Productivity and Responsible AI in Adult Social Care

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Abstract

This paper examines how artificial intelligence (AI) can be responsibly harnessed to enhance productivity in England's adult social care (ASC) sector, which is grappling with increasing demand, workforce shortages, and persistent concerns about financial sustainability. The paper begins by addressing the challenge of measuring the sector's performance where outcomes are inherently complex and centred around individual needs. It is concluded that irrespective of which measure is being considered, productivity in the sector has declined for a decade or more.

Using a delivery chain framework, the paper identifies pathways for productivity gains through both improved task performance and more effective case mix management. We introduce a new framework highlighting the potential of AI to support these gains by automating administrative tasks, enhancing care planning and scheduling, and strengthening decision-making.

Despite these opportunities, the paper finds that AI adoption remains limited due to ethical concerns, workforce readiness, governance constraints, and financial instability. Realising AI's full potential will require aligned organisational and governance reforms, including investment in digital skills, staff wellbeing, and the development of ethical AI practices.

It also calls for regulatory frameworks that strike a balance between innovation and accountability, and procurement models that support long-term partnerships. Integrated Care Systems are identified as a key mechanism for enabling cross-sector collaboration between health and social care.

Overall, 'responsibility' is a critical feature for ensuring that new AI opportunities contribute to a more sustainable, effective, and person-centred care system.

Contents

1. Introduction

Addressing the weak productivity performance of public services has become a top priority for the UK government. In 2023, the previous Conservative government launched a plan to boost public sector efficiency by 0.5 per cent per year aiming to generate £1.8 billion in benefits over five years from 2024-2029.[1] The current Labour government has intensified this focus by stepping up initiatives to use new technologies in the public sector more intensively. This includes the introduction of a new suite of AI tools across public services, coordinated by the Department for Science, Technology and Innovation (DSIT, 2025).

England's adult social care (ASC) sector exemplifies the complex challenges confronting many public services today. On the one hand, it faces unprecedented challenges in meeting growing demand while operating under severe financial constraints. On the other hand, as the population ages care needs become more complex. Hence the sector faces a dual challenge of delivering more care while simultaneously improving its quality despite limited resources. As productivity in the ASC sector has declined for over a decade and has failed to recover to pre-pandemic levels (see below), technology is increasingly viewed as a potential lever to enhance performance, save on resources, and support better outcomes for service users.

This paper addresses two critical issues related to the push for AI usage in ASC. Firstly, the concept of productivity in ASC is under-researched. This knowledge gap implies that policy development, resource allocation, and service delivery in the sector are insufficiently evidence-based. Secondly, the paper investigates the barriers to responsible use of AI to promote productivity in ASC. Although many applications have been developed and tested, only a few have reached the level of maturity where AI is scaled across the entire social care sector and embedded into processes of continuous innovation. While principles of responsible AI like transparency, accountability, and stakeholder buy-in are widely endorsed, their practical implementation is challenging.

The first part of this paper addresses three key questions:

- How can productivity in ASC be defined and measured, given the sector's unique characteristics? (Section 2)
- What opportunities for productivity growth exist within and across the various delivery chains in ASC? (Section 3)
- What role can digital technology, and AI in particular, play in driving productivity in ASC? (Section 4)

We introduce a new framework on how AI technologies can be applied in social care and assess their potential impacts on productivity. We argue that significant

[1] https://www.gov.uk/government/news/18-billion-benefits-through-public-sector-productivity-drive

productivity gains seem possible through more personalised care models enabled by technological innovation, better coordination of information and resources within organisations as well as between different parties delivering the care.

The second part of the paper addresses the following three questions:

- What are the potential barriers to the use of technology, in particular AI, in ASC? (Section 5)
- Which technological, organisational and workforce-related factors influence the responsible use of AI? (Section 6)
- Which governance issues in ASC are key to support responsible adoption of AI? (Section 7).

We conclude that realising the productivity benefits from a responsible use of AI requires co-ordinated organisational and governance reforms. Organisations must invest in skills, staff wellbeing and responsible AI use. Governance should strengthen oversight over appropriate use of new technologies, reduce managerial burden, stabilise funding and procurement, and promote collaboration through Integrated Care Systems to support sustainable, innovation-driven service improvement.

Our paper contributes to the ongoing policy debate on the importance of productivity enhancement as a complement to funding increases in addressing the social care crisis. The findings have implications for policymakers, commissioners, providers, and technology developers seeking to create a more sustainable and effective adult social care system.

2. Measuring the Adult Social Care Sector

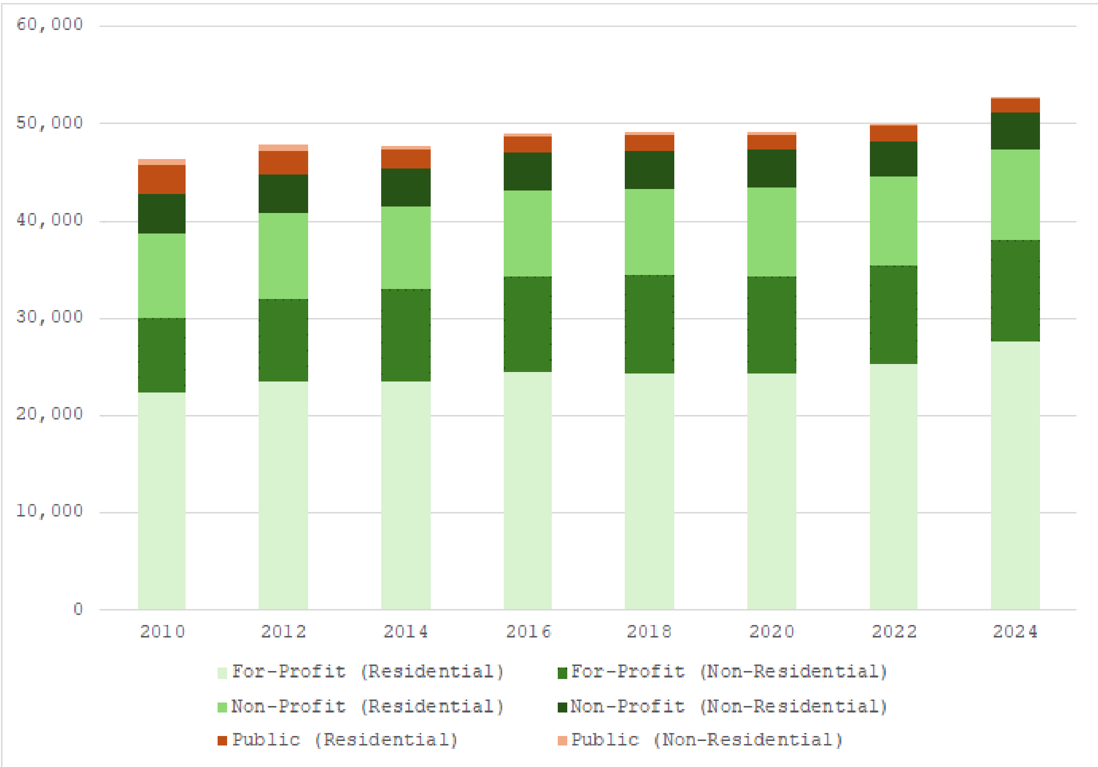
Sector Structure and Spending

The social care sector in the UK is a significant and growing part of the economy, employing a substantial workforce and providing essential services to millions of people. In 2023, the sector employed 1.705 million people, with 665,000 working in residential care and 1.04 million in non-residential social care. This represents a 6.9% increase in employment from 2016/17 to 2023/24, highlighting steady growth in demand for social care services (Skills for Care, 2024).

The sector has also experienced structural shifts. While the sector has been dominated by privately run local entities for very long, their share increased strongly in recent years from 92% of all units in 2019 to 97% in 2024. The bulk of the increase in private entities is commercially-run, with a faster rise in residential entities (by 5,225 units) than non-residential entities (by 2,780 units). Public entities declined by 64% in relative terms, and by 1,990 units between 2010 and 2024 (Figure 1)

The funding model for adult social care relies on a combination of public and private contributions, determined primarily through financial assessments. Individuals with assets exceeding the upper limit (£23,250) are required to fully fund their care. Those with assets between the upper and lower limits (£14,250) contribute based on a means-tested tariff, which imputes a weekly income of £1 for every £250 of capital between these thresholds. Individuals with assets below the lower limit do not contribute from their capital but may still need to pay from their income. The value of an individual's house is not included in the calculation of their assets if they are receiving at-home care. However, if they move into a care home, the value of the house is included in the assessment.

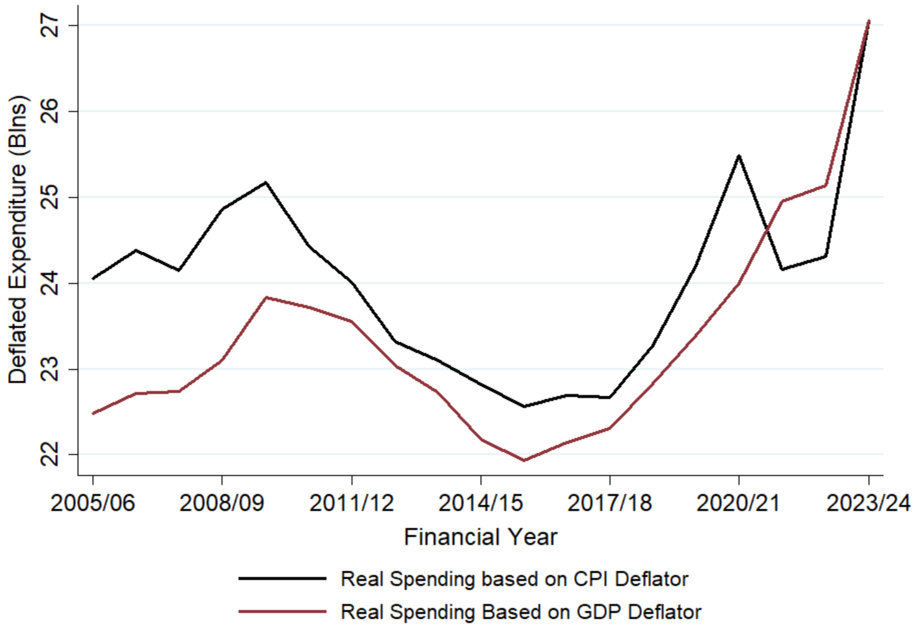
Figure 1: Quantity of Local Units that Provide Adult Social Care



Source: Inter-Departmental Business Register (Office for National Statistics, 2024)

Local authorities' real-terms spending on social care has risen substantially since 2016, exceeding £27 billion in the financial year (FY) 2023/24 (Figure 2). However, this increase masks a significant shift in the way care is funded with the public increasingly purchasing care provision directly. As a proportion of the total economy (GVA), direct government spending on social care declined from 1.6% in 2006 to 1% in 2023. In stark contrast, the GVA share of the *entire* social care sector, including private out-of-pocket spending, has grown from 2% to 2.7% over the same period (Office for National Statistics, 2025a).

Figure 2: Gross Current Expenditure by Local Authorities on Adult Social Care in England, real terms by Financial Year in bln. £ (prices of 2024)

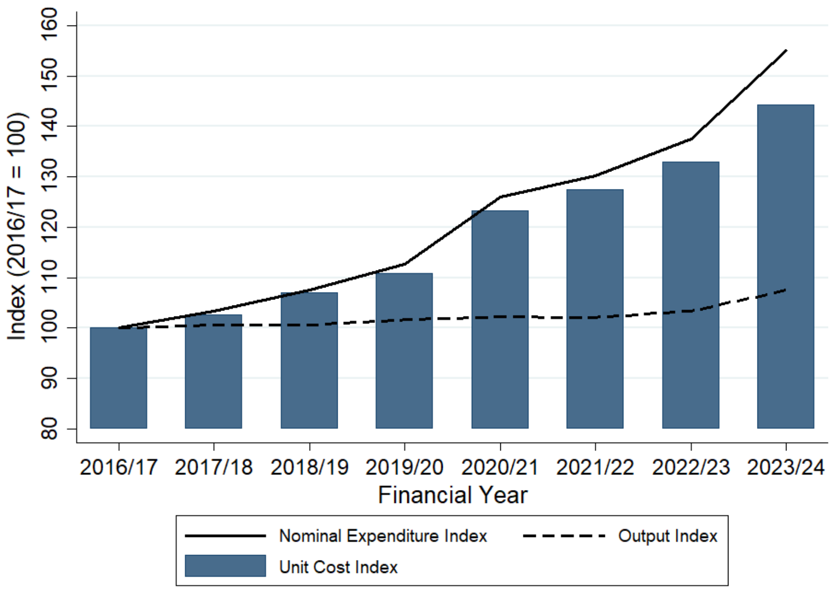


Note: Data refer to expenditure from local authorities, deflated by either the Consumer Price Index (CPI) deflator or the Gross Domestic Product (GDP) deflator. Expenditure does not include capital charges, but it does include joint arrangements with the NHS, and NHS financial contributions to the local authority.

Source: Adult Social Care Activity and Finance Report (NHS Digital, 2024a).

Figure 3 presents indexed measures of nominal government expenditure and real output provided by the publicly funded care service, and a resulting unit cost measure. The expenditure index shows a steady positive trend rising by 45% from FY 2016/17 to FY 2023/24. The output index measures the total number of people served by the system within a given year, including recipients of both long-term and short-term care. This index remained stable between 2016/17 and 2022/23 and only increased in 2022/23 and 2023/24, implying an overall growth of only 5% since 2016/17. Hence the expenditure per unit of output has increased by about one third over this period.

Figure 3: Nominal Expenditure, Output, and Unit Cost for Publicly Funded Adult Social Care, FY 2016/17=100



Note: The Nominal Expenditure Index represents the change in nominal government expenditure on publicly funded adult social care. The Output Index is based on the total number of people receiving long-term and short-term care services within a given year. The Unit Cost Index is calculated as the Nominal Expenditure Index divided by the Output Index, representing the expenditure per person served.
Source: Authors' own calculations from the Adult Social Care Activity and Finance Report (NHS Digital 2024a).

Productivity

Measuring productivity in social care is hampered by a number of factors, including the precise definition of its outputs and inputs, adjusted for any changes in quality, and their valuation in monetary terms. Under conditions of perfect market competition, the price of each output would reflect the relative marginal valuations of the provided good or service, i.e. what the marginal customer is willing to pay for the derived benefit of the service (Dunleavy, 2015; 2017).[2]

Clearly, England's adult social care (ASC) sector does not operate as a perfect market. One practical approach to measuring its productivity is to treat overall spending on ASC as a proxy for the monetary value of its output. Under this assumption, any increase in the value of inputs, which is primarily expenditure, is considered equivalent to growth in output. As this method essentially assumes that productivity growth is zero in value terms, regardless of the effectiveness or efficiency of the public service delivery, it

[2] While a substantial private market for social care exists alongside public provision, it does not function in a way that provides such reliable prices. For example, the Competition and Markets Authority (2017) finds that self-funders paid on average 41% more for an equivalent unit of care than local authority commissioners who purchase this care in bulk (p. 40).

cannot be used for assessing "true" productivity or understanding its drivers. (Dunleavy, 2017)

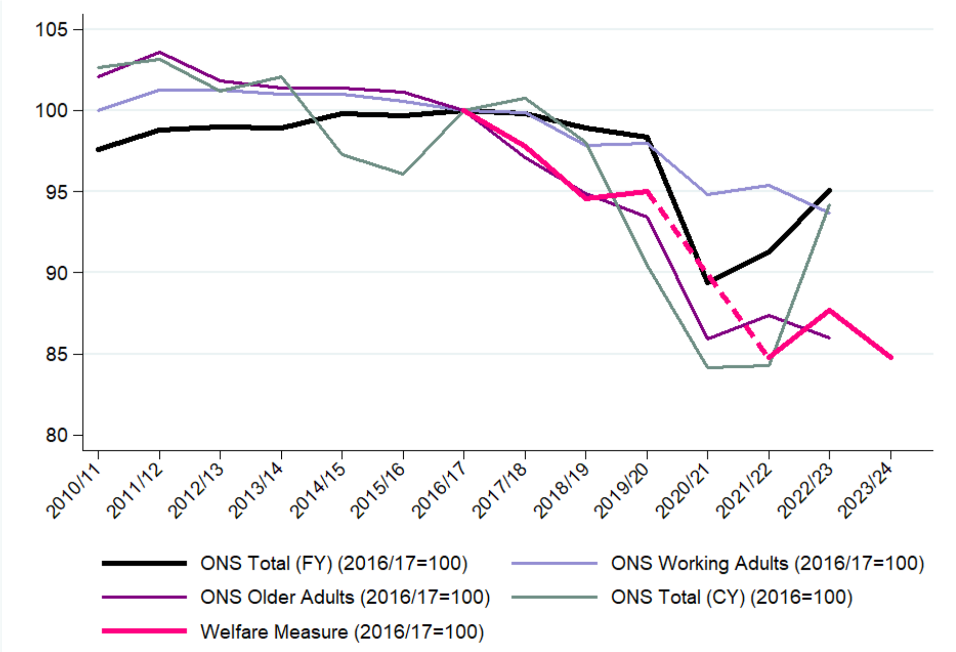
A second method for estimating the value of the output of a public service is to create a system of physical output measures, adjusted for quality. This requires one to obtain weights which proxy the marginal contribution to aggregate welfare made by each unit of output delivered (Atkinson, 2005). The formulation of such values can be based on information on average unit cost (Diewert, 2012), estimated contribution to outcomes (Schreyer, 2010; 2012; Office for National Statistics, 2019), or other qualitative features that users care about (Atkinson, 2005).

The Office for National Statistics (ONS) employs a similar method for their estimates of productivity in adult social care, which includes publicly funded services delivered by public providers, such as local authorities, as well as those commissioned from the independent sector. Outputs are calculated based on activity indices for residential and nursing care, which are cost-weighted based on the expected unit cost of those activities (UK Statistics Authority, 2025). The quality adjustment uses the Adult Social Care Outcomes Framework, which captures changes in social care-related quality of life across domains such as personal care, accommodation, and dignity, accounting for factors outside service control (Netten et al., 2012). The primary input measure is total public spending on these services, adjusted using a specific deflator for the social care sector, which accounts for key input prices like staff wages and energy. Although comprehensive, this measure is limited by gaps in activity data, especially after 2015, when data collection narrowed to focus on residential and nursing care (Office for National Statistics, 2025b). When activity data is unavailable, outputs are assumed to equal inputs. For example, community care and at-home care services are not included in the preferred productivity metric.

There are a number of outstanding issues with the measure collected by the ONS. Firstly, there appears to be a reduction in the breadth of data being collected over time – with data items like the number of hours of home care and the number of 'meals on wheels' delivered being discontinued from 2014 (UK Statistics Authority, 2025). Secondly, the question of how to account for interdependencies between services remains unresolved. Many care packages are delivered in close collaboration with the National Health Service, and the impact of these packages depends significantly on the quality of accompanying healthcare services. Yet, this complementarity is not reflected in the current statistical methodology (Office for National Statistics, 2025c).

Figure 4 presents quality-adjusted productivity measures from the ONS for England. All estimates indicate a notable decline in the productivity of publicly funded adult social care (ASC) services. The Financial Year (FY) data can be disaggregated into components such as care for older adults and working-age adults. Between 2010/11 and 2022/23, productivity in older adult care declined by nearly 16%, compared to a 6.5% drop in working-age adult care.[3]

*Figure 4: ONS Productivity Measures for Adult Social Care in England and ASC Welfare measure, FY 2016/17=100**



* All measures are for Financial Year (April-March) except for ONS Total (CY) where the first quarter of the Calendar Year (CY) does not overlap (i.e., 2010/11 = 2010)

Note: 2020/21 is omitted for the Welfare Measure due to incomplete data collection in that year from the Adult social care outcomes framework.

Source: ONS, Public Service Productivity, Total, UK, 2022, March 2025; ONS, Public Service Productivity, adult social care, England (FY ending 2023), March 2025. Adult social care activity and finance report (NHS Digital 2024a) and Adult social care outcomes framework (NHS Digital 2024b).

In addition to FY estimates for England, the ONS also provides Calendar Year (CY) productivity estimates for the UK as a whole. To convert FY data to CY format, the ONS applied a technique known as cubic splining, which interpolates quarterly values from FY data to align with calendar years (ONS, 2018). The CY estimates show a more pronounced decline in ASC productivity across the UK (nearly 9% between 2010 and 2022) compared to just 2.5% in the FY estimates for England. This decline was primarily driven by a sharp increase in inputs, which rose by 17% in the CY data versus 8% in the FY data. In contrast, output growth — adjusted for service quality — was more modest

[3] No separate data are available from ONS on home and day care services, "meals on wheels" and care assessment and support services. (ONS, 2018)

and relatively consistent across both measures: just over 7% in the CY estimates and 5.4% in the FY estimates.

Welfare gains

An alternative to quality-adjusted output measures is to estimate welfare gains directly (Atkinson, 2005; Schreyer, 2012). Cutler et al. (2022) exemplify this approach by using quality-adjusted life years (QALYs) as the outcome metric for individuals with specific diseases, and consumer spending on those diseases as the input. This approach differs from the methods mentioned above for two reasons. Firstly, the numerator of the productivity equation directly estimates the contribution from health and social care to aggregate welfare. Secondly, it captures productivity improvements across the delivery chain (as explained in the next section), including cases where high-cost services (e.g., surgery) are substituted with lower-cost alternatives (e.g., pharmaceuticals). As a result, it better reflects how effectively care is matched to individual needs.

A key limitation of the welfare method is its reduced granularity. It becomes more difficult to isolate the productivity of individual activities, particularly when substitution effects occur across services. This limits its usefulness as a management tool for decision-makers in adult social care, where understanding the performance of specific interventions is often essential. However, there is potential to also develop QALY's for individual parts of the ASC, and link it to dashboards and other measurement systems that are being used at organisational level.

The welfare methodology can be applied to the adult social care sector, thanks to the creation of a metric which is equivalent metric to QALYs. The Adult Social Care Outcomes Toolkit (ASCOT) (Netten et al., 2012) aims to capture 'social care-related quality of life' (SCRQoL) by assessing how effectively the impact of disability has been mitigated. It uses survey data to measure the presence of eight attributes: *(1) personal cleanliness and comfort, (2) accommodation cleanliness and comfort, (3) food and drink, (4) safety, (5) social participation and involvement, (6) occupation, (7) control over daily life,* and *(8) dignity*. Survey questions that capture the recipients' view on these attributes were then weighted according to measured preference and aggregated into an overall index of the quality of life resulting from the social care provision. Bulamu et al. (2015) and Makai et al. (2014) find that ASCOT is amongst the most useful metrics for economic analysis of the social care sector.

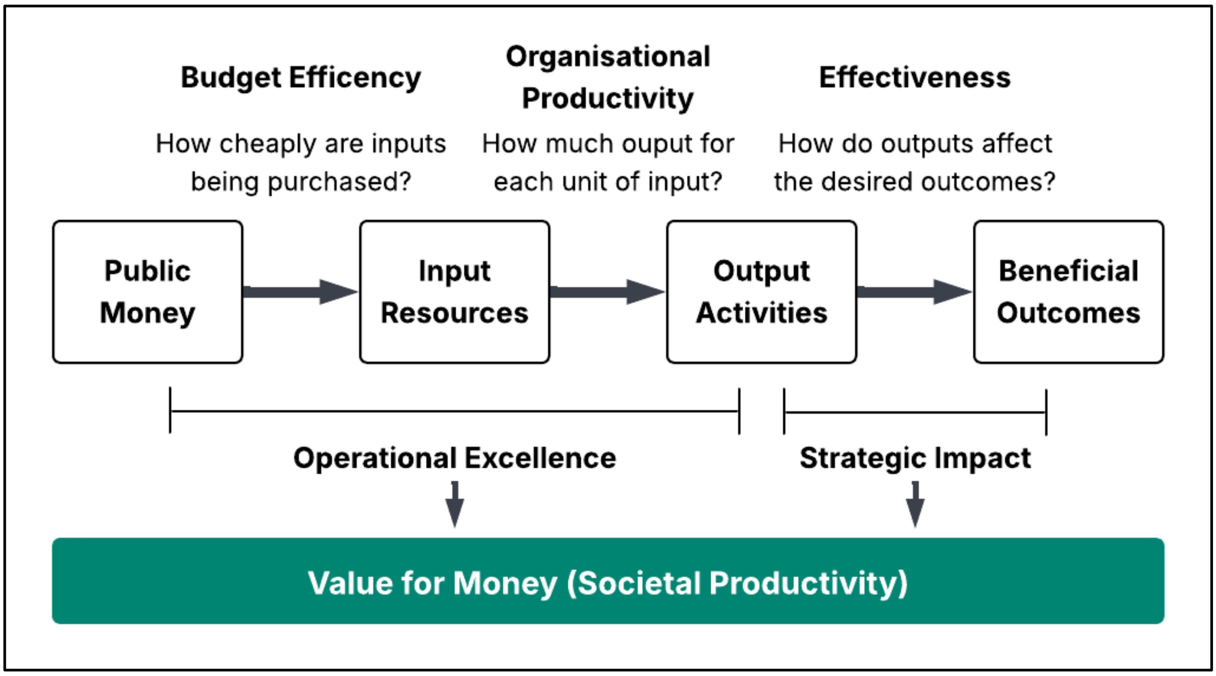
To estimate the overall outcome of the adult social care sector, we use the Adult Social Care Outcomes Toolkit (ASCOT) to augment the measure of the total number of people served. By weighting the number of people supported by the service with how well their needs have been met, we can aggregate these values into an index. Multiplying the number of people served by their average satisfaction provides an estimate of the total welfare impact of social care services.

The welfare measures for ASC, which is only available as of 2016/17 but can be extended to 2023/24, shows a relatively large decline compared to the other measures in Figure 4. While it somewhat stabilised from 2018/19 to 2021/21, it dropped sharply during the year following the pandemic with no trend improvement since - in contrast to the recovery in the last year available (2022) in the ONS data.

3. Service Delivery Chains in Adult Social Care

To identify opportunities for productivity gains in the public sector, the concept of a service delivery chain offers a useful analytical framework (van Ark, 2022). Figure 5 maps out the flow of resources through a public sector activity, starting from initial budgets, moving through input resources and output activities, and culminating in beneficial outcomes for the target population. This way, the productivity of the public sector organisation is assessed by how effectively resources are transformed along the delivery chain. The ratio of budgets into input resources represents *budget efficiency* (sometimes also referred as ”economy”). The ratio of input resources into output activities indicates *organisational efficiency*. The ratio of output activities into beneficial outcomes corresponds to *effectiveness*.

Figure 5: The Delivery Chain of Public Services



Source: Van Ark (2022). Adapted from Aldridge, Hawkins and Xuereb (2016).

The provision of ASC is delivered through different delivery chains. Firstly, *care at home* allows people to receive support in their familiar environment, supporting both their independence and comfort. This can include assistance with daily living activities, medical care, and companionship. Secondly, *community-based care* involves services provided within local settings, such as day centres, community groups, and outreach programs, helping individuals stay connected and engaged with their community (Care Learning, 2025). Thirdly, *residential facilities*, such as care homes and nursing homes, offer a more structured environment with round-the-clock care for those who require intensive support.

With the introduction of the Care Act in 2014, local authorities were given the statutory duty to ensure the delivery of social care. They are required to assess the needs of individuals seeking care and support and fund that care subject to a means test. The Act also tasks local authorities with exploring alternative methods to achieve the same outcomes, such as preventative services and community-based interventions. The Act also requires local authorities to assess and address the needs of carers, even when the individuals they support do not formally qualify for local authority services (Marczak et al., 2022).

Task Improvement and Case Mix in Adult Social Care

Defining the delivery chain in social care is challenging, as the support provided varies widely between individuals and across different localities. These activities can range from basic assistance with daily living tasks, such as bathing and dressing, to more specialised medical interventions like physical therapy or medication management. The suitability of each activity depends on the individual's unique circumstances, including their health condition, personal preferences, and social context (Ajibade, 2021). For instance, a person with mobility issues might benefit from regular physiotherapy sessions, while someone with cognitive impairments might require memory therapy and medication management.

A key aim to improve outcomes is to enhance the variation in care delivery through increased personalisation and a greater focus on working with the assets and support networks that individuals already possess. This approach, known as strengths-based care, requires tailoring care plans to each individual's unique strengths, resources, and preferences, rather than focusing solely on risks or deficits. This method aligns with policy frameworks such as the Care Act 2014, which advocates for personalised and preventative care strategies (Care Act, 2014). Strengths-based care can lead to improved satisfaction among service users, as well as greater levels of wellbeing (Caiels et al., 2024).

To accommodate the combining and substituting of social care activities to deliver value for money in ASC, the delivery chain for each activity in Figure 5 can be further broken down into whether an improvement in productivity is due to better performance of an individual activity ("task performance") or a change in the mix of activities ("case mix"). Task performance focuses on improving productivity by making existing procedures and resources more efficient, while case mix performance involves replacing them with substantially different approaches that deliver higher overall productivity (Table 1).

Table 1: The Types of Improvement Across ASC Delivery Chains

	Budgetary Efficiency	**Organisational Productivity**	**Effectiveness**
Improving task performance	(1) A given task can be delivered more efficiently through improved sourcing of inputs	(2) A given task is adapted to take less time or resource	(3) A given task is adapted to make a greater contribution to outcomes
Improving the case mix	(4) An input resource is removed or substituted for another that is more efficient	(5) A given task is substituted for another that requires less time/resource	(6) A given task is substituted for another that makes a greater contribution to outcomes

Note: Section 4 provides examples of technology applications at different stages of the delivery chain.

Improving case mix performance is particularly important in ASC, as local councils must continually decide which care packages to allocate to individuals. In particular, moving an individual into a care home requires a substantial increase in expenditure. As such, local authorities can be much more productive if they achieve the same outcomes using at-home or community care. As we discuss in the following section, AI technology offers significant potential for productivity gains across the delivery chain from case mix improvements of this kind.

4. The Role of Artificial Intelligence in Adult Social Care

The challenges by the ASC sector have intensified the need to identify innovative solutions that can enhance productivity, improve service delivery, and support workforce sustainability. Digital transformation has been an important area of focus for decades (Government Digital Service, 2014). Recently, artificial intelligence (AI) has been identified as offering new potential to transform various aspects of social care through automation, data-driven insights, and enhanced decision-making.

The key distinction of modern AI systems is their ability to learn patterns and make predictions from large datasets, rather than being explicitly programmed with a fixed set of rules. This data-driven approach is the foundation for the most relevant AI applications in adult social care, which include machine learning for predictive analysis, natural language processing for administrative tasks, and optimisation algorithms for planning and logistics. These capabilities can be applied to transform various aspects of care delivery through automation, data-driven insights, and enhanced decision-making. This section will focus on how AI can be specifically harnessed to achieve productivity gains through the task and case mix improvements discussed previously.

While the framework in Table 1 categorises productivity gains into distinct cells for analytical clarity, in practice a single technological intervention often creates a cascade of effects across the delivery chain. These effects are not always isolated; instead, they can exhibit strong complementarities, where a gain in one area directly enhances the potential for gains in another. Conversely, a focus on one type of gain can create trade-offs that negatively impact another. Examining some specific cases reveals how these forces operate.

The AI-enabled camera system for fall detection (Xiong et al., 2019) provides a powerful example of how strong complementarities can manifest. The technology addresses the critical problem of unwitnessed falls by detecting and recording the event in real-time and immediately notifying on-site care staff. This enables a case mix improvement in organisational productivity (cell 5 in Table 1), as staff can substitute the precautionary, high-cost activity of calling an Emergency Medical Team (EMT) with the rapid, informed task of reviewing the video footage. This procedural change creates a direct complementary benefit in effectiveness, also through a case mix improvement (cell 6): by enabling an immediate response, the system substitutes a high-risk scenario (a "long lie" on the floor) with a low-risk one (immediate on-site care), preventing complications and reducing hospital admissions. In turn, this gain in effectiveness generates a further complementary gain in budgetary efficiency via a case mix improvement on inputs (cell 4), substituting the high costs of emergency services with the lower operational cost of the AI system.

In contrast, technologies based on predictive machine learning can highlight the risk of significant trade-offs, where a potential gain in one area is undermined by a negative impact on another. The study by Sandhu et al. (2020) on a machine learning system for early sepsis detection illustrates this risk. The intended goal of the system was a task performance improvement in effectiveness (cell 3 in Table 3), using the AI model to make the existing task of diagnosing sepsis faster and more accurate. However, the qualitative study revealed concerns among clinicians who suggested they would be "more confident in the model if it had fewer false positives." This highlights a potential trade-off with organisational productivity. The concern is that an excessive number of false alarms could lead to a negative case mix improvement (cell 5), requiring clinicians to substitute valuable time from other duties to perform a new, low-value task of investigating erroneous alerts. Such an erosion of trust, coupled with the risk of alert fatigue, could ultimately negate the intended effectiveness gain.

Other examples of trade-offs which need to be managed are, for instance, an AI-powered scheduling tool which may improve resource allocation and organisational efficiency (cell 5 in Table 1) but also prioritise shorter travel time over continuity of care. Hence, a care recipient could be assigned different carers daily undermining trust and care quality (cell 3), lengthening visits (cell 2) or forcing carers to deprioritise other tasks (cell 6). This underscores the need for organisational leaders to assess all potential impacts of technology—not just cost savings, time efficiency, or outcome improvements—and to gather evidence across the full productivity spectrum.

Investing in technology goes beyond improving task performance. It is also an indirect investment in the care workforce's human capital. By automating routine tasks and reducing administrative burdens, AI enhances job satisfaction and wellbeing (Davenport & Ronanki, 2018), which is key to retaining staff in a high-turnover sector (Skills for Care, 2024). Stability enables the accumulation of skills and institutional knowledge, making technology a strategic tool for building a more resilient and productive workforce, essential for long-term sustainability.

A New Framework for Applications in Adult Social Care

There is no universally accepted classification for how AI technologies have been applied in social care (Seibert et al., 2021; Wahl et al., 2018). On the basis of a detailed assessment of the literature, we propose the following key areas of AI applications:

1. *Managing planning and scheduling*

   Predictive analytics can enhance care planning and scheduling, enabling more efficient allocation of resources and better anticipation of individual needs (The Institution of Engineering and Technology, 2022). AI-powered predictive analytics enable care providers to anticipate individual needs, ensuring timely interventions and reduce the risk of service gaps (Seibert et al., 2021). AI-driven scheduling tools can dynamically adjust staff rosters in response to sudden changes, such as absences or spikes in care needs, improving operational flexibility. This ensures that care is both timely and appropriately tailored, enhancing outcomes for both recipients and providers. These systems can also factor in staff well-being like fatigue and work-life balance issues to reduce burnout and increase job satisfaction.

2. *Reducing administrative burdens*

   AI has been applied to *alleviate administrative tasks* in nursing care, helping to reduce the time spent on documentation and operational processes. AI-powered systems can automate the taking and processing of clinical notes, transcribing spoken interactions into structured data, and extracting key information from unstructured text (Wahl et al., 2018). AI chatbots facilitate efficient and accurate communication supporting both professional collaboration and patient interaction They help streamline information exchange among healthcare providers and between providers and patients (von Gerich et al., 2021), while also assisting in the identification and reduction of errors (Moreno-Fergusson, 2021).

3. *Contributing to operational research*

   In *operational research*, AI tools have been effectively applied to datasets of all sizes and forms, including unstructured datasets such as natural language (Davenport and Ronanki. 2018). In nursing care, AI has supported managerial decision-making by analysing workflow patterns to identify inefficiencies and performance (Rojas et al., 2016). Machine learning algorithms can process large volumes of data from electronic health records, staff schedules, and patient care activities to uncover meaningful trends such as peak workload periods, variations in staff performance, and correlations between staffing levels and patient outcomes (Zampieri et al., 2019). Additionally, AI has been used to monitor compliance with best practices, including adherence to hand hygiene protocols (Yamamoto, 2020). It can also detect workflow inefficiencies, such as unnecessary delays or administrative bottlenecks, enabling targeted process improvements that boost productivity and care quality (Davenport & Ronanki, 2018).

4. *Improving the functionality of assistive and medical equipment*

   The *functionality of assistive and medical technologies* can be improved by integrating AI-powered algorithms into assistive devices. For example, intelligent wheelchairs have demonstrated improved navigation capabilities, reducing the frequency of frontal collisions (Viswanathan et al., 2012). Similarly, Yu et al. (2019) describe an AI-augmented ventilation system, which is trained on historical patient outcome data to automatically adjust settings - such as oxygen concentration and airflow - to optimise both clinical outcomes and patient comfort.

5. *Supporting clinical decision-making*.

   AI applications have been widely used in nursing care to *support clinical decision-making* by generating data-driven insights (Ventura-Silva et al., 2024). For example, AI can process motion sensor data to detect sudden incidents like falls (Seibert et al., 2021). Machine learning algorithms can analyse existing datasets to detect patterns and predict potential health risks, such as hospital-acquired pressure ulcers (Cho et al., 2013). These predictive insights enable staff to take preventive measures, reducing the need for costly interventions later (Song et al., 2021). AI tools can also process systematically collected image and signal data from motion sensors, cameras and audio devices to aid in detecting long-term health changes

(Gerke et al., 2020; NHS Transformation Directorate, 2024). For example, Huang et al. (2022) describe an AI application that uses video analysis to detect signs of abnormal physical conditions such as coughing, back pain, and prolonged inactivity. This tool improved nurses' understanding of patients' conditions and reduced the average evaluation time from 18 minutes to 10.

While the above categorisation provides a useful framework, it masks the vast diversity of AI applications in health and social care. For example, AI applications have also been used for the training of nurses and care providers (Martinez-Ortigosa, 2023). Such applications have been found to increase both the efficacy of the programme for patient outcomes and staff engagement (Chang et al., 2022; Chang, 2022). Seibert et al. (2021) identifies 20 areas where AI tools have been applied in nursing care. Even within these areas there is considerable variation regarding the features of the applications, the types of data required, and the interface with the workforce, highlighting the complexity and adaptability of AI in this sector.

It is concerning that there remains limited evidence on which AI applications are meaningfully improving productivity in ASC. When closely examined, not all AI tools have proven to be cost-effective (Ala-Kitula et al., 2017; Mervin et al., 2018). In a systematic review of AI in nursing care, Seibert et al. (2021) found that 77% of studies were based on a single descriptive or qualitative study, and 83% relied on data collected under laboratory conditions. Similarly, Wei et al. (2025) noted that much of the existing literature consists of small-scale, short-duration pilot studies, making it difficult to assess their broader impact on outcomes. While these pilots offer valuable insights, they often lack systematic evaluation of how AI tools integrate with existing workflows, limiting their usefulness for assessing overall productivity gains. As a result, it remains challenging to predict how widely these technologies will be adopted in practice.

5. Why is AI Adoption in Social Care Slow?

Despite the growing interest in AI applications across public service domains, its adoption remains limited and fragmented, particularly in social care (National Audit Office, 2024; Public First, 2024). While isolated pilot programs showcase AI's capacity to enhance care planning, streamline administrative workflows, and augment clinical decision-making, the sector still lacks comprehensive evidence demonstrating sustained, widespread impact. This implementation gap mirrors challenges observed in the private sector, where translating AI capabilities into measurable productivity gains has proven challenging (Khanfar et al., 2024).

The social care landscape presents unique adoption barriers, including nuanced ethical considerations, workforce digital readiness challenges, complex governance frameworks, persistent uncertainties regarding investment returns, and a general lack of incentives to raise productivity vis-à-vis cost savings. This disconnect between AI's theoretical promise and practical implementation represents a critical challenge for policymakers and care providers alike.

In England, only 0.8-1.1% of council spending is allocated to investment in technology-enabled care (TEC), and just 30% of councils plan to increase this investment (TSA, 2024). The Better Care Fund (BCF), intended to support independent living, allocated only 3% of its 2022-23 budget to explicit investment in assistive technology and equipment, underscoring the limited prioritisation of AI and related innovations in social care (NHS England, 2023).

International studies also indicate a general hesitancy towards AI and robotic technologies in care settings from a more ethical standpoint, especially in patient-facing and clinical tasks. For instance, a 2012 European Commission survey revealed significant resistance to the use of robots: 60% of respondents reported a belief that the use of robots should be banned in the care of the elderly, disabled, and children (Eurobarometer, 2012). Even more recently, a Finnish study found that care professionals doubted the effectiveness of home-care robots in reducing anxiety and loneliness (Rantanen et al., 2018).

The cases discussed in the previous section suggest that most AI applications in social care remain in the early stages of exploration and piloting. As a recent Enterprise AI Maturity model by Burnham (2025) shows, many AI tools are still in an experimental phase, where individuals test them informally before they are integrated into an organisation’s standard practices. Once formally recognised, these applications may progress to structured pilot studies and scale-up efforts. However, only a small number of applications have advanced to the later stages of maturity, where AI is scaled across systems and embedded in processes of continuous innovation. In common with previous waves of innovation, reaching these advanced stages requires not only the collection and curation of high-quality data, but also significant investment in workforce skills and organisational capability (Hoskins, 2025). These topics are explored in the next section of this paper.

Uncertainty around the outcomes of AI investments remains another major barrier to AI adoption in ASC. Many organisations are reluctant to allocate resources without clear, evidence-based demonstrations of tangible benefits, which slows the uptake of potentially transformative technologies. Perceived value plays a critical role in whether care professionals embrace AI or robotics-assisted care (Suwa et al., 2020). Even in Japan, where technology integration has long been a strategic priority in social care, adoption remains limited. As of 2023, only around 10% of Japanese care homes had implemented any form of AI or robotic application (Wright, 2023).

In addition to inadequate processes for gathering and disseminating evidence on the value of AI in ASC, several concerns around ethical, equitable and responsible use continue to hinder adoption. Some of key barriers include (Ayling & Chapman, 2022):

- *Accuracy*: AI systems can make incorrect predictions or decisions, which may lead to harmful consequences, particularly in sensitive care settings (Chakravorti, 2024).
- *Bias*: These systems often learn from historical data that may reflect existing societal inequalities, thereby perpetuating or even amplifying them.
- *Gamability*: AI tools can be manipulated or exploited, undermining their fairness and reliability (Zick et al., 2024). For example, care agencies might tweak input data, such as caregiver availability or preferences, to influence AI-generated schedules in their favour.
- *Privacy*: AI systems in this context process large volumes of sensitive personal data. In social care, this raises serious concerns about data protection and consent (Seibert et al., 2021).

More broadly, the public still tends to be more tolerant of human errors than machine errors, largely because questions of accountability in the latter case are far more complex and harder to resolve. Defining what constitutes responsible AI is itself a complex task. While principles like transparency, accountability, and ethics are widely endorsed, their practical implementation remains challenging (Zick et al., 2024). Frameworks from organisations such as Gartner, Microsoft, and the OECD emphasise fairness, safety, and transparency (Fjeld et al., 2020) but translating these into actionable steps is far from straightforward. For instance, ensuring transparency might involve developing explainable AI models. However, what qualifies as a "sufficient explanation" can vary depending on the stakeholder. For example, in a care home setting, caregivers might consider an explanation sufficient if it clarifies why they were assigned certain shifts. Meanwhile, care recipients may value transparency that reassures them their care is prioritised based on fair and consistent criteria (Spisak et al., 2023).

At its core, many of these questions about responsible use of AI point to deeper organisational challenges, such as decision making culture and people skills as well as the role of policy institutions and government to improve responsible AI use in the ASC sector. These themes will be explored in the next two sections.

6. Skills, Acceptance and Responsibility

The impact of AI applications on workforce productivity depends not only on the technology itself but also on how organisations adapt their skills, workflows, and governance structures in response. Public sector organisations can achieve greater productivity gains from a new technology when they adjust a broader set of complementary inputs, such as skills, organisational capital and other economic competencies (Van Ark, 2022; Van Ark, Hoskins and Jörden, 2023). Below we explore how organisations shape workforce ability to accept and engage with the technology, responsibly is deploy AI applications within the organisation, and translate those into productivity gains.

Skills

Skill development in the ASC sector faces several systemic challenges. One of the most pressing issues is the absence of consistent, comprehensive training programmes. As a result, many care workers feel underprepared to meet the demands of their current roles, let alone the added complexity of using advanced technologies (Singleton, 2025). High turnover rates, driven by low wages and demanding working conditions, disrupt continuity in training and skill acquisition (Skills for Care, 2024). Consequently, only a small percentage of care workers receive the training needed to provide high-quality, personalised care. This not only affects service quality but also limits the sector's ability to realise productivity gains from new AI applications (Singleton, 2025).

The impact of new technologies on skill requirements and human capital in social care can be difficult to predict. A recent survey by Public First (2024) found that 71% of public administration managers cited a lack of skills as a key barrier to greater AI adoption in their institution. Some AI applications in social care, particularly those involving predictive analytics for patient monitoring, require direct investments in new human capital. These applications forecast potential health issues before they become critical, but to use them effectively, nurses must acquire new skills in data interpretation and technology management. This includes understanding AI-generated predictions, integrating them into clinical decision-making, and troubleshooting technical issues (Teixeira, 2024).

New AI applications can also increase the value of existing human capital by serving as a complement to workers' skills. For examples, employees with strong judgment and decision-making abilities are best positioned to interpret and act on AI-generated outputs (Agrawal et al., 2019). In such cases, AI amplifies human capabilities rather than replacing them. For example, AI-powered scheduling tools in social care can automate routine administrative tasks, thereby reducing the demand for traditional administrative skills.

Some AI applications have no direct effect on the skill requirement because they are embedded into other technological applications and require no additional skills beyond operating the main application. For instance, tools like Magic Notes and Copilot are used to transcribe meetings and generate case notes from visits (London Borough of Camden, 2024). These tools streamline documentation processes, enabling social workers to dedicate more time to direct care without needing extra training to use the AI.

While automating these tasks doesn't change the fundamental skills needed for social work, it does free up time for other responsibilities. Therefore, although it has no direct effect on the skill requirement, it may raise the value of other skills that apply to the tasks that workers are now able to spend more time on.

Managerial Skills

Leadership skills that help managers to be aware and confident of the capabilities of new technologies are critical to making informed decisions when adopting new AI applications. Managers with adequate understanding of technology are better equipped to assess whether a particular application will improve productivity, considering factors such as cost, efficiency, service quality, and ethical concerns. Additionally, technically proficient managers can critically evaluate supplier claims, reducing the risk of being misinformed about project costs, timelines, or expected outcomes (PASC, 2011). These skills also enable effective communication with developers and other stakeholders, fostering a transparency and collaboration (Holgeid and Thompson, 2013). Without these skills, managers risk making poor decisions that could limit the potential benefits of AI in enhancing productivity.

A significant number of care managers report deficits in their staff's digital skills, with smaller care homes often having no technical expertise at all (Dunn, Braddell and Sunderland, 2014; Litchfield et al., 2023). This managerial skills gap extends to higher levels of decision-making as well: 42% of council leaders identified limited access to appropriate skills as a critical challenge in adopting new technologies, while 45% cited challenges in developing strong financial cases for technological investment (TSA, 2024). This is likely to affect procurement and hiring decisions by local council executives.

Acceptance

Workforce acceptance of new technological applications is crucial for achieving productivity gains. When employees embrace new technologies with minimal resistance, they are more likely to engage with and effectively utilise these tools, leading to smoother integration and improved efficiency (Skoumpopoulou et al., 2018). High levels of acceptance reduce the time and resources needed for training and troubleshooting, allowing care organisations benefit from the technology more quickly. Moreover, an engaged workforce may provide valuable feedback for refining and improving the technologies, further boosting productivity.

However, workforce acceptance may decline if AI applications negatively impact employee wellbeing, such as by increasing inequality among workers (Card et al., 2012). While automation can relieve staff of ‘drudge work’ like data classification or note-taking, it can affect job satisfaction if it displaces tasks that employees find meaningful or enjoyable, reduces opportunities for creativity, or prevents the use of skillsets that are a source of professional pride (Autor, 2015).In social care, a key consideration is how technology affects the relationship between the caregiver and the recipient, which is a central and highly valued aspect of the role (Wild et al., 2016).

When AI applications significantly disrupt existing workflows, the risk of a trade-off between worker and organisational interests can be greater. This is particularly true if the firm prioritises short-term efficiency gains, potentially favouring cost-cutting technologies that reduce skill requirements, limit worker autonomy or increase workload. Such approaches can undermine employee wellbeing (García-Madurga et al., 2024) and ultimately reduce long-term productivity growth.

Responsibility

Addressing workers' concerns about AI ethics, as outlined in Section 5, is also crucial for successful adoption. Effective implementation of AI requires balancing multiple factors, including privacy, bias, security, and potential workforce disruption, against goals like cost-efficiency and development speed. To achieve meaningful productivity gains and encourage widespread adoption organisation must focus on maximising the value of AI tools while minimising development costs.

Empowering workers to use AI responsibly involves encouraging critical thinking about the technology they are using, enabling them to identify potential biases, inaccuracies, and ethical concerns that may not be apparent during the development phase. Involving employees in the AI implementation process not only enhances the technology's effectiveness but also fosters greater trust and acceptance among the workforce (Wang et al., 2023). Moreover, workers play an important role in uncovering unethical practices or highlighting issues that may not be visible to the public or regulators (Transparency International, 2024)

Managerial staff can use organisational levers to address responsibility issues. They make key decisions about the tools' features, including how to balance privacy concerns with the effectiveness of data-driven applications. Managers can also allocate resources towards developing complementary skills and investments in organisational infrastructure. Additionally, they are responsible for adapting workflows to maximise the new applications' impact on productivity while ensuring that appropriate safeguarding procedures are in place.

7. The Role of Governance in Responsible AI Use

The successful adoption of AI in the social care sector is shaped by several governance challenges that impact organisations' ability to implement these technologies responsibly and effectively. Regulatory and monitoring constraints can hinder proactive oversight of AI-driven decision-making. Regulations may also be more focused on cost savings than on improving outcomes, thereby reducing incentives to focus on productivity more broadly. High managerial workloads further reduce the capacity to innovate, while financial constraints often compel organisations to prioritise short-term cost savings over long-term investments in transformative technologies.

Oversight and Regulation

The regulatory environment plays a vital role in maintaining a balance between protecting public interests and enabling innovation. Well-designed regulations should be flexible and adaptive, promoting ethical AI development while avoiding excessive bureaucracy that could hinder technological progress (Parameshwaran, 2024). To ensure AI delivers equitable benefits, particularly for underrepresented and medically vulnerable groups, regulators must also consider the risks of discrimination and modelling errors (Turner Lee et al., 2025; Government Digital Service, 2025).

Regulations and oversight bodies can foster AI adoption by establishing clear operational frameworks that promote successful collaboration and ensure mutual benefits for all stakeholders. For example, they help organisations set realistic expectations about their interactions with partners (Ruttan, 2001). This includes ensuring that public sector bodies accurately evaluate a supplier's track record in delivering reliable, cost-effective AI solutions. Likewise, suppliers need assurance that public sector clients will provide the necessary data, respond constructively to unforeseen challenges, and meet payment obligations. When there is uncertainty about a partner's reliability, organisations may hesitate to invest in innovation, leading to broader underinvestment (Akerlof, 1978).

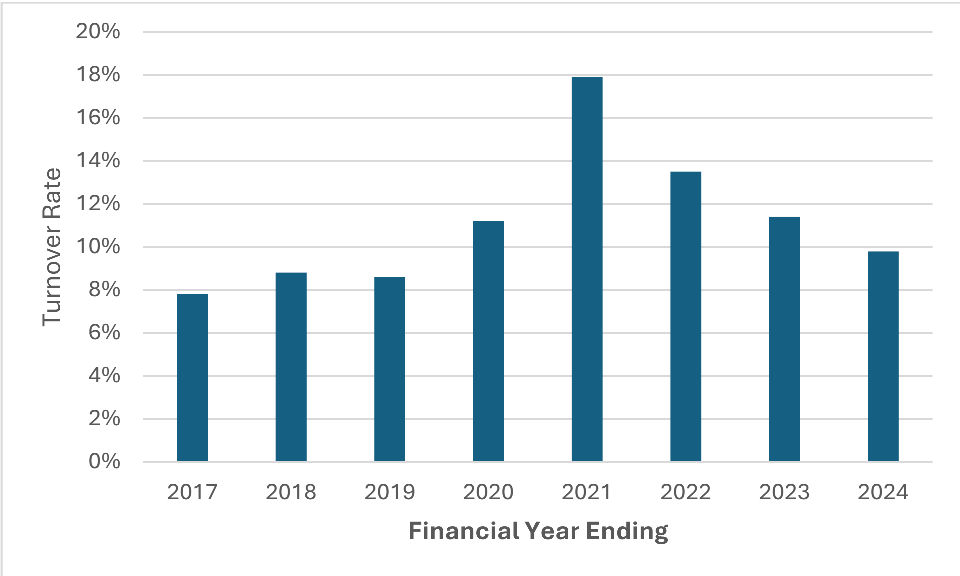
There are significant concerns about the monitoring procedures in ASC, particularly due to the lack of reliable and systematic data collection (Curry and Oung, 2021). For example, there is no accurate record of how many individuals receive private care in England. The Care Quality Commission (CQC), which is responsible for inspecting and regulating care providers, has limited statutory power and can only intervene in organisations already identified as being at risk (Curry and Oung, 2021). This lack of comprehensive data and limited oversight capacity hinders the CQC to proactively identify and address responsibility-relevant issues in the development and deployment of AI.

Accountability, audit, and transparency processes in the public sector often focus more on highlighting failures than recognising successes (OECD, 2019), This affects staff members' willingness to engage in innovation as they respond to signals they receive from colleagues, management, and other public sector bodies about the risks of change. Similarly, managers may avoid investing in frontier technologies if the potential for failure could negatively impact their careers. Therefore, governance frameworks should be designed to acknowledge the inherent risk of innovation without fostering risk-aversion decision-making.

Managerial Overwork

High work pressures can significantly limit managers' ability to focus on developing and implementing AI applications, thereby reducing their potential contribution to productivity. Managers are often required to juggle operational demands with the longer-term need to improve systems and processes. This balance is particularly challenging to maintain in resource-constrained environments (Tushman & O'Reilly, 1996). Without protected time for structured, focused project management, critical aspects such as integrating AI into existing workflows or addressing unforeseen challenges may be neglected (Oung et al., 2021). Moreover, the absence of slack resources means many organisations struggle to divert time and effort from daily tasks to support long-term innovation (Damanpour, 1991).

Figure 6 – Turnover Rate of Managerial Staff in the Independent Sector



Source: Skills for Care (2024)

Evidence suggests that resource constraints are widespread, with 21% of the workforce in ASC too busy to undertake digital skills training and 16% lacking access to employer-provided training opportunities (Blake et al., 2021). Low pay and small pay differentials between frontline workers and managerial roles further discourage progression into leadership positions, contributing to high managerial turnover (Figure 6) and a 12% vacancy rate for registered managers (Skills for Care, 2020). Additionally, 70% of social care workers say that understaffing negatively impacts their mental health (Parker-Dean, 2024). These systemic issues make it increasingly difficult for managers to dedicate the time and attention required for responsible development of AI projects, limiting the sector's ability to realise the productivity and quality improvements such technologies could offer.

Financial Pressure

As discussed in Section 2, local authority (LA) spending on social care has increased sharply in recent years, potentially destabilising their overall financial management. For example, the proportion of councils relying on reserves to meet social care commitments has gone up from 15% in 2022/23 to 37% in 2024/25 (Association of Directors of Adult Social Services, 2024). This growing financial strain is reflected in the rising number of councils declaring effective bankruptcy: only three such cases occurred between 1989 and 2017, compared to ten between 2018 to 2024 (Hoddinott, 2023). The Local Government Association (2023) reports that 20 percent of council leaders believe that their council is now at risk of declaring bankruptcy.

The financial pressures facing the ASC sector have also led to procurement practices that prioritise short-term cost savings, often at the expense of long-term innovation. For example, practices like spot purchasing care hours for individual placements can undermine the development of long-term partnerships to advance integrated and transformative care solutions (Bottery et al., 2018; Needham et al., 2020). In contrast, procurement models that provide a more stable and predictable funding help care providers to co-develop innovative and adaptive care models, which are better tailored to individual needs and more consistent in the quality of service delivery (Department of Health and Social Care, 2021).

Interservice Dependencies

ASC activities are often interdependent with other healthcare provision, making co-ordination with organisations like the NHS crucial. For example, NHS community health services often collaborate with social care services to provide comprehensive home care, reducing hospital admissions and facilitating smoother transitions from hospital to home care (Powell and Mutebi, 2025). Additionally, the evidence suggests that greater integration is linked to improved population health, reduced health disparities, and increased public service productivity (Department of Health and Social Care, 2021).

Since the introduction of the Health and Social Care Act 2011, many government reforms have aimed to strengthen collaboration between organisations across the health and care system. This has culminated in the formalisation of Integrated Care Systems (ICSs) in 2022. A key objective of ICSs is to engage a broader range of care providers in the development of a comprehensive health and care strategy, including those from the private, voluntary, community, and social enterprise (VCSE) sectors (Timmins, 2024). One of the purposes of ICSs is to involve more care organisations, including those from the private and voluntary, community, and social enterprise (VCSE) sector in creating a health and care strategy (Timmins, 2024). Forty-two of these organisations were established across England to oversee the commissioning of health services and to manage the allocation of central government funding within the care system.

Collaboration between social care and other healthcare providers is expected to be essential to improve productivity growth, as it facilitates service coordination, efficient data sharing, and helps prevent duplication of efforts. As ICSs are still relatively new the evidence on productivity gains is still largely qualitative with few systems yet able to demonstrate quantitative productivity gains, which is exacerbated by the lack of shared metrics across different institutions (Care Quality Commission, 2024; Care England, 2023). There are certainly challenges to be overcome. For example, among 42 local authority leaders, two thirds reported that integrating systems with other parts of the health and care system is challenging, especially when it comes to the adoption of new technology (TSA, 2024). More widely, integration itself is acknowledged as a greater barrier to technology adoption than access to skills or technology transfer costs, emphasising the need to simplify processes and improve incentives to collaborate.

8. Conclusion

The ASC sector in England faces an urgent imperative to improve productivity amid rising demand, workforce pressures, persistent financial constraints, and its recent negative productivity trend. While limited resources remain a defining challenge, they do not rule out the potential for meaningful productivity gains. Achieving these gains will require a strategic focus on technology, includingthe responsible use of AI. This, in turn, calls for a broader understanding of productivity that goes beyond cost efficiency, sustained attention to opportunities across the major delivery chains in ASC, and organisational and governance interventions that support continuous improvement at every level of the care system.

This paper shows that opportunities to improve productivity exist at every stage of the social care delivery chain—from the conversion of financial resources into inputs (budgetary efficiency), to the transformation of those inputs into services (organisational productivity), and ultimately to the impact of those services on people's lives (effectiveness). By analysing care provision through this lens, it becomes possible to identify and target specific areas for improvement.

Crucially, productivity gains can be achieved in two distinct ways: by enhancing *task performance*, which makes existing activities more efficient or impactful, and by optimising the *case mix*, which requires choosing more effective combinations of activities to meet care needs. Both strategies offer significant potential, especially when supported by technology and better integration between care and health services.

However, realising this potential depends on the alignment of interventions within organisations in the ASC sector and governance frameworks of the sectors. Organisations must invest in workforce and managerial skills, foster employee acceptance and ensure ethical and responsible AI use. Empowering staff, addressing wellbeing, and supporting innovation through stable leadership and infrastructure are essential for sustainable impact.

Governance reforms should prioritise oversight that emphasises outcomes rather than merely cost-cutting or risk minimisation. Regulatory frameworks must aim to reduce managerial burden by offering clear, actionable guardrails instead of adding layers of bureaucracy. The sector's funding model requires both long-term stability in overall budget and the flexibility to respond swiftly to emerging challenges. This includes improving data systems, enabling innovation-friendly governance, stabilising procurement practices, and fostering collaboration through Integrated Care Systems. Importantly, investment often needs to precede reaping the rewards, which is at the heart of the productivity J-curve (Brynjolfsson et al. 2021).

Improving productivity in ASC is central to building a more sustainable, equitable, and effective system that can deal with an aging population. Ultimately, this will require a dual strategy, namely to continue addressing the management of limited resources while embedding a culture of continuous improvement focused on productivity to achieve better outcomes. This includes better measurement tools, support for frontline innovation, and reforms that align financial mechanisms with the goal of delivering high-quality, person-centred outcomes. In doing so, the sector can move beyond crisis response and towards a model of care that is both more resilient and more responsive to the diverse needs of those it serves.

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