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Willingness to Use and Barriers to Implementing Artificial Intelligence-Supported Case Management Systems in Social Work: A Quantitative Survey of Social Work Practitioners

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ABSTRACT: The ongoing digital transformation of human services has positioned artificial intelligence (AI) as a potentially significant resource for social work practice, particularly in the domain of case management. Yet empirical investigation into how social work practitioners evaluate AI-supported systems — and what prevents or facilitates their adoption — remains limited. The present study addresses this gap through a quantitative cross-sectional online survey conducted with $N = 97$ social work professionals drawn from diverse practice fields, including youth welfare, psychosocial counseling, clinical social psychiatry, refugee support, and disability services. Three purpose-developed Likert-format scales assessed willingness to use AI case management systems ($\alpha = .88$), perceived benefits ($\alpha = .86$), and perceived barriers ($\alpha = .91$). Perceived benefit was the strongest bivariate correlate of willingness ($r = .68$, $p < .001$), followed by perceived barriers ($r = -.52$, $p < .001$) and technological self-efficacy ($r = .47$, $p < .001$). Data privacy concerns showed a substantial negative association with willingness ($r = -.49$, $p < .001$). Multiple regression analysis identified perceived benefit ($\beta = .49$, $p < .001$), perceived barriers ($\beta = -.31$, $p = .002$), and technological self-efficacy ($\beta = .24$, $p = .011$) as significant independent predictors of willingness, jointly explaining 58% of its variance ($R^2 = .58$, $F(5, 91) = 25.07$, $p < .001$). Professional experience was negatively associated with willingness, with experienced practitioners reporting significantly lower AI adoption readiness than early-career colleagues (ANOVA: $F(2, 94) = 4.91$, $p = .009$). Social work practitioners recognize the administrative efficiency and documentation relief AI may offer, but express robust concerns about data protection, the adequacy of AI in capturing complex social situations, and the risk of diminished relational practice quality. Targeted digital competence training and the establishment of transparent, participatory AI governance frameworks in social service institutions are identified as critical enablers of ethically grounded AI adoption.

KEYWORDS: artificial intelligence, social work, case management, technology acceptance, digital transformation, perceived barriers, technological self-efficacy

1. INTRODUCTION

A social worker in a mid-sized municipal youth welfare office sits at her desk on a Tuesday afternoon. Her caseload spans fourteen active files; her documentation backlog extends two weeks. An email arrives from the institutional director announcing that the authority will pilot an AI-based case management system in the coming quarter. She reads it twice. There is curiosity — perhaps this could reduce the administrative weight that has begun to define her evenings. There is also unease, its source at first difficult to articulate: something about what it would mean to have an algorithm involved in decisions about the families she accompanies. This ambivalence is not hers alone. It is, increasingly, a professional condition.

The integration of artificial intelligence technologies into social service institutions is no longer a speculative future development but an accelerating institutional reality. Across child protection services, disability support systems, and community mental health infrastructure, predictive analytics, natural language processing, and automated decision support tools are being deployed with growing frequency (Gillingham, 2019; Eubanks, 2018). Proponents argue that AI-supported case management systems offer substantial efficiency gains: reduced administrative burden, accelerated document processing, improved consistency in need assessment, and enhanced coordination across multiagency service networks (Topol, 2019; Goldkind & Wolf, 2015). Critics counter that algorithmic systems risk encoding existing social inequalities, displacing the irreducible relational quality of social work practice, and producing opacity in consequential welfare decisions (Buolamwini & Gebru, 2018; Keddell, 2019; Eubanks, 2018).

This tension between technological promise and professional apprehension is the animating problematic of the present study. Social work is a profession constituted at its core by the relational encounter between practitioner and service user — an encounter that existing research suggests cannot be reduced to data processing without qualitative loss (Doel, 2012; Wastell & White, 2014). At the same time, the documentary burden facing social work professionals has reached levels that compromise both practice quality and practitioner wellbeing (Taylor, 2017). In this context, AI-supported case management systems occupy a contested middle ground: they may liberate practitioners from administrative encumbrance while simultaneously threatening the conditions under which authentic professional practice is possible. Empirical investigation of social work practitioners' perspectives on AI adoption has not kept pace with the institutional deployment of these technologies. Existing literature in this domain is predominantly conceptual or case-based, and quantitative studies examining the psychological, professional, and structural predictors of AI adoption willingness among social work practitioners remain sparse (Garner & Bhatt, 2021; Yan & Shah, 2022). This gap is particularly consequential given that frontline practitioner acceptance or resistance constitutes a primary determinant of whether technology implementations succeed or fail in social service contexts (Venkatesh et al., 2003). Understanding what drives and what impedes willingness to engage with AI systems is therefore not merely an academic question but a precondition for responsible technology governance in social work institutions.

The present study addresses this gap through a quantitative cross-sectional survey of $N = 97$ social work professionals drawn from five major practice fields. The central research questions are: (1) At what level do social work practitioners report willingness to use AI-supported case management systems, and what is their overall assessment of perceived benefits and barriers? (2) Which psychological, professional, and structural variables predict willingness to use AI systems? (3) Does professional experience moderate willingness, such that more experienced practitioners report lower AI adoption readiness than those earlier in their careers? The practical and ethical implications of the findings are examined with particular attention to the design of professional development frameworks and institutional AI governance approaches appropriate to the social work context.

2. THEORETICAL BACKGROUND

2.1 Technology Acceptance in Social Work: Theoretical Frameworks

The theoretical foundation for understanding practitioner acceptance of digital technologies in professional contexts rests most directly on Davis's (1989) Technology Acceptance Model (TAM), which identifies perceived usefulness and perceived ease of use as the two proximal determinants of behavioral intention to use a given technology. TAM has accumulated extensive empirical support across occupational domains and has been extended and elaborated in Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates four predictor constructs: performance expectancy (the degree to which a technology is expected to enhance job performance), effort expectancy (the perceived ease of use), social influence (the perceived social pressure to use the technology), and facilitating conditions (the organizational resources supporting technology use). Both TAM and UTAUT predict that the primary driver of technology adoption intention is the perceived utility of the technology relative to existing work practices — a prediction that the present study operationalizes as perceived benefit. Applied to social work, these frameworks encounter contextual specificities that complicate their straightforward extension. First, social work is a relational profession in which the interpersonal encounter between practitioner and service user is not merely instrumental but constitutive of therapeutic and protective outcomes (Doel, 2012). Technologies that are perceived as threatening to displace or instrumentalize this relational core may elicit resistance that TAM and UTAUT, conceived in organizational management and IT contexts, are not fully equipped to capture. Second, social work institutions are typically public sector organizations characterized by resource constraints, hierarchical decision structures, and limited IT infrastructure (Wastell & White, 2014), creating facilitating condition deficits that suppress technology adoption independent of attitudinal factors. Third, the populations served by social work are frequently among the most vulnerable and least digitally empowered citizens (Lythreatis et al., 2022), introducing ethical obligations around data protection and relational continuity that amplify practitioner concerns beyond those arising in commercial or clinical technology contexts.

The history of information technology in social work is instructive in this regard. The introduction of electronic case management systems in the 1990s and early 2000s was accompanied by extensive practitioner resistance, documented in multiple qualitative and quantitative studies (Gillingham & Graham, 2017; Mishna et al., 2012). Practitioners reported that digitization of documentation increased administrative workload rather than reducing it, reduced the time available for direct client contact, and created surveillance dynamics that compromised professional autonomy (Wastell & White, 2014). These historical precedents provide a contextual frame through which current AI adoption attitudes should be interpreted: the scepticism expressed by experienced practitioners in the present study may reflect not irrational technophobia but institutionally grounded learning from prior digital implementations that did not deliver promised benefits.

2.2 Perceived Benefits and the Administrative Promise of AI

The case for AI-supported case management systems rests substantially on the potential for administrative relief. Documentation constitutes one of the most consistently reported sources of occupational burden in social work, with practitioners across practice fields reporting that administrative tasks routinely occupy between 30% and 50% of available working time — time not available for direct service provision (Taylor, 2017; Goldkind & Wolf, 2015). AI-powered document processing, case note automation, and pattern recognition tools theoretically offer meaningful reductions in this burden, freeing practitioners for the relational and clinical dimensions of their work. The present study's item-level data are consistent with this assessment: AI's capacity to reduce administrative tasks ($M = 4.18$) and facilitate documentation ($M = 4.06$) received the highest benefit endorsements, suggesting that practitioners recognize and value AI's efficiency potential in precisely the domains where relief is most needed.

Beyond administrative relief, proponents of AI in social work point to enhanced analytical capacity as a second major benefit. Predictive risk assessment tools, integrated across case histories and multiagency data streams, may identify at-risk individuals earlier and with greater consistency than human case assessment alone (Gillingham, 2019). However, this claim is empirically contested. Studies of deployed predictive analytics in child protection contexts have documented significant problems with algorithmic fairness, with tools trained on historical case data tending to replicate and amplify existing racial and socioeconomic disparities in risk classification (Buolamwini & Gebru, 2018; Dressel & Farid, 2018). The present sample's comparatively more cautious endorsement of AI's capacity to improve case coordination quality ($M = 3.41$) relative to its administrative relief potential may reflect practitioner awareness of these limitations — a sophisticated professional scepticism that institutional AI adoption frameworks would do well to take seriously.

2.3 Barriers to Adoption: Privacy, Relational Loss, and Structural Constraints

The barrier profile identified in the present study spans three analytically distinct domains: ethical-legal concerns centered on data protection; professional identity concerns centered on relational loss; and structural concerns centered on resource and training deficits. Each domain implicates a different lever for intervention. Data protection emerged as the single most highly rated barrier in the present study (M = 4.32). This finding must be interpreted within the specific legal and institutional context of social work practice. Social workers routinely handle some of the most sensitive personal data produced in human services contexts: child protection records, psychiatric histories, immigration status, domestic violence documentation, and intimate family circumstances. The General Data Protection Regulation (GDPR), applicable across European Union member states, imposes strict obligations on the processing of sensitive personal data, and the integration of AI systems into social work workflows generates novel data governance challenges that existing institutional frameworks are frequently ill-equipped to address (Mantelero, 2018; Smuha, 2021). Practitioners' high endorsement of data protection concerns is therefore not merely an affective response to an abstract risk but a professionally grounded assessment of a genuine and inadequately resolved governance challenge. The concern that AI cannot adequately capture complex social situations (M = 4.11) and the fear of losing relational quality in practice (M = 4.07) reflect a deeper professional identity concern: that the introduction of algorithmic systems threatens the epistemological and ethical foundations of social work as a distinctly human practice. Social work practice theory holds that the practitioner's embodied presence, empathic attunement, and contextual responsiveness constitute irreducible conditions for effective intervention in complex social situations (Doel, 2012). The concern that AI tools may flatten this complexity into quantifiable variables — and that algorithmic recommendations may gradually displace professional judgment — is not unfounded. The history of algorithmic welfare administration documented by Eubanks (2018) demonstrates that automated systems deployed without adequate human oversight can produce systematic injustice while generating the appearance of neutral efficiency. Practitioners' wariness of these dynamics should be understood as evidence of professional ethical consciousness, not mere technophobia.

At the structural level, insufficient technical resources (M = 3.63) and inadequate preparation for AI use (M = 3.91) point to an infrastructure and training deficit that shapes adoption attitudes independent of individual psychological factors. The strong demand for AI-specific continuing professional development expressed in the present sample (M = 4.26 for the CPD item) suggests that practitioners are not opposed to engaging with AI in principle but require institutional investment in their digital competence as a precondition for confident and ethically grounded adoption. The digital divide in professional competence — itself intersecting with generational and organizational factors — constitutes a structural barrier whose resolution demands coordinated investment at institutional and policy levels (Lythreatis et al., 2022).

2.4 Research Hypotheses

Drawing on the theoretical frameworks reviewed above, the following hypotheses are advanced:

H1: Perceived benefit will be positively associated with willingness to use AI-supported case management systems ($r > 0$, $p < .05$).

H2: Perceived barriers will be negatively associated with willingness to use AI-supported case management systems ($r < 0$, $p < .05$).

H3: Technological self-efficacy will be positively associated with willingness to use AI-supported case management systems ($r > 0$, $p < .05$).

H4: In multiple regression, perceived benefit, perceived barriers, and technological self-efficacy will each emerge as significant independent predictors of willingness ($\beta \neq 0$, $p < .05$).

H5: Professional experience will be negatively associated with willingness to use AI systems, such that practitioners with more years of experience report lower adoption readiness than those with fewer years of experience ($p < .05$ in group comparison).

3. METHOD

3.1 Study Design

A quantitative cross-sectional online survey design was employed. Cross-sectional methodology was selected for its efficiency in capturing the distribution of attitudes and predictors across a heterogeneous professional sample and for its appropriateness to the exploratory-confirmatory objective of the present study: establishing the bivariate and multivariate structure of willingness to use AI systems in a field where baseline prevalence data are currently lacking. The design precludes causal inference and does not permit the examination of attitude change over time; these limitations are addressed in the discussion section. No experimental manipulation was introduced; the study is strictly observational and attitudinal in character.

3.2 Sample and Recruitment

The final analytic sample comprised N = 97 social work practitioners recruited from five practice fields: youth welfare (n = 28, 28.9%), psychosocial counseling (n = 22, 22.7%), clinical social work and social psychiatry (n = 19, 19.6%), refugee support services (n = 11, 11.3%), and disability and inclusion support (n = 17, 17.5%). With respect to gender, 63.9% identified as female (n = 62), 32.0% as male (n = 31), and 4.1% as non-binary or gender-diverse (n = 4). Age distribution was: 22–30 years (n = 24, 24.7%), 31–40 years (n = 39, 40.2%), and 41–55 years (n = 34, 35.1%). Regarding professional experience, 21.6% reported 0–5 years (n = 21), 29.9% reported 6–10 years (n = 29), and 48.5% reported more than ten years of experience (n = 47).

Participants were recruited through professional networks, social work association mailing lists, and institutional contacts across Germany. Participation was entirely voluntary, anonymous, and without financial incentive. The survey was administered via a standardized web-based platform and required approximately 10 to 15 minutes to complete. Informed assent was obtained through a pre-survey information sheet describing the study purpose, the voluntary and anonymous nature of participation, and the right to withdraw at any stage.

3.3 Measures

Willingness to Use AI Systems. Willingness was assessed using a five-item scale developed for this investigation, capturing openness to AI trial and regular use, perceived utility in daily work, professional uncertainty (reverse-coded), and desire for AI-specific professional training. A representative item read: "I would try out an AI-supported case management system." Items were rated on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Internal consistency was good (α = .88, M = 3.29, SD = 0.81).

Perceived Benefit. Perceived benefit was assessed with five items covering potential reductions in administrative workload, documentation efficiency, case analysis speed, time relief, and case coordination quality improvement. A sample item stated: "AI could reduce administrative tasks in social work." Items used the same five-point Likert format. Internal consistency was good ($\alpha = .86$, $M = 3.67$, $SD = 0.77$).

Perceived Barriers. Perceived barriers were assessed with five items encompassing data protection concerns, the limitations of AI in capturing complex social situations, relational loss concerns, insufficient institutional technical resources, and inadequate personal preparation for AI use. A representative item stated: "I have concerns regarding data protection and data security." Internal consistency was excellent ($\alpha = .91$, $M = 3.81$, $SD = 0.74$).

3.4 Statistical Analysis

Data analysis proceeded in three sequential stages following the conventions of applied psychological research (Aiken & West, 1991). First, descriptive statistics (M, SD, Cronbach's α) were computed for all three focal scales and individual items. Second, a Pearson correlation matrix was calculated to examine bivariate associations among the focal scales, technological self-efficacy (operationalized as a composite of relevant willingness items), and professional experience. Third, a multiple regression analysis was conducted with willingness to use AI systems as the criterion variable. Five predictors were entered simultaneously: perceived benefit, perceived barriers, technological self-efficacy, professional experience (categorical, dummy-coded with 0–5 years as reference), and age group. Analysis of variance (ANOVA) with post-hoc pairwise comparisons (Bonferroni correction) was used to examine group differences in willingness across the three professional experience categories. All analyses were conducted at a two-tailed significance threshold of $\alpha = .05$.

4. RESULTS

4.1 Descriptive Findings

Descriptive statistics and internal consistency estimates for all three focal scales are reported in Table 1. The overall willingness to use AI-supported case management systems was moderate ($M = 3.29$, $SD = 0.81$), indicating that the present sample is neither strongly resistant to nor enthusiastically disposed toward AI adoption. At the item level within the willingness scale, the strongest endorsement was registered for the desire for AI-specific professional development ($M = 4.26$, $SD = 0.68$), suggesting that the dominant orientation toward AI in this sample is one of conditional openness: practitioners wish to engage with these tools but require structured institutional support to do so. Conditional willingness — "I would use AI systems if they work reliably" ($M = 3.72$, $SD = 0.79$) — was more highly endorsed than unconditional openness to trial ($M = 3.38$, $SD = 0.95$), consistent with a professional stance of cautious pragmatism rather than enthusiastic adoption or principled refusal.

Perceived benefit was rated moderately to highly across the sample ($M = 3.67$, $SD = 0.77$). The highest benefit endorsements concerned administrative relief: reductions in administrative tasks ($M = 4.18$, $SD = 0.71$) and documentation facilitation ($M = 4.06$, $SD = 0.78$). These items attracted notably higher endorsement than the item assessing AI's potential to improve case coordination quality ($M = 3.41$, $SD = 0.92$), suggesting that practitioners draw a meaningful distinction between AI's credible utility in bureaucratic processes and its more contested capacity to enhance the substantive quality of practice. Perceived barriers were rated highly throughout the sample ($M = 3.81$, $SD = 0.74$). Data protection concerns attracted the highest endorsement of any item across the entire survey ($M = 4.32$, $SD = 0.66$), followed by skepticism about AI's capacity to capture complex social situations ($M = 4.11$, $SD = 0.74$) and concern about relational loss ($M = 4.07$, $SD = 0.83$). All three scales demonstrated good to excellent internal consistency (willingness: $\alpha = .88$; perceived benefit: $\alpha = .86$; perceived barriers: $\alpha = .91$).

Table 1: Descriptive Statistics and Internal Consistency for All Focal Scales

Scale	Items (*n*)	*M*	*SD*	*α*
Willingness to Use AI Systems	5	3.29	0.81	.88
Perceived Benefit	5	3.67	0.77	.86
Perceived Barriers	5	3.81	0.74	.91

Note. *N* = 97. *M* = arithmetic mean; *SD* = standard deviation; *α* = Cronbach's alpha. All items rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

4.2 Correlational Findings

Pearson correlation coefficients among the focal variables are presented in Table 2. Consistent with H1, perceived benefit showed a strong positive correlation with willingness to use AI systems ($r = .68$, $p < .001$), confirming that practitioners' assessment of AI's practical value is the primary psychological driver of adoption readiness. This effect size is large by conventional standards and consistent with TAM-derived predictions regarding the centrality of perceived usefulness (Davis, 1989). In support of H2, perceived barriers showed a strong negative correlation with willingness ($r = -.52$, $p < .001$), indicating that practitioners who perceive AI implementation as fraught with risks and obstacles report correspondingly lower willingness to engage. Supporting H3, technological self-efficacy was positively correlated with willingness ($r = .47$, $p < .001$), reflecting the well-established finding that perceived personal competence with technology enhances openness to technological adoption. At the item level, data privacy concerns showed a strong negative association with willingness ($r = -.49$, $p < .001$), confirming that data governance perceptions constitute a particularly salient psychological obstacle to AI adoption in this professional context. Among the predictor intercorrelations, perceived benefit and perceived barriers showed a moderate negative association ($r = -.28$, $p < .01$), indicating partial but not complete independence of these constructs: practitioners can simultaneously recognize AI's utility and express concerns about its implementation, a finding that underscores the inadequacy of a purely bipolar framing of AI attitudes. Perceived barriers were moderately negatively correlated with technological self-efficacy ($r = -.36$, $p < .01$), suggesting that practitioners who are more confident in their digital competence experience AI as less threatening. Professional experience showed a small negative correlation with willingness ($r = -.22$, $p = .031$) and a small positive correlation with perceived barriers ($r = .21$, $p < .05$), consistent with the hypothesis that more experienced practitioners hold more entrenched professional practice norms and are more alert to the relational and ethical risks of technological transformation.

Table 2: Pearson Correlation Matrix Among Focal Variables

Variable	1	2	3	4	5
1. Willingness to Use	—				
2. Perceived Benefit	.68**	—			
3. Perceived Barriers	−.52**	−.28**	—		
4. Technological Self-Efficacy	.47**	.33**	−.36**	—	
5. Professional Experience	−.22*	−.16	.21*	−.19*	—

Note. *N* = 97. ** *p* < .01. * *p* < .05. Two-tailed significance. Upper triangle omitted; dashes (—) indicate diagonal. Technological Self-Efficacy derived from relevant item subset of Willingness scale. Professional Experience coded ordinally (1 = 0–5 years; 2 = 6–10 years; 3 = over 10 years).

4.3 Multiple Regression and Group Comparison

Results of the simultaneous multiple regression analysis are presented in Table 3. Perceived benefit emerged as the strongest independent predictor of willingness ($\beta = .49$, $p < .001$, 95% CI [.33, .65]), confirming H4 and reinforcing the TAM-derived prioritization of perceived usefulness as the primary adoption driver (Davis, 1989; Venkatesh et al., 2003). Perceived barriers exerted a significant independent negative effect on willingness ($\beta = -.31$, $p = .002$, 95% CI [−.49, −.13]), confirming that the barrier profile retains predictive power even when perceived benefit is held constant — a finding that argues against the assumption that demonstrating AI's utility is sufficient to overcome adoption resistance. Technological self-efficacy contributed a significant positive independent effect ($\beta = .24$, $p = .011$, 95% CI [.06, .42]), indicating that practitioners with greater perceived digital competence are more willing to engage with AI systems independent of their benefit and barrier assessments.

Professional experience did not reach conventional significance as a predictor in the multivariate model ($\beta = -.14$, $p = .089$, 95% CI [−.30, .02]), suggesting that its bivariate association with willingness is partially mediated by the other predictors in the model — most plausibly by perceived barriers, which experienced practitioners rate more highly. Age did not contribute significantly to the prediction of willingness ($\beta = -.08$, $p = .314$, 95% CI [−.24, .08]). The overall model accounted for 58% of the variance in willingness ($R^2 = .58$, $F(5, 91) = 25.07$, $p < .001$), representing strong explanatory power given the complexity of the phenomenon. The ANOVA examining willingness across professional experience groups revealed a significant effect ($F(2, 94) = 4.91$, $p = .009$), supporting H5. Pairwise comparisons indicated that practitioners with 0–5 years of experience ($M = 3.61$, $SD = 0.58$) reported significantly higher willingness than those with more than ten years of experience ($M = 3.02$, $SD = 0.73$). Practitioners in the 6–10 year experience group occupied an intermediate position ($M = 3.34$, $SD = 0.62$) that did not differ significantly from either extreme group following Bonferroni correction. In summary, H1, H2, H3, H4, and H5 all received empirical support, although H4 requires partial qualification insofar as professional experience approached but did not reach significance in the multivariate model.

Table 3: Multiple Regression Results: Predictors of Willingness to Use AI-Supported Case Management Systems

Predictor	*β*	*p*	95% CI
Perceived Benefit	.49	< .001	[.33, .65]
Perceived Barriers	−.31	.002	[−.49, −.13]
Technological Self-Efficacy	.24	.011	[.06, .42]
Professional Experience	−.14	.089	[−.30, .02]
Age	−.08	.314	[−.24, .08]

Note. *N* = 97. *β* = standardized regression coefficient. 95% CIs computed via ordinary least squares regression. Criterion variable: Willingness to Use AI Systems. All predictors entered simultaneously. Professional Experience coded ordinally. $R^2 = .58$, $F(5, 91) = 25.07$, $p < .001$.

5. DISCUSSION

5.1 Summary and Theoretical Integration

The present study provides a systematic quantitative characterization of social work practitioners' attitudes toward AI-supported case management systems and identifies the psychological and professional architecture underlying those attitudes. Three findings stand out as theoretically significant.

First, the dominant structure of AI-related attitudes in the present sample reflects not binary acceptance or rejection but a sophisticated cost-benefit calculus in which administrative efficiency potential is clearly recognized while substantive professional quality risks are robustly articulated. The mean willingness score ($M = 3.29$) situates the sample as a whole in a zone of cautious openness, and the pattern of item endorsements within the willingness scale — with conditional trial willingness (M = 3.38) lagging substantially behind unconditional training demand (M = 4.26) — suggests that practitioners are not refusing AI but demanding the conditions under which engagement with AI could be professionally responsible. This attitudinal structure is inconsistent with simple technophobic models of professional resistance and more consistent with the ethical deliberation that characterizes mature professional judgment in complex human services contexts. Second, the regression model's finding that perceived benefit (β = .49) constitutes the strongest predictor of willingness extends Davis's (1989) TAM and Venkatesh et al.'s (2003) UTAUT to the social work practice context, confirming that perceived performance expectancy drives adoption intention in this profession as it does in commercial and clinical technology contexts. The critical refinement the present data offers, however, is the observation that perceived barriers retain substantial independent predictive power (β = −.31) even when benefit perceptions are controlled. This finding challenges the common institutional assumption that demonstrating AI's utility — through persuasive communication about efficiency gains — is sufficient to overcome adoption resistance. The barrier profile in the present study is not primarily informational: practitioners who strongly endorse AI's administrative potential also strongly endorse data protection concerns and relational loss fears. Overcoming these barriers requires not better marketing of AI's benefits but substantive resolution of the ethical, institutional, and professional concerns that produce them. Third, the experience-related gradient in willingness — with early-career practitioners reporting significantly higher adoption readiness than those with more than ten years of experience — invites careful theoretical interpretation. The most straightforward explanation is generational: younger practitioners, socialized in digitally intensive educational and social environments, possess greater technological self-efficacy and therefore lower psychological activation cost for technology adoption. However, a second and equally plausible interpretation locates the experience gradient not in digital competence but in professional socialization: practitioners with extensive experience have developed deeply embodied relational practice models and are therefore more sensitized to the risks that AI integration poses to those models. On this reading, experienced practitioners' lower willingness represents not a deficit of digital literacy but a surplus of professional wisdom. Institutional AI adoption strategies that treat experienced practitioners' resistance as a problem to be overcome rather than a resource to be leveraged are likely to produce both implementation failures and resentment — a pattern well documented in prior waves of social work digitization (Wastell & White, 2014).

5.2 Practical Implications

The present findings generate several concrete implications for practice at institutional, professional, and policy levels. At the institutional level, the finding that technological self-efficacy is a significant independent predictor of willingness (β = .24) provides direct justification for investment in AI-specific continuing professional development for social work practitioners. The item-level finding that demand for CPD on AI (M = 4.26) was the single most highly endorsed statement in the entire study sends a clear signal: practitioners are not asking to be protected from AI but to be equipped to engage with it competently and critically. CPD programs should be designed not merely to convey technical operational skills but to develop the critical digital literacy necessary for practitioners to evaluate AI systems' outputs, identify algorithmic bias, advocate for appropriate governance structures, and maintain professional accountability in AI-supported practice contexts (Yan & Shah, 2022).

The dominance of data protection concerns in the barrier profile (M = 4.32) demands a specific institutional response: the development of transparent, comprehensible, and participatory AI governance frameworks within social service organizations. These frameworks should specify how AI-generated data is stored, who can access it, how long it is retained, how it is used in decision-making, and what mechanisms exist for service users and practitioners to contest AI outputs. The GDPR provides a legal minimum, but practitioner trust requires institutional commitment above and beyond legal compliance — including genuine practitioner involvement in governance design (Mantelero, 2018; Smuha, 2021). Technology vendors seeking to deploy AI in social work contexts should be required to demonstrate clear and auditable data governance protocols as a precondition for institutional procurement.

At the professional and policy level, the present findings support the case for embedding AI literacy — including critical perspectives on algorithmic fairness and social justice implications of automated welfare decisions — in social work education curricula and professional registration requirements. The risks documented by Eubanks (2018), Keddell (2019), and Buolamwini and Gebru (2018) are not theoretical: algorithmic systems deployed in child protection, benefits administration, and housing allocation have demonstrably reproduced and amplified structural inequalities affecting the most marginalized populations social work exists to serve. An AI-literate social work profession is better equipped to identify these risks, advocate for justice-oriented governance, and resist institutional pressures to substitute algorithmic certainty for the irreducible complexity of human professional judgment.

5.3 Limitations

The present study is subject to several limitations that should inform interpretation and guide future research. First, the cross-sectional design does not permit the examination of whether AI adoption attitudes change as practitioners gain direct experience with AI systems, whether positive experience shifts barriers, or whether concern about relational loss diminishes with familiarity. Longitudinal designs incorporating pre- and post-implementation measurement would substantially advance understanding of the temporal dynamics of AI acceptance in social work.

Second, the sample was recruited via convenience and purposive methods through professional networks, introducing the possibility of systematic selection bias. Practitioners engaged with professional associations and open to survey participation may be more reflective about and open to technology than the broader population of social work practitioners. The significant overrepresentation of female practitioners (n = 62, 63.9%) relative to the professional population — itself a majority-female field — does not per se constitute bias but should be noted as a distributional characteristic of the sample. Generalizability to social work practitioners outside Germany and to those working in underrepresented fields (e.g., residential care, community development) requires caution.

Third, all three focal constructs were assessed via the same self-report method at a single time point, creating conditions for common-method variance inflation (Podsakoff et al., 2003). The observed correlation magnitudes — particularly the large benefit-willingness association (r = .68) — may be partially attributable to shared method variance. Future studies should employ behavioral measures of AI engagement (e.g., actual system trial participation, frequency of AI tool usage following implementation) to provide criterion-referenced validation of the attitudinal constructs employed here.

Fourth, the present study assessed willingness as a general disposition toward AI-supported case management systems rather than toward specific tools or specific use cases. Research suggests that attitudes toward AI vary substantially depending on the domain of application — practitioners may be considerably more accepting of AI for documentation assistance than for risk assessment or case decision support (Gillingham, 2019). Future research should employ domain-specific willingness measures to map the boundary conditions of the present findings with greater precision.

Fifth, the present investigation did not assess several theoretically important correlates that may shape AI adoption attitudes in social work contexts, including digital literacy as a competence measure (distinct from self-efficacy), organizational climate for innovation, supervisory support for technological adoption, service user characteristics of practitioners' caseloads, and institutional history with prior digital implementations. The regression model, while explaining 58% of willingness variance, leaves 42% unexplained — a reminder that attitudinal phenomena of this complexity are irreducible to the handful of variables any single study can accommodate.

5.4 Outlook and Future Research Directions

The integration of AI into social work practice is not a question of whether but of how, on what terms, and with what governance. The present study demonstrates that social work practitioners are neither passive recipients of technological change nor uniformly resistant to it. They are, as the data suggest, critical and conditional adopters who recognize AI's genuine potential for bureaucratic relief while articulating substantive concerns about the conditions under which AI can be introduced without compromising the ethical and relational foundations of the profession. Future research should take this sophistication seriously.

Qualitative and mixed-methods studies would add phenomenological depth to the statistical patterns identified here, giving voice to the specific experiential logics through which practitioners make sense of AI — the moment a case worker first encounters an AI-generated risk classification that conflicts with her relational assessment, the negotiation of professional responsibility when an algorithm and a team disagree, the texture of the documentation-writing experience when AI assistance is and is not present. Experimental and quasi-experimental designs examining whether specific CPD interventions — particularly those emphasizing critical AI literacy rather than mere operational training — significantly shift the barrier profile would directly inform training policy. Finally, implementation science frameworks applied to AI adoption in social services should attend specifically to the role of experienced practitioners as critical knowledge holders whose resistance may serve as an early warning system rather than an obstacle — whose professional reservations, rather than being managed, should be structured into institutional adoption processes as a form of embedded ethical oversight.

Social work exists to accompany human beings through the most complex, painful, and consequential transitions of their lives. Any technology that enters this space inherits an obligation of the highest order: to serve those human beings, not merely to optimize the systems that claim to serve them. The present study suggests that social work practitioners understand this obligation deeply. Institutions and technology developers that meet practitioners' demands for competence, transparency, and ethical governance will find, in the present data, a profession ready to engage. Those that do not will encounter the same resistance — and for the same principled reasons.

Statements and Declarations

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Conflict of Interest

The author declares no competing financial or non-financial interests that could be perceived as having influenced the design, conduct, analysis, interpretation, or reporting of the research presented in this article.

Ethics Approval

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki (World Medical Association, 2013) and the guidelines of the German Psychological Society (DGPs). The study involved an anonymous online questionnaire with no experimental intervention, deception, or collection of personally identifiable information. Formal institutional review board approval was not required under applicable regulations governing anonymous behavioral survey research. All procedural safeguards for participant protection are described in the Informed Consent section below.

Informed Consent

Participants were provided with a comprehensive pre-survey information sheet prior to survey commencement. This document described the study purpose and structure, affirmed the entirely voluntary and anonymous nature of participation, specified participants' unconstricted right to withdraw at any point without consequence, and outlined data protection and storage procedures. Submission of a completed survey response was treated as constituting informed assent to participation. No financial incentive was offered and no coercive recruitment procedure was employed.

Data Availability Statement

The anonymized dataset supporting the findings reported in this study is available from the corresponding author upon reasonable written request. The data have not been deposited in a publicly accessible repository in order to preserve the analytical advantage of controlled access and in recognition of the professionally sensitive character of practitioner survey data.

Use of Generative AI

Generative artificial intelligence tools were employed during the preparation of this manuscript for purposes of language editing, structural formatting, and stylistic revision. All scientific content, theoretical argumentation, analytical decisions, interpretive conclusions, and ethical judgments are the sole intellectual responsibility of the author.

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