Social work practice and artificial intelligence: A scoping review

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ABSTRACT

INTRODUCTION: This scoping review explores artificial intelligence (AI) in social work between 2014 and 2024. It focuses on: a) the volume of the literature; b) the functions and benefits of AI in social work practice and the influence on social justice and social change on clients; c) the ethical considerations for social workers using AI; and d) the skills and knowledge social work practitioners need to have to navigate the AI-influenced landscape.

METHODS: Three electronic databases were searched, and 53 articles related to four research questions were identified. A PRISMA checklist and tool were followed. The articles were critically analysed for content, methodology, and findings through the research questions.

FINDINGS: The review found an emergent volume of literature indicating that AI applications in social work practice are heavily influenced by the AI model and design process implemented. Social workers' use of AI has both benefits and challenges. Ethical issues related to bias and social justice, as well as the reliability and trustworthiness of AI outcomes and decisions, were identified. The need for specific training in AI and social work to assist social workers in critically evaluating AI contributions and using them effectively was also noted.

CONCLUSIONS: The article recommends further research to identify the prevalence of AI use in social work practice and its implications regarding ethics, social justice, and Te Tiriti o Waitangi. It also recommends re-evaluating the scope of AI in social work and the need for social worker training.

Keywords: Artificial intelligence, social work practice, scoping review

In the past 10 years, social work research and practice have needed to address the increasingly wide range of applications and ethical implications for social workers using AI, particularly when engaging with clients (Goldkind, 2021). Within the literature identified in this scoping review, AI is often used synonymously with other terms, such as algorithms (Gillingham, 2019c; Keddell, 2019), machine learning (Ahn et al., 2021; Gillingham, 2015), natural language processing (Coulthard & Taylor, 2022), decision support systems (Meilvang & Dahler, 2024; Schneider & Seelmeyer, 2019), predictive analytics (Glaberson, 2019; Russell, 2015), predictive risk modelling (Keddell, 2015; Krakouer et al., 2021), and automated decision-making (Ranerup & Henriksen, 2022). Social work is a complex, human-oriented profession (Payne, 2024). Encompassing notions of social change and justice, social work concerns itself with human betterment and advocacy in often complex and unpredictable situations

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(Keddell, 2019). This scoping review aims to explore the following research questions:

1. What is the volume of literature published in the past 10 years that has discussed using AI (including applying algorithms and machine learning) with the focus on decision-making, critical thinking, professional judgement, evidence-informed and reflective practice in social work practice?
2. What are the functions and benefits of using AI in social work practice that may influence social justice and social change on clients?
3. What are the ethical considerations for social workers who use AI (e.g., ChatGPT)?
4. What are the required skills and knowledge social work practitioners need to have to navigate in an increasingly AI-influenced landscape?

The scoping review method and the strategy utilised are outlined first. This includes the justification for the scoping review, the search strings, report results, and critical appraisal tools. The results section examines how each research question is answered, dividing the literature between expert opinion and empirical studies. The discussion considers the results with broader issues of social justice, practice ethics, and social work training. The article ends with recommendations, limitations, and concluding remarks on AI use within social work.

Methods

Scoping reviews provide an examination of existing literature when it is unclear what literature exists and what issues or topics are prevalent (Munn et al., 2018). Drawing on the four research questions, this study elaborates on other existing scoping reviews, such Claus Brygger and Christensen's (2023) examining of the benefits and limitations of AI in social work, and Krakouer et al. (2021), on biases in predictive risk modelling within child protection.

The eligibility criteria for inclusion were:

- peer-reviewed, empirical studies;
- literature review papers;
- published in peer-reviewed journals since January 1, 2014;
- articles published in English;
- study informants were social workers or clients involved with AI in social work practice or service provision;
- AI and its related e.g., ChatGPT, Generative AI were used in social work assessment and service delivery;
- papers such as opinion pieces, theoretical papers, practice notes, and commentaries are also included.

A six-stage methodological approach was followed (Arksey & O'Malley, (2005). In preparation for developing the search strategy, the online databases Discover (EBSCO), and Scopus were used to explore search terms (Table 1). These initial terms were based on the research questions and the eligibility criteria. A librarian was consulted until the final search strings were formed.

A concept table from the preliminary searches was formed to document synonyms that could inform the final search strings. The Social Services Abstracts database was

Table 1. Initial Search Results

Search string	Discover (EBSCO)	Scopus
"social work" AND "machine learning" AND ethic	25	16
"social work" AND "machine learning" AND "benefit"	17	4
"social work practice" AND "machine learning"	26	5
"social work" AND "AI" ethics	38	7
"social work practice" AND "AI"	24	7

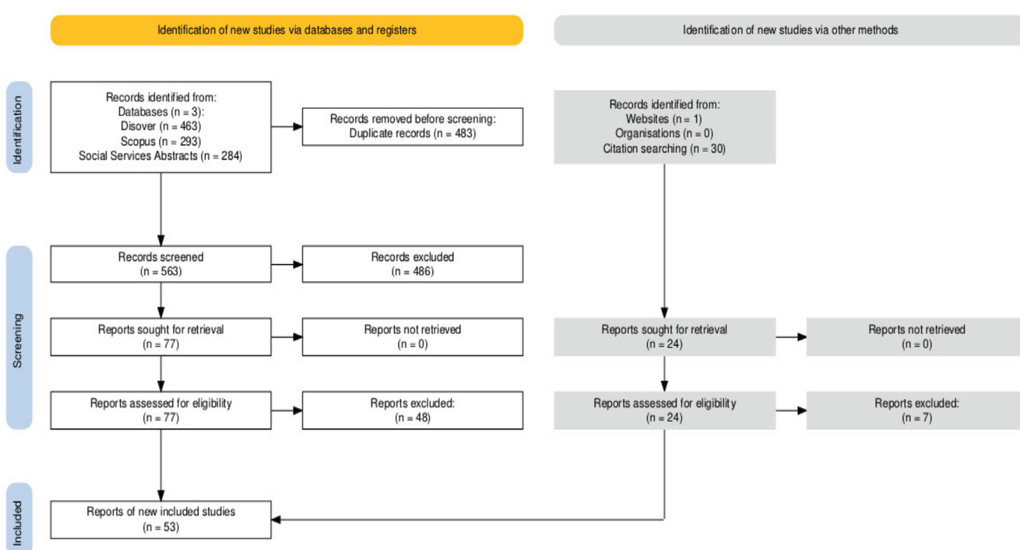
added to the full search. The final search strings were:

1. ("Social work*" AND "ethic*") AND ("machine learning" OR "AI" OR artificial learning
OR "AI" OR "predictive analytics" OR "algorithms" OR "Decision support*" OR "chat*").
2. ("Social work*") AND ("Automation" OR "intelligen*" OR "forecasting" OR "generative" OR "automat**" OR "Innovation").
3. ("Social service*" OR "Social case*" OR "social work*" AND "artificial") AND ("Automation" OR "predictive" OR "Data" OR "Information" OR "accountability" OR "impact" OR "utiliI*")

The full search was conducted on September 8, 2024. Limiters were used to scope for English-only and social work-specific references. The searches returned 752 articles, reduced to 563 after removing duplicates. The titles and abstracts were screened, reducing them to 77 articles chosen for full-text review. The search strategy and result screening process were reviewed with co-authors to minimise selection bias. Following the full-text review, 29 articles were selected, and their reference lists were reviewed for missed studies. An additional search retrieved a recently published study. From the reference lists and the online search, 24 articles were added, totalling 53 articles. The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) checklist (Page et al., 2021) was used, and an online interactive PRISMA tool (Haddaway et al., 2022) assisted with the creation of the flow diagram (Figure 1).

A data table categorised the articles by publication year, noting the journal, author(s), title, research aim, methodology, population sample, findings, critical appraisal score, and relevance to the research questions via a numerical score respective to Questions Two, Three, or Four. A critical appraisal of the articles was conducted (Table 2) utilising two sets of questions, dependent on the article type. Articles that are theoretical in nature with no stated

Figure 1. PRISMA Diagram



(Haddaway et al., 2022)

methodology were termed *expert opinion*, drawn from the Strength of Evidence Hierarchy, which deems expert opinions as the lowest level of evidential strength in academic publications (Rochester Regional Health, 2024). For empirical studies with a stated methodology, the CASP Systematic Review checklist was adapted (CASP, 2024). Both questionnaires were slightly modified for this review's research purposes.

The results from each article were categorised by the nature of the study, grouping findings from expert opinions and empirical studies separately. The next level of analysis involved evaluating the broad ideas that emerged distinctly from the different research approaches.

Results

The results for each research question are presented in this section. Concerning the first research question about the volume of AI literature published in the past 10 years, from the 53 articles identified, 26 are expert opinion articles, and 27 are empirical. Of the empirical studies, 17 have a qualitative methodology comprising 10 case study analyses, and seven field studies. The remaining 10 studies consist of seven quantitative experiments and three mixed-method studies. Among the expert opinion articles, five were literature reviews, and two were scoping reviews. The largest volume of literature was from Europe (including the UK) (20), then North America (17), Australasia (12), Asia (3) and Africa (1). Most studies were in one country except for a cross-national study involving case studies from Aotearoa New Zealand, England, and Denmark (Jørgensen et al., 2022). Overall, the literature volume indicates emerging research and literature base concerning AI use in social work practice.

Functions and benefits

Concerning the functions and benefits of using AI in social work practice and its influence on social justice and social change for clients, it was found that both expert opinion (Considine et al., 2022; Reamer, 2023) and empirical studies emphasised the cost-saving elements involved (Gillingham, 2019c; Isbanner et al., 2022; Meilvang & Dahler, 2024; Perron et al., 2024; Rice et al., 2017). Examples included the ability of AI to allocate social work resources (Reamer, 2023) and automate administration tasks (Fernando & Ranasinghe, 2023; Gillingham, 2019c; Meilvang & Dahler, 2024). Due to these innovations, social workers can complete more complex tasks that require interpersonal interaction to effectively bring about social justice and change (Markovič, 2024; Perron et al., 2024). Nonetheless, concerns about the social justice risks that AI poses remain. While AI is theoretically argued as a way to combat social injustice

Table 2. Critical Appraisal Questions

Empirical studies	Expert opinions
• Was there a clear statement of the aims of the research? • Is the methodology (qualitative, quantitative or mixed-method) appropriate? • Was the research design appropriate to address? • Was the recruitment strategy appropriate to the aims of the research? • Was the data collected in a way that addressed the research issue? • Have ethical issues been taken into consideration? • Was the data analysis sufficiently rigorous? • Is there a clear statement of findings? • How valuable is the research?	• Was the author a known expert in the field being studied? • Did the author declare any bias? • Was the issue clearly described? • Was a literature search/background section included? • Was the background literature clearly described/discussed? • Was more than one point of view reported or referenced? • Were the author's conclusions clearly presented? • Was there freedom from conflict of interest? • Were implications for practice suggested?

in light of historical uses of data to advance social work practice (Goldkind et al., 2021; Rodriguez et al., 2024), multiple authors argue that AI programming is more susceptible to perpetuating social injustice (Fernando & Ranasinghe, 2023; Gillingham, 2019b; Gorin et al., 2024; Keddell, 2019). Social workers must engage in dialogue on this issue and participate in training to advance social justice despite AI limitations (Goldkind et al., 2024; Keddell, 2019; Molala & Makhubele, 2021). How AI systems are designed heavily influences how social workers perceive them. Amongst expert opinions, AI is perceived as an aide for social work decision-making (Schneider & Seelmeyer, 2019). By integrating easier retrieval of client information to obtain a more holistic picture of the client's needs (Fernando & Ranasinghe, 2023; Zetino & Mendoza, 2019), AI helps create better transparency and consistency of social work decision-making (Coulthard et al., 2020). Examples of this might include greater detection of client need based on database information (James et al., 2023), including the ability to identify risk factors in documentation (Coulthard et al., 2020; Coulthard & Taylor, 2022). Other authors noted that AI would better match social work models of practice by adopting a more preventative stance that focuses on early support (Glaberson, 2019; Russell, 2015) or a more neutral analysis by focusing on objective outcomes that can be statistically measured (Keddell, 2015). Empirical studies echo the benefits and concerns identified within the expert literature. AI can enhance social work practice through the conveying of complex information (Ahn et al., 2021; Church & Fairchild, 2017; Kasthurirathne et al., 2018; Rice et al., 2018), particularly if there is the opportunity to input new data to obtain a more accurate AI-generated outcome (Leung et al., 2023; Søbjerg et al., 2021). This is especially true as work environments become more remote (Cearns & Knox, 2024). For example, in their study looking at online therapeutic support groups, Leung et al. (2023) found AI beneficial in analysing text and facial responses from clients as a way for the facilitator to track the group dynamics and individual wellbeing of clients. Several caveats undermining the benefits of AI design are also apparent. Because AI is built on existing case records and database information in current client systems, its benefits are limited to how well it can read and use existing client information. (Claus Brygger & Christensen, 2023; Keddell, 2019; Meilvang, 2022). AI proved more beneficial in systematic, process-driven environments than in dynamic and complex social work environments (Claus Brygger and Christensen (2023) Germundsson and Stranz (2024). While AI is beneficial in retrieving data, decision-making should remain with the social work practitioner because of the complexity of the social work situations (Krakouer et al., 2021; Meilvang, 2022; Rodriguez et al., 2019). The client benefits of AI in social work practice are mirrored across both expert opinions and empirical research. Multiple studies highlight AI as a means to improve the identification of client needs (Cascella et al., 2024; Coulthard et al., 2020; Goldkind, 2021; Kasthurirathne et al., 2018; Ranerup & Henriksen, 2022; Ranerup & Svensson, 2023; Shah et al., 2024). In their expert opinion articles, Shah et al. (2024) and Goldkind et al. (2024) propose that this could be achieved by using LLMs to assist clients with written tasks that can be auto-generated.

Where language barriers inhibit social worker practice, these hurdles could be addressed by including AI in social work tasks (Considine et al., 2022; Tulğan & Pak Güre, 2024). AI is also perceived as beneficial to improving interpersonal interaction between social workers and clients (Coulthard & Taylor, 2022; James et al., 2023; Ranerup & Henriksen, 2022; Trahan et al., 2019). For example, AI could assist clients by reducing the influence of negative face-to-face interactions (James et al., 2023) or even assist clients with difficult interpersonal settings through virtual reality simulated scenarios (Trahan et al., 2019). In practice, empirical research highlights that, despite the use of algorithms, social workers still remain in close contact with clients, emphasising the notion that AI operates as a decision aide for social workers rather than replacing them (Lehtiniemi, 2024; Ranerup & Henriksen, 2022). While AI has value and benefits in social work practice, the extent to which AI positively influences social justice and change for clients remains inconclusive and debatable.

Ethical considerations

Concerning the ethical considerations for social workers who use AI, it was found that bias and the accuracy of AI outcomes are important ethical questions when using AI within social work. As AI moves from being an information-retrieval tool to an aide for decision-making, the ethical risks of AI increase (Cearns & Knox, 2024). Across the literature, there was alarm about the potential of adverse client outcomes as a result of biased AI (Cascella et al., 2024; Church & Fairchild, 2017; Considine et al., 2022; Molala & Makhubele, 2021; Tulğan & Pak Güre, 2024), including the impact of AI outcomes on marginalised groups and data privacy and security (Fernando & Ranasinghe, 2023; Glaberson, 2019; Reamer, 2023; Zetino & Mendoza, 2019). Bias can impact both the outworking of AI (Considine et al., 2022) and the evaluation tools utilised to examine the effectiveness of AI (Krakouer et al., 2021). While it is theoretically argued that social workers could counteract biases in AI outputs and counteract the likelihood of AI producing biased results (Meilvang, 2022) and that AI may be a means to reduce bias in practice (Busch & Henriksen, 2018), these arguments are unfeasible owing to existing unrecognised biases within social work practice (Goldkind et al., 2024; James et al., 2023; Keddell, 2015).

Further ethical issues arise within the design approach of AI. As AI is a product of its socio-political environment, it reflects cost-efficient and neoliberal ideas impacting social work (Considine et al., 2022; James & Whelan, 2022; Jørgensen & Nissen, 2022). Jørgensen and Nissen (2022) noted that AI relies on ideological views of the family unit, perceiving individuals as problematic rather than recognising systemic issues and their impact on families. This would perpetuate normative ideas that may be inaccurate and could result in further biases (Gillingham, 2019a). The reliance of AI on flawed data, coupled with the existing literature highlighting the underreporting of client needs (such as child abuse), means that AI will be influenced by inaccurate and erroneous data (Gillingham, 2015, 2019b; Keddell, 2015).

In contrast, some empirical literature challenges these ideas by suggesting that a redirection of AI priorities towards strength-based outcomes, rather than deficit-based, could improve client outcomes via the use of AI, thus advancing social justice rather than hindering it (Rodriguez et al., 2019; Søbjerg, 2022). In their quantitative model-building study, Rodriguez et al. (2019) found that focusing AI development on variables that reduce risk could assist with alleviating the ethical concerns posed by AI use within social work, as this would avoid the likelihood of undue prejudice and surveillance of marginalised groups. Another area of concern centres on the need to regulate and standardise AI. As AI becomes more prevalent as a social work practice aide, calls within the expert opinion and empirical literature for regulation have increased (Cascella et al., 2024; Fernando & Ranasinghe, 2023; Glaberson, 2019). To address the ethical risk, procedures should be implemented regular review of AI functionality to maintain transparency (Krakouer et al., 2021; Meilvang, 2022; Petersen et al., 2020). While Busch and Henriksen (2018) found that the great risk remains with who controls the AI rather than the AI itself, Isbanner et al. (2022) indicated that clients are more concerned about the transparency of AI decisions. Other literature supports this by suggesting the greater ethical impact of AI results from clients being unaware of the presence of AI in decision-making and the absence of informed consent when AI is present, particularly as clients may be made to feel invisible by the use of AI in social work (Cascella et al., 2024; Glaberson, 2019; Isbanner et al., 2022; Zetino & Mendoza, 2019). Another ethical issue concerns the potential inaccuracy of AI-generated outcomes. Several articles, reflecting heavily on the context of child protection practice, identified the issue of population samples from which AI algorithms justify decisions (Gillingham, 2015; Keddell, 2015; Keddell, 2019).

The issues of additional and flawed data skewing AI decision-making raise ethical problems for how AI adapts and responds to population groups (Gillingham, 2019c; Goldkind, 2021; Gorin et al., 2024; Krakouer et al., 2021; Russell, 2015; Segal, 2024; Shah et al., 2024; Søbjerg, 2022). Surprisingly, as Kasthurirathne et al. (2018) found, additional accurate data does not necessarily lead to better results, challenging the idea that more data leads to greater accuracy. Studies have shown that large language models based on large amounts of data, such as ChatGPT, struggle to accurately interpret ethical issues, lending to the concern that AI may not accurately respond to dilemmas that social workers face (Segal, 2024). Compounding these issues is the reality that social work domains, such as child protection, are inherently difficult to predict when measuring risk (Keddell, 2015; Keddell, 2019). Overall, the ethical considerations for social workers are complex and range across data justice, client rights, social justice and the integrity and reliability of AI and those who control it.

Social workers' AI knowledge and skills

Training for social workers in the knowledge and skills necessary for using and understanding the implications of AI was identified as key to navigating AI systems as they are integrated with social work practice (Cascella et al., 2024; Cearns & Knox, 2024; Fernando & Ranasinghe, 2023; Molala & Makhubele, 2021). Understanding how AI systems work assists social workers with understanding client patterns not otherwise perceived in the data and upholds social justice (Keddell, 2019; Schneider & Seelmeyer, 2019). Where large-language models are utilised, social workers may require technical knowledge in programming and prompting or prompt engineering to fully engage with AI (Perron et al., 2024). This level of understanding is especially important due to the high-pressure environments social workers often work in and the ethical requirement for social workers to explain to clients how a decision was reached (Isbanner et al., 2022). The research identifies that, without training on how to navigate AI systems, social workers are more prone to blindly accepting an AI-generated outcome and are likely not to engage with how the AI tool arrived at the outcome resulting in a social work decision (Church & Fairchild, 2017; Germundsson & Stranz, 2024; Lehtiniemi, 2024; Leung et al., 2023; Søbjerg et al., 2021). Other factors, such as inexperience, lack of training, and age, may also increase a social worker's likelihood of accepting an AI outcome without question (Busch & Henriksen, 2018; Busch et al., 2018; Claus Brygger & Christensen, 2023).

Social workers should integrate their understanding of AI systems with their expertise in social work practice. A core issue identified across literature, though predominantly within the research, is the relationship between a social worker's understanding of AI systems and the need for social worker discretion when interpreting AI-generated outcomes (Gillingham, 2019b; James et al., 2023; Keddell, 2015). This tension includes the ethical predicament when social workers cannot justify an AI-generated outcome, particularly when an AI-generated outcome may appear unjust (Cascella et al., 2024; Gillingham, 2019b; Keddell, 2015; Reamer, 2023). The research articles emphasise the need for social work discretion when handling AI systems (Busch

& Henriksen, 2018; Coulthard & Taylor, 2022; Jørgensen, 2022; Jørgensen & Nissen, 2022; Peeters, 2020). While the primary role of social workers as decision-makers may be diminished by the existing use of AI (Coulthard & Taylor, 2022; Ranerup & Henriksen, 2022), some level of AI oversight is required by social workers due to the loss of relational judgements in practice (Busch & Henriksen, 2018; Coulthard & Taylor, 2022; Jørgensen, 2022). For example, Ranerup and Henriksen (2022) found that social work discretion was more likely in cases where AI produced negative client outcomes, while positive outcomes resulted in less human override. This highlights that social workers should be trained to understand and supervise AI while being certain of their practice discretion (Peeters, 2020).

Discussion

Outcomes of the review

The literature explored revealed a wide array of perspectives and evidence regarding the impact of AI within social work practice. All identified articles tended to address Questions Two and Three, while Question Four was addressed less often. Of the quantitative studies, over half (seven) addressed the functions of AI (Ahn et al., 2021; Coulthard & Taylor, 2022; Isbanner et al., 2022; Kasthurirathne et al., 2018; Perron et al., 2024; Rice et al., 2018; Rodriguez et al., 2019), while only two considered social work training implications (Isbanner et al., 2022; Perron et al., 2024). Question Three was most likely to be addressed within the literature, indicating that research often links the question of AI integration into social work practice to the problem of social work ethics. This appeared most relevant for qualitative studies employing field research, where over half (five) addressed the ethical implications of AI in social work practice.

Contested nature of AI use

The potential (and realised in some countries) benefits and functions of AI in social work practice varied across the literature. Some articles identified the successful application of AI in strictly process-driven domains, such as employment; a large portion of articles emphasised the application of AI as complementary to social work practice rather than a replacement, thus suggesting AI could benefit social work systems. For example, when completing administrative tasks or to assist with identifying risk in a text-based environment, a key issue was the design of defining variables in AI programming. This raises the question of who defines risk, what is considered *normal*, and how priority should be evaluated when different worldviews and ideas of need exist. Within social work, these arguments are heightened by a fraught concept of social justice, which is not entirely consistent or clear in practice (Atteberry-Ash, 2022). As a result, social injustice can be perpetuated when AI is used in social work.

Bias in AI

Issues arise with AI integration and functionality when social work ethics are considered regarding potential bias and AI design. Ethical issues came to the fore of discussion when evaluating how AI could operate in a social work environment due to the influence of socio-political elements on AI development. Ioakimidis and Wyllie (2023) noted that social work is dominated by its political context. This aligns with the conclusion that a level of power for social workers over AI decision-making is required to maintain compliance with the social work code of ethics in their own countries. Furthermore, as AI is reliant on text-based datasets, such as case recording, the accuracy and construction of case recording as an ethical issue requires examination. The use of case records and supplementary client information systems is viewed as cumbersome and sometimes antithetical to social work practice (De Witte et al., 2016; Huuskonen & Vakkari, 2013; Huuskonen & Vakkari, 2015; O'Keefe, 2024). Due to the time required to input case records, social workers sometimes perceive recording as a non-essential task, limiting the accuracy or thoroughness of case records (De Witte et al., 2016). Therefore, AI algorithms reliant on case records are susceptible to inaccurate outcomes due to incorrect or imprecise case records in the dataset. Many articles highlight the need for social workers to understand how AI works within social work and to undergo training where needed. However, while social workers would benefit from training in understanding AI, AI integration is hindered by programming variables in AI algorithms, which may or may not result in incorrect AI-generated assessments. This results in the conclusion that social work training in AI is not necessarily about using AI, but about understanding the appropriateness of overriding it, where necessary, in decision-making. This precipitates the need to understand AI, social work theory and ethics when adopting technology.

Training in AI

Literature on the adoption of technology and social work training resonates with the review literature, highlighting the need for specific guidelines and training to improve the likelihood of technology adoption in social work (Gallivan et al., 2005). When training and resources are not specific, this hinders the successful utilisation of technology within social work. Additionally, as AI training is predicated on both understanding AI decisions and when to override them, this links with existing literature which identifies the need for both increased exposure to this developing technology coupled with the support of experienced social workers to assist less experienced staff when it comes to using this technology and exercising discretion (Choi et al., 2002; Kateb et al., 2022).

Indigenous people and AI

While the current review did not specifically examine the impact of AI on Indigenous population such as Māori, it is interesting to note that only three articles were identified from Aotearoa New Zealand or with Aotearoa New Zealand content included in the review (Jørgensen et al., 2022; Keddell, 2015, 2019) and none of them have provided any specific discussions in relation to designing and evaluating AI according to Indigenous Māori principles. Despite the many benefits of AI, expeditious growth is also a cause for concern, such as ethical issues, as outlined in the current review discussion. Dubay and Nalbandian (2021) argued that Indigenous people, minorities and vulnerable communities are the most negatively affected by issues such as surveillance, inaccurate data and bias. Bias is of particular ethical concern for Indigenous people and AI technology. Jones et al. (2023) stated that currently there are almost no AI tools that have been developed by Indigenous people or from an Indigenous perspective, which continue perpetuating colonising ideology and preventing the authentic inclusion of Indigenous people's knowledge and wisdom in areas such as health care, welfare, communication and human resources. As the current AI paradigms become increasingly problematic, it is crucial to establish alternative visions, values and frameworks urgently to ensure prior consent and appropriate use of data belonging to Indigenous peoples to ensure data sovereignty and retain rightful ownership of intellectual property (Munn, 2024).

Recommendations

Three recommendations emerge from this review. First, there is a need for further research on practising social workers' knowledge, skills and use of AI, particularly, in the Aotearoa New Zealand context, to identify the prevalence of the use of AI in social work practice and the awareness and capability of social workers to manage the implications regarding ethics, social justice and Te Tiriti o Waitangi. Sir Hirini Moko Munn (2024), a renowned Māori scholar developed the five tests (Tapu, Mauri, Take-utu-ea, precedent and principles) to confront and decolonise AI to address social justice demands. The five tests may potentially offer complementary insights on our current values and ethical principles (Rangatiratanga, Manaakitanga, Whanaungatanga, Aroha, Kotahitanga, Mātātoa and Wairuatanga) in our Aotearoa New Zealand social work *Code of Ethics* (ANZASW, 2019), which could create equitable space for Māori in a Western-dominated landscape to indigenise AI and the digital domain. Secondly, there needs to be a re-evaluation of the scope of AI in social work. AI often appears to operate from a deficit-based model of identifying risk or prioritising need, supplanting social work decision-making. Issues come to the fore with this approach due to disagreements regarding the definitions of risk and need and the possibility of AI inaccuracies (Rodriguez et al., 2019). Further consideration should be given to AI use outside of a deficit model that could better support social work decision-making. A third recommendation centres on social workers' needs regarding AI use. The literature identifies that social workers would benefit from training in understanding and confidently overriding AI. However, what type of training might this be, given the novelty of the research field and the varied models and designs of AI, requires further examination regarding its benefit to social work practice outcomes.

Limitations

The limitations of this review are the use of only three research databases and the limitations on keywords used in the search strings. While more databases could have been utilised, the high number of duplicates and non-relevant search results in the searches conducted rendered further searching impractical. Additionally, while the search strings were optimised to capture as many articles as possible, they were limited in scope due to the high number of duplicates. The review was also limited due to the review process adopted with only one reviewer scanning and selecting the eligible articles under the supervision of other researchers; the list of eligible articles may have been limited due to reviewer bias or inconsistent application of research criteria. Many studies retrieved via the search strings were excluded because they did not mention social work practice. Several articles focused on social work education and other research contexts exclusive of practice. Though this was beyond the research scope of this study, these articles might have included findings that could have been of benefit.

Conclusion

AI poses a complex issue in an already complex social work environment. This scoping review identifies an emerging literature in which the existing benefits exist in some contexts where AI has been successfully implemented. However, the broader AI discourse identifies ongoing unresolved questions of appropriate AI design, balancing social work ethical obligations, and the role of social work discretion in navigating AI decision-making. There remain many unknowns due to the rapidly evolving nature of AI globally. As this scoping review notes, unless there are clear social work-driven approaches to AI design and use based on social work principles for a specific purpose, AI will inevitably perpetuate inequities and biases already prevalent in social work.

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