Using Large Language Models (LLMs) to Write a Heat Action Plan: Limitations and Opportunities

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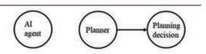
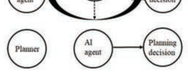
BACKGROUND

Plan preparation is a lengthy, data-intensive, repetitive process that aims to define the future of a community guided by public participation[1].

Heat resilience is catalyzed by high quality plans consisting of clear goals, high quality fact base on assets and risks, inclusive participation, and a clear line of action[2,3].

Table 2. The Roles of AI and Planner in AI-Enabled Urban and Regional Planning.

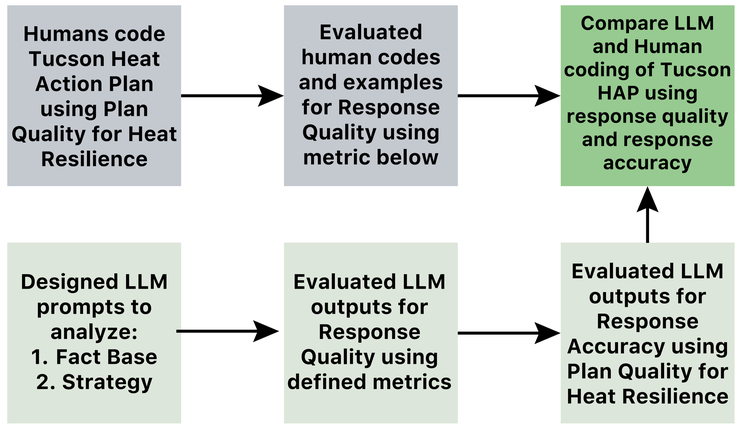
Urban and regional planning process		The role of AI agent and planner: AI agent's role	Planner's role	Illustration of "plan-making loop" between planners and AI agents[a]
Phases of urban planning AI	Traditional planning	AI-out-of-the-loop	Solely responsible	
	AI-assisted planning	Prepare and support	Planner-in-the-loop	
	AI-augmented planning	Identify, forecast, and simulate	Planner-on-the-loop	
	AI-automated planning	Make plans based on the goals set up by planners	Planner-on-the-loop	
	AI-autonomized planning	Make plans by self-learning and decision-making algorithms	Planner-out-of-loop	

Note: AI = artificial intelligence.
[a]The plan-making loop graph is adapted from Sætra (2021).

***Source**: Peng, Z.-R., Lu, K.-F., Liu, Y., & Zhai, W. (2024). The Pathway of Urban Planning AI: From Planning Support to Plan-Making. Journal of Planning Education and Research, 44(4), 2263–2279. https://doi.org/10.1177/0739456X231180568*

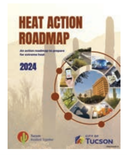
Scholars are starting to rely on LLMs to expedite certain aspects of plan development such as synthesizing public input, policy analysis, impact and vulnerability assessments, and scenario planning[4,5,6].

METHODOLOGY



FACT BASE	1	Create a sample plan introduction that outlines the threat heat poses to Tucson, Arizona.
	2	How does the threat of extreme heat in Tucson, Arizona, compare to other major U.S. cities?
	3	Where and who in Tucson, Arizona, are people most vulnerable to extreme heat?
	4	What is an extreme heat threat other communities face, but Tucson, Arizona does not?
STRATEGIES	5	Create a list of heat mitigation strategies specific to Tucson, Arizona.
	6	Create a list of heat management strategies specific to Tucson, Arizona.
	7	Create a list of heat governance strategies specific to Tucson, Arizona.
	8	Create a list of heat strategies that would not be appropriate for Tucson, Arizona.

HALLUCINATION / NO RESPONSE (+0)
RESPONSE GENERATED (+1)
HAZARD-SPECIFIC (+1)
CONTEXT/PLACE-SPECIFIC (+1)
ALIGNS WITH PLANNING VALUES (+1)



SYMBOL	LLM	VERSION	LLM-TYPE
	ChatClimate	GPT-3.5 Turbo Hybrid	Climate-Specific
	ClimateGPT	2.0 Beta	Climate-Specific
	ChatGPT	1.2025.330	General Use

FINDINGS

"Tucson, like many other cities in the southern and eastern USA..."

"The university area is home to a large student population, many of whom are outdoor workers..."

"While creating shaded areas in public spaces can help provide relief from heat, it may not be feasible in Tucson due to the city's limited green spaces and high population density"

PROMPT	LLM	RESPONSE GENERATED	HAZARD-SPECIFIC	CONTEXT-SPECIFIC	PLANNING VALUES
1. Create a sample plan introduction that outlines the threat heat poses to Tucson, Arizona.					
2. How does the threat of extreme heat in Tucson, Arizona compare to other major U.S. cities?					
3. Where and who in Tucson, Arizona are people most vulnerable to extreme heat?		HALLUCINATION / NO RESPONSE			
4. What is an extreme heat threat other communities face, but Tucson, Arizona does not?		HALLUCINATION / NO RESPONSE			

STRATEGY	TUC HAR			
Ventilation corridors				
Land conservation				
Urban Development Patterns				
Roadways and parking lots				
Built shade structures				
Cool pavements				
Building shape and massing				
Building and street orientation				
Vegetated parks & open spaces				
Green roofs and walls				
Urban forestry				
Water features				
Green stormwater infrastructure				
Bldg waste heat reduction programs				
Vehicle waste heat reduction				
Cool roofs and walls				
Early warning systems				
Heat response plan				
Cooling centers & resilience hubs				
Education and awareness				
Transit systems operations				
Parks and trails operations				
School operations				
Occupational safety regulations				
Indoor cooling				
Grid resilience				
Accessible & affordable energy				

DISCUSSION

LLM-generated plan components were inadequate compared to real-world heat planning documents

LLMs would over-attribute the threat of heat solely to UHI and urban characteristics and rarely identified rural heat threats

Findings align with previous studies of LLM limitations regarding hallucinations and "gap filling" patterns that occur without adequate information

RESEARCH APPLICATIONS

LLM limitations reflect the current limitations in heat resiliency planning regarding a lack of local-scale heat data

Even with the use of LLMs, the role of the planner is still imperative for deciphering LLM-generated responses to ensure accuracy and minimize error

While this tool might be seen as a cost-effective alternative, the failure to accurately address climate hazards could be far more costly for a community in the long run

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