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From Practitioners to Algorithms: Predictors of Public Preferences towards AI-led Domestic Violence Risk Assessment

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Abstract

Domestic violence (DV) is a major social and population health issue across the globe, and risk assessment remains an important element in timely intervention and prevention. Conventionally, DV risk assessments have been based on human practitioners with structured instruments, although time, resource constraint, and bias are likely to restrain such methods. Artificial intelligence (AI) has recently been considered as an additional tool to provide efficiency, scalability and detecting complex data patterns. Nevertheless, the AI use in such a sensitive setting is not yet accepted by the general population. This research paper explored the psychological and attitudinal determinants of AI- vs practitioner-led DV risk assessment preferences. The study is a quantitative cross sectional survey involving adults in the general population, who completed validated scale measuring attitudes to AI, attitudes to help-seeking, confidentiality concerns and openness to experience. It was found that the majority of respondents preferred practitioner-led assessments. Although the variables explored did not significantly predict AI vs practitioner-led risk assessments in DV context, findings suggest that those who chose AI had significantly more positive attitudes to AI, more negative attitudes to help seeking, and higher confidentiality concerns. It is concluded that the public is not ready for AI use in such sensitive context, and AI must be viewed as an improving, but not a replacing, technology.

Keywords: Artificial intelligence; Domestic violence; Risk assessment; Attitudes to AI; Attitudes to help-seeking; Openness to experience; Confidentiality concerns

1. Introduction

Domestic Violence (DV) is recognised worldwide as critical public health and human rights concern, affecting people across cultural, socioeconomic, and religious contexts (Capinha et al., 2024; Huda et al., 2023; Quinn-Graham, 2024). DV is defined as an abusive behaviour pattern in intimate or family relationships (past or current), including physical violence, emotional and psychological abuse, sexual coercion or financial control (Huda et al. 2023; WHO, 2022). Within England and Wales, it is estimated that 2.3 million people over the age of 16 experienced domestic abuse in 2024, 67% of these were women (ONS, 2024). According to the World Health Organisation (2022), approximately 26% of women reported experiencing physical and/or sexual violence perpetrated by a male partner in 2021. The consequences of DV are both immediate and long-term, contributing not only to acute physical and emotional harm but also to chronic health problems, trauma, and wider social destabilisation (Campbell, 2002; Huda et al., 2023). Consequently, risk assessments in the context of DV are very important to prevent and to provide those who have experienced it with support.

Risk assessments are widely used to evaluate both risk of victimisation and perpetration of DV (Graham et al., 2019; Robinson & Rowlands, 2009). They allow for early detection and prevention of escalation (AbiNader et al., 2023). Many countries take on a multi-agency approach to DV risk-assessment (Lamb et al., 2022; Mann & Tosun, 2021; Stanley &

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Humphreys, 2014). However, research suggests that there are no universal standards and guidelines on how risk assessments are conducted and how they should inform risk management (Cunha et al., 2024; Lamb et al., 2022; Robinson & Rowlands, 2009). Although this allows for a more nuanced approach, it also leaves room for interpretation and errors in evaluating the level of risk. Recent research has highlighted that common risk assessment tools are not reliable (e.g., Turner et al., 2022) or sufficiently tailored to non-heteronormative relationships (e.g., Graham et al., 2019; Nicholls et al., 2013). Furthermore, risk assessments decisions are prone to error, as practitioners do not perfectly follow the risk assessment guidelines (Riedl et al., 2024), have limited resources and experience high levels of stress (Kulkarni et al., 2013; Maple & Kebbell, 2024).

Over the past few years, there has been escalating interest in using artificial intelligence (AI) in social care (e.g., Gongar & Tutsoy, 2024). AI allows the application of computational algorithms and systems that work over a versatile data, and aid in decision-making processes. AI-based solutions are proposed to be more efficient, consistent, and more capable in analysing multidimensional and complex data than humans (Sarker, 2022; Zarei et al., 2023). This offers a faster, more cost effective, and precise evaluations, as well as constant monitoring and support, which can cover more people than can be assisted in the remote or underserved regions (Kumar et al., 2025; Mishra et al., 2023). Within the context of DV specifically, literature suggests that using AI produces more sensitive, accurate, faster, and comprehensive risk assessments of DV than human-based risk assessments (Isijola et al., 2025). In fact, experiments in training ChatGPT to identify intimate partner violence showed 91.2% accuracy (Zhang et al., 2025).

In spite of these benefits, the introduction of AI in such sensitive areas as DV entails certain questions of acceptance, trust, and ethical consequences (Novitzkiy et al., 2023). It is argued that AI has no empathy or the skills of humans in deciphering subtle emotional and relationship patterns (Barnes & Hutson, 2024; Rauhaus et al., 2020). Furthermore, AI learning could be based on biased information, producing biased evaluations, and the models are not easy to explain making those biases difficult to identify and correct (Chinu & Bansal, 2024). Research on intentions to use AI discovered that even when individuals are aware of the enhanced AI accuracy, speed and efficiency, they still prefer relying on human decision making (He et al., 2023). These findings align with research in medical care (Riedl et al., 2024). A review of literature on AI use in clinical practice suggests that overall, both clinicians and clients prefer AI use in data interpretation and synthesis, rather than in decisions making, with clients sharing concerns regarding client-clinician relationship and being part of the decision marking (Scott et al., 2021). Interestingly, these strong preferences are not necessarily based on evidence. Föyen and colleagues (2025) conducted a double-blind study asking licensed mental health clinicians to rate suggestions made by AI and experts. The clinicians were unable to accurately identify whether the suggestions were made by AI or experts, and in fact rated the AI suggestions as higher in emotional and motivational empathy. This suggest that acceptance of AI use may have psychological underpinnings.

It could be argued that embracing new technologies is a matter of personality. Openness to experience is a personality characteristic that focuses on creativity, intellectual curiosity, and preference for variety (McCrae & John, 1992). Research suggests that openness to experience has been associated with more tolerance towards new technologies (Kaya et al., 2022) and more favourable perceptions of AI use (Bergdahl et al., 2023; Grassini & Koivisto, 2024). However, DV is a very sensitive context, accompanied by strong emotions, trauma, and self-disclosure (Heron & Eisma, 2021). Consequently, a more nuanced understanding is required to better understand the choice of AI versus human risk assessments.

The relationship between attitudes and behaviour is well established, with many theoretical explanations, including Theory of Reasoned Action, Theory of Planned Behaviour (Ajzen, 2011), Technology Acceptance Model (Davis et al., 1989). Within the context of AI vs human decision making, many studies have alluded to the importance of attitudes in choosing AI (e.g., Bowen, 2024; De Freitas et al., 2023; Gkinko & Elbanna, 2022). However, not many have directly measured attitudes and embracing of AI as two distinct factors. In fact, many of these studies used embracing of AI as indications of positive attitudes (e.g., He et al., 2023; Riedl et al., 2024; Scott et al., 2021). Attitudes refer to positive or negative evaluation of a phenomenon, and, as such, are distinct from a behaviour or intent of behaviour (Ajzen, 2001). In this context, how favourably one feels about using AI is conceptually distinct from whether they will use it in the future. The relationship between attitudes to AI and acceptance of AI use in clinical setting has largely been explored in the context of medical care. Studies found a strong association between attitudes to AI and intentions to use AI in practice among nursing and medical students in Korea (Cho & Seo, 2024; Si, 2025), USA (Labrague et al., 2023) and Arab countries (Al Omaru et al., 2024). These findings align with research in other context, such as industrial professions (Eman & Khan, 2025). Exploring the attitudes of the prospective users, Arkin et al. (2022) found that attitudes to AI significantly predicted whether individuals prefer to engage with human or AI based therapy. Although the literature is clear that more positive attitudes to AI will lead to higher chances of using AI, no research has explored this relationship in the context of domestic violence assessment, where the outcome of the AI use is more life changing.

When faced with a choice of AI vs human risk assessment in cases of DV, one needs to also consider the sensitive context and broader attitudes to help seeking (Ellsberg & Heise, 2002). Research suggests that a common barrier for coming forward in cases of domestic violence is shame and embarrassment the victims fear, resulting in self-blaming (Heron et al., 2022; Lelaurain et al., 2017). Human practitioners can break through these barriers, because they allow for empathetic collaborative relationship between the practitioner and client, which is an essential component of developing a therapeutic alliance and helps to achieve open communication and disclosure (Goodman et al., 2016). However, developing this alliance is not easy in light of the legal and social context of DV (Lømo et al., 2018; Tufford et al., 2010) and many victims of DV prefer to seek help from informal helpers (e.g., Kim & Hogge, 2015). Overstreet and Quinn (2013) argue that stigmatisation surrounding DV is a serious barrier to coming forward in cases of DV, with help-seeking behaviour significantly impacted by fear of judgment. These findings align with previous research (Lelaurain et al., 2017). On the other hand, it could be argued that AI lacks those preconception and biases, and therefore would not be passing judgment, which could make the AI risk assessment more appealing to those with negative attitudes regarding help seeking behaviour.

Concerns regarding confidentiality are commonly raised by individuals as barriers for not engaging with mental health practitioners (Del Mauro & Williams, 2013). In the context of DV specifically, practitioners ensuring a safe and confidential environment is a facilitator for disclosure (Heron & Eisma, 2020). Fear of breaking confidentiality has been a significant barrier for victims not seeking help, with many being concerned about their safety and consequences of disclosing (Fugate et al., 2005; Heron & Eisma, 2020). Recent development in use of virtual consultations for DV have offered even greater assurances of confidentiality by not requiring victims to travel in for an assessment (Henson et al., 2025). On the other hand, the nature of AI programming and the recent uses of AI have highlighted issues with confidentiality (Alhitmi et al., 2024; Chamola et al., 2023; Hearth et al., 2024), a concern echoed by clinicians (Scott et al., 2021), and the general public (Aktan et al., 2022; Liehner et al., 2023). As such, it could be argued that individuals who are more apprehensive about confidentiality, would prefer human-led risk assessments in the context of DV.

Although AI use is increasing across all domains, most literature has focused on concerns surrounding ethical use of AI tools, which is especially relevant to DV context. However, little research focused on exploring the choice of AI vs Human decision making, and none exploring it in the context of DV. In light of the literature, the current study explores whether attitudes and concerns about confidentiality can predict preferences for AI vs Human risk assessments in DV context, while controlling for personality. It is hypothesised that openness to experience, attitudes to AI, attitudes to help seeking, and confidentiality concerns will predict AI vs Human risk assessment. Specifically, those higher on openness to experience, with more positive attitudes to AI, more negative attitudes to help seeking, and lower confidentiality concerns will be more likely to choose AI risk assessments.

2. Materials and Methods

2.1. Design

This study utilised a cross-sectional correlational design to collect data through an online questionnaire using Qualtrics. The dependent variable was the preference of assessor (2 levels: practitioner vs AI assessment), while the independent variables were attitudes to AI, attitudes to help-seeking, confidentiality concerns, and openness to experience.

2.2. Participants

The study focused on adults (over the age of 18) from the general population. Convenience and snowball sampling were used to recruit participants. Adverts were shared on social media(e.g., Facebook, Twitter/X, and WhatsApp groups), university forums, and survey exchange platforms (Survey Circle and Survey Swap). The final sample consisted of 121 participants between the ages of 18 and 58 (M = 29.901; SD = 10.354).

The study obtained ethical approval from the Forensic Psychology Research Ethics Committee at University of Roehampton London (Reference number: 24_25-000024) and complied with the British Psychological Society ethical guidelines (BPS, 2021), Data Protection Act of 2018 and the UK General Data Protection Regulation (2016).To safeguard the participants, the information sheet clearly outlined the nature of the study and the subject matter of domestic violence, to ensure that the participants were fully informed. Furthermore, those who had experience of domestic violence or may be triggered by the topic were discouraged from taking part in the study. Finally, the participants were provided with sources of support in the debrief if they felt distressed by the topic.

2.3. Measures

To measure the preference of assessor, the participants were asked to directly choose if they believed that risk assessments in cases of domestic violence should be conducted by AI or by a practitioner (2 levels). The remaining variables were measured by validated scales.

Attitudes to AI was measured by the General Attitudes towards Artificial Intelligence Scale (GAAIS; Schepman & Rodway, 2023). The scale consists of 20 items, which include 12 positive (e.g., "Artificial Intelligence can provide new economic opportunities for this country") and 8 negative (e.g., "I think artificially intelligent systems make many errors") attitudes. The participants were asked to rate each item on a 5-point Likert-type scale indicating their level of agreement (1 = strongly disagree; 5 = strongly agree). The negative items were reverse scored and the answers were summed, with higher scores indicating more positive attitudes towards AI. The scale has good reliability for both positive (Cronbach's alpha = 0.85) and negative (Cronbach's alpha = 0.82) items (Schepman & Rodway, 2023)

Attitudes to help seeking was measured by the Attitudes Toward Seeking Professional Psychological Help - Short Form (ATSPPH-SF; Fischer & Farina, 1995). This 10-item scale was developed to explores help-seeking behaviour in mental health context. However, the items focus on engaging with the most common type of psychological practitioner in seeking this help (e.g., "I might want to have psychological counseling in the future."). Each item was rated on a 4-point Likert-type scale indicating level of agreement (3 = strongly agree; 0 = strongly disagree). Items 2, 4, 8, 9, and 10 were reverse scored and all responses were summed, such that higher scores indicated more positive attitudes to help seeking. The original study reported good reliability of the scale, with Cronbach's alpha of 0.84 (Fischer & Farina, 1995).

To evaluate openness to experience, the subscale Openness to Experience from the NEO Five-Factor Inventory (NEO-FFI; Costa & McCrae, 1992) was used. This is a 12-item subscale, which includes items such as "I often enjoy playing with theories or abstract ideas." The participants were asked to indicate their strength of agreement on a 5-point Likert-type scale (0=strongly disagree; 4=Strongly agree). After reverse scoring of 7 items, the responses were summed, with higher scores indicating higher levels of openness to experience. Published reliability statistics range between 0.62 to 0.75, which is acceptable (Dwan et al., 2017; Korner et al., 2015).

To measure confidentiality concerns, the Confidentiality Scale (Gilbert et al., 2007) was adapted for the purpose of this study. The scale includes 7 items, such as "I would worry that the person I talk to would share the information with my family." The original scale provided instructions for the participants to specifically reflect on confidentiality concerns in a mental health context. However, for the purpose of the current study, any mention of mental health specific context was removed from the instructions. The participants were asked to indicate how frequently they worried about the concerns outlined in each item on a 7-point Likert-type scale (0 = Never; 4 = Almost Always). Items 3 and 5 were reverse scored, before all responses were summed, with higher scores indicating greater concerns regarding confidentiality. The scale has high reliability (Cronbach's alpha = 0.80; Gilbert et al., 2007).

2.4. Procedures

The study was advertised through social networks (e.g., Facebook, Twitter/X, and WhatsApp groups), university forums, and survey exchange platforms (Survey Circle and Survey Swap). Those who were interested in participating, followed a Qualtrics link where they were provided with a detailed information sheet about the study and a consent form. Once they consented, they confirmed their age to ensure that all are aged 18 or above. The participants were then provided with the four scales in randomised order to avoid order effects. Finally, they were asked to choose who should be conducting risk assessments in DV cases. Once the participants completed the study, they were provided with a debrief sheet and contact details of the researchers.

3. Results

Originally, 124 participants consented to take part, but 3 were removed from the sample due to systematically missing data. The reliability analysis indicated that the scales had very good reliability, except for openness to experience (Table 1). Furthermore, descriptive analysis revealed that the participants had normally distributed scores across openness to experience, negatively skewed attitudes to help seeking and Attitudes to AI, and positively skewed confidentiality concerns (Table 1). Finally, the sample showed greater preference for practitioner led risk assessments (85.1%), with only 18 participants (14.9%) choosing to AI led assessment.

Table 1 Measures of central tendency and reliability analysis for predictor variables

Variables	M	SD	D (121)	Cronbach's alpha
Openness to Experience	29.595	5.240	0.075	0.567
Attitudes to Help Seeking	17.120	3.634	0.141*	0.777
Attitudes to AI	55.455	11.070	0.105**	0.813
Confidentiality Concerns	8.120	4.429	0.123**	0.796

To test the hypothesis a logistic regression was performed, with openness to experience, attitudes to help seeking, attitudes to AI and confidentiality concerns entered as the independent variables, while preference of assessor was entered as the dependant variable. Analysis indicated that assumption of linearity was met (the interactions between the predictor variables and their log were all not significant, $p>0.05$). Furthermore, there were no concerns of multicollinearity (all VIF < 10; all Tolerance > 0.1). Finally, there were no strongly influential outliers (Cook's distance < 1). The model significantly predicted preference of assessor (χ^2 (4)=11.980, p = 0.018; R^2 = 0.094 (Cox & Snell) to 0.166 (Nagelkerke)). However, the model was efficient at predicting Practitioner preference (100% accuracy), but not at predicting AI preference (5.6% accuracy), with none of the variables showing significant contribution (see Table 2 for summarises of the coefficients).

Table 2 Summary of logistic regression coefficients

Variables	B(SE)	Wald (1)	Sig	Exp(B)	95% CL Exp (B)
Openness to Experience	0.005 (.056)	1.842	0.931	1.005	0.900 < B < 1.122
Attitudes to Help Seeking	0.107 (.079)	3.644	0.175	1.113	0.954 < B < 1.299
Attitudes to AI	-0.064 (.034)	3.188	0.056	0.938	0.896 < B < 1.002
Confidentiality Concerns	-0.110 (.062)	2.806	0.074	0.896	0.794 < B < 1.011

The difference between those who preferred AI vs practitioner led risk assessment was further explored. Levene's analysis indicated that homogeneity of variance assumptions were met (see Table 3). However, the Kolmogorov-Smirnov analysis (Table 3) indicated that only openness to experience met the assumption of normality, with most variables found significantly skewed within the practitioner preference group. However, in line with the Central Limit Theorem the sample size was sufficient large (N=103), and exploration of graphical representations (histograms and Q-Q plots) showed no significant deviations from normality for openness to experience, attitudes to help seeking, attitudes to AI and confidentiality concerns. As such, the independent t-test analysis was performed to evaluate the differences across these variables. The analysis indicated that those who preferred practitioner led risk assessments reported significantly more positive attitudes to help seeking, more negative attitudes to AI, and lower confidentiality concerns (Table 4).

Table 3 Kolmogorov-Smirnov test of normality

Variables	AI D(18)	Practitioner D(103)	F (1,119)
Age	0.225*	0.239***	0.738
Openness to Experience	0.101	0.076	0.132
Attitudes to Help Seeking	0.124	0.149***	0.147
Attitudes to AI	0.161	0.106**	1.120
Confidentiality Concerns	0.153	0.125***	2.868
Notes: * p <0.05; ** p < 0.01; *** p < 0.001			

Table 4 Independent samples t-test analysis

Variables	AI M(SD)	Practitioner M(SD)	t (119)	Sig	Cohen's d
Openness to Experience	29.222 (4.953)	29.660 (5.309)	-0.326	0.745	5.260
Attitudes to Help Seeking	15.556 (3.240)	17.394 (3.644)	-2.005	0.047	3.589
Attitudes to AI	60.167 (9.313)	54.631 (11.186)	1.981	0.049	10.938
Confidentiality Concerns	10.531 (5.674)	7.700 (4.063)	2.560	0.012	4.330

Finally, since age violated assumptions of normality (see Table 3), a Mann-Whitney U test was performed to evaluate the differences between preferences on age. The analysis indicated that those who chose AI (*Mdn* = 28.50; *M* = 33.556; *SD* = 10.982) were significantly older than those who chose practitioner (*Mdn* = 25.000; *M* = 29.262; *SD* = 10.161), *U* = 3654.000, *z* = −1.993, *p* = 0.046, *r* = -0.181.

4. Discussion

The use of AI in decision making has attracted extensive attention in the recent literature. However, most of this research has focused on practitioners (e.g., Al Omaru et al., 2024; Cho & Seo, 2024; Labrague et al., 2023; Si, 2025), with little attention to the likely service users. This quantitative study explored the perspective of the general public, as potential service users, on their preference for DV risk assessments to be conducted by AI vs human practitioners. It was hypothesised that those higher on openness to experience, with more positive attitudes to AI, more negative attitudes to help seeking, and lower confidentiality concerns will be more likely to choose AI risk assessments. Logistic regression analysis indicated that the hypothesis was not supported. In fact, from the 121 participants, an overwhelming majority (85.1%) preferred DV risk assessments to be led by human practitioners, indicating that the public is not ready to entrust such sensitive decisions to AI.

Although these factors cannot be used to predict preferences for decision making in the context of DV risk assessments, further explorative analysis found significant differences on these factors between those who chose AI vs those who chose a human practitioner. It was found that participants who preferred practitioner led DV risk assessments were significantly younger and had significantly more positive attitudes to help seeking, more negative attitudes to AI, and lower confidentiality concerns. With the increased use of AI in decision making and the significant benefits it offers in improving services and reducing workload (e.g., Kulkarni et al., 2013; Maple & Kebbell, 2024; Riedl et al., 2024), this allows to create a better understanding and a profile of those choosing AI vs those who prefer human practitioners.

The significant difference in attitudes to AI between those who chose AI vs practitioner led DV risk assessment aligns with past research (e.g., Al Omaru et al., 2024; Cho & Seo, 2024; Eman & Khan, 2025; Labrague etal., 2023; Si, 2025). These findings underscore the central role of attitudes in shaping preferences for decision-making agents, consistent with established attitude–behaviour frameworks such as the Theory of Reasoned Action and the Theory of Planned Behaviour (Ajzen, 2001, 2011), as well as technology-specific models like the Technology Acceptance Model (Davis et al., 1989). Unlike previous research (e.g., He et al., 2023; Riedl et al., 2024; Scott et al., 2021), the current study differentiated between attitudes to AI and the choice of using AI for decision making. Although it was found that attitudes could not be used to predict choice in DV risk assessments, the study did find that those who preferred AI led risk assessment had more positive attitudes to AI. However, the current study did not explore these frameworks fully. For example, the Theory of Planned Behaviour (Ajzen, 2001) suggests that it is the combined effect of attitudes, subjective norms and perceived behavioural control that can be used to predict behaviour. Subjective norms refer to perceptions about what important others think about using AI, while perceived behavioural control refers to ease of using AI. It could be argued that given the complexity of AI programming and lack of public understanding surrounding it (Chinu & Bansal, 2024), perceived behavioural and subjective norms could play a much stronger predictive role than general attitudes about AI. As such, further research should aim to explore these frameworks more fully.

The finding that those who chose practitioner led risk assessment held more positive attitudes to help seeking is not surprising, given the sensitive context of DV. Help-seeking in DV cases is heavily influenced by stigma, shame, and fear of judgment (Ellsberg & Heise, 2002; Heron et al., 2022; Lelaurain et al., 2017). Individuals who already hold more favourable attitudes toward seeking help may therefore be more willing to engage with human practitioners, despite the potential emotional challenges involved. This aligns with research emphasising the importance of empathetic, collaborative relationships in facilitating disclosure and building therapeutic alliances in DV contexts (Goodman et al., 2016). Human practitioners may be perceived as better equipped to respond with empathy and contextual understanding, which can help overcome barriers related to self-blame and fear of negative evaluation (Overstreet & Quinn, 2013). In contrast, those with more negative help-seeking attitudes may be more drawn to AI-based assessments, which could be perceived as less judgmental and less socially threatening, an argument previously raised but not empirically tested in DV contexts. Further research should delve deeper into the relationship between the specific barriers to help-seeking and use of AI in DV context.

Interestingly, the finding that those who had higher confidentiality concerns chose AI-led risk assessment seems to contradict recent discourse highlighting concerns about AI-related data security, surveillance, and misuse (Aktan et al., 2022; Alhitmi et al., 2024; Chamola et al., 2023; Scott et al., 2021). However, it does align with previous literature identifying confidentiality fears as a major barrier to engaging with human practitioners in DV and mental health settings (Del Mauro & Williams, 2013; Fugate et al., 2005; Heron & Eisma, 2020). This may heighten apprehension among those who are more cautious about confidentiality, pushing them towards AI-led risk assessments and away from the subjective, partial and less uniformed assessments by practitioners. Alternatively, it could be argued that the public does not quite understanding the risks associated with AI use, assuming that it offers a more anonymous and safer environment than it actually does. Further research should explore the level of understanding that the public possesses regarding the risks of AI use and how this may impact their choice of risk assessment in DV context.

The analysis showed that there was a statistically significant difference in age between those who chose AI vs practitioner led DV risk assessment, with those who chose AI being significantly older. These findings align with previous research (e.g. Cinalioglu, et al., 2022). However, the mean difference between the two groups was only 4 years apart, suggesting that they fit within the same generational group. As such, the difference could not be accounted by difference in generations and does not provide meaningful insight.

Finally, openness to experience was not a significant predictor of risk-assessment choice and was not significantly different between those who chose AI vs practitioner led assessments. Although previous research highlighted the importance of personality in embracing AI, it also found that agreeableness is a stronger predictor of AI use, than openness to experience (e.g., Kaya et al., 2024; Park & Woo, 2022). As such, future research should include a more comprehensive evaluation of the different personality types in embracing AI-led risk assessments.

Overall, the findings of the study suggest a profile of those individuals who feel comfortable embracing AI-led DV risk assessments. Specifically, those who have more positive attitudes to AI, those who have more negative perceptions about help-seeking, and those who have higher concerns regarding confidentiality preferred AI-led assessments. However, the current study did not fully explore individual differences (e.g., demographics and personality), other predictors of intentions and behaviour (e.g., subjective norms and perceived behavioural control, or knowledge about how AI works and pitfalls). Furthermore, the study chose to focus on DV broadly, allowing the participants to self-define on whether the “risk assessment” refers to assessment of victims or risk of reoffending. It could be argued that this differentiation could impact opinions. As such, further research is needed to fully understand all the nuances involved in the public’s choice. Nevertheless, this was the first study to explore the public perceptions and preferences of AI vs human practitioner led risk assessments in domestic violence.

The findings highlight that the public is not ready to entrust risk assessments in sensitive context like DV to AI, with most participants choosing practitioner-led risk assessments. Those who did choose AI-led risk assessment, seem to have greater trust in AI, perceiving it as more confidential and trustworthy than practitioner-led risk assessments. This is quite concerning considering the ethical and practical discourse surrounding the nature of AI (e.g., Chinu & Bansal, 2023), especially given the high stakes in DV context (e.g., ONS, 2024). As such, it is essential to ensure that the control in such cases remains in human hands, and although AI can be used as a support tool, clients must have clear detailed information on how it is used and the choice to having it used. To conclude, although AI has potential benefits to improving efficiency of DV risk assessments, its adoption should be done cautiously. Ethical protection, such as transparency, privacy, fairness, and survivor-centred design, is not a choice, but a prerequisite of responsible deployment.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that there is no conflict of interest.

Statement of ethical approval

Ethical approval was obtained from the Forensic Psychology Research Ethics Committee of University of Roehampton London.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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