AI & SOCIETY (2023) 38:1135–1150
https://doi.org/10.1007/s00146-022-01450-x

ORIGINAL ARTICLE

Artificial intelligence in local governments: perceptions of city managers on prospects, constraints and choices

Tan Yigitcanlar[1] · **Duzgun Agdas**[2] · **Kenan Degirmenci**[3]

Received: 29 May 2021 / Accepted: 6 April 2022 / Published online: 3 May 2022

Abstract

Highly sophisticated capabilities of artificial intelligence (AI) have skyrocketed its popularity across many industry sectors globally. The public sector is one of these. Many cities around the world are trying to position themselves as leaders of urban innovation through the development and deployment of AI systems. Likewise, increasing numbers of local government agencies are attempting to utilise AI technologies in their operations to deliver policy and generate efficiencies in highly uncertain and complex urban environments. While the popularity of AI is on the rise in urban policy circles, there is limited understanding and lack of empirical studies on the city manager perceptions concerning urban AI systems. Bridging this gap is the rationale of this study. The methodological approach adopted in this study is twofold. First, the study collects data through semi-structured interviews with city managers from Australia and the US. Then, the study analyses the data using the summative content analysis technique with two data analysis software. The analysis identifies the following themes and generates insights into local government services: AI adoption areas, cautionary areas, challenges, effects, impacts, knowledge basis, plans, preparedness, roadblocks, technologies, deployment timeframes, and usefulness. The study findings inform city managers in their efforts to deploy AI in their local government operations, and offer directions for prospective research.

Keywords Artificial intelligence (AI) · Urban AI · Local government AI · Technology adoption · Technology perception · Local government · City manager

1 Introduction and background

Rapid technological advancements, particularly recent developments in disruptive urban technologies, have provided novel opportunities for tackling increasing complexities and associated problems of our cities (Batty 2020; D'Amico et al. 2020; Regona et al. 2022a). Artificial intelligence (AI) is a disruptive technology of our time with significant implications on cities and how local government services are planned and delivered (Margetts and Dorobantu 2019; Mikalef et al. 2019). In simple terms, AI is a collection of interrelated technologies and systems that impersonate the cognitive functions of the human mind for solving problems, performing tasks, making recommendations and decisions without any or with limited explicit guidance from humans (Cugurullo 2020; Yigitcanlar and Cugurullo 2020; Xiang et al. 2021).

Recently, many nations have started to implement AI throughout all levels of governments (Androutsopoulou et al. 2019; De Sousa et al. 2019; Wu et al. 2020). For instance, in the US and UK, federal, state and local government agencies have begun to adopt a variety of AI solutions to enhance service delivery (Mikhaylov et al. 2018; Desouza et al. 2020a, b; Vogl et al. 2020). Similarly in Australia, the three-tier government use of AI ranges from border security to public safety, from predicting and managing traffic congestion to

✉ Tan Yigitcanlar
tan.yigitcanlar@qut.edu.au

Duzgun Agdas
duzgun.agdas@qut.edu.au

Kenan Degirmenci
kenan.degirmenci@qut.edu.au

1 Faculty of Engineering, School of Architecture and Built Environment, Queensland University of Technology, 2 George Street, Brisbane, QLD 4000, Australia

2 Faculty of Engineering, School of Civil and Environmental Engineering, Queensland University of Technology, 2 George Street, Brisbane, QLD 4000, Australia

3 Faculty of Science, School of Information Systems, Queensland University of Technology, 2 George Street, Brisbane, QLD 4000, Australia

environmental monitoring and protection, from chatbots for customer services to tax services and debt calculation, and many other areas (Williams 2019; Yigitcanlar et al. 2020c).

Local governments have been also deploying AI systems to improve efficiencies in different aspects of the city (Kankanhalli et al. 2019; Meng and Cheng 2020). In the context of cities, AI is the engine of automated algorithmic decisions that generate various efficiencies in the complex and complicated local government services and operations (Soe and Drechsler 2018; Ortega-Fernández et al. 2020; Yigitcanlar et al. 2020a). Managing city assets with structural health monitoring, energy infrastructure fault detection and diagnosis, accessible customer service with chatbots, and automated transportation with autonomous shuttle busses are among the many examples of how AI is being utilised in the local government context (Faisal et al. 2019; Zhao et al. 2019; Wang et al. 2020; Bertino et al. 2021; Yigitcanlar et al. 2019; Dennis et al. 2021).

Many of these AI systems are utilised in the context of smart city initiatives, where local government implements digital data and technologies to deploy efficiencies to boost economic developments, enhancing the quality of life and improving the sustainability of the city (Allam and Dhunny 2019; Yigitcanlar et al. 2020b). The smart city movement pushed the popularity of AI in urban policy circles (Yigitcanlar and Kamruzzaman 2019). This is particularly due to the opportunities AI-based automated decision-making offers for urban management in the context of smart cities (Graaf 2018; Zambonelli et al. 2018; Engin et al. 2020). As Kandt and Batty (2021, p.8) stated, "although it remains uncertain how the practice of AI will influence the way we might plan cities, social science critiques demonstrate that—if data-driven urban policy is enacted through instrumental rationality—automated 'software-sorting' will become fundamental to organising cities".

In this regard, opportunities and challenges of AI adoption in the public sector, particularly in local governments, have been a subject of scholarly investigation (Susar and Aquaro 2019; Wirtz et al. 2019; Campion et al. 2020). This issue is important particularly from two interconnected streams of research and development. The first one is smart cities and the second is urban governance. In recent years, the literature on both smart cities and urban governance has paid special attention to the opportunities and constraints of AI (Batty 2018; Golubchikov and Thornbush 2020; Jiang et al. 2020; Leon and Rosen 2020; Nikitas et al. 2020; Zhu 2021).

While the opportunities and constraints of algorithmic decision-making with AI have been a trending subject of scholarly urban studies literature (Wu and Silva 2010; Newell and Marabelli 2015; Kitchin 2017; Yigitcanlar et al. 2021a), there are only a few academic studies focused on the perceptions on automated decision-making concerning cities by AI (Cui and Wu 2019; Kassens-Noor et al. 2021). These studies mostly concentrated on public perceptions (Yigitcanlar et al. 2020c; Araujo et al. 2020; Kankanamge et al. 2021; Schiff et al. 2021) or the perceptions of the stakeholders from a specific sector, most commonly health (Sun and Medaglia 2019; Lai et al. 2020), or data sources and the analytical techniques (including AI) that local governments use (Vogl et al. 2020; Watson and Ryan, 2020). To the best of our knowledge, there is no clear understanding or thorough empirical studies on city manager perceptions concerning urban AI systems. Research on the topic however has just started to emerge (Luusua and Ylipulli, 2021).

Given this background, addressing the knowledge gap in the literature on city manager perceptions concerning urban AI systems is the *raison d'etre* of this study. This paper aims to consolidate our understanding of the perceptions of city managers on AI systems in the context of local government services and operations. We conducted interviews with 14 city managers—from six cities in Australia and two in the US with strong smart city and AI agendas. The collected interview data was subjected to both qualitative and quantitative content analyses. Qualitative content analysis was conducted with Nvivo software, and the quantitative content analysis, also known as lexicon analysis, was conducted with Leximancer software.

Following this introduction, Sect. 2 of the paper presents the methodological approach and research design, Sect. 3 reveals the results of the analysis, Sect. 4 discusses the generated findings and insights, and Sect. 5 concludes the paper by underlining the key contributions and implications of the study.

2 Research design

This paper concentrates on addressing the research question of 'how do city managers perceive AI systems in the context of local government services and operations?' As the definition of city manager, we adopted the following: A city manager is an officially appointed administrative manager in charge of either the entire or one or more specific portfolios/services/functions of a local government agency. In the most contemporary practice, especially in the smart city cases, these managers have extended knowledge and experience on the specific portfolio/service/function on top of the managerial/administrative skills required (Michelucci et al. 2016). In the case of our paper, city managers with AI knowledge and experience are targeted.

The study adopts qualitative interviews as the primary technique of the data collection. The rationale for the selection of the method is that "qualitative interviews generate a new insight into the investigated phenomenon as they allow the respondents to reflect and reason on a variety of subjects in a different way" (Judger 2016, p.2).

As for the methodological approach, semi-structured interview-based thematic analyses approach was employed using appropriate software packages. We used Leximancer v4.5 and Nvivo 12 to analyse the interviews both qualitatively and quantitatively. Thematic analysis is the most commonly used approach to analysing interviews (Maguire and Delahunt 2017). To conduct such analysis, data was collected through semi-structured interviews with city managers that have experience with AI—either exploring, experimenting, formalising, optimising or transforming AI utilisation in their city. In conducting this research, we followed the research ethics guidelines and an ethics approval was obtained from Queensland University of Technology's Human Research Ethics Committee. As part of the ethics procedure, before the interview took place, a consent form was completed by the interviewees.

To recruit participants to the study, 109 city managers, from Australia and the US, were contacted through emails and LinkedIn messages, also the snowball method was used to contact another 23 potential participants—in total 132 city managers were invited to participate in the study. The initial list of targeted city managers ($n = 109$) was formed with help from the academic and professional contacts of the research team.

Eligibility criteria for the interviewees were: (a) Holding a managerial position in a local government agency at least for five years in Australia or the US; (b) Having a sound understanding and experience with technologies relevant to local government and urban operations and services, and; (c) Having a reasonably good understanding and experience with AI systems and technologies. From the invited 132 city managers, 14 participated in the study (with about 10.6% participation rate), 11 of whom were from Australia and three were from the US. While the participation rate seems to be low (10.6%), we have secured adequate number of participants to the study (see Pancholi et al. 2019). Table 1 lists the salient characteristics of the study participants/ interviewees.

All 14 interviews were conducted via Zoom or Microsoft Teams, due to the pandemic restrictions, between August

Table 1 Salient characteristics of study participants

Interviewee	Local government	Position	Experience with urban technologies (years)	Experience with local governments (years)	Experience with AI systems (level)
Interviewee #1	Brisbane City Council, QLD, Australia	Information Architecture and Security Manager	30	20	High
Interviewee #2	Brisbane City Council, QLD, Australia	Innovation and Planning Manager	15	20	High
Interviewee #3	Logan City Council, QLD, Australia	Environmental Information Systems Manager	10	5	Reasonably high
Interviewee #4	Logan City Council, QLD, Australia	Innovation and City Transformation Manager	5	10	High
Interviewee #5	Moreton Bay Regional Council, QLD, Australia	Assets Management Department Director	5	15	Reasonably high
Interviewee #6	Moreton Bay Regional Council, QLD, Australia	Chief Digital Officer	10	10	High
Interviewee #7	Redland City Council, QLD, Australia	Governance Services Manager	10	30	High
Interviewee #8	Redland City Council, QLD, Australia	Business Innovation and Development Manager	10	10	Reasonably high
Interviewee #9	Sunshine Coast City Council, QLD, Australia	Head of Information Technology Department	20	20	High
Interviewee #10	Sunshine Coast City Council, QLD, Australia	Smart City Program Director	15	20	High
Interviewee #11	Ipswich City Council, QLD, Australia	Smart City Program Director	10	20	High
Interviewee #12	Pearland City Council, TX, USA	City Administration Manager	5	30	Reasonably high
Interviewee #13	Pearland City Council, TX, USA	City Budget Manager	5	10	Reasonably high
Interviewee #14	Raleigh City Council, NC, USA	City Manager	5	20	High

2020 and October 2020. The interviews were limited to 60 min to avoid interviewee fatigue. The duration of each interview ranged between 30 and 60 min. Interviews were digitally recorded and then manually transcribed into text. For the semi-structured interviews, 16 questions listed in Table 2 were used as conversation starters, and where appropriate, other impromptu questions were directed. All interviews also included a final question on whether the interviewee wanted to add, comment or elaborate any other relevant issues.

Data collected from the city managers were subjected to a thorough thematic analysis. For such analysis, a summative content analysis approach was employed (Hsieh and Shannon 2005). Before commencing the analysis, each transcribed interview text was carefully read and their suitability for the study and analysis was assessed. After all transcribed interview texts were found adequate for the analysis, the codes/nodes of the analysis were identified. An initial lexicon analysis was conducted with the Leximancer v4.5 software. In total, 12 nodes and 74 sub-nodes were identified. These nodes included the following: AI adoption areas; AI cautionary areas; AI challenges; AI effects; AI impacts; AI knowledge basis; AI plans; AI preparedness; AI roadblocks; AI technologies; AI deployment timeframes; AI usefulness.

Data analysis was done using computer software—Leximancer v4.5 and Nvivo 12. They were used to conduct quantitative and qualitative content analyses, particularly to facilitate the analysis of the dataset and to reduce the risk of biased interpretation. Quantitative content analysis, or lexical analysis, discloses the most frequent issues/factors by word count in a descriptive manner; where the qualitative content analysis helps in generating insights into the identified issues/factors in an explanatory manner (Esmaeilpoorarabi et al. 2018). Table 3 presents the coding information of the interview data—i.e. nodes, sub-nodes and origin of data from the relevant interview question.

The interview data were collected from city managers' AI-related prospects, constraints and choices concerning six case cities from Australia and two from the US. The salient characteristics of these eight cities with smart city agendas are presented in Table 4. In a nutshell, all case cities are located in metropolitan regions. They are either a capital city or at a close proximity to the state capital. Besides Brisbane, all are smaller cities population-wise, and all have developed strong local smart city and AI strategies and/or agendas.

Table 2 Interview questions

No	Category	Question
Q1	Participants' backgrounds	Please tell us about your experience in local government management, such as how many years and which positions you have had at the local government level
Q2		Please tell us your experience with deploying, using or managing information and decision support systems at the local government level
Q3		Please tell us your experience with leading or contributing technological innovation initiatives at the local government level
Q4		Please tell us your knowledge on and experience with AI in the context of cities and local government services
Q5	Participants' general views on AI	When do you think AI will affect or reshape the future of local government services (including your local government), and why?
Q6		How do you think AI will affect or reshape the future of local government services, and why?
Q7		How useful is AI and how useful will it be (within the next 20 years) in supporting local governments to achieve desired outcomes, and why?
Q8		In which areas should AI be adopted in local government services, and why?
Q9		What are the reasons that make local governments approach to AI with caution, and why?
Q10		Do you think local governments are prepared (e.g. in terms of know-how, technology, finance, regulation, ethics) for AI adoption, and why?
Q11		What are the main roadblocks in AI adoption in local governments, and how can they be overcome?
Q12	Participants' specific views on AI deployment in their local government	How knowledgeable is your local government on AI and its potentials in transforming the city and its communities (e.g. in the delivery of public services, and so on)?
Q13		Which AI technologies, applications and systems are currently being considered by your local government, and how are they used?
Q14		What AI adoption challenges is your local government experiencing, and how are these challenges being addressed?
Q15		How are you evaluating the impact of deploying AI systems in your city and community?
Q16		What are your plans for future deployments of AI in your local government area?

Table 3 Coding of the interview data

Node	Sub-node	Relevant interview question
Adoption areas	Asset management, Automation, Buildings, Businesses, Communication and complaints, Data analytics, Enforcement, Maintenance work, Public services, Service delivery, Urban infrastructure, Waste management	Q8
Cautionary areas	Blackbox nature, Human interaction, Privacy and cybersecurity, Transparency	Q9
Challenges	Bias and inaccuracy, Culture, Ethics, Financial management, Innovation, Risk management, Staff redundancy, Unfamiliarity, Validation	Q14
Effects	Broder purpose of use, Drag behind some councils, Increased capacity, Increased expectations, Increased experimentations, Increased system maturity	Q6
Impacts	Bridging knowledge gap, Increased efficiency, Increased investment, Revenue generation	Q15
Knowledge basis	Broad, Intermediate, Limited	Q12
Plans	Data, Development, Engagement, Ethics, Management	Q16
Preparedness	Not ready and not focused, Not ready but focused, Ready	Q10
Roadblocks	Budget restrictions, Change management, Elderly population, Legal issues, Pace of implementation, Trust issues	Q11
Technologies	Machine learning, Deep learning, Natural language processing, Neural networks, Robotic process automation, Asset maintenance systems, Automated decision support, Autonomous vehicles, Chatbots, Data analytics, Identification systems, Innovation portals, Smart maps	Q13
Deployment timeframes	Long term (in 20 years), Mid-term (in 10 years), Short term (in 5 years)	Q5
Usefulness	Automating routine decisions, Creating efficiencies, Improving productivity, Managing repetitive tasks, processes and decisions, Minimising errors, Tackling complexity	Q7

Table 4 Salient characteristics of case cities

City	State	Country	State Capital	Metropolitan Location	Population	Smart City Strategy	AI Agenda
Brisbane	QLD	AUS	Yes	Yes	2,439,467	Yes	Yes
Logan	QLD	AUS	No	Yes	303,386	Yes	Yes
Moreton Bay	QLD	AUS	No	Yes	425,302	Yes	Yes
Redland	QLD	AUS	No	Yes	160,331	Yes	Yes
Sunshine Coast	QLD	AUS	No	Yes	336,482	Yes	Yes
Ipswich	QLD	AUS	No	Yes	229,845	Yes	Yes
Pearland	TX	USA	No	Yes	122,078	Yes	Yes
Raleigh	NC	USA	Yes	Yes	464,485	Yes	Yes

3 Results

3.1 Quantitative content analysis

The interview data were explored thoroughly with quantitative content analysis using NVivo in a descriptive manner. First, a word cloud was prepared to visually present the word frequencies of the transcribed 14 interview texts—the higher the frequency is the larger the word appears in Fig. 1a. Additionally, a separate word cloud for the coding references was prepared and presented in Fig. 1b. Second, frequencies of the nodes and sub-nodes were calculated. Table 5 lists the nodes, sub-nodes, number of interviews mentioning the sub-nodes, and frequency of the sub-nodes. All listed sub-nodes of the AI 'usefulness' node were touched on in all interviews ($n=14$), and AI 'challenges', 'technologies' and 'roadblocks' and 'plans' nodes were revealed during the interviews of 13 interviewees (out of 14). The sub-nodes of the 'adoption areas' ($n=76$), 'challenges' ($n=67$), 'technologies' ($n=47$) and 'roadblocks' ($n=42$) nodes were the most frequently mentioned ones across all sub-nodes—followed by 'plans' (n = 31) and 'cautionary areas' ($n=30$). The sub-nodes of the AI 'usefulness' and 'cautionary areas' nodes were touched on by 11 interviewees. The sub-nodes of 'preparedness' ($n=26$) and 'effects' ($n=25$) nodes were covered by 10 interviewees. This was followed by the sub-nodes of the AI 'knowledge', 'impacts' and 'timeframes' nodes were covered by 7, 5, 6 interviewees, and mentioned 11, 11 and 8 times, respectively.

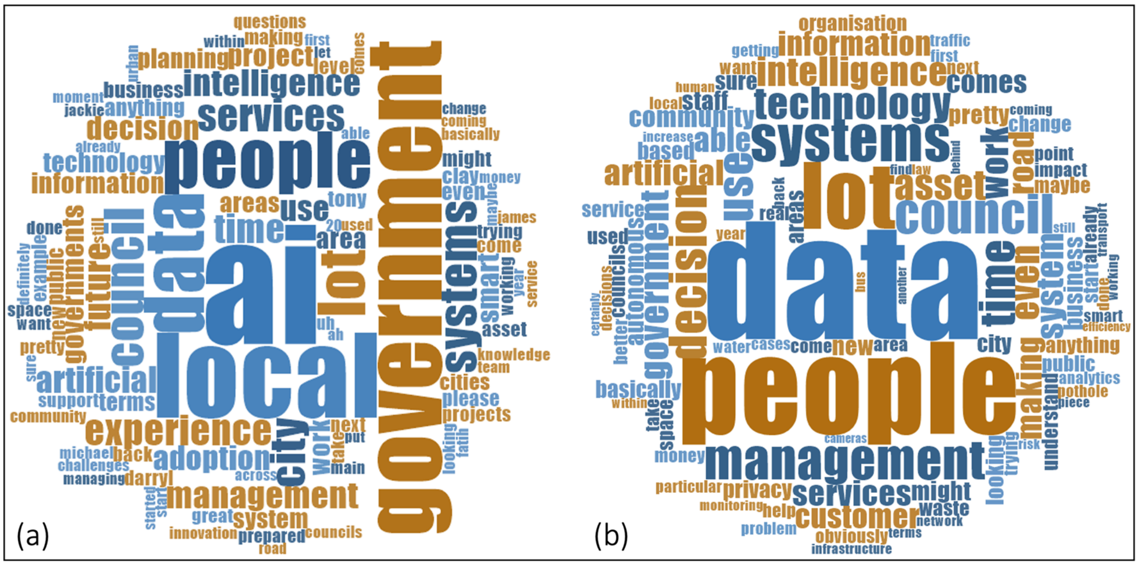

Fig. 1 **a** Word cloud of interview texts; **b** Word cloud of coding references

Table 5 Nodes, sub-nodes and mention frequencies

Node	Sub-node	Sub-nodes mentioned by interviewees	Frequency of sub-nodes
Adoption areas	Asset management, Automation, Buildings, Businesses, Communication and complaints, Data analytics, Enforcement, Maintenance work, Public services, Service delivery, Urban infrastructure, Waste management	14	76
Cautionary areas	Blackbox nature, Human interaction, Privacy and cybersecurity, Transparency	11	30
Challenges	Bias and inaccuracy, Culture, Ethics, Financial management, Innovation, Risk management, Staff redundancy, Unfamiliarity, Validation	13	67
Effects	Broder purpose of use, Drag behind some councils, Increased capacity, Increased expectations, Increased experimentations, Increased system maturity	10	25
Impacts	Bridging knowledge gap, Increased efficiency, Increased investment, Revenue generation	5	11
Knowledge basis	Broad, Intermediate, Limited	7	11
Plans	Data, Development, Engagement, Ethics, Management	13	31
Preparedness	Not ready and not focused, Not ready but focused, Ready	10	26
Roadblocks	Budget restrictions, Change management, Elderly population, Legal issues, Pace of implementation, Trust issues	13	42
Technologies	Machine learning, Deep learning, Natural language processing, Neural networks, Robotic process automation, Asset maintenance systems, Automated decision support, Autonomous vehicles, Chatbots, Data analytics, Identification systems, Innovation portals, Smart maps	13	47
Deployment timeframes	Long term (in 20 years), Mid-term (in 10 years), Short term (in 5 years)	6	8
Usefulness	Automating routine decisions, Creating efficiencies, Improving productivity, Managing repetitive tasks, processes and decisions, Minimising errors, Tackling complexity	11	32

Third, the hierarchy of nodes and sub-nodes are examined. The hierarchy chart of nodes and sub-nodes illustrated in Fig. 2 represents the interview data as aggregated, and helps us to see the big picture view. The size of each rectangular in the chart indicates the amount of coding references. The chart visualises the distribution patterns of the nodes and sub-nodes, in other words, it surfaces the prominent themes. As revealed in Fig. 2, the most prominent theme is the AI 'adoption areas'. This is followed by the second-tier themes of AI 'challenges', 'technologies', 'plans',

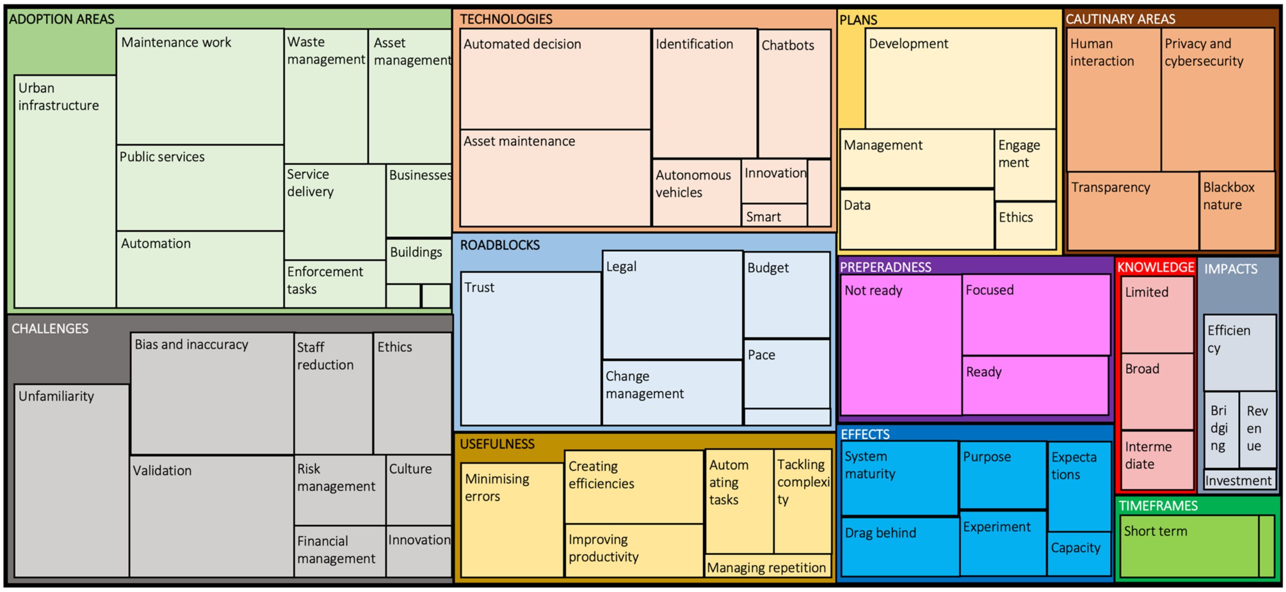

Fig. 2 Hierarchy of nodes and sub-nodes

'cautionary areas' and 'roadblocks'. The third-tier themes are AI 'preparedness', 'effects' and 'usefulness'. The least prominent themes are AI 'knowledge basis', 'impacts' and 'timeframes'.

3.2 Qualitative content analysis

The interview data were explored through a qualitative content analysis with NVivo in an explanatory manner. The results were presented under the areas that each corresponds to a specific node. These areas were clustered under the following three subsections: (a) Prospects; (b) Constraints, and; (c) Choices. Figure 3 illustrates city manager AI adoption prospects, constraints and choices drawn from the analysis. In addition to this, to further analyse the data qualitatively, a concept map was prepared by running a lexicon analysis with Leximancer. Figure 4 presents this concept map that identified and visualised the high-level concepts.

3.2.1 Artificial intelligence adoption prospects

The responses to the interview question 'Q13: Which AI technologies, applications and systems are currently being considered by your local government, and how are they used?' offered an understanding into the popular AI technologies, applications and systems in the context of local governments. Popular AI technologies, applications and systems in local government services and operations are identified by the interviewees under the following categories: (a) Machine learning; (b) Deep learning; (c) Natural language processing; (d) Neural networks; (e) Robotic process automation; (f) Asset maintenance systems; (g) Automated decision support; (h) Autonomous vehicles; (i) Chatbots; (j) Data analytics; (k) Identification systems; (l) Innovation portals, and; (m) Smart maps. Study participants also elaborated how their council utilises these AI technologies, applications and systems in their operations and services. For example, Interviewee #6 elaborated the use of AI for road maintenance as follows:

> *"In the Moreton Bay Regional Council, we have been working with our Arup and Brent divisions since the middle of 2018, about two years now, where we have got a camera connected to a Raspberry Pie with a GPS unit and modem that sits on the dashboard of a garbage truck, and it effectively just captures video as the truck drives along the road. That video is then transferred to some computers through the 4G/5G network, and those computers then run various algorithms over that footage to detect all sorts of different road defects—so potholes and cracking and all that kind of stuff".*

In another example, Interviewee #5 shared the utilisation of AI in the Moreton Bay Regional Council as follows:

> "We *are using our smart drones and machine learning to capture issues on the roofs of over 1,700 buildings. Besides, we are also building an underground drone to cruise in the 2,700 km stormwater pipe network to check connectivity, blockages and parts that need maintenance*".

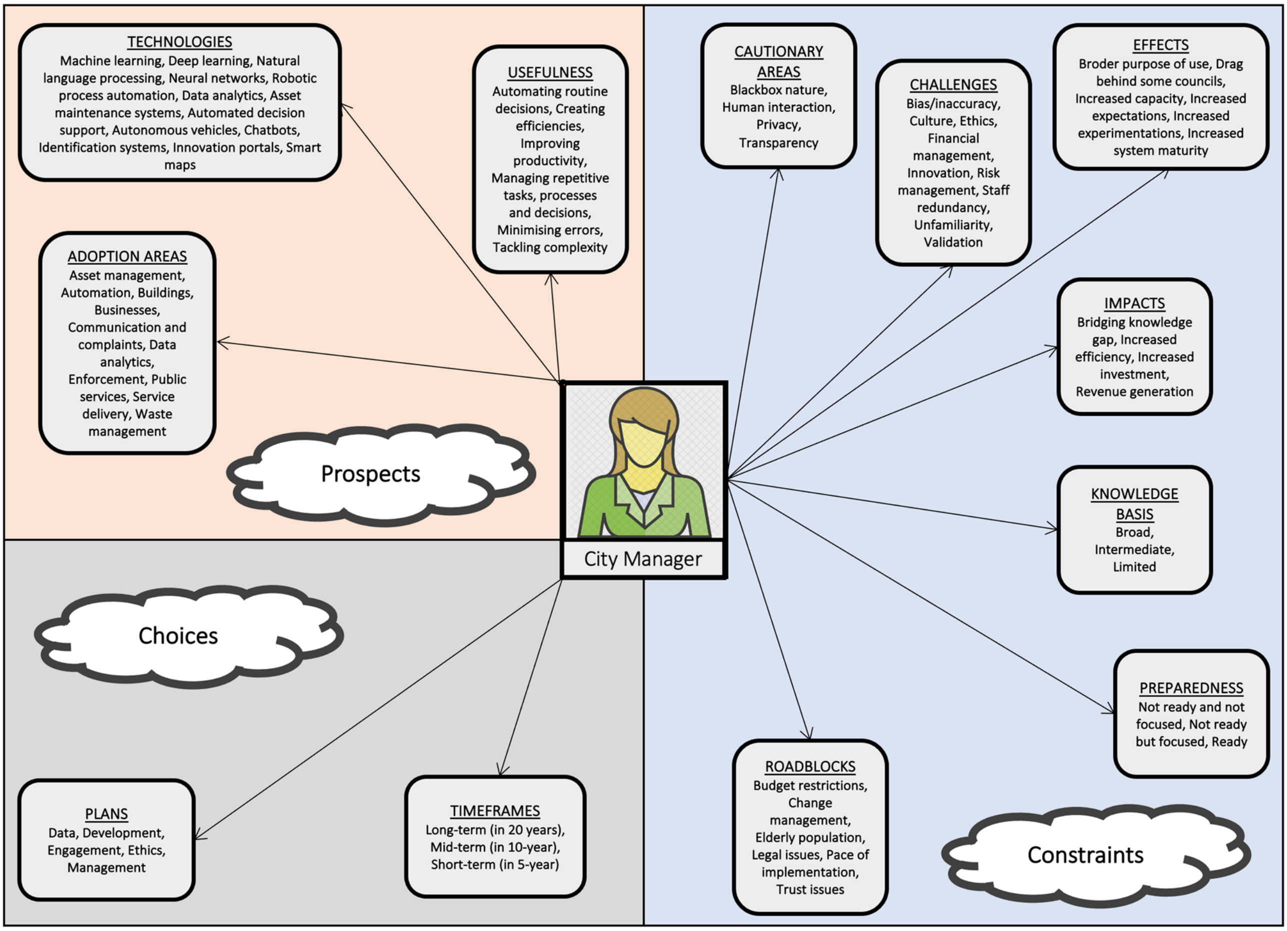

Fig. 3 City manager AI adoption prospects, constraints and choices

The responses to the interview question 'Q7: How useful is AI and how useful will it be (within the next 20 years) in supporting local governments to achieve desired outcomes, and why?' have generated insights into the AI technology usefulness. The main AI usefulness areas in the context of local government services and operations are identified by the interviewees as: (a) Automating routine decisions; (b) Creating efficiencies; (c) Improving productivity; (d) Managing repetitive tasks, processes and decisions; (e) Minimising errors, and; (f) Tackling complexity. Not to our surprise, the findings on the usefulness of AI to achieve the desired outcomes are also commonly associated to the usefulness of information and communication technologies (ICTs) in general. This is to say the interviewees see AI as a powerful ICT, and thus, there were no specific comments on what AI could add on top of ICTs. This underscores that interviewed city managers are highly knowledgeable, realistic, and hence, do not see AI as a mysterious miracle technology. After all, the healthy approach to AI is to see it as a means to an end rather than an end in itself (Dignum 2019; Yigitcanlar et al. 2021b). On that very topic, a variety of specific views were shared by the interviewees on the usefulness issue. For example, according to Interviewee #11:

> "*The council is interested in automating some of the routine tasks to create efficiencies and save time and resources in the long run…. We have realised that robotic parking was a good way to go because it opened up commercial opportunities for the rest of the land*".

As for Interviewee #2 the prospects of AI adoption for Brisbane City Council also included the following uses:

> "*We use AI-driven data analytics on all of the phone calls, letters, complaints, and everything the council receives from the residents and suppliers. This really helps us to understand what our performance was, are people happy or are there particular areas of council performance that people want to see improvements. These analytics process has been very useful to deliver better services… It is also very helpful for improving service productivity and minimising human errors*".

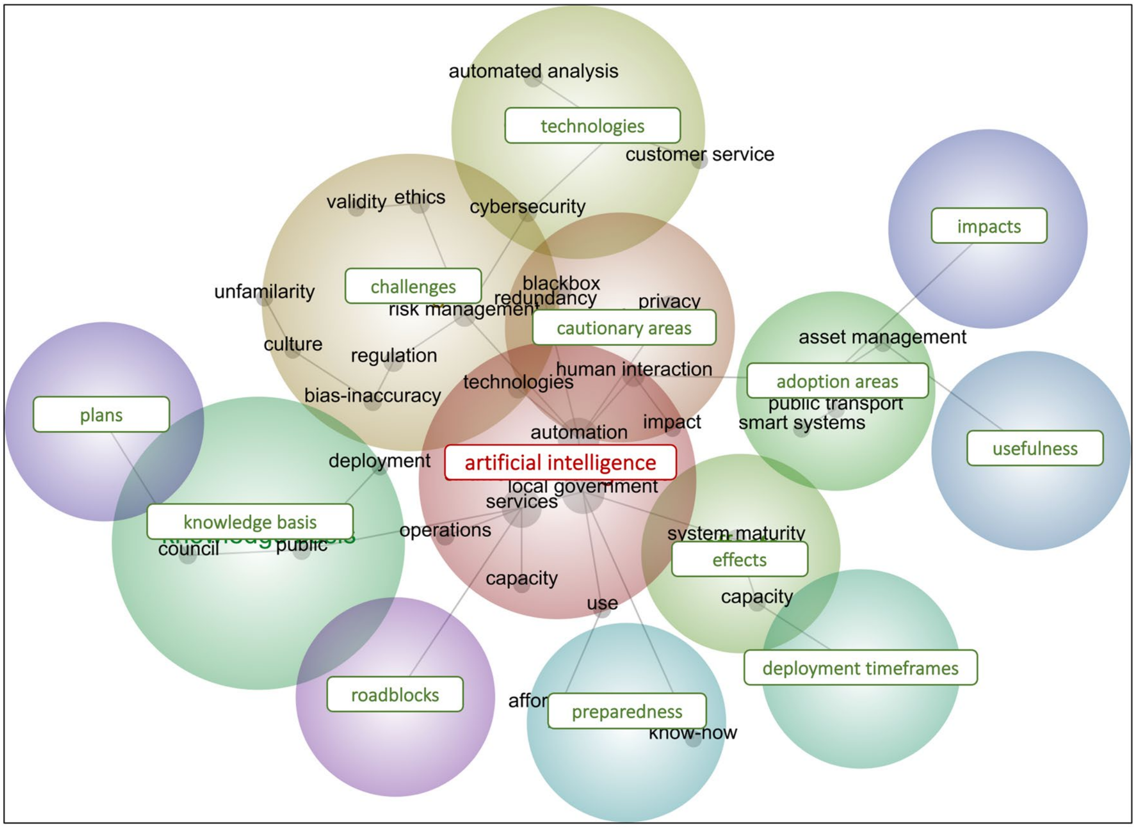

Fig. 4 Local government AI adoption concept map

Similarly, in the context of Logan City Council, Interviewee #4 disclosed the prospects of AI adoption as below:

> "*We conducted thorough sentiment and analyses over the council communication data to work out what is going on with customers. We have done a lot with the structured data as well, like emails coming in to the main council mailbox. It was extremely helpful to improve customer relationships and satisfaction… This gave us an opportunity to first better understand and then tackling relatively complex customer relations matters*".

Lastly, the responses to the interview question 'Q8: In which areas should AI be adopted in local government services, and why?' generated insights into AI adoption areas. The most common AI adoption areas in local government services and operations are identified by the interviewees as follows: (a) Asset management; (b) Service automation; (c) Building management; (d) Business efficiency; (e) Communication and complaints; (f) Data analytics; (g) Enforcement tasks; (h) Maintenance work; (i) Public service delivery; (j) Service efficiency; (k) Urban infrastructure, and; (l) Waste Management. This wide range of application areas indicate the high potential of AI infiltration in the near future in local governments to generate impact on the council operations and services. After commenting on the current and future AI adoption areas in general, some interviewees listed several AI applications and adoption areas in operation in their council. Interviewee #10 was one of them. After elaborating the AI use in the Sunshine Coast City Council, he emphasised that:

> "*We are at an early stage in the service automation journey, however our prior BIM (building information modelling) experience is guiding us in adopting suitable AI applications to automated decisions concerning buildings and infrastructures*".

Likewise, Interviewee #9 stated the followings for the prospects of AI adoption in the Sunshine Coast City Council:

> "*We have already got an autonomous lawnmower. So, at our stadium it goes and cuts the grass for us without needing a person to do that for us. This saves time and money*".

Moreover, the wide spectrum of AI potential in local governments highlights the potential of AI not being in one or two specific departments or tasks of the local government, but across the local government. Probably this is due to urban mobility being one of the top issues in our cities—e.g. concession, pollution, infrastructure cost, and other negative externalities—several interviewees mentioned autonomous vehicles as the leading AI solution for cities, particularly their contribution to public transport services. As stated by Interviewee #7:

> *"Autonomous shuttle buses are critical solutions for urban accessibility. We already have one trial going on here in Redlands (Redlands Coast Smart Mobility Trial), and getting more of these busses in service, let's say to and from Cleveland Rail Station or where the boats come in from Stradbroke Island, will help in solving the first and last mile connectivity"*.

3.2.2 Artificial intelligence adoption constraints

The responses to the interview question 'Q14: What AI adoption challenges is your local government experiencing, and how are these challenges being addressed?' revealed information on AI adoption challenges. The main AI adoption challenges in local government services and operations are identified by the interviewees as the following: (a) Bias and inaccuracy; (b) Workplace culture; (c) Ethics; (d) Financial management; (e) Innovation; (f) Risk management; (g) Staff redundancy; (h) Unfamiliarity, and; (i) Validation. The discussion around AI adoption challenges was a significant portion of the interview conversations. For instance, according to Interviewee #3:

> "*The biggest challenge around AI in local government is removing bias in training data for machine learning. Unless this obstacle is removed, AI systems will always generate inaccuracies. Hence, the risk is high for a public entity to adopt AI systems and deploy them in confidence at this instance*".

In addition to the listed issues, Interviewee #14 also brought up important challenges of skill training and accountability. She stated that:

> "*You have to explain to employees why you are using AI, you have to explain to residence how they are benefiting from AI, why it is important, council staff has to have the training and skills to be successful operating whatever AI application it is and then there has to be accountability if the AI system fails or generates undesired outcomes*".

The responses to the interview question 'Q11: What are the main roadblocks in AI adoption in local governments, and how can they be overcome?' disclosed new insights into AI adoption roadblocks. AI adoption roadblocks in local government services and operations are identified by the interviewees as: (a) Budget restrictions; (b) Change management; (c) Elderly population; (d) Legal issues; (e) Pace of implementation, and; (f) Trust issues. The issue of AI adoption roadblocks was another largely discussed issue in the interviews. One of the interesting issue was the concerns around user acceptance, such as elderly residents' reluctance. Concerning this matter, Interviewee #8 emphasised that:

> "*Adoption of new technology such as AI and adoption of change processes are not only challenging for local council personnel, but these are quite difficult and perplexing for the public, particularly for the senior citizens*".

Most of the interviewees touched on the regulation roadblock for wider AI adoption. For instance, Interviewee #5 underlined the legal side of AI by stating that:

> "*AI is fast moving, new, and full of exciting promises, however, there is the critical legal side of it. In my opinion, the lack of AI regulations is a big roadblock for local governments to thoroughly deploy AI systems. Just getting all the laws around it sorted is complicated*".

The responses to the interview question 'Q9: What are the reasons that make local governments approach to AI with caution, and why?' captured the understanding on AI cautionary areas. The most significant AI cautionary areas in local government services and operations are identified by the interviewees as follows: (a) Blackbox nature; (b) Human interaction; (c) Privacy and cybersecurity, and; (d) Transparency. Due to the listed issues, almost all interviewees indicated their reservations not only on AI, but also how it is deployed in local governments. For example, according to Interviewee #1:

> "*Government organisations, and certainly local councils such as Brisbane City Council, are very risk adverse organisations, therefore, we have got duty of care to our customers and rate payers, particularly on the matters of AI service user privacy and security. We are highly cautious at the absence of statutory AI ethics frameworks and legislations*".

The responses to the interview question 'Q6: How do you think AI will affect or reshape the future of local government services, and why?' unveailed the perspectives on AI adoption effects. AI adoption effects in local government services and operations are identified by the interviewees as: (a) Broder purpose of use; (b) Drag behind some councils; (c) Increased capacity; (d) Increased expectations; (e) Increased experimentations, and; (f) Increased system maturity. Along with the positive effects such as increased AI system adoption and trial, there are also some negative aspects that have been raised. For example, a couple of interviewees strongly warned us that in the case of AI systems not being frugal, many local councils with limited budgets will be left out of reaping the benefits of AI systems. Additionally, Interviewee #10 highlighted the issues around capacity and maturity of AI systems not actually meeting the expectations. In this regard, he stated that:

> *"We have had a robot, which we had to actually decommission it last year, because its associated code was not the latest generation, and it was not delivering what was expected from it. I am wondering when robotics will reach to the desired human-robot interaction level so we can use them with an ease of the mind"*.

The responses to the interview question 'Q10: Do you think local governments are prepared (e.g. in terms of know-how, technology, finance, regulation, ethics) for AI adoption, and why?' helped in developing an understanding on AI adoption preparedness. AI adoption preparedness in local government services and operations are identified by the interviewees as in the following scale: (a) Not ready and not focused; (b) Not ready but focused, and; (c) Ready. There was a consensus among the interviewees on almost all local governments in both county contexts not being ready and not having an AI focus. In general, most of the interviewees see their local government as not ready straightaway for comprehensive AI adoption, but ready for incremental adoption in some competency areas and focused to consider a more comprehensive approach in the near future. For instance, Interviewee #12 saw his own and many other local councils being far from prepared for the AI disruption. He elaborates the reason being:

> "*Not financially ready, mainly due to the financial crisis triggered by COVID. Nevertheless, these challenges make us think out of the box and force us to do things differently. Perhaps despite preparedness, this age of digital transformation will speed up the AI uptake at the local governments*".

Unsurprisingly, none of the interviewed city managers indicated preparedness of their local council for comprehensive AI system deployment, while many of them specified a not ready but focused status for a near future (within 5–10 years) holistic implementation.

The responses to the interview question 'Q12: How knowledgeable is your local government on AI and its potentials in transforming the city and its communities (e.g. in the delivery of public services, and so on)?' generated insights into AI knowledge basis. The required knowledge basis for the utilisation of AI in local government services and operations were identified by the interviewees in the scale of: (a) Broad; (b) Intermediate, and; (c) Limited. Among these three levels no interviewee disclosed all their council departments having a broad knowledge base. Most of the commentary was about all participant councils having a broad to intermediate knowledge base on AI in some departments, and limited to none in other departments. Interviewee #8 underpinned the reasons for limited to intermediate knowledge basis at the council. He strongly believed that:

> "*It is training, awareness and partnership with industry and academia that lacks in the councils to develop their skill and knowledge basis to be comfortably planning, deploying, and managing AI systems. As the technology continues to grow and becomes disruptive, councils should find ways to build their competencies on AI*".

Finally, the responses to the interview question 'Q15: How are you evaluating the impact of deploying AI systems in your city and community?' offered expansions into AI adoption impacts. AI adoption impacts in local government services and operations were identified by the interviewees as: (a) Widening knowledge gap; (b) Increased efficiency for those can afford; (c) Increased public investment and resulting taxation, and; (d) Revenue loss for councils missing out adoption. The majority of the interviewees have expected positive impacts of wider AI deployment in local government services and operations, but given that current ethical, bias and regulation issues are resolved. Even then, as highlighted by Interviewee #12:

> "*Local governments could have financial restraints due to the cost of AI systems, consultancy services, staff training/upskilling, and campaigns for residence acceptance of new AI-driven local services*".

Nonetheless, eventually AI systems could generate direct or indirect revenue for the local government to cover the cost of these investments. On these points, Interviewee #3 argued that:

> *"AI is going to create a major impact in the local government service particularly in increasing efficiency of service delivery in the council, but only those can afford and be prepared for it. The proper adoption will require large financial investment and knowledge skill up among the employees. Also, there might be some resistance in the council employees thinking that they will either lose their jobs in the near future to algorithmic decision systems or need to upskill themselves to be competitive"*.

3.2.3 Artificial Intelligence Adoption Choices

The responses to the interview question 'Q16: What are your plans for future deployments of AI in your local government area?' assisted us to understand AI adoption plans.

The main action areas concerning AI adoption plans in local government services and operations were identified by the interviewees as follows: (a) Data; (b) Development; (c) Engagement; (d) Ethics, and; (e) Management. While big data quality, AI ethics and system management, including human oversight on AI decisions, were the main conversation topics concerning the future AI plans, some interviewees also underlined the wider stakeholder engagement issue in AI plans. For example, Interviewee #13 raised the need for engaging citizens in the AI planning conversation. He advocated that:

> "*I think citizen overview, or a community where the citizens are a part of the planning committee, is essential. At the least, this creates transparency, fairness and responsiveness in planning for AI and convinces many residents that sensors are not the eyes and ears of a 'big brother', rather they are there for responsible uses benefiting them*".

Lastly, the responses to the interview question 'Q5: When do you think AI will affect or reshape the future of local government services (including your local government), and why?' disclosed likely AI adoption timeframes. The identified timeframes for AI impact or adoption were: (a) Long term (in 20 years); Mid-term (in 10 years), and; (c) Short term (in 5 years). For the AI adoption timeframes, most councils were targeting to experiment AI in some projects in the short term, and make more bold moves in the mid-term, and hoping most of the local government operations and services will benefit, at a degree, from AI in the long term. On that point, Interviewee #3 said that:

> "*The adoption is going to happen step by step, and I can see the signs of them already in Logan City Council. But it may take a bit of time, maybe not 20 years but not overnight either. Federal government regulations and state government initiatives at the local level will definitely speed up the adoption process in the local councils*".

4 Discussion and conclusion

4.1 Insights from the interviews

The analysis captured not only the views and perceptions of participating city managers (who are AI champions in their local councils), but also helped gain an understanding on the level of AI adoption capacity at some of the local governments that are already testing and trialling AI technologies, applications and systems in their council operation and urban service delivery. The insights generated from city manager interviews on AI adoption prospects, constraints and choices are discussed below.

The analysis of interviewed data revealed that city managers see a wide spectrum of AI adoption prospects. Interviewees mentioned many AI technologies—e.g. machine learning, deep learning, natural language processing, neural networks, and robotic process automation—which are of benefit to local government operations and service delivery. The benefits of these technologies in local governments are specified as creating efficiencies, tackling complexity, managing repetitive tasks, processes and decisions, automating routine decisions, minimising errors, and improving productivity. The areas that particularly benefit from these are identified as customer services, cybersecurity, policy and decision-making, environmental and development control, service and infrastructure management, and performance review. These are also acknowledged as the main AI adoption areas in local governments. Overall, interviewed city managers showed high optimism in the promise of AI to bring efficiencies for local governments.

Nevertheless, the analysis has disclosed that while city managers advocate for the prospects of AI adoption in local governments, they also have serious reservations, due to the substantial AI adoption constraints. These AI adoption constraints are stressed as data bias and resulting inaccuracies, lack of ethical frameworks and regulations, unaffordability of technological investment, automation risks, limited in-house know-how, and difficulties in validating autonomous decisions. The analysis of interviewees' views has determined a number of important AI adoption roadblocks. These are limited funds for adoption and deployment, difficulties in operational change management, lack of trust and resistance from the users, particularly senior citizens, uncertainties around legal issues, and limited local council personnel knowledge and experience. The issues that local councils are most cautionary when it gets to AI adoption are unveiled as the Blackbox nature of the technology, uncertainties around human interaction with AI systems, privacy and cybersecurity risks, and the lack of transparency in automated decisions of AI systems.

The analysis sheds light on how AI adoption would affect local governments as increasing operation and service capacities and user expectations. Along with this, the analysis also reveals the diversifying purpose of uses and experimentations in local councils. On the one hand, this generated knowledge will eventually lead councils to learn from and maturing their AI systems—particularly those councils that are at the forefront of experimenting with AI and have the necessary leadership and funding support. On the other hand, some councils will be left behind that cannot afford, prioritise, have the know-how or be unprepared for AI adoption. This is to say, the disruptive impacts of AI adoption are predicted as a widening knowledge gap between councils, lagging behind who cannot afford, as well as increasing public investment and taxation, and revenue loss for some councils.

In consideration of the AI adoption prospects and constraints, participating city managers raised their council's choices—i.e. plans and timeframes—for a sound AI deployment. The most common AI adoption plans in local government services and operations are concentrated on data, system and personnel capacity development, engagement with technology provides other government agencies and stakeholders, giving more attention to the ethical applications and consequences, and gaining knowledge and experience in competent AI system management.

While there are different AI experience and system maturity levels between participating local governments, most of them showed high interest in deploying AI systems holistically. Nevertheless, in consensus, all underlined the importance of a step-by-step approach spreading between the short and the mid-term—in other words, moving towards a holistic adoption within 10 years. The interviewees also emphasised the planning challenges ahead, particularly due the local political leadership being somewhat reluctant to wider decision automation.

In sum, this study presented the views of city managers on various aspects of local government AI adoption prospects, constraints and choices. Additionally, it revealed insights to inform city managers in their decisions and efforts in deploying AI in their local government operation and service delivery. Furthermore, the study generated directions for prospective research to further investigate local government AI adoption empirically.

4.2 Limitations of the study

The study at hand explored city manager perspectives on AI in the context of local government. Nonetheless, the following limitations should be noted when interpreting the results of the study: (a) Relatively small number ($n=14$) of city managers from a small pool of cities ($n=8$) have been interviewed and their views have been obtained. While the number is found adequate to generate valid insights (Malterud et al. 2016), representation of a larger managerial group would have been more ideal; (b) The participants of the study are only from two country contexts, inclusion of other country contexts would have provided perhaps richer and more context-driven results; (c) Even though the portfolios of the participant managers are quite broad, they still do not provide a full coverage of all local government operations and services; (d) Despite two software packages are employed to assist the analysis, there might be some unintentional bias originating from the interview question design, conducting interviews, selecting codes/nodes and interpreting the interview results, and; (e) Aforementioned limitations might cast a shadow on the generalisable findings presented. Our prospective study will aim to address these limitations.

4.3 Concluding remarks

Recently, there is a growth on the attempts to benefiting from AI technologies and systems in the context of public/urban services, particularly following the smart cities movement (Chen et al. 2020; Yigitcanlar et al. 2021b, c; Regona et al. 2022b). Whilst initially AI has been adopted at the federal or national government level, today we see the increasing use of AI in also state and local government levels (Engstrom et al. 2020; Kuziemski and Misuraca 2020). The adoption of AI at the local government level brings new challenges to the table mainly due to local government agencies, in general, having limited staff and resources and being more indirect interaction with the public members they serve (Agarwal 2018; Falco and Kleinhans 2018; Sun and Medaglia 2019). Nonetheless, there is limited investigations on how local governments adapt to technological changes and disruption, including AI (Matibag 2020; Wang et al. 2020), and particularly understanding city managers' perspectives on AI systems is an understudied area of research.

The study reported in this paper generated insights into how city managers perceive AI systems in the context of local government services and operations. One of the key insights was that even the city managers with experience in AI (some are AI champions—technology advocates that drive AI adoption in their organisations) being not so certain of the immediate holistic utilisation of AI in local governments. This finding is in line with Johnk et al.'s (2021) work investigating organisational AI readiness factors.

The hesitance to a holistic adoption of AI is due to the high contemporariness of AI technologies, applications and systems and reluctance of city administrations in making bold deployment decisions before the right conditions raised—such as regulations, affordability of the technology, best practice cases to learn from, wider public acceptance, growth of know-how, having more experimentation with incremental implementation, and so on—along with the other AI adoption challenges (Duan et al. 2019). Along with this for many local governments organisationally being not ready for change is a key factor (Johnk et al. 2021).

While many local councils choose to adopt a 'wait-and-see' approach (Bughin 2018; Walch 2020), the local governments of our participant city managers choose to undertake a 'trial-and-error' approach on an incremental level, rather than a holistic one (Desouza et al. 2020a, b; Wang et al. 2020). The shared experiences and views of study participants are of interest for other councils and managers to plan their moves in the AI adoption in their local government operations and services. This pioneering study captured the views and perceptions of city managers on AI adoption that is an under-investigated area of research. We believe this study only scratched the surface of AI in the local government context, and there is a need for further empirical investigations on this understudied topic.

Lastly, we conclude the paper by echoing Johnk et al.'s (2021, p.8), views on AI adoption; "AI's variety of adoption purposes requires organisations to create the necessary conditions, and introduce managerial practices for successful AI adoption… Differing from other digital technologies, AI can hardly be characterised as easy-to-use or easy-to-deploy… Specifically, AI adoption comprises technical (e.g. limited technology capabilities) and non-technical (e.g. lack of leadership support) challenges that arise before and during implementation".

Acknowledgements The authors thank the guest editors and two anonymous referees for their constructive comments. Research assistants', Emily Windle and Frederick Natanael, diligent work in data collection and thematic analysis tasks, and Kevin Desouza's support in linking the authors with the participants from the US are deeply appreciated. The authors are grateful to and cordially thank all 14 study participants for sharing their views and experiences, despite their hectic work schedule, and limited time availability.

Author contributions The first author undertook the conceptualisation, research design, data curation, formal analysis, and writing—original draft preparation—tasks. The second and third authors undertook the writing—review and editing—task.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions. This research was funded by the Australian Research Council Discovery Grant Scheme, grant number DP220101255.

Availability of data and materials Not applicable.

Code availability Not applicable.

Declarations

Conflict of interest The author declares no known competing financial interests or personal relationships that could have appeared to influence the study reported.

Ethics approval An ethical approval is obtained from Queensland University of Technology's Human Research Ethics Committee (approval no: 2000000257).

Consent to participate Interviewees provided their written consent to participate in the study and publication of their views by completing an interview consent form.

References

Agarwal PK (2018) Public administration challenges in the world of AI and bots. Public Adm Rev 78:917–921

Allam Z, Dhunny ZA (2019) On big data, artificial intelligence and smart cities. Cities 89:80–91

Androutsopoulou A, Karacapilidis N, Loukis E, Charalabidis Y (2019) Transforming the communication between citizens and government through AI-guided chatbots. Gov Inf Q 36:358–367

Araujo T, Helberger N, Kruikemeier S, De Vreese CH (2020) In AI we trust? Perceptions about automated decision-making by artificial intelligence. AI & Soc 35:611–623

Batty M (2018) Artificial intelligence and smart cities. Environment and Planning B: Urban Analytics and City Science https://doi.org/10.1177/2399808317751169

Batty M (2020) How disruptive are new urban technologies? Environment and Planning B: Urban Analytics and City Science https://doi.org/10.1177/2399808320902574

Bertino E, Jahanshahi MR, Singla A, Wu RT (2021) Intelligent IoT systems for civil infrastructure health monitoring: a research roadmap. Discover Internet of Things 1:1–11

Bughin J (2018) Wait and see could be a costly AI strategy. https://sloanreview.mit.edu/article/wait-and-see-could-be-a-costly-ai-strategy. Accessed 26 October 2021.

Campion A, Gasco-Hernandez M, Jankin Mikhaylov S, Esteve M (2020) Overcoming the challenges of collaboratively adopting artificial intelligence in the public sector. Soc Sci Comput Rev. https://doi.org/10.1177/0894439320979953

Chen T, Guo W, Gao X, Liang Z (2020) AI-based self-service technology in public service delivery: user experience and influencing factors. Gov Inf Q. https://doi.org/10.1016/j.giq.2020.101520

Cugurullo F (2020) Urban artificial intelligence: from automation to autonomy in the smart city. Front Sustain Cities 2:1–14

Cui D, Wu F (2019) The influence of media use on public perceptions of artificial intelligence in China: evidence from an online survey. Inf Dev. https://doi.org/10.1177/0266666919893411

D'Amico G, L'Abbate P, Liao W, Yigitcanlar T, Ioppolo G (2020) Understanding sensor cities: insights from technology giant company driven smart urbanism practices. Sensors 20:4391

De Sousa WG, De Melo ER, Bermejo PH, Farias RA, Gomes AO (2019) How and where is artificial intelligence in the public sector going? A literature review and research agenda. Gov Inf Q 36:101392

Dennis S, Paz A, Yigitcanlar T (2021) Perceptions and attitudes towards the deployment of autonomous and connected vehicles: insights from Las Vegas, Nevada. J Urban Technol 28:75–95

Desouza KC, Dawson GS, Chenok D (2020a) Designing, developing, and deploying artificial intelligence systems: lessons from and for the public sector. Bus Horiz 63:205–213

Yigitcanlar T, Desouza KC, Butler L, Roozkhosh F (2020b) Contributions and risks of artificial intelligence (AI) in building smarter cities: insights from a systematic review of the literature. Energies 13:1473

Dignum V (2019) Responsible artificial intelligence: how to develop and use AI in a responsible way. Springer Nature, Singapore.

Duan Y, Edwards JS, Dwivedi YK (2019) Artificial intelligence for decision making in the era of big data: evolution, challenges and research agenda. Int J Inf Manage 48:63–71
Engin Z, van Dijk J, Lan T, Longley PA, Treleaven P, Batty M, Penn A (2020) Data-driven urban management: mapping the landscape. J Urban Manag 9:140–150
Engstrom DF, Ho DE, Sharkey CM, Cuéllar MF (2020) Government by algorithm: artificial intelligence in federal administrative agencies. Public Law Research Paper No, NYU School of Law, pp 20–54
Esmaeilpoorarabi N, Yigitcanlar T, Guaralda M (2018) Place quality in innovation clusters: an empirical analysis of global best practices from Singapore, Helsinki, New York, and Sydney. Cities 74:156–168
Faisal A, Kamruzzaman M, Yigitcanlar T, Currie G (2019) Understanding autonomous vehicles: a systematic literature review on capability, impact, planning and policy. J Transp Land Use 12:45–72
Falco E, Kleinhans R (2018) Beyond technology: identifying local government challenges for using digital platforms for citizen engagement. Int J Inf Manage 40:17–20
Golubchikov O, Thornbush M (2020) Artificial intelligence and robotics in smart city strategies and planned smart development. Smart Citi 3:1133–1144
Graaf SV (2018) In Waze we trust: algorithmic governance of the public sphere. Media Commun 6:153–162
Hsieh HF, Shannon SE (2005) Three approaches to qualitative content analysis. Qual Health Res 15:1277–1288
Jiang H, Geertman S, Witte P (2020) A sociotechnical framework for smart urban governance: urban technological innovation and urban governance in the realm of smart cities. Int J E-Plann Res 9:1–19
Johnk J, Weißert M, Wyrtki K (2021) Ready or not, AI comes: an interview study of organizational AI readiness factors. Bus Inf Syst Eng 63:5–20
Judger N (2016) The thematic analysis of interview data: an approach used to examine the influence of the market on curricular provision in Mongolian higher education institutions. University of Leeds, Hillary Place Papers
Kandt J, Batty M (2021) Smart cities, big data and urban policy: towards urban analytics for the long run. Cities 109:102992
Kankanamge N, Yigitcanlar T, Goonetilleke A (2021) Public perceptions on artificial intelligence driven disaster management: evidence from Sydney, Melbourne and Brisbane. Telemat Informat 13:101729
Kankanhalli A, Charalabidis Y, Mellouli S (2019) IoT and AI for smart government: a research agenda. Gov Inf Q 36:304–309
Kassens-Noor E, Wilson M, Kotval-Karamchandani Z, Cai M, Decaminada T (2021) Living with autonomy: public perceptions of an AI-mediated future. J Plan Educ Res. https://doi.org/10.1177/0739456X20984529
Kitchin R (2017) Thinking critically about and researching algorithms. Inf Commun Soc 20:14–29
Kuziemski M, Misuraca G (2020) AI governance in the public sector: three tales from the frontiers of automated decision-making in democratic settings. Telecommun Policy 44:101976
Lai MC, Brian M, Mamzer MF (2020) Perceptions of artificial intelligence in healthcare: findings from a qualitative survey study among actors in France. J Transl Med 18:1–13
Leon LF, Rosen J (2020) Technology as ideology in urban governance. Ann Am Assoc Geogr 110:497–506
Luusua A Ylipulli J (2021) Nordic cities meet artificial intelligence: city officials' views on artificial intelligence and citizen data in Finland. Proceedings of the 10th International Conference on Communities & Technologies-Wicked Problems in the Age of Tech, pp. 51–60.
Maguire M, Delahunt B (2017) Doing a thematic analysis: a practical, step-by-step guide for learning and teaching scholars. All Ireland J Higher Educ 9:3351
Malterud K, Siersma VD, Guassora AD (2016) Sample size in qualitative interview studies: guided by information power. Qual Health Res 26:1753–1760
Margetts H, Dorobantu C (2019) Rethink government with AI. Nature 568:163–165
Matibag T (2020) Artificial intelligence for local governance. Urban Lawyer 50:415–435
Meng T, Cheng D (2020) Research on local government governance structure reform and function change based on artificial intelligence technology. Int J Wireless Mobile Comput 18:303–310
Michelucci FV, De Marco A, Tanda A (2016) Defining the role of the smart-city manager: an analysis of responsibilities and skills. J Urban Technol 23:23–42
Mikalef P Fjørtoft SO Torvatn HY (2019) Artificial intelligence in the public sector: a study of challenges and opportunities for Norwegian municipalities. Conference on e-Business, e-Services and e-Society, pp. 267–277.
Mikhaylov SJ, Esteve M, Campion A (2018) Artificial intelligence for the public sector: opportunities and challenges of cross-sector collaboration. Philosoph Transact Royal Soc 376:20170357
Newell S, Marabelli M (2015) Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification.' J Strateg Inf Syst 24:3–14
Nikitas A, Michalakopoulou K, Njoya ET, Karampatzakis D (2020) Artificial intelligence, transport and the smart city: definitions and dimensions of a new mobility era. Sustainability 12:2789
Ortega-Fernández A, Martín-Rojas R, García-Morales VJ (2020) Artificial intelligence in the urban environment: smart cities as models for developing innovation and sustainability. Sustainability 12:7860
Pancholi S, Yigitcanlar T, Guaralda M (2019) Place making for innovation and knowledge-intensive activities: The Australian experience. Technol Forecast Soc Chang 146:616–625
Regona M, Yigitcanlar T, Xia B, Li R (2022a) Artificial intelligent technologies for the construction industry: how are they perceived and utilized in Australia? J Open Innov 8:16
Regona M, Yigitcanlar T, Xia B, Li R (2022b) Opportunities and adoption challenges of AI in the construction industry: a PRISMA review. J Open Innov 8:45
Schiff DS, Schiff KJ, Pierson P (2021) Assessing public value failure in government adoption of artificial intelligence. Public Admin. https://doi.org/10.1111/padm.12742
Soe RM, Drechsler W (2018) Agile local governments: experimentation before implementation. Gov Inf Q 35:323–335
Sun TQ, Medaglia R (2019) Mapping the challenges of artificial intelligence in the public sector: evidence from public healthcare. Gov Inf Q 36:368–383
Susar D Aquaro V (2019) Artificial intelligence: opportunities and challenges for the public sector. 12th International Conference on Theory and Practice of Electronic Governance, pp. 418–426.
Vogl TM, Seidelin C, Ganesh B, Bright J (2020) Smart technology and the emergence of algorithmic bureaucracy: artificial intelligence in UK local authorities. Public Adm Rev 80:946–961
Walch K (2020). AI laws are coming. https://www.forbes.com/sites/cognitiveworld/2020/02/20/ai-laws-are-coming/?sh=67b59c98a2b4. Accessed 26 October 2021.
Wang Y, Zhang N, Zhao X (2020) Understanding the determinants in the different government AI adoption stages: evidence of local government chatbots in China. Soc Sci Comput Rev. https://doi.org/10.1177/0894439320980132
Watson RB, Ryan PJ (2020) Big data analytics in Australian local government. Smart Cities 3:657–675

Williams MA (2019) The artificial intelligence race: will Australia lead or lose? J Proc Royal Soc New South Wales 152:105–114

Wirtz BW, Weyerer JC, Geyer C (2019) Artificial intelligence and the public sector: applications and challenges. Int J Public Adm 42:596–615

Wu N, Silva EA (2010) Artificial intelligence solutions for urban land dynamics: a review. J Plan Lit 24:246–265

Wu F, Lu C, Zhu M, Chen H, Zhu J, Yu K, Pan Y (2020) Towards a new generation of artificial intelligence in China. Nat Mach Intellig 2:312–316

Xiang X, Li Q, Khan S, Khalaf OI (2021) Urban water resource management for sustainable environment planning using artificial intelligence techniques. Environ Impact Assess Rev 86:106515

Yigitcanlar T, Cugurullo F (2020) The sustainability of artificial intelligence: an urbanistic viewpoint from the lens of smart and sustainable cities. Sustainability 12:8548

Yigitcanlar T, Kamruzzaman M (2019) Smart cities and mobility: does the smartness of Australian cities lead to sustainable commuting patterns? J Urban Technol 26:21–46

Yigitcanlar T, Wilson M, Kamruzzaman M (2019) Disruptive impacts of automated driving systems on the built environment and land use: an urban planner's perspective. J Open Innov 5:24

Yigitcanlar T, Butler L, Windle E, Desouza KC, Mehmood R, Corchado J (2020a) Can building 'artificially intelligent cities' protect humanity from natural disasters, pandemics and other catastrophes? An Urban Scholar's Perspective. Sensors 20:2988

Yigitcanlar T, Kankanamge N, Regona M, Maldonado M, Rowan R, Ryu A, Desouza KC, Corchado J, Mehmood R, Li R (2020b) Artificial intelligence technologies and related urban planning and development concepts: how are they perceived and utilized in Australia? J Open Innov Technol Mark Complex 6:187

Yigitcanlar T, Corchado J, Mehmood R, Li R, Mossberger K, Desouza KC (2021a) Responsible urban innovation with local government artificial intelligence: a conceptual framework and research agenda. J Open Innov Technol Market Complex 7:71

Yigitcanlar T, Mehmood R, Corchado JM (2021b) Green artificial intelligence: towards an efficient, sustainable and equitable technology for smart cities and futures. Sustainability 13:8952

Yigitcanlar T, Kankanamge N, Vella K (2021c) How are smart city concepts and technologies perceived and utilized? A systematic geo-Twitter analysis of smart cities in Australia. J Urban Technol 28:135–154

Zambonelli F, Salim F, Loke SW, De Meuter W, Kanhere S (2018) Algorithmic governance in smart cities: the conundrum and the potential of pervasive computing solutions. IEEE Technol Soc Mag 37:80–87

Zhao Y, Li T, Zhang X, Zhang C (2019) Artificial intelligence-based fault detection and diagnosis methods for building energy systems: advantages, challenges and the future. Renew Sustain Energy Rev 109:85–101

Zhu W (2021) artificial intelligence and urban governance: risk conflict and strategy choice. Open J Soc Sci 9:250

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.