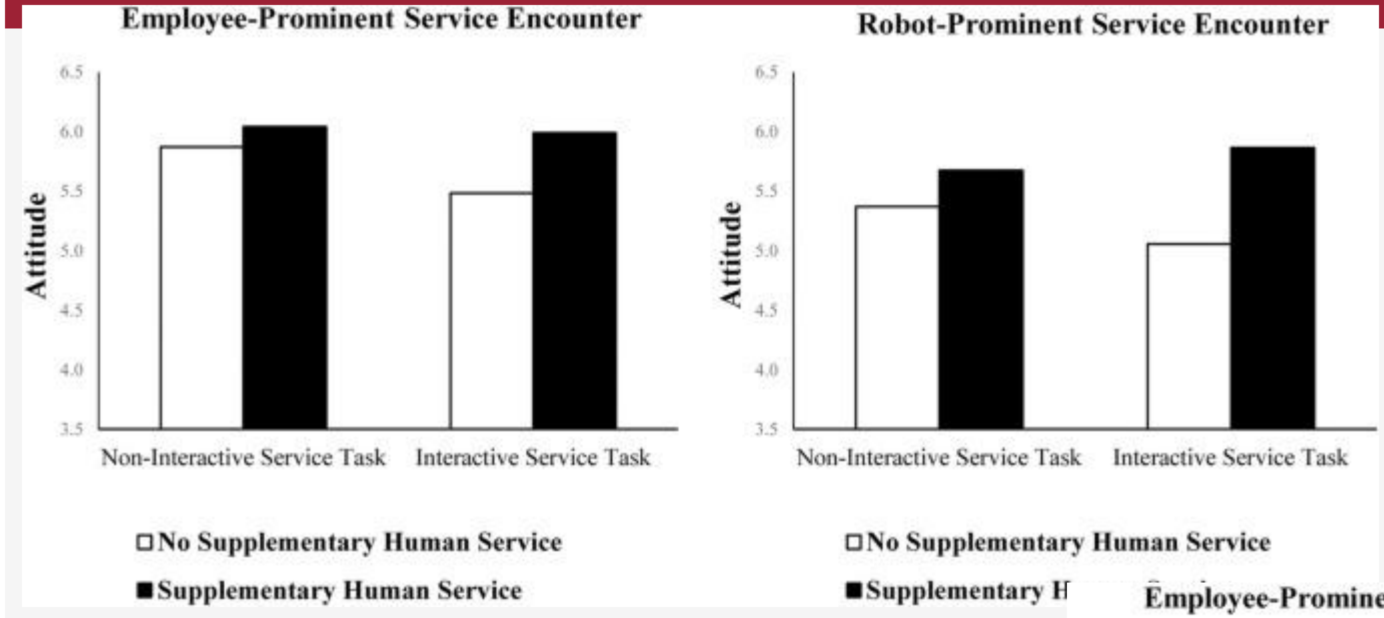
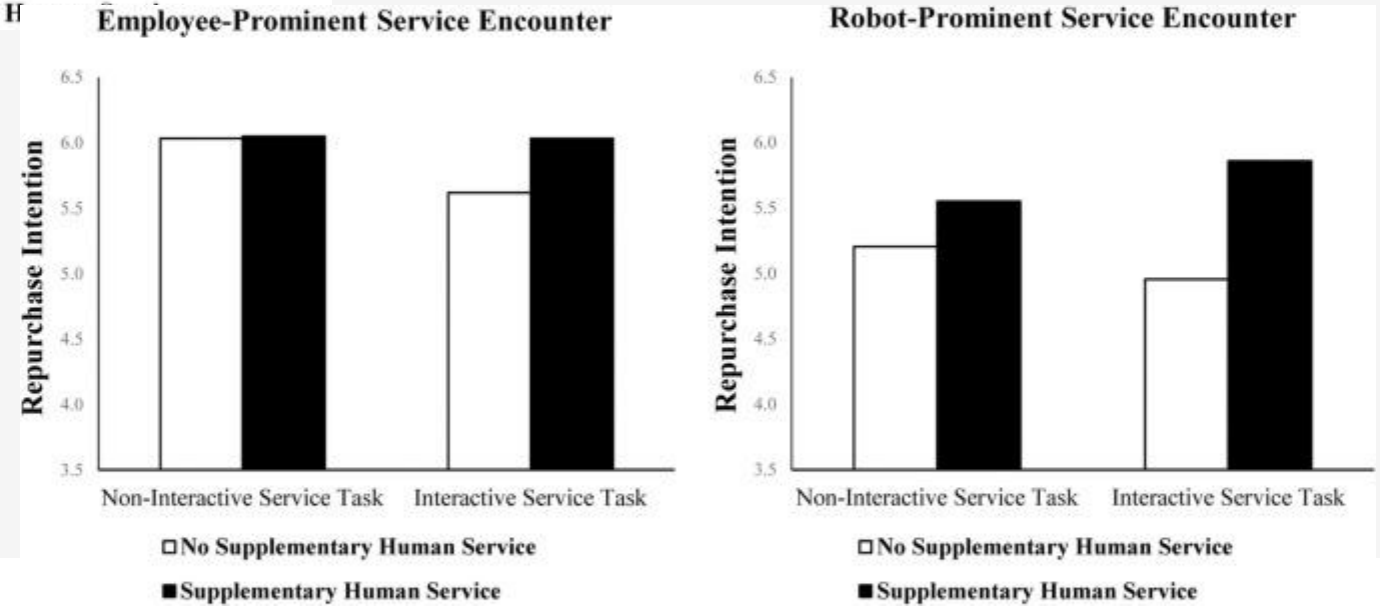


The presence (vs. not) of supplementary human service (in the form of managerial follow-up) could lead to stronger attitude and repurchase intention towards a service business in robot-prominent service encounters where robots were programmed to complete interactive service tasks but not when programmed to complete non-interactive service tasks (H1 and H2 supported).



Other popular areas of studies

- Tourism demand forecasting and revenue management
- Tourist spatial trajectory mining and itinerary recommendation
- Emotion and sentiment mining of service experience
- Service failure prediction and remedy

Future research

- Four research priorities are suggested: designing beneficial AI, facilitating adoption, assessing the impacts of intelligent automation, and creating a sustainable future with artificial intelligence (Iis, 2020).
- Dictionary specific to the tourism and hospitality context.
- Field experiment on AI applications.

Contact

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