Oxford Commission on
AI & Good Governance

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Artificial Intelligence in Local Government:

Enabling Artificial Intelligence for Good Governance in UK Local Authorities

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EXECUTIVE SUMMARY

Local governments face increased challenges providing services to their communities, especially in light of austerity, shifting central government policies that impact local responsibilities, changing demographics, and diverse resident needs. UK local authorities are exploring the use of artificial intelligence (AI) to fully or partially automate tasks or support their frontline workers to deliver services more efficiently and effectively. While there have been a number of successful projects related to back-office automation, predictive analytics for decision support, or the use of chatbots for interactions with residents, little is known about the practical challenges that local authorities face in making these projects realities. This briefing note synthesizes academic, grey, and journalistic literature to identify the key practical challenges that local authorities face when collaborating with industry or striking out on their own.

Analysis based on this synthesis of the literature led to a set of findings indicating that local authorities are faced with three key challenges and three key enablers. In terms of challenges, local authorities need to both get their data in order and clearly define problems before seeking information technology (IT) solutions. The third challenge is when suppliers lack contextual knowledge about the local authority, its processes, its residents, and the way it carries out its services, which may require local authorities to take products that are not fit for purpose and modify them to align with their work. In terms of the three enablers, local authorities benefit from in-house capacity, opportunities for collaboration, and project transparency.

The findings suggest that some foundational governance arrangements need to be in place both locally and nationally before AI technologies can realise benefits for good governance. More specifically, this briefing note proposes that the following measures are necessary for the implementation of artificial intelligence for good governance in the UK:

- Minimum mandatory data standards and dedicated resources for the maintenance of data quality.
- Minimum mandatory guidance for problem definition and project progress monitoring.
- Minimum mandatory supplier standards and flexible procurement to avoid lock-in and align projects with local context.
- Dedicated resources to ensure that local authorities can be intelligent consumers and capable developers of AI.
- A formal mechanism for collaboration across all local authorities and with the third sector (e.g., universities and non-profit organisations).
- A platform to compile all relevant information about information technology projects in local authorities.

In what follows, this briefing note will present the context for AI in local authorities and then provide the rationale and greater detail for the recommendations summarised here.

1 INTRODUCTION

Local government is experimenting with AI applications. Movements to adopt these solutions have been stimulated by prolonged fiscal austerity, political pressure, and the hope that new technology will lead to sufficient efficiencies to make up for funding reductions.[1,2] While there have been many critiques of these technologies based on ethical, political, or social concerns,[3–5] and a number of high-profile failures have been reported in the media,[6] there are examples where AI tools appear to have become everyday parts of local authority operations.[7] This briefing note examines some potential factors that have been in operation in cases where the use of AI tools has persisted, in an effort to equip those hoping to pursue their own projects with insights into the key challenges and enablers that require their attention.

In what remains of the introduction, this briefing note will provide key contextual details. The subsequent section will outline the methodology and data sources before then undertaking a discussion of the findings. The findings are broken down into three key challenges (data quality, problem definition, and degree of supplier contextual knowledge) and three key enablers (in-house capacity, collaboration, and transparency and accountability). The conclusion recommends some foundational governance arrangements needed to address these challenges and enablers and help create AI applications that can support good governance.

Local Government Policy Context

There has been a growing use of AI by local governments in the UK over the past decade, influenced by demographic change, changing public expectations, the impact of austerity measures, and greater digitisation.

In addition to navigating demographic changes including population aging and population growth from international migration,[8,9] one of the most significant pressures facing local authorities has been the protracted period of austerity instigated by a reduction in grants from central government, starting in 2010.[10,11] This, combined with the continuing control maintained by the central government over local funding streams and policy priorities, has left local governments with less funding and continued constraints on how they can raise and spend their funds.[12,13] Figure 1 shows an overall decrease in local government spending: while funding for adult social care and children's services have remained relatively stable, spending on other services has declined.

Researchers at the Oxford Internet Institute have argued that "while a desire to preserve frontline staff, at the expense of back-office analytics staff, is understandable, these cuts may end up being counterproductive in the long term".[14,p.150] One local authority customer insights and engagement officer said that "Preserving key analytical skills in local authorities is a new challenge due, in part, to public sector cuts, which in turn degrades organisational memory".[15,p.30]

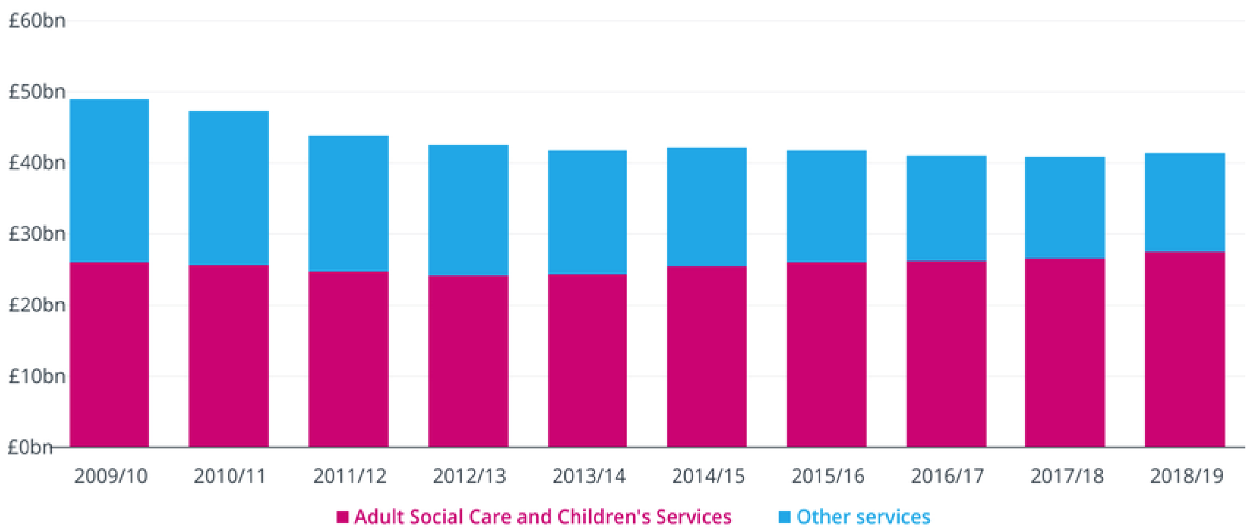

Figure 1. Spending by local authorities in England, 2018/19 prices[10]

Source: Institute for Government analysis of MHCLG, Local Authority Revenue expenditure and financing in England: individual local authority data. Excludes 'Other' authorities, excludes spending on education services, police, and public health and includes some NHS social care transfers to ensure consistency over time. (CC BY-NC)

These types of issues reduce local government capacity to execute innovative technology projects that are intended to make them operate more efficiently.

In the context of a decade of austerity, demographic change, and requirements to implement centrally driven programmes and then report on centrally determined performance metrics,[8–10,16] local authorities are stretched to find the time to develop AI projects. Despite these constraints, there are numerous projects being undertaken, some with help from the private sector.

Current IT Trends in Local Government

Local authorities were originally less IT-intensive than central government.[17] More recently, this pattern has begun to change with local authorities having IT systems that capture administrative data, allowing them to explore new data-enabled ways to enhance services.[18]

As IT in local authorities has intensified, these organisations face challenges in delivery from both suppliers and central government. As can be seen in Table 1, which represents local authority spending on the Digital Marketplace,[1] spending has continually increased since 2012 and there has been a shift from majority SME contracts to majority large company contracts (this shift is represented in Table 1 by the figures in bold).[19] The available data on IT contracting in local government suggests that between 2012 and the present, there has been a concentration in the supplier market towards large suppliers. This, combined with the benefits of technological advances, such as data efficiency gains, which disproportionately accrue to large AI firms,[20] may increase supplier strength. An example of this strength is Nesta's[2] finding that "where services or IT are outsourced, a public sector body may even find that it cannot access the data relating to its own service or must pay an additional fee".[21]

While this data is only illustrative, as not all AI-related contracts are agreed through the Digital Marketplace,[22,p.11] and information about contracts outside the Marketplace may be withheld on the grounds of commercial sensitivity,[22,23] this public market data may represent a similar pattern to what occurred in central government in earlier decades, where IT-industry strength, as measured by market and technical predominance, was negatively related to the performance of government IT projects.[17] This was due in part to outsourcing and a reduction of internal government IT expertise, decreasing capacity to manage, oversee, and monitor ever-larger contracts in public procurement,[17] reducing governmental ability to act as an "intelligent customer".[24] This led to limited performance in IT when compared to other nations,[17] and a situation some have described as "a recipe for rip-offs".[24]

Table 1. Summary of local government expenditures as a % of total in £ by company size on the Digital Marketplace, adapted from [19]

Year	SME %	Large %	Total
2019/20	39%	**58%**	£ 143,648,407
2018/19	45%	**49%**	£ 92,773,045
2017/18	49%	49%	£ 60,623,172
2016/17	**55%**	44%	£ 41,115,414
2015/16	**60%**	37%	£ 28,539,218
2014/15	**65%**	31%	£ 24,349,365
2013/14	**67%**	25%	£ 8,362,019
2012/13	**47%**	44%	£ 1,294,244

Note: Not all rows sum to 100% because there is a small third "unclassified" contract category in the data.

Other challenges particular to local authorities may be directly related to long-standing IT issues within central government. The Local Government Association (LGA) has stated that "different digital strategies and programmes are being pursued by different government departments. This means the landscape of digital government is fragmented and disjointed."[25] Fragmentation has been a long-standing issue since research in the late 1990s showed that the structure of IT systems in benefits offices prevented service integration.[26] One local government official said that "there is no understanding in central government of operational reality. Different silos just lob things over the fence."[16,p.14] The LGA summarized: "To improve councils' ability to interact with these platforms, Whitehall should work harder to co-design digital services from the start of their development and also keep abreast of changing technologies."[25]

However, keeping up to date on technological change might be challenging, because there is no single authoritative

[1] An online digital procurement service for all public sector organisations, operated by the Government Digital Service and the Crown Commercial Service, https://www.digitalmarketplace.service.gov.uk/.

[2] Formerly the National Endowment for Science, Technology and the Arts, this organisation promotes innovation across a range of sectors.

source for information on the extent of AI use in local government, despite calls to create one.[27] As a consequence of this lack, a number of organisations have been investigating the use of these technologies by local authorities. The Data Justice Lab at Cardiff University sent Freedom of Information (FOI) requests to a list of 423 local authorities asking if they had any "uses of data analytics, predictive analytics, or algorithmic automated systems used for risk assessment, scoring systems or automated decision making".[23,p.132]

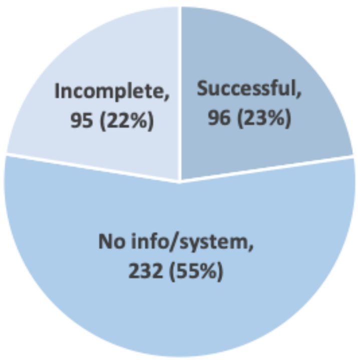

Figure 2. Breakdown of FOI request outcomes, adapted from [23]

Reports in *The Guardian* and from the Oxford Internet Institute have identified similar numbers.[28,29,15] While, together, these findings suggest that, as of 2020, about one fifth to one quarter of local authorities are using some form of AI to support their work, this is by no means definitive due to the limitations in the data. The next two sections set out how such projects were identified and what findings emerge from these cases.

2 METHODOLOGY

This briefing is based on an interpretive qualitative meta-analysis of the scholarly, grey, and journalistic literature on the topic of AI for good governance in local authorities.[30,31] A systematic literature review was conducted using bibliographic databases and supplementary search methods[3] with consistent search terms.[4] This was followed by snowball and citation searches. The existing body of literature on the state of AI in UK local authorities includes surveys, interviews, and case studies. There is also some quantitative data on FOI requests, local government finances, and information technology expenditures through the Digital Marketplace.

Bringing this literature and data together raises some practical challenges around comprehensiveness, equivalencies, and comparisons. As mentioned previously, complete public information on AI procurement, development, and use in local authorities in the UK is not readily accessible. Of the information that is, the topics under study are not exactly the same (such as the study of data science, predictive analytics using machine learning, automated decision making, or software, more generally). Despite these limitations, it was possible to extract relevant cases that illustrate the current state of AI in local government and there are a number of similar themes.

Themes were emergent but informed by existing literature and based on an effort to extract key practical challenges and enablers that local authorities and third parties experience when trying to deliver AI projects. Analysis focused on the foundations of AI for good governance and the findings suggest recommendations at both local and national levels.

3 FINDINGS

This section provides a description of AI projects in local authorities, setting out a typology and several illustrative cases to help present the three key challenges and three key enablers. Each challenge and enabler includes analysis of what it means for the role of AI in good governance.

Table 2 illustrates that AI can be understood in a number of ways: it can identify patterns, respond to queries, or automate tasks. In general, AI in the public sector is used for complex information processing towards specific objectives using administrative data and computation. We can also see that software and data infrastructure changes are key precursors to AI development by providing frameworks for application development and training data for machine learning tools. Based on available data, these projects occur across all business areas and have a range of purposes.

Challenges

Frequently cited reasons for AI projects not working as expected are issues at the local authority level either around

[3] ProQuest, Scopus, Web of Science, Factiva, and Google
[4] First [UK and "local authority" and "artificial intelligence"], followed by [UK and ("local authority" or "local government") and ("artificial intelligence" or cloud or "data science" or "machine learning" or "predictive analytics")]

Table 2. Typology of AI-related projects in UK local government

Types of AI-related projects	Purposes	Sectors
Artificial Intelligence		
Predictive analytics and pattern recognition	Risk profiling, targeting for inspection, intervention, or prevention services	Children's social care, house in multiple occupation inspections, homelessness, adult social care, council tax benefits claims, social housing applications, housing planning (sometimes using IoT data)
Automated agents	Chatbots, call centre support, care support, traffic management	Waste and recycling, adult social care, planning permissions, routine queries, traffic
Matching algorithms for business and service automation	Matching across data sets, matching topics using natural language processing	Health, children's social care, adult social care, education, childcare
Foundations for Artificial Intelligence		
Integrated databases	Combining data sets, assisting with search and retrieval of enterprise data, dashboards, reporting	Resident services, health and social care
Case management systems	Facilitating collection and manipulation of data by frontline service providers and back-office administrators	Education, children's social care, planning applications, housing benefits, call centre software

data quality or problem definition, and at the supplier level around a lack of understanding of contextual factors at the local level. The issue is that algorithms can be harmful if they use proxies rather than measuring what is actually of concern, do not learn from feedback to improve their performance, and are set to achieve the wrong objectives.[32]

Data Quality

With respect to data quality, there are foundational challenges that local authorities need to address before AI applications become feasible, including connecting and merging data held in different systems, in different formats, and without necessarily having unique identifiers for individuals or cases.[15,21,33–36] Where people are collecting the data, it may be inaccurate or incomplete.[37,38] Further, rigid categories in information systems may impose limitations on those inputting data.[37] But data quality issues are not just related to technical factors. Efforts between local authorities to collaborate have also revealed social factors.

Efforts to combine data across local authorities have revealed concerns related to data interpretation and meanings.[21,38,39] Research on data science in local government found that "things such as different IT systems, differences in the way data is collected and collated, and small differences in the way services themselves are delivered all make this type of collaboration a real challenge".[15,p.34] Nesta has ascribed some of these issues to idiosyncratic data collection across teams, infrequent data quality checks, and a lack of agreed and adopted data standards across the local government sector.[38] In addition, poor understanding of the law around data protection set out in the GDPR has also made local authority staff "reluctant to share data".[15,p.31]

These types of data quality issues impact projects where local authorities engage with suppliers. Suppliers often cite data quality issues as a reason why anticipated results from using their systems have not been achieved.[28,29]

The implications of these issues on machine learning (ML) models have been clearly stated by an ethics review of predictive analytics, which found that "when inaccurate data are used to fit models, it will affect the inferences and correlations an ML model 'learns' and undermine the model's performance".[37,p.40] The following two cases look at technical and social issues.

Case 1: Data quality and predictive analytics for House in Multiple Occupation (HMO) inspections

When the London offices of data analytics were piloted, they investigated whether predictive analytics could be used to help prioritize HMO inspections. The first phase of the project encountered a number of data quality issues. The pilot found that data required "significant cleaning, processing and merging".[34,p.26] The reasons for this included a lack of unique housing identifiers (such as Unique Property Reference Numbers) and incomplete or inconsistent address data inputted across separate information systems.[34] These limitations impacted the quality and quantity of data, and thus the quality of analysis.[34]

In addition, certain types of information were either missing, such as data on the private rental sector, or had incompatible formatting, for example commercial data on physical property features such as building height.[34] There were also issues with small numbers in some data sets; for example, the number of known HMOs (as few as thirty in one borough) left too few cases to train the model.[34] The other issue was that some data was not deemed relevant, for example, data relating to properties that were "definitely not HMOs", and was not collected.[34,p.18]

The complexity of the problem combined with the data quality issues "were ultimately too intractable to produce successful predictions in this first phase".[34,p.22]

Case 2: Data quality and predictive analytics in children's social care (CSC)

Many local authorities have been exploring the use of predictive analytics to assess risk in children's social care. Third party organisations have been evaluating the viability of these tools in this service sector. At the root of some data quality issues is divergence in meanings over place, time, and purpose.

After experiencing poor model performance in the prediction of risk for re-referral to or escalation of services, researchers from What Works for Children's Social Care[5] tried to find ways to increase the volume of data with the aim of enhancing the accuracy of their predictions, indicating that "often the solution proposed to low model performance is 'more data'".[39,p.63]

They found that data was limited and not easily integrated across agencies or aggregated over time because of differences in data fields across information systems, different interpretations of the meanings of those fields across local authorities, and changes in practice over time.[39] The researchers found that "data from local authorities with different practice models, interpretation of thresholds and populations is likely to add considerable noise as well as signal".[39,p.63]

Another challenge is related to the performance-monitoring-related purposes for collecting the administrative data typically used to train these predictive tools. An ethics review of machine learning in children's social care found that it is inappropriate to apply population-level data to individual cases, indicating that "context matters".[37,p.14] The review found that AI tools supporting a more "strengths-based" approach focussed on family functioning, and it could be more appropriate to focus on a child's educational, behavioural, emotional, cognitive, and social development.[37] However, there is a paucity of immediately available and usable data of this type.[37] Changing the type of data collected and the aims for its use could thus open new application areas for AI. In summary, the meanings and values inscribed in the data play a crucial role in setting the parameters of its usefulness.

This section has highlighted not only the technical challenges associated with data quality, but also those related to the meaning and the congruence between data elements and phenomena. One head of knowledge and intelligence summarised the problem as follows: "predictive analytics might just be a little blip, if we can't sort out all the data underneath it".[7,p.952]

Problem Definition and Objectives

Local authorities need to clearly state the problem, manage expectations, and establish meaningful metrics. Researchers have found that data projects must be well-defined, realistic, and represent a shared vision of all affected stakeholders,[18] while avoiding control-management styles, setting clear

[5] An independent research organization whose objective is to provide evidence for public sector decision makers.

goals, and keeping expectations about positive outcomes realistic for senior managers.[40]

Case 3: AI applications on an integrated Troubled Families database

In response to recommendations from the Troubled Families Programme, Manchester City Council implemented an integrated database that allowed them to automate record search and build predictive tools. A clear problem definition with a clear objective facilitated this work.

Research into the project found that the clearly stated problem of identifying troubled families in order to participate in the government's payment-by-results programme gave Manchester "a very specific focus and easily measurable first assessment of success".[38,p.47]

A local authority staff member explained that it was important to know why they were putting the system in place, to have senior strategic partner support, and to incorporate a means to analyse their program over time.[41]

Additionally, problems must be amenable to technological solutions. Nesta has commented that it is necessary to "start with a problem that can be solved by data".[38] Once a problem is defined, a key element of this work is around managing leadership expectations. Researchers at the Oxford Internet Institute have found that management might expect "major results without an understanding of the time it might take to put it together".[15,p.27]

Further, research from the Alan Turing Institute has suggested that joint working and measurement are key elements of defining problems and objectives, indicating that technical and non-technical team members "should work together to translate project goals into measurable targets".[42,p.16] In the absence of such up-front work, local authorities risk getting products that do not meet their needs or being unable to articulate their impact once implemented.

Supplier Contextual Knowledge

Supplier issues may arise where local knowledge is needed to identify the appropriate data to be fed into an algorithm, tune a model, or fit a tool into existing processes. Sometimes a lack of contextual knowledge has resulted in suppliers being dropped, or in unanticipated development work after the fact.[7,15,28]

Case 1 (continued): Supplier contextual knowledge and predictive analytics for HMO inspections

A local authority staff member working on the HMO project explained that "we provided the data that the company requested but the model that was produced didn't do what we hoped".[7,p.951] A data scientist working on the project said that "through no fault of their own, the company who developed this particular model simply didn't have the detailed knowledge of the borough. … But this knowledge is crucial."[15,p.9] The concern is that "if the system makes predictions that are clearly absurd to seasoned workers, trust in the system as a whole could be undermined."[7,p.951]

The Local Government Association (LGA) is aware of these concerns and has suggested actions to improve work with suppliers. The LGA has stated that some cases where AI tools (such as those for predictive analytics) have been dropped have led to negative media coverage, fuelling caution at both the frontline and senior leadership levels.[33] To improve procurement outcomes, the LGA suggests that local authorities work with suppliers "to improve their understanding of local government—its challenges and its needs".[43,p.8]

In some cases, companies are able to work with local authorities to pivot their projects and respond to the local context, for example by repurposing a project to support frontline staff.

Case 2 (continued): Repurposing AI projects to benefit frontline social workers in CSC

At a round table to discuss the application of machine learning for predictive analytics in children's social care, a number of stakeholders discussed the unanticipated benefits that had emerged from pursuing these projects. A company shared that "an initial exhilaration about having all information in a central location is common among local authorities".[37,p.55] A public body at the round table shared their experience of pivoting a project that was "originally intended to provide general level strategic overview of the functioning of the CSC system towards instead providing social workers with information and supporting their practice".[37,p.55]

A Principal Children and Families Social Worker indicated that predictive risk scores may lack the accuracy to help frontline workers, but that “algorithms and machine learning can be used in other areas to intelligently support practitioners”, for example “in time-taking tasks, ranging from gathering historical data to information sharing and partnership working with other agencies”.[44] Suppliers that understand context can make products that work for staff across the local authority.

While suppliers are sometimes able to pivot projects to meet local needs, often in-house expertise is required to help make those technologies work in a local government setting. As the London Office of Data Analytics found, “data has little value without local context; frontline staff can help validate findings, spot biases in the data, and errors in the output of algorithms”.[34,p.33] This involvement of relevant staff can help to set the context for projects. The next section looks at this type of AI-project enabler.

Enablers

Some of the most frequently cited enablers of AI projects are local authority in-house capacity; collaboration to share capacity, lessons learned, and best practices; and increased transparency around data, models, standards, and projects, regardless of organisation types involved in development.

Internal Capacity

Staff with the expertise to pursue AI projects are present in certain local authorities;[15] however, they are often tied up on mundane reporting tasks.[34] Where councils have available capacity, they sometimes lead in-house AI projects. In other cases, they have to take over from suppliers, either if expected benefits were not realised or as part of planned handovers.

The Data Science for Local Government project found many examples of “skilled analysts and business intelligence specialists working on remarkable projects with shoestring budgets”.[15,p.2] But not all projects are delivered exclusively in-house. There are instances where local authorities have had to modify,[7] build upon,[7] or take over from suppliers.[15,21,45] The following cases of a chatbot for resident queries and a predictive tool for prioritising HMO inspections help illustrate these instances.

Case 4: In-house modifications to a chatbot

One local authority implemented a chatbot to deal with planning permission applications. In this project, there was “very much a significant divide between what was perceived as being this avatar that could speak to anybody and the reality of a system that required expert coding at the back end to actually deliver it”.[7,p.950]

An assistant director provided detail about the complexities within the local authority, citing “more than 600 processes touching on multiple applications. … So AI may become the face of the council, but behind the scenes is a whole body of things that have to work together”.[7,p.950] Bringing together subject matter, business process, and resident expertise is a crucial part of this administrative work. In the end, while natural language processing may apply to the structure of a resident’s question, behind the scenes, in-house staff have an important role to play as the chatbot is “fed by a logical workflow hand-coded into the system”.[7,p.950]

Case 1 (continued): In-house staff building upon a predictive tool for HMO inspections

After the disappointing results in the first phase of the HMO project, in-house data scientists in one of the original participating local authorities developed their own solution. They worked with service staff to identify the variables and properties to include in the test and the training sets and achieved much better results with their model. The issue was not just data quality, it was also the data that was selected to fit the model.[7] They found that, “together with that and the local knowledge of the officers and phone calls from members of the public or councillors, the staff have a much better idea of which properties are worth inspecting”.[7,p.951] Changing features or specifications that were not part of the original model after engaging with in-house domain experts achieved better results.

Others have suggested that in-house capacity is also important for allowing local authorities to act as intelligent customers[24] and play an active role in the oversight of their AI tools.[37] However, this might not be possible for all local authorities, if they lack technical capacity or expertise.[38] However, there are ways to overcome skills gaps through learning,[38] collaboration,[33] or shared services.[43]

Collaboration

Individual local authorities do not exist and operate in isolation and the work they are doing is occurring within the context of broader national and international trends in AI development. As a result, many have suggested that collaboration between local authorities should be pursued.[21,43,46] Current efforts around collaboration are centred on voluntary standardisation, informal communities of practice, a limited number of central government grants, or working with third parties.

The LGA and the Ministry of Housing, Communities and Local Government (MHCLG) have been encouraging greater standardisation among local authorities. They have stressed the importance of openness, including open standards and open data, to ensure that systems are interoperable, data can be interlinked, vendor lock-in can be avoided, and knowledge and lessons learned can be shared.[43,47] MHCLG has also set up a limited and application-based Local Digital Fund to support training and projects that address common local service challenges.[48]

Case 4 (continued): Chatbot collaboration

A group of thirteen councils conducted exploratory research into chatbots and conversational AI through the Local Digital Fund.[49] "Waste and recycling" was identified as the best candidate area because it has high call volume with low complexity queries, residents want to self-serve, and the service is consistent across local authorities.[50]

The project consultant noted that not only does this collaboration "provide efficiencies and economies of scale, it also reduces duplication of effort".[50,p.23] A local authority project team member said that the project had broader collaborative objectives and that they were "trying to get ahead of the game and stop everyone running off and reinventing the wheel".[51] By generating and providing accessible research and templates, they were hoping to "give something back to the community so it can start where we are".[51] Collaborative projects can lead to shared learning that can extend beyond the immediately participating councils.

There are also a number of mechanisms for collaboration, typically in the form of communities of practice to support the sharing of lessons learned and best practices while also providing mutual support and leverage, but they are voluntary, disparate, and not fully subscribed. Examples of these fora include LocalGov Digital,[52] Local Digital at MHCLG,[53] Socitm's local CIO council,[54] and others.[55,56]

There are also under-utilised, but meaningful, opportunities to work with the higher education sector.[15,46,57] While such collaborations may appear to face barriers, these can be overcome.[58] There have also been successful collaborations with independent public organisations such as What Works for Children's Social Care and the Behavioural Insights Team.[59,60] With these alternatives for collaboration, it is not just about being an intelligent customer, but an intelligent decision maker, and not assuming that the solution will necessarily come from the private sector.

These mechanisms for collaboration provide opportunities for local authorities that lack in-house capacity to leverage the capacity of others, learn from these experiences, and develop their own internal capacity. However, the voluntary and circumscribed nature of these collaborative efforts limits their broad adoption.

Transparency, Openness, and Accountability

An emergent theme involved transparency, openness, and accountability in projects, contracts, data, and model specifications. Those working in local government expressed concerns about not only the transparency of AI tools, but around transparency in the sector in terms of what projects are being undertaken nationally.

Local authorities wish to have a baseline when it comes to the transparency of AI tools from suppliers. An ethics review of machine learning in children's social care found that "rigorous standards of transparency and reporting (regarding these aspects of data recency and model training) should be agreed upon and codified in advance".[37,p.40] This could help to assess whether suppliers are making verifiable claims about their AI systems.[61] This kind of transparency may reveal cases where it is desirable to forgo AI tools in favour of more interpretable traditional approaches.[37] Alternatively, a desire for transparency may encourage local authorities to develop projects in-house, as in the following case.

Case 5: Transparency, openness, and accountability in local intelligence tools

One local authority was concerned about transparency and decided to develop their suite of intelligence tools in-house. A data scientist explained that this was to have "complete control over everything" out of concern that "if you get somebody else with a black box, no one really knows how it works", concluding that if "you've got to explain it to somebody, you've got no chance".[23,p.28] A manager explained that the decision was also to ensure that the tools fit with "the existing IT" and that they "wouldn't have high level maintenance costs going into the future".[23,p.28] The local authority was concerned about transparency in terms of being able to both explain how their tools work and understand how those tools fit with their existing information infrastructure.

Local authorities also sought greater transparency about where and what kinds of projects were happening in the local government sector so that knowledge, approaches, and bargaining power could be shared.[62] While there are tools for sharing information about procurement, such as the Digital Marketplace,[63] not all contracting takes place there. In addition, the Cabinet Office removed data about product type as of 2017[64] which has made it difficult for the public and local authorities to see what projects are underway. Greater transparency about contracts could help to make local authorities more intelligent customers.[6] This could also improve the public's ability to scrutinize decisions and thus enhance democratic accountability.[23,66–68]

With the appropriate information infrastructure in place, greater transparency for all affected stakeholders could enable greater model oversight, knowledge of similar projects, and enhanced public scrutiny.

4 CONCLUSIONS

In the context of austerity, increasing strength of IT suppliers, and the expansion of the application of AI technologies in local government, there appear to be three key challenges and three key enablers that local authorities need to consider. The challenges are related to (1) data quality, (2) problem definition, and (3) the absence of contextual knowledge in suppliers. The enablers are related to (4) in-house capacity, (5) collaboration, and (6) transparency.

For AI to meet good-governance objectives, there need to be prerequisite governance arrangements to overcome challenges and augment the enablers. These governance preconditions broadly align with the four principles of the Oxford Commission on AI and Good Governance.[69] Each precondition can be associated with a recommendation, drawn from existing work in the sector.

5 RECOMMENDATIONS

Local authorities must establish data governance mechanisms to ensure clear data definitions, priorities for key data elements, consistent and accurate data collection by frontline staff, effective data cleaning and data management practices, clear identifiers that allow data to be linked across sets, and implementation of data standards needed for AI.[32,37,42]

Recommendation 1: Central government, particularly the Government Data Standards Authority,[70] should work with local authorities to establish a set of minimum mandatory data standards to ensure comparability while leaving room for local variation; and local authorities should be given additional funding to support real-time technologically enhanced data cleaning efforts, such as those supported by the Local Digital Fund.[71]

Local authorities need to be clear about what problems they are trying to address with AI and what would constitute success. Without clear governance to ensure the establishment of outcomes and objectives from the outset, mechanisms to monitor whether those objectives and outcomes are being achieved, and clear options to address unanticipated issues, change direction, or abandon a project, then local authorities may not be able to state their accountability or exercise their authority with legitimacy.

Recommendation 2: Building on the guide for responsible development of AI in the public sector,[42] the Committee on Standards in Public Life, the Ministry of Housing, Communities, & Local Government, and the Local Government Association should work with The Alan Turing Institute to develop a minimum mandatory practical process for problem definition, project development, and evaluation across all local authorities with accompanying guidance.

Local authorities should develop governance arrangements to ensure that contracts include provisions related to open standards, open data, and openness about model specifications (to evaluate consistency and fairness) and that suppliers are expected to develop a contextual

[6] This type of transparency should be possible under section 20 of the Local Government Transparency Code 2015, which allows local authorities to share information about their contracts.[65]

understanding of the local area, working with staff and residents on the ground to develop comprehensible and meaningful interfaces and gaining sufficient knowledge of local authority business processes to make meaningful contributions to the existing organisational infrastructure.

Recommendation 3: Building on recommendations from the Local Government Association,[43] procurement rules should embed a workable and enforceable supplier standard and be modified to ensure a more flexible relationship which ensures that off-the-shelf products can be assessed on their ability to meet local specifications and that custom-built products include a process of local engagement with domain experts and users throughout development.

If a decision is made to develop AI in-house, governance is needed to ensure that there are dedicated and protected local authority resources to support internal IT, programming, and data analytics staff, that such staff could be recruited, or that relevant expertise could be leveraged from partners. In addition, in-house IT team projects should be transparent, and there should be collaborative working with all relevant stakeholders to ensure that solutions work for those who have to use them.

Recommendation 4: Building on the recommendation in "Growing the artificial intelligence industry in the UK" to develop a programme of action in the public sector,[72] dedicated resources should be provided to local authorities to ensure that they can be intelligent consumers and capable developers of AI technologies.

Collaborative governance needs to be in place across local authorities to ensure that lessons learned and best practices can be shared and that there is the option to engage in a collaborative relationship with another local authority or third-party with the appropriate capacity so that projects can move ahead and knowledge can be transferred to enable the development of in-house expertise.

Recommendation 5: Stakeholders who have developed voluntary avenues for collaboration should be brought together by the Ministry of Housing, Communities and Local Government and the Local Government Association and a formal mechanism for collaboration across all local authorities should be established that can help to formalise standards, promote best practices, and support collaboration with third parties.

Finally, transparent, open, and accountable governance needs to be in place to ensure that there is internal oversight, where code, data, objectives, partners, processes, and governance are auditable and amenable to feedback; that there is perfect information about contracting and local government AI projects underway so that this information is easily retrievable and usable across the local government sector (such as through notifications); and that there is external oversight to enhance the democratic accountability and legitimacy of these types of projects. This governance needs to go "beyond current voluntary ethical frameworks or narrowly defined technical interpretations of fairness, accountability and transparency".[73,p.5]

Recommendation 6: In line with previous recommendations that there should be more transparency around the use of AI in the public sector,[27,74] a platform to compile all relevant information about information technology projects in local authorities (whether with suppliers, in-house, or in collaboration with third-parties) should be developed to equip local authorities with useful information about what projects colleagues across the country are pursuing, enable greater collaboration, and support democratic accountability.

With governance arrangements that ensure data quality, clarity about purpose, expectations from suppliers, internal capacity, collaboration, and public transparency about data, purposes, and models, then AI tools that are developed for local authorities may satisfy good governance objectives by both delivering more efficient and effective service and being open to public scrutiny about the values they embody and their ability to achieve public good.

There is long-standing advice that because the possibilities for technology implementation depend on previous policy, and that technology implementations can constrain future policies, public sector leaders need to be aware that "information systems are not discrete entities that may be selected from competing solutions but rather inextricably intertwined with policy-related tasks".[26,p.180] Hopefully, this briefing provides relevant guidance to public sector leaders hoping to develop AI solutions that satisfy policy-related tasks and support good governance at the local level.

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ABOUT THE OXFORD COMMISSION ON AI AND GOOD GOVERNANCE

The mission of the Oxford Commission on AI and Good Governance (OxCAIGG) is to investigate the artificial intelligence implementation challenges faced by governments around the world, identify best practices for evaluating and managing risks and benefits, and recommend strategies for taking full advantage of technical capacities while mitigating potential harms of AI-enabled public policy. Drawing from input from experts across a wide range of geographic regions and areas of expertise, including stakeholders from government, industry, and technical and civil society, OxCAIGG will bring forward applicable and relevant recommendations for the use of AI for good governance.

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