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research article

What do the public think about artificial intelligence note-taking tools in social care?

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Dozens of local authorities across England are piloting automated note-taking tools, often called 'digital scribes', in social care assessments and other interactions. These artificial-intelligence-enabled technologies automatically record, transcribe and summarise assessment meetings into standardised templates, promising a reduction in administrative burden and more time to focus on interpersonal interactions. While research has begun to explore staff attitudes towards these tools, public perspectives remain heavily underexplored. This article details findings from a survey experiment with 1,127 carers in England, examining attitudes towards these automated note-taking technologies. The article compares perceptions of automated versus manual note-taking and of fully automated systems versus those with human review ('human in the loop') and investigates demographic differences in attitudes. We draw on these data to set out a fourfold typology of attitudes: 'enthusiasts', 'cautious adopters', 'pragmatists' and the 'resistant'.

Keywords social care • needs assessments • automated note-taking • artificial intelligence • human in the loop

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Introduction

Social workers spend most of their working week writing. Based on self-reported measures and observations, Lillis et al (2020: 442–7) estimate that at least 68 per cent of social workers' time is spent on text-based activity: inputting information into case management systems, keeping notes from assessments and phone calls, preparing documentation for meetings, writing emails, and so on – routine writing tasks that dominate the working day and often stretch into the evenings and weekends beyond it. Writing is, therefore, both 'central' to social work practice – it is part-and-parcel of undertaking assessments and formulating professional judgements – and a time-consuming activity that is often characterised as a problematic 'administrative burden' on increasingly resource-constrained staff (for a review of the literature to date, see Rai et al, 2025).

It is perhaps no surprise, therefore, that tools to automate parts of the writing process are some of the first widespread applications of artificial intelligence (AI)-enabled technologies in social work (for an outline of the broader adoption of AI-enabled technologies in social care, see Coulthard et al, 2025). In the English social care sector, one such provider, MagicNotes.ai, has been piloted by over 40 local authorities. The self-described 'AI assessment solution' claims to 'transform social workers' productivity with AI' by recording and then summarising social work needs assessments (or other interactions) into pre-designed templates, ready to copy and paste into a local authority's case-management system (Magic Notes, 2025). Similar tools, often called 'digital scribes', have been adopted in primary healthcare settings, where clinician and patient interactions are summarised using advanced speech recognition and natural language processing technology to provide a summary (for one such example, see Misurac et al, 2025).

These tools are often evaluated from the point of view of staff. Prior research has explored how they can reduce burnout, minimise administrative burden and save money (Coiera and Liu, 2022; Misurac et al, 2025). Work on staff attitudes demonstrates that many have 'unanimous aversion' to the use of 'algorithmic decision systems' but have a 'strong interest' in AI tools that are instead designed to help them 'spend less time on administrative tasks' (Wassal et al, 2024). This article instead addresses a question that has remained underexplored in the context of the use of these tools in both social care settings and more broadly: what do the public and people accessing social care think of their use? These tools have the potential to improve experiences of public interactions with staff. As Magic Notes put it, automatic note-taking 'allows caseworkers to focus on in-person conversation' (Gov.uk Marketplace, 2025). However, in other contexts, the use of AI-enabled technologies can raise procedural fairness concerns, particularly in respect of privacy, feelings of being heard and transparency (see Meers et al, 2023).

This article explores this question in four sections. The first provides a precis of existing work on AI-supported 'note-taking' tools and 'digital scribes'. The second details the method in this article: a survey experiment with 1,127 carers in England testing attitudes to three scenarios, each adopting a different 'note-taking' approach. The third sets out the quantitative findings of the study, before the fourth and final section sets out the qualitative findings from open-text data in the survey instrument. In the latter, we set out a fourfold typology of attitudes to the use of these systems based on the qualitative data in our survey: 'enthusiasts', 'cautious adopters', 'pragmatists' and the 'resistant'. In doing so, we aim to contribute to understanding of public attitudes on the use of these tools and set out an agenda for future research on their design and implementation in social care settings.

Digital scribes: AI note-taking tools

Note-taking tools, such as Magic Notes and other similar platforms, view their offer as a simple win–win proposition. The tool is installed on a device (such as a smartphone), records an interaction (whether face to face or over the phone) and then uses a temporary transcription as the basis for generating a summary and parsing the meeting for information to include in a predetermined template. Similar tools existed before the proliferation of generative AI, but the widespread availability of these technologies has increased the adoption and sophistication of these tools while decreasing the cost.

An existing evidence base on similar note-taking tools, generally referred to as 'digital scribes', exists in the medical context. Publicly available data from the dozens of authorities piloting the tool point to early findings on their use mirroring this existing evidence in two ways. First, reductions in the administrative burdens placed on staff are highlighted. In their trial of Magic Notes, Sandwell Council (2025) estimates a '63 per cent reduction in admin time', with the tool 'significantly reducing the time social workers spent on paperwork'. In the medical context, empirical work with nurses has identified several perceived 'staff-facing' advantages of digital scribes: paperwork reduction (Dinari et al, 2023); saving time and decreased administrative costs (Swan, 2021); and more accurate and consistent documentation (Dinari et al, 2023). Nevertheless, staff are also wary of glitches and the potential of 'de-skilling' if technology is deployed to make assessments (Wieben et al, 2024). Studies that carried out specific trials of AI-assisted note-taking tools found that these technologies do significantly reduce the time that practitioners spend on documentation, without changing the time spent with patients (Balloch et al, 2024). On-site recording has particular efficiency gains for visiting nursing staff, who would otherwise be required to return to a computer station (Ferizaj and Neumann, 2024).

Second, evidence that the availability of the tool can affect the quality of the interaction it is recording has been noted. Solihull Council (2025) refers to their Magic Notes trial as a 'gamechanger' which led to 'better quality conversations with the people we are supporting' given that 'the social worker was able to concentrate fully … rather than having to take notes'. This mirrors evidence in the medical context that the use of AI technology may enhance consultations by enabling practitioners to be more present with patients without the distraction of making notes (Wang et al, 2022; Balloch et al, 2024). Despite these benefits, such trialled software posed some problems, including: occasional omissions of information (Balloch et al, 2024); less accurate speech recognition for certain accents, dialects or speech disorders (Suominen et al, 2014; Wang et al, 2022; Ferizaj and Neumann, 2024); and difficulties in retroactive editing (Balloch et al, 2024). The importance of training or meetings to improve staff education about the software has been emphasised throughout the literature (Wang et al, 2022; Balloch et al, 2024; Ferizaj and Neumann, 2024).

What emerges is a clear evidence base focused on the (largely positive) views of staff using these tools. What remains heavily underexplored are the attitudes of either the public or those navigating the social care system themselves. These perspectives are important not only normatively but also because they may affect the effective design and implementation of these tools. In other contexts, the use of AI-enabled technologies can raise procedural fairness concerns, particularly in respect of privacy, feelings of being heard and transparency (see Meers et al, 2023). The next section turns to the method before setting out our quantitative and qualitative findings.

Method

To explore these issues, we delivered a survey experiment to 1,127 carers in England via the Prolific UK panel – a panel provider widely utilised in social science research, including for recruiting panels in similar studies (see Fine et al, 2025). Participants were quota-sampled to ensure a spread of demographics across the sample, with full descriptive characteristics of the sample detailed in Table 1. We examined the attitudes of carers (as opposed to the public more generally), as a greater proportion of this group have engaged with the social care system (or may do so in future). Indeed, many carers have direct experience accompanying care recipients to assessments, helping to implement care plans or navigating the system on behalf of others. Additionally, carers themselves are entitled to their own needs assessments under the Care Act 2014. As in the sample demographics set out in Table 1, this allowed us to achieve a greater proportion of people with the same experience of the care system than would be the case for a public sample. We do not claim that this is a representative sample, and we acknowledge the limitations of this for the generalisability of our findings, but our sampling approach did ensure that the total ethnicity split in the sample reflects the UK public as a whole (with 81 per cent white respondents), a spread of age ranges and a split between male and female respondents. The study has ethical approval from the Economics, Law, Management, Politics and Sociology Ethics Committee at the University of York.

The survey was in three stages (the full instrument is available in the Online Appendix). The first set out a hypothetical scenario where an individual ('Alex') sought social care support because of mobility issues (related to a chronic health condition) and was subsequently contacted by a social worker from their local authority to conduct a needs assessment. Participants were randomly allocated to one of three different scenarios providing details of this meeting: one with manual note-taking, a second with the use of an AI-enabled note-taking tool where the notes were reviewed by a social worker, and a third using the same tool but where the notes were not reviewed. The scenario and condition texts are detailed in Figure 1.

After viewing the randomly assigned scenario, participants were asked a series of questions about their view of its procedural fairness, namely, whether the participant thought the following:

- that the process allowed Alex to express themselves;
- that the process provided the social worker with enough information to make a fair decision about Alex;
- that the process respected Alex's privacy and confidentiality;
- that the process treated Alex as a person, not just like a case to be processed;
- that the process was designed to fully understand Alex's situation;
- that the process gave Alex sufficient control over the assessment and the information recorded;

- that the process collected only the minimum necessary personal information required to determine Alex's care needs;
- that the process was transparent; and
- that the process followed due impartiality, with no prejudice.

Table 1: Descriptive statistics of survey sample

Characteristic	*n*	% of the sample
Age		
18–24	58	5.3%
25–34	237	21.5%
35–44	254	23.0%
45–54	245	22.2%
55–64	222	20.1%
65+	86	7.8%
Mean (years)	44.9	
Median (years)	45	
Range (min–max)	18–78	
Gender		
Female	586	53.2%
Male	516	46.8%
Ethnicity		
White	898	81.5%
Asian	106	9.6%
Black	53	4.8%
Mixed	35	3.2%
Other	10	0.9%
Region		
South East	200	18.1%
North West	161	14.6%
London	133	12.1%
West Midlands	121	11.0%
East of England	111	10.1%
Yorkshire and the Humber	109	9.9%
South West	106	9.6%
East Midlands	98	8.9%
North East	63	5.7%
Care experiences		
Has had a social care needs assessment	110	10.0%
Cares for someone who has had a needs assessment	545	49.5%
Works in the social care sector	95	8.6%
Cares for someone under 18	168	15.2%
Prefers not to disclose who they care for	66	6.0%

Note: N = 1,102.

Figure 1: Experimental conditions in the survey instrument

What happened at the meeting

Alex was quite nervous about the assessment. The social worker travelled to Alex's home to meet with them. At the meeting, they spoke with Alex about their circumstances and asked them some questions – this lasted around one hour.

During the conversation, Alex became visibly upset and tearful. The social worker allowed Alex time to compose themselves before continuing with their questions.

[Condition A: The social worker took notes throughout the whole conversation by typing onto their laptop.

After the meeting, the social worker reviewed these notes and used them to take a decision about Alex's needs. **[END]]**

[Condition B: The social worker recorded the audio of the whole conversation on their laptop with software that automatically generated a summary of the discussion using AI (artificial intelligence) technology.

After the meeting, the social worker reviewed this summary to ensure it accurately reflected what was discussed, making corrections where necessary. The social worker then used the summary to take a decision about Alex's needs. **[END]]**

[Condition C: The social worker recorded the audio of the whole conversation on their laptop with software that automatically generated a summary of the discussion using AI (artificial intelligence) technology.

After the meeting, the social worker downloaded this summary without manually checking its accuracy against the recording. The social worker then used this summary to take a decision about Alex's needs. **[END]]**

These questions were developed from prior studies assessing procedural fairness using experimental methods in other contexts (see Meers et al, 2025).

This experimental condition was then followed by a series of items exploring the participants' attitudes to AI taken from a well-established scale (Schepman and Rodway, 2020) and an open-ended question asking for their general views on the use of automated tools to record social care needs assessments. The latter collected a total of 45,804 words of qualitative data. Of the original sample of 1,127, a total of 25 participants failed an attention check and were excluded from the study. This led to a final sample of 1,102, of which 358, 378 and 366 received the first, second and third scenarios, respectively.

The open-text qualitative data (45,804 words in total) were analysed using a thematic analysis approach (Braun and Clarke, 2006). Initial coding was conducted independently by two researchers to identify recurring patterns and themes in participants' responses. These initial codes – based on process qualities identified in prior work (see Halliday et al, 2024) – were then discussed, refined and grouped into broader themes through an iterative process of comparison and review. This analysis led to the development of the fourfold typology presented in this article, which we return to in more detail later.

Results of the survey experiment

The results of the experiment show significant differences in attitudes between the three scenarios. In short, the AI-supported note-taking without human oversight (Condition C) was consistently rated significantly lower across nearly all procedural fairness dimensions compared to both manual note-taking (Condition A) and AI-supported note-taking with human oversight (Condition B). Table 2 provides a broad overview of the trends across the dependent variables using a simple net agreement measure, where the total percentage agreeing is subtracted from the total percentage disagreeing. Here, the 'no human in the loop' condition had a significantly lower net agreement score across eight of the nine measures.

Table 2: Net agreement score ([% Somewhat agree + % Strongly agree] – [% Somewhat disagree + % Strongly disagree]) for dependent variables by experimental condition

Statement	Human notes	AI – Human in the loop	AI – No human in the loop
Allowed Alex to express themselves	72.7%	64.5%	52%
Provided enough information for a fair decision	38.6%	42.9%	–14.2%
Respected Alex's privacy and confidentiality	52.5%	15.3%	–2.8%
Treated Alex as a person, not just a case	52.8%	27.3%	–17.2%
Was designed to fully understand Alex's situation	56.8%	44.7%	–4.1%
Gave Alex sufficient control over the assessment	18.1%	5.6%	–43.7%
Collected only the minimum necessary information	18.4%	8.5%	15%
Was transparent	35.4%	41.1%	–20%
Followed due impartiality, with no prejudice	48.8%	45%	10.7%

Source: Available at: https://datawrapper.dwcdn.net/Z44NK/1/.

To explore these results further, we undertook a one-way analysis of variance (ANOVA) on the mean ratings for each fairness dimension across the three experimental conditions. Table 3 details the results of this analysis. It shows the mean ratings for each experimental condition, followed by the ratio of variance between groups to variance within groups (F), the statistical significance of the variation (p), and the effect size (n^2). The final column ('Pattern') shows the order of the mean ratings by experimental condition.

Two key patterns emerge in the data. First, overall, AI-supported note-taking without human oversight (Condition C) was consistently rated significantly lower across nearly all procedural fairness dimensions compared to both manual note-taking (Condition A) and AI-supported note-taking with human oversight (Condition B). The largest differences were for providing enough information for a fair decision (M = 2.86, compared to M = 3.66–3.69 in other conditions), treating Alex as a person (M = 2.76, compared to M = 3.49–3.85) and the transparency of the process (M = 2.78, compared to M = 3.63–3.65).

Second, the presence of a 'human in the loop' checking the notes was pivotal for attitudes. For five of the nine fairness variables, participants did not perceive significant

Table 3: Mean ratings and ANOVA results for three experimental conditions

Statement	Human notes	AI with human oversight	AI without human oversight	F(2, 1099)	p	η^2	Pattern
Allowed Alex to express themselves	4.13 (0.97)	4.08 (1.10)	3.72 (1.14)	15.44	< .001	.027	A = B > C
Provided enough information for a fair decision	3.66 (1.19)	3.69 (1.18)	2.86 (1.30)	54.79	< .001	.091	A = B > C
Respected Alex's privacy and confidentiality	3.96 (1.09)	3.38 (1.32)	3.01 (1.27)	54.97	< .001	.091	A > B > C
Treated Alex as a person, not just a case	3.85 (1.11)	3.49 (1.33)	2.76 (1.33)	70.26	< .001	.113	A > B > C
Designed to fully understand Alex's situation	3.87 (1.06)	3.69 (1.13)	2.95 (1.37)	61.22	< .001	.100	A = B > C
Gave Alex sufficient control over the assessment	3.36 (1.23)	3.14 (1.29)	2.37 (1.27)	62.11	< .001	.102	A = B > C
Collected only the minimum necessary information	3.54 (1.28)	3.28 (1.28)	3.33 (1.25)	4.36	.013	.008	A > B; C = A, B
The process was transparent	3.63 (1.13)	3.65 (1.14)	2.78 (1.27)	64.45	< .001	.105	A = B > C
Followed due impartiality, with no prejudice	3.94 (1.05)	3.79 (1.10)	3.21 (1.22)	42.44	< .001	.072	A = B > C

Notes: Values are means, with standard deviations in parentheses. A = human notes; B = AI with human oversight; C = AI without human oversight. The 'Pattern' column indicates significant differences between conditions based on Tukey's honestly significant difference (HSD) post-hoc tests (p < .05), where '=' indicates no significant difference and '>' indicates significantly higher ratings.

differences between traditional human note-taking and AI-supported note-taking with human oversight. Specifically, the ability for Alex to express themselves, the provision of sufficient information for fair decision-making, the understanding of Alex's situation, the level of control over the assessment and perceptions of transparency and impartiality were all rated similarly between these two conditions. Manual note-taking was rated more favourably than AI-supported note-taking with human oversight in regard to respecting privacy and confidentiality (M = 3.96 versus M = 3.38), treating Alex as a person rather than a case (M = 3.85 versus M = 3.49) and collecting only the minimum necessary information (M = 3.54 versus M = 3.28).

This suggests that while AI-supported note-taking with human oversight may compare favourably with manual note-taking in terms of procedural elements like information gathering and transparency, participants still had concerns about privacy, personalisation and data minimisation when AI technology was involved, even with human review. These findings highlight the critical importance that participants placed on human review of AI-generated notes. Without human oversight, ratings dropped below the midpoint of the scale (3.0) on several dimensions, indicating predominantly negative perceptions.

These results suggest that while participants expressed some concerns about AI-supported note-taking in general, the presence of human oversight significantly mitigated these concerns across most dimensions of procedural fairness. The removal of human oversight, however, substantially reduced perceived fairness across almost all dimensions. This highlights the crucial role that human review plays in maintaining public confidence in automated assessment processes within social care contexts.

A typology of attitudes

The quantitative results demonstrate that the use of AI-enabled note-taking tools has a significant impact on carers' attitudes to our procedural fairness measures. To explore the possible rationales for this further, we analysed the 45,804 words of open comments data provided by participants at the end of the survey.

Extensive literature exists on technology acceptance and adoption, with well-established frameworks, such as the technology acceptance model (TAM) and its extensions, the unified theory of acceptance and use of technology (UTAUT), and more recent work examining AI-specific attitudes (for examples of these being discussed in the context of generative AI technology, see Ma et al, 2024). For instance, influential work by Kelley et al identifies a fourfold typology of AI attitudes: 'exciting', 'useful', 'worrying' and 'futuristic' (Kelley et al, 2021). While these frameworks provide valuable theoretical foundations, research demonstrates that attitudes towards AI are highly context dependent: views on AI-enabled technologies in one domain (such as education) do not always translate to another (such as defence or healthcare) (Ada Lovelace Institute and The Alan Turing Institute, 2023).

The social care context presents unique considerations that warrant the adaptation of existing frameworks. Social care involves particularly vulnerable populations, complex ethical considerations around consent and autonomy, and distinctive professional relationships between carers and service users. While general technology acceptance models offer important insights, they may not fully capture the specific tensions and concerns that emerge when AI is deployed in intimate caregiving contexts. As Isbanner et al (2022) argue specifically for the health and social care contexts, there is a need to 'better understand the reasons underpinning people's judgements' in these sensitive domains.

Building on established technology acceptance literature while remaining attentive to the specificities of social care, our analysis of the qualitative data reveals four distinct attitudinal positions that both echo and extend existing typologies. We identify 'enthusiasts', 'cautious adopters', 'pragmatists' and the 'resistant' – categories that map partially onto traditional adoption categories but incorporate social-care-specific concerns around dignity, human connection and professional judgement. This typology thus bridges general technology acceptance frameworks with the particular ethical and practical considerations of AI deployment in social care settings. We address each perspective in turn.

The 'enthusiast'

Enthusiasts saw the use of the technology as an unalloyed positive and thought it held potential to improve the social care needs assessment process. For example:

> I think the use of AI could be crucial in the field of social care, as it is so stretched at present, and anything that could save time and resources can only be for the good.

> I think that it was a splendid idea that was quite fair, seeing as the AI has no bias and can be objective while making the summary. I also believe it was efficient in the analysis, without forgetting important details that can help their case.

Here, participants tended to identify instances where they thought AI-enabled technologies could improve upon human-only capabilities. For instance, because they have 'no bias and can be objective while making the summary' or can be 'efficient in the analysis, without forgetting important details'. As one participant put it:

> I think the use of automated tools is a useful and proactive way of summarising information gathered in a more concise and accurate way. It can help to capture details which the human professional may 'forget' while trying to ask questions and process responses while paying attention to the individual being assessed.

In line with the quantitative results outlined earlier, enthusiasts did not call for complete automation or the removal of the 'human in the loop'. Indeed, participants who saw the use of the technology in very positive terms also tended to reflect a view that its use would free up the social worker to 'stay present with the person they're meeting' and to avoid making notes feel 'off-putting for the person being assessed'. For instance: 'I think it is a good idea, allowing the social worker to concentrate fully on the needs of the client without constantly having to refer to their laptop to transcribe what is being discussed. The more attention the client receives, the more valued they are made to feel.' The enthusiasts' perspective centred on the potential for AI note-taking to enhance rather than replace human elements of care. Significantly, even these most positive participants retained a commitment to human oversight, viewing the technology as complementary to professional judgement rather than a substitute.

The 'cautious adopter'

Cautious adopters in the sample were generally positive about the use of the technology in principle but had specific concerns they wanted addressed or clarified. These tended to be at least one of three issues. The first was that the summary was not used as a substitute for the final decision, or that there was still a 'human in the loop'. As one participant put it, it is important to avoid a 'computer says no sort of thing':

> Whilst I'm not against such tools per se, they should only be just that: a tool. It should not have the decision power (the computer says no sort of thing). It should only be a recording tool, no different than a tape, for example. The claimant should definitely be able to accept or reject whatever is subsequently summarised, as indeed– so should the assessor. Lack of the software's ability to have intuition and an understanding of spoken intonation concerns me, as does any assessor who simply would accept the tool's output regardless.

The second concern was that there should be clear consent from the person being assessed. The idea that the person 'absolutely needs to be offered the chance to give their consent' arose routinely in the open comments, along with concerns about whether 'vulnerable people can consent'. This was seen as important given that some people may feel more 'uncomfortable' with the use of this technology than others:

> I believe the tools can be helpful; however, consent should be sought from the person who is having the needs assessment. They may feel uncomfortable with a third-party AI app having access to their personal answers and their recorded voice.

> It makes sense to use such technology so that the social worker can assess more cases. However, it is important that the person is aware of the use of such technology and how it will inform the decision-making process.

Third, a widespread view in this typology was that the 'human in the loop' should extend to the person being assessed themselves: they should also have access to the outputs from the technology and a chance to respond or make 'corrections':

> Is the person being assessed given a copy of the summary and also allowed to make corrections? This should be done automatically. Will the summary reflect any inherent bias that the assessor has? I have no problem with this as long as humans make the final decision/the summary can be challenged.

These participants' concerns about human oversight, informed consent and service user participation suggest that acceptance of AI note-taking tools depends heavily on implementation details rather than an in-principle concern about the technology itself: 'It's ok, but to a degree. The social worker needs to manually check the summary and make sure that it's correct, and the social worker needs to make the end results decision, not AI, as they were there visualising the person. AI can record, but it doesn't have feelings.' 'Cautious adopters', therefore, were broadly welcoming of the use of the tool, provided their caveats on implementation were adequately addressed.

The 'pragmatist'

Pragmatists in the sample had a more fatalistic viewpoint about the use of technology. Here, participants had concerns about the use of AI-enabled technologies but saw their increased future use as 'an inevitable development', either because of the resource pressures facing social care and the state more generally or because of its allure as a new technology. Unlike the 'cautious adopters', their concerns were not focused on how the technology would or should be implemented but more a fatalism that current pressures mean that developments are inevitable regardless. As one participant put it:

> I can see that it would reduce a significant amount of admin time for the human worker, but I cannot believe that it is capable of picking up on the nuances of an interaction, and the sixth sense one hopes professionals will possess will surely be bypassed. Inevitably, it's on its way, however. One just has to hope that blunders in dealing with humans will be erased over the course of time.

Pragmatists were clearly aware and concerned about resource pressures in the social care sector. The use of this kind of technology was 'probably needed due to limited resources that the social care industry is experiencing' or has 'absolutely a place in overstretched public services', as they should be 'using all tools available for efficiency'. This resource issue was particularly important for some participants, who saw that it 'could be crucial in the field of social care, as it is so stretched at present and anything that could save time and resources can only be for the good'.

For pragmatists, the adoption of AI note-taking technology represented a necessary compromise between ideal practice and practical realities. Unlike enthusiasts, who embraced the technology wholeheartedly, or the resistant, who rejected it on principle, pragmatists recognised both the limitations of automated systems and the mounting pressures on social care services that make such tools increasingly attractive. Their perspective suggests a resigned acceptance of technological change, coupled with hope that implementation challenges can be addressed over time.

The 'resistant'

The resistant in the sample were far more critical about the use of AI-enabled technologies. These sentiments were rarely targeted at the use of AI technologies in any context but, instead, focused on their use in social care contexts (or needs assessments themselves) specifically. As a sector that is 'primarily about human contact', resistant participants were sceptical that AI-enabled technologies were ever capable of capturing the nuances of human interaction:

> I think recording is fine, but I think when it comes to social care, there is a need to feel the emotions of that person through their voice. AI may be able to transcribe and summarise the meeting, but I think listening and making note of a person's tone, reaction and engagements in the meeting can pinpoint issues that AI cannot. Social care needs to have a human element at the end of the day; it is someone's life that they are trying to help.

These limitations were frequently reflected in participants' responses. Many expressed concern about the technology's inability to understand emotional nuance, body language and the subtle contextual factors that are critical in social care assessments:

> I disagree with them greatly. I believe that it is taking away the person-centred approach that these things should have. I would feel very uncomfortable if my care assessment were done with AI, and it would make me feel nervous. I really don't think this is the right idea, especially with people who are neurodivergent.

This group frequently emphasised that AI lacks the capacity for empathy and human judgement that are essential in understanding vulnerable individuals' needs:

> Terrible. It does not factor in the patient's emotional state at the time of assessment and can't possibly ascertain a true reflection. What if a patient changes their mind about something? Does the AI pick up on this and factor it into the decisions or just take the first answer? What if the patient is confused due to emotional distress and gives an answer they have not thought through properly.... I don't like the idea at all.

Concerns about appropriateness for maintaining a person-centred approach were central to the resistant perspective. These participants viewed AI-enabled note-taking as fundamentally incompatible with the values and practices of effective social care, particularly its emphasis on individual dignity and personalised assessment. The resistant group often framed their objections in terms of how the technology might affect service users' comfort and trust in the process: 'It appears to make what was already a difficult process even more impersonal. Although the tools may ensure that important facts are not missed, I feel the thoughts and feelings of clients may be overlooked in the process.'

Overall, resistant participants rejected AI-enabled note-taking tools as fundamentally misaligned with social care's core purpose: understanding and supporting people in vulnerable situations. They saw the technology as incapable of grasping the emotional subtleties, contextual factors and non-verbal cues essential to needs assessments. For this group, efficiency gains were less important than maintaining the human element of care. Their views highlight a key implementation challenge: reconciling technological innovation with deeply held beliefs about the interpersonal nature of social work practice.

Conclusion

As local authorities across the country increasingly pilot and indeed adopt automated note-taking tools, this article makes three key contributions to understanding attitudes towards the use of this technology in social care assessments. First, we demonstrate that the presence of human oversight, the so-called 'human in the loop', is pivotal in shaping perceptions of procedural fairness. In our experiment, AI-supported note-taking without human review was consistently rated lower across nearly all procedural fairness dimensions, while maintaining a 'human in the loop' preserved similar levels of trust to traditional manual note-taking methods. This finding aligns with staff preferences identified in prior research for AI tools that augment rather than replace human judgement (Wassal et al, 2024).

Second, our qualitative typology reveals that attitudes are not binary but, instead, fall along a spectrum from enthusiastic acceptance to deep resistance. However, even the most positive participants maintained that human oversight was essential, while the most resistant were not necessarily against the use of these tools in all contexts but had particular concerns about their adoption in social care contexts or needs assessments specifically. This contingency of attitudes reinforces findings from wider research on public attitudes towards AI, which demonstrate that views depend upon specific use cases (see Ada Lovelace Institute and The Alan Turing Institute, 2023). The resistant participants, in particular, articulated concerns about AI's capacity to capture emotional nuance and maintain person-centred approaches in the social care context that may not arise in other settings.

Third, our findings highlight specific implementation concerns: the importance of informed consent, service user control over outputs and preserving the emotional and interpersonal dimensions of social care assessments. These findings suggest that the successful deployment of AI note-taking tools must address these procedural issues, such as how to communicate the use and functionality of the tool and ensure consent, as well as the technical aspects of how they work or can be integrated into a social worker's workflow.

Overall, our findings underscore the importance of examining what people think about the use of these tools. The use of AI-enabled tools like digital scribes holds potential in the social care context (and elsewhere). However, predominantly focusing on staff attitudes to their use and adoption misses an important part of the overall picture for their successful implementation. If AI-enabled tools struggle to achieve legitimacy among the public and people accessing social care, then they are unlikely to be effective. Our results suggest that there is scope for a design and implementation of digital scribes that the public thinks are procedurally legitimate.

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Research ethics statement

Ethical approval was obtained from the Economics, Law, Management, Politics and Sociology Ethics Committee at the University of York.

Conflict of interest

The authors declare that there is no conflict of interest.

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