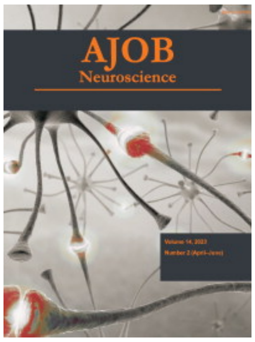

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The Influence of Using Novel Predictive Technologies on Judgments of Stigma, Empathy, and Compassion among Healthcare Professionals

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ABSTRACT

Background: Our objective was to evaluate whether the description of a machine learning (ML) app or brain imaging technology to predict the onset of schizophrenia or alcohol use disorder (AUD) influences healthcare professionals' judgments of stigma, empathy, and compassion.

Methods: We randomized healthcare professionals ($N = 310$) to one vignette about a person whose clinician seeks to predict schizophrenia or an AUD, using a ML app, brain imaging, or a psychosocial assessment. Participants used scales to measure their judgments of stigma, empathy, and compassion.

Results: Participants randomized to the ML vignette endorsed less anger and more fear relative to the psychosocial vignette, and the brain imaging vignette elicited higher pity ratings. The brain imaging and ML vignettes evoked lower personal responsibility judgments compared to the psychosocial vignette. Physicians and nurses reported less empathy than clinical psychologists.

Conclusions: The use of predictive technologies may reinforce essentialist views about mental health and substance use that may increase specific aspects of stigma and reduce others.

KEYWORDS
Brain imaging; empirical bioethics; healthcare workers; machine learning; mental disorders; neuroethics; stigma; substance-related disorders

INTRODUCTION

Mental health and substance use disorders (MHSUD) pose major public health challenges and are among leading causes of the global burden of disease (Whiteford et al. 2015). These conditions are also highly stigmatized (Avery and Avery 2019; Link and Phelan 2001). For instance, people with MHSUDs are often considered dangerous and blameworthy (Talbott 2012; Pescosolido et al. 2021). Stigma can be a barrier to recovery and accessing healthcare for people living with MHSUD and can lead to worse health outcomes (Paquette, Syvertsen, and Pollini 2018; Corrigan, Druss, and Perlick 2014). Despite efforts to reduce stigma, stigma related to MHSUD persists among lay publics and health professionals (Sukhera et al. 2022; Pescosolido et al. 2021; van Boekel et al. 2013; Henderson et al. 2014). Stigma from healthcare professionals is particularly concerning, as it may lead to less empathic and compassionate care (van Boekel et al. 2013; Nyblade et al. 2019; Boysen et al. 2020; Henderson et al. 2014).

Stigma is enacted through a process that includes labeling, stereotyping, power, status loss, discrimination, and normative judgments of deviance (Goldberg 2017; Link and Phelan 2001). As a social determinant of health inequities, stigma is rooted in prejudice, discrimination, and marginalization (Hatzenbuehler, Phelan, and Link 2013). Stigma is an ethical issue as it can threaten what matters most for people (Yang et al. 2007). A concept related to stigma called social distance is the degree to which one person is willing to interact with another person in different types of relationships (Jorm and Oh 2009). It has most commonly been used as a proxy measure for mental illness stigma (Marie and Miles 2008; Lucas and Phelan 2019; Talbott 2012) but has also been

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used as a measure for stigma in obesity (Sikorski et al. 2015) and addiction (Barry et al. 2014).

Biological Attributions of Mental Illness and Addiction

A vast literature on the neurobiological and genetic contributions to MHSUD has emerged over the past half-century. The results of this research have been taken up enthusiastically by various publics (Vidal and Ortega 2017; Rose and Abi-Rached 2013). The knowledge has captured various publics' imagination, in part, because scientific knowledge is socially authoritative. Research has found that neuroscientific explanations can have a "seductive allure" shaping the public's ability to critically interrogate explanations of psychological phenomena (Weisberg et al. 2008; Fernandez-Duque et al. 2015). Studies focused on people who are affected by mental illness have found that there is a relationship between perceived biological causes of mental disorders, treatment expectations, and support for pharmacotherapy (Schroder et al. 2020; Lebowitz and Ahn 2014). Lay or non-content expert publics have also incorporated the language of neurobiology to describe their mental suffering (Buchman et al. 2013; Davis 2022).

Since MHSUD have long been considered moral failings by many, some scientists and policy makers have argued that a biological framing of MHSUD will reduce stigma and attributions of personal responsibility, and lead to less punitive policies. However, the evidence for these claims is mixed. For example, biological attributions of MHSUD may increase stigma and reduce empathy by promoting essentialist views (Loughman and Haslam 2018; Kvaale, Gottdiener, and Haslam 2013; Lebowitz and Ahn 2014). A randomized controlled trial found that biomedical messaging about mental illness did not increase stigma and had a more positive impact on stigmatizing attitudes than non-biomedical messaging (e.g., recovery-oriented, social inclusion; Ojio et al. 2019). In one qualitative study of people diagnosed with a mood disorder, participants reported that a brain scan would help mitigate stigma and provide an objective representation of their subjective experiences (Buchman et al. 2013). Other studies suggest that knowledge of neuroscience can decrease attributions of personal responsibility in addiction (Racine, Sattler, and Escande 2017), and brain disease models will lead to increased treatment-seeking and reduce stigma for people living with a SUD (Bell et al. 2014; Barnett et al. 2018). Other scholars note that a reductionist focus on the brain within a brain disease framework will distract from a broader focus on racism, classism, and other structural determinants that shape substance use problems (Lie et al. 2022). Furthermore, brain disease explanations on compassionate policy responses in addiction have been limited (Hall, Carter, and Forlini 2015).

AI and Machine Learning in Psychiatry: Potential Unintended Consequences?

There is excitement surrounding the potential uses of AI and ML in healthcare and psychiatry in particular, with some considering it a "paradigm shift" (Graham et al. 2019; Mak, Lee, and Park 2019; Bedi et al. 2015; Chekroud et al. 2021). ML has been used to predict the risk of suicidal ideation (Roy et al. 2020) and treatment outcomes in psychosis (Rezaii, Walker, and Wolff 2019), and help to identify underlying biological mechanisms of diagnoses such as schizophrenia (de Boer et al. 2020).

Proponents of AI and ML in psychiatry laud the ability of AI/ML systems to synthesize and analyze large datasets with tremendous speed and accuracy superior to what is possible with traditional methods. AI and ML techniques are designed to integrate a broad array of data including behavioral data from sources like social media and smart devices to generate digital phenotypes (Torous, Onnela, and Keshavan 2017; Torous et al. 2018). These advanced prediction algorithms are also thought to enhance the objectivity of psychiatric decision-making and remove uncertainty regarding diagnosis, prognosis, and treatment (Lane and Broome 2022). Much of this enthusiasm for AI and ML mirrors claims made by proponents in the 1990s and 2000s that advances in neuroscience and genetics will transform psychiatry (Kandel 1998; Insel and Wang 2010; Kendler and First 2010). Despite the considerable scientific progress, identifying psychiatric biomarkers with clinical utility remains elusive (Scull 2021; Singh and Rose 2009).

Given the high level of hope and expectation attached to AI and ML (Wilkinson et al. 2020), there may be similar unintended ethical consequences for stigma that emerged from biological framings of MHSUD. Since stigma can have a pernicious effect on the health of already disadvantaged populations, it is critical to understand whether AI and ML technologies may similarly influence healthcare professional stigma, empathy, and compassion toward people living with MHSUD. Furthermore, the anticipated clinical implementation of ML and brain imaging technologies highlight the importance of understanding stakeholder judgments that can help promote the potential benefits of these technologies in MHSUD while forestalling unintended harms.

MATERIALS AND METHODS

The objective of the study was to evaluate whether the description of a ML app or brain imaging technology to predict the risk of MHSUD influences healthcare professionals' judgments of stigma, empathy, and compassion toward a person with MHSUD. We sought to inform normative discussions on the potential clinical integration of AI and ML and brain imaging technologies in psychiatric settings (Earp et al. 2021). The study protocol was approved by the Research Ethics Board at the Center for Addiction and Mental Health (007/2021).

Participant Recruitment

We recruited participants through social media posts on Twitter and LinkedIn, direct email recruitment of the professional networks of the study team, healthcare professional colleges with publicly available email directories, and snowball sampling. Participants were required to be at least 18 years of age and either a regulated or unregulated healthcare professional, practicing in Canada or the US. At the conclusion of the survey, participants were given the option on a web page separate from the survey to enter their email address for a chance to win one of three iPads.

Study Design

We used a contrastive vignette technique (CVT) study design (Burstin, Doughtie, and Raphaeli 1980). A CVT design is well established in social psychology and an emerging approach in experimental philosophical bioethics (Fitz et al. 2014; Cabrera, Fitz, and Reiner 2015; Reiner 2019; Earp et al. 2020). In a CVT design, participants are randomized to one vignette and are unaware that other contrastive conditions exist; the vignettes are identical but differ in one or more details. All participants answer the same questions on Likert-scales regarding their judgments toward the information presented in the specific vignette. This approach is used to evaluate the impact of the contrastive manipulation.

We used a 2×3 between-subjects design to examine the effect of diagnosis and method of predictive technology. The vignettes varied on the diagnosis (schizophrenia or alcohol use disorder; AUD) and the method of prediction: a natural language processing ML app, a brain scan, or a psychosocial assessment. The vignettes described a fictitious 22-year-old person named Jane who has a family history of either mental illness or addiction (depending on the vignette), and is worried about developing schizophrenia or AUD, respectively. A healthcare professional orders a technology to predict the onset of schizophrenia or an AUD. We chose schizophrenia and AUD because they are widely researched and known diagnoses, and participants were likely to have some familiarity with them clinically. Additionally, both diagnoses have a strong hereditary component (Kinreich et al. 2021), and are the focus of current AI/ML research as well as brain imaging research (Bedi et al. 2015; Corcoran et al. 2020; Singh et al. 2022; Khalil et al. 2022). We compared ML to brain imaging because of previous research suggesting an impact of the perceived role of brain imaging technologies in shaping mental health stigma including factors such as reducing blame and personal responsibility (Buchman et al. 2013; Dumit 2021). Psychosocial assessment (e.g., family history, environment) was the control condition because psychosocial factors are part of a holistic approach to current diagnostic processes for both schizophrenia and AUD. We tested the hypothesis that the technologies (i.e., ML and brain imaging) would result in lower participant attributions of stigma toward Jane as compared to the psychosocial assessment condition. Our main outcome was beliefs about personal responsibility, and secondary outcomes were emotional responses to stigma, including anger, empathy, and compassion.

The vignettes were developed iteratively by members of the research team, and were informed by feedback from content experts in psychiatry and AI/ML. To improve the face validity of our vignettes and surveys, and ecological validity of the study, we pilot-tested the vignettes and the survey with interdisciplinary research and clinical colleagues as well as members of the research team who identify as lived experience advisors. The feedback from this pilot testing was used to establish the final versions of the vignettes (see Table 1). We used the Flesch-Kincaid Reading Ease and Grade Level readability tests to analyze the vignettes.

Data Collection

We administered the surveys using the Research Electronic Data Capture (RedCAP) software ("REDCap" n.d.). Prior to beginning the survey,

Table 1. Contrastive vignettes used in the study.

	Machine Learning App	Brain Imaging	Psychosocial (Control)
Schizophrenia	Your colleague tells you about a patient, Jane, a 22-year-old woman who has a family history of mental illness. At a recent appointment, Jane reported that she is worried about developing schizophrenia in the future. Your colleague wants to accurately predict whether Jane will develop schizophrenia. **She asks Jane to download an approved passive mobile data collection app on her smartphone for two weeks. The app discreetly analyzes Jane's data including web browser history, emails, text messages, and social media posts, as well as geolocation and sleep patterns. Using machine learning, the app generates predictions about the user's future health.** Your colleague gets the results which indicate **atypical thinking, as well as cognitive and frequent mood changes. This suggests that Jane is likely to develop schizophrenia.**	Your colleague tells you about a patient, Jane, a 22-year-old woman who has a family history of mental illness. At a recent appointment, Jane reported that she is worried about developing schizophrenia in the future. Your colleague wants to accurately predict whether Jane will develop schizophrenia. **She orders a functional MRI (fMRI) scan of Jane's brain to identify biomarkers.** Your colleague gets the results which indicate **abnormal activity patterns in the fronto-limbic circuits, areas of the brain which mediate cognition and emotional states. This suggests that Jane is likely to develop schizophrenia.**	Your colleague tells you about a patient, Jane, a 22-year-old woman who has a family history of mental illness. At a recent appointment, Jane reported that she is worried about developing schizophrenia in the future. Your colleague wants to accurately predict whether Jane will develop schizophrenia. **She takes a medical history and conducts a psychosocial assessment and physical exam.** Your colleague gets the results which indicate **various psychosocial risk factors, including Jane having an older father and growing up downtown in a major city. This suggests that Jane is likely to develop schizophrenia.**
Alcohol Use Disorder	Your colleague tells you about a patient, Jane, a 22-year-old woman who has a family history of addiction. At a recent appointment, Jane reported that she is worried about developing an addiction to alcohol in the future. Your colleague wants to accurately predict whether Jane will develop an alcohol use disorder. **She asks Jane to download an approved passive mobile data collection app on her smartphone for two weeks. The app discreetly analyzes Jane's data including web browser history, emails, text messages, and social media posts, as well as geolocation and sleep patterns. Using machine learning, the app generates predictions about the user's future health.** Your colleague gets the results back which indicate **atypical thinking, as well as cognitive and frequent mood changes. This suggests that Jane is likely to develop an alcohol use disorder.**	Your colleague tells you about a patient, Jane, a 22-year-old woman who has a family history of addiction. At a recent appointment, Jane reported that he is worried about developing addiction to alcohol in the future. Your colleague wants to accurately predict whether Jane will develop an alcohol use disorder. **She orders a functional MRI (fMRI) scan of Jane's brain to identify biomarkers.** Your colleague gets the results back which indicate **abnormal activity patterns in the fronto-limbic circuits, areas of the brain which mediate cognition and emotional states. This suggests that Jane is likely to develop an alcohol use disorder.**	Your colleague tells you about a patient, Jane, a 22-year-old woman who has a family history of addiction. At a recent appointment, Jane reported that she is worried about developing addiction to alcohol in the future. Your colleague wants to accurately predict whether Jane will develop an alcohol use disorder. **She takes a medical history and conducts a psychosocial assessment and physical exam.** Your colleague gets the results back which indicate **various psychosocial risk factors, including Jane having an older father and growing up downtown in a major city. This suggests that Jane is likely to develop an alcohol use disorder**.

The contrastive manipulation appears in bold.

participants were provided an informed consent form to read and gave their eConsent by clicking a digital button labeled "I agree."

The survey had two parts. The first part served to collect demographic information and participants were invited to self-report their age, gender, racial or ethnic group identities, profession, years of practice, practice location (country; urban, suburban, or rural), and their professional and personal familiarity with mental illness and substance use disorders (Corrigan et al. 2003). In the second part, participants were randomized to one of the six vignettes and were asked to complete outcome measures to assess stigma, empathy, compassion, and predictive ability of the technology described in the vignette.

Measures

To measure stigma and social distance, we used the Attribution Questionnaire developed by Corrigan et al. (2003). This well validated and widely used questionnaire consists of 21 items measuring six subscales (i.e., personal responsibility beliefs, pity, anger, fear, helping, coercion-segregation) using a 9-point Likert scale (1 = none at all to 9 = very much). We measured empathy using a scale that was designed to measure empathy toward a stigmatized group (Batson et al. 1997; Lebowitz and Ahn 2014). The scale includes a list of adjectives that participants use to describe their feelings about Jane, on a seven-point Likert scale that ranged from 1 = not all to 7 = extremely. The six adjectives measure *empathic concern* (sympathetic, softhearted, warm, compassionate, tender) and *personal distress* (alarmed, troubled, distressed, upset, disturbed, and worried). We used the 10-item Compassion Scale developed by Martins et al. (2013) that measures *generosity, hospitality, objectivity, sensitivity* and *tolerance* using a 1 = none to 7 = all Likert scale. For example, one item under generosity included the question "How much of your future savings would you give away now to help a stranger in need of financial help?"

Participants were also asked two questions about the predictive ability of the technology described in the vignette. Question 1 asked, "How likely is it that Jane will develop her future illness condition?" and was rated from 1 = not at all likely to 7 = very likely. Question 2 asked, "How accurate are the clinical tools described in the vignette in predicting a future illness state?" and was rated on a Likert scale from 1 = not at all accurate to 7 = very accurate.

Statistical Analysis

We reported descriptive statistics to characterize the sample and responses. The main analyses used an ANOVA or MANOVA with the explanatory factors of Technology (3: ML, brain imaging, psychosocial) x Illness (2: AUD, schizophrenia). Although preliminary analyses indicated that the distributions of gender and profession were not statistically different across treatment conditions, we examined participant gender and profession as control factors. These factors were kept in models when significant and were dropped when non-significant. The main outcome was the personal responsibility beliefs subscale from the Corrigan et al. (2003) Attribution Questionnaire. Secondary outcomes were the remaining Corrigan subscales (i.e., pity, anger, fear, helping, and coercion-segregation), compassion, and empathy. Pairwise comparisons were used to interpret ANOVA effects and logistic regression was used to interpret multivariate effects detected by MANOVA. All tests were two-tailed and conducted with α=0.05. For mean comparisons, we provide descriptions of Cohen's d as a standardized measure of effect size. By convention, $d = 0.20$ is considered a small effect, $d = 0.50$ is a medium effect, and $d = 0.80$ is a large effect. When reviewing results, we used statistical significance (i.e., $p \leq 0.05$) to flag those effects worth interpretation, having occurred beyond chance. We focus on the value of d to provide the reader a sense of the magnitude of the detected effect.

RESULTS

Three hundred and ten health care professionals participated in this study (see Table 2 for Demographics and Table 3 for Descriptive Statistics). Participants were primarily female (72%, $n = 224$), white (74%, $n = 227$) and were employed in one of several health-care professions. The largest professional representation was clinical psychologists (21%, $n = 64$). Sixty-five percent of participants were between the ages of 25 and 64. Participants had a wide range of experience with 20% of our sample having less than 5 years in practice and 23% of the sample having more than 25 years in practice. Most respondents resided in Canada (92%) and practiced in urban environments (71%). There was a high degree of familiarity with MHSUD, with 84% reporting that their job involves providing services/treatment for persons with MHSUD and 65% reporting they have a relative who has a severe MHSUD.

Personal Responsibility Beliefs

The data for personal responsibility beliefs were derived from the personal responsibility subscale of the Corrigan et al. (2003) Attribution Questionnaire. There were statistically significant differences on beliefs about personal responsibility across the three Technology vignettes (see Table 4 and Figure 1). Greater personal responsibility was attributed to Jane in the psychosocial vignette than in the ML vignette, $d = 0.28$, and the brain imaging vignette, $d = 0.24$, in support of the main prediction.

There were also significant differences based on Illness condition. Greater personal responsibility was attributed to Jane when AUD was indicated compared to schizophrenia, $d = 1.22$ (see Table 4 and Figure 2). Male participants attributed more personal responsibility to Jane compared to female participants, $d = 0.45$, and non-binary participants, $d = 0.73$ (see Table 4 and Figure 3).

Table 2. Participant demographic characteristics.

Variable	Total n (%)
Gender ($n = 310$)	
Female	224 (72%)
Male	79 (26%)
Other (e.g., non-binary, two-spirit)	4 (1%)
No information	3 (1%)
Age ($n = 310$)	
18–24	10 (3%)
25–34	72 (23%)
35–44	92 (30%)
45–54	61 (20%)
65–74	25 (8%)
75+	5 (1%)
Race/ethnicity ($n = 310$)	
White	227 (74%)
South Asian	26 (8%)
East Asian	9 (3%)
Other	40 (13%)
No information	8 (2%)
Years in practice ($n = 310$)	
Less than 5	61 (20%)
5–10	53 (17%)
10–15	58 (19%)
15–20	30 (10%)
20–25	35 (11%)
Over 25	73 (23%)
Profession ($n = 310$)	
Clinical Psychologist	64 (21%)
Nurse	54 (17%)
Physician	49 (16%)
Social Worker	32 (10%)
Physical Therapist	18 (6%)
Occupational Therapist	10 (3%)
Other	83 (27%)
Country of Practice ($n = 310$)	
Canada	286 (92%)
United States	24 (8%)
Practice Location ($n = 310$)	
Urban	219 (71%)
Suburban	64 (21%)
Rural	27 (8%)
Familiarity with mental illness (adapted from Corrigan et al. 2003)	
My job involves providing services/ treatment for persons with mental illness or addiction.	259 (84%)
I have observed, in passing, a person I believe may have had a severe mental illness or addiction.	296 (95%)
I have observed persons with a severe mental illness or addiction on a frequent basis.	213 (67%)
I have worked with a person who had a severe mental illness or addiction at my place of employment.	231 (75%)
A friend of the family has a severe mental illness or addiction.	181 (58%)
I have a relative who has a severe mental illness or addiction.	201 (65%)
I live with a person who has a severe mental illness or addiction.	35 (11%)

Stigma, Empathy, and Compassion Outcomes

We conducted a Technology x Illness vignette MANOVA on the Stigma subscales (pity, anger, fear, helping, and coercion-segregation) to limit issues of multiple testing. The multivariate tests indicated the presence of a significant Technology effect. To interpret this effect, we conducted a multinomial logistic regression specifying technology group as the categorical dependent variable and the remaining Stigma subscales as predictive covariates.

The multinomial logistic regression generated two binary logistic regressions, one in which the outcome modeled is the odds of being randomized to the ML vs. psychosocial vignette, and the other the odds of being in the brain imaging vs. psychosocial vignette. There were significant effects involving the former function and a marginal effect involving the latter (see Table 5 for details).

The ML vignette was associated with less anger and more fear, relative to the psychosocial vignette. An increase in anger ratings was associated with a 55% reduction in the odds of having been exposed to the ML vignette. Stated conversely, a decrease in anger ratings was associated with 2.2 times greater likelihood of having read the ML vignette. An increase in fear ratings was associated with an almost two-fold increase in the odds of having been exposed to the ML vignette. There was a marginally significant effect between the brain imaging vignette and pity, OR $=$ 1.30, $CI_{.95}(1, 1.69)$. An increase in the pity rating was associated with a 30% increase in the odds of having been exposed to the brain imaging vignette.

There were no effects of Technology or Illness vignette on the outcomes of empathy and compassion. However, physician and nurse participants were less empathetic than clinical psychologists, $d = 0.44$, and other health care professionals, $d = 0.34$ (see Table 4 and Figure 4).

Prediction Questions

The mean ratings on the prediction questions indicated low overall confidence in the ability of brain imaging and ML to predict a future illness, M_{Q1}=3.46, M_{Q2}=2.73 (see Table 3) and both ratings were highly correlated, $r = 0.53$, $p < 0.0001$. There were significant Technology vignette effects on Questions 1 and 2.

Concerning the likelihood of illness (Question 1), brain imaging was rated as more convincing than psychosocial assessment in predicting Jane would become ill, $d = 0.47$, but ML did not differ from either (see Table 4 and Figure 5).

About the perceived accuracy of prediction (Question 2), brain imaging was rated as more accurate than ML, $d = 0.37$ and psychosocial assessment, $d = 0.34$ (see Table 4 and Figure 6). Participants who were clinical psychologists were less likely to believe in the accuracy of any predictive technology compared to physicians and nurses, $d = 0.43$, and other health care professionals, $d = 0.40$ (see Table 4 and Figure 7).

Table 3. Descriptive statistics.

	N	Minimum	Maximum	Mean	Standard Deviation
Prediction Questions					
Question 1	303	1	7	3.46	1.12
Question 2	303	1	7	2.73	1.23
Stigma Subscales					
Personal Responsibility Beliefs	303	1	9	3.05	1.50
Pity	303	2.67	7.33	5.62	1.09
Anger	303	1	7.67	1.21	0.74
Fear	303	1	8.25	1.30	0.80
Helping	303	2	9	6.87	1.54
Coercion-Segregation	303	1	8.75	1.23	0.73
Empathy					
	310	2.56	5.83	4.31	0.55
Compassion					
	298	1	6	3.45	0.76

Table 4. Pairwise mean comparisons.

Outcome	M_{PS}	M_{ML}	*p*-Value	*d*
Personal Responsibility Beliefs	3.24 (2.91, 3.57)	2.82 (2.47, 3.16)	0.008	0.28
		M_{BR} 2.88 (2.53, 3.23)	0.03	0.24
	M_{AUD} 3.90 (3.58, 4.21)	M_{SCZ} 2.06 (1.74, 2.38)	<.0001	1.22
	M_{Male} 3.57 (3.31, 3.83)	M_{Female} 2.89 (2.74, 3.05)	<.0001	0.45
		$M_{Non\text{-}Bin}$ 2.75 (1.67, 3.28)	0.01	0.73
Outcome	$M_{Medical}$	$M_{Psychol}$	*p*-Value	*d*
Empathy	4.17 (4.07, 4.28)	4.41 (4.28, 4.54)	0.006	0.44
		M_{HCPs} 4.36 (4.27, 4.45)	0.008	0.34
Outcome	M_{PS}	M_{BR}	*p*-Value	*d*
Prediction Question 1 (Likelihood of Illness)	3.21 (3.01, 3.42)	3.74 (3.51, 3.96)	0.001	0.47
		M_{ML} 3.46 (3.25, 3.68)	n.s.	–
Outcome	M_{BR}	M_{ML}	*p*-Value	*d*
Prediction Question 2 (Accuracy of Prediction)	2.97 (2.72, 3.22)	2.51 (2.27, 2.75)	0.009	0.37
		M_{PS} 2.55 (2.32, 2.78)	0.01	0.34
	$M_{Psychol}$ 2.33 (2.03, 2.64)	$M_{Medical}$ 2.87 (2.63, 3.10)	0.006	0.43
		M_{HCPs} 2.83 (2.63, 3.03)	0.008	0.40

Note. Means with 95% confidence intervals are reported. Cohen's *d* is the measure of effect size. M_{PS}: Mean of the Psychosocial vignette; M_{ML}: Mean of the Machine Learning vignette; M_{BR}: Mean of the Brain Imaging vignette; M_{AUD} : Mean of the Alcohol Use Disorder vignette; M_{SCZ} : Mean of the Schizophrenia vignette; M_{Male} : Mean of Male participants; M_{Female} : Mean of Female participants; $M_{Non\text{-}Bin}$: Mean of Non-Binary participants; $M_{Medical}$: Mean of Physician and Nurse participants; $M_{Psychol}$: Mean of Clinical Psychologist participants; M_{HCPs} : Mean of other Health Care Professional participants.

DISCUSSION

The objective of our study was to evaluate whether the description of a ML app or brain imaging technology to predict the onset of schizophrenia or AUD influences healthcare professionals' judgments of stigma, empathy, and compassion. Our results suggest what Haslam and Kvaale (2015) have referred to as a "mixed blessing" model of stigma, meaning that perceptions of predictive technologies in MHSUD can help reduce some forms of stigma while simultaneously increasing other forms.

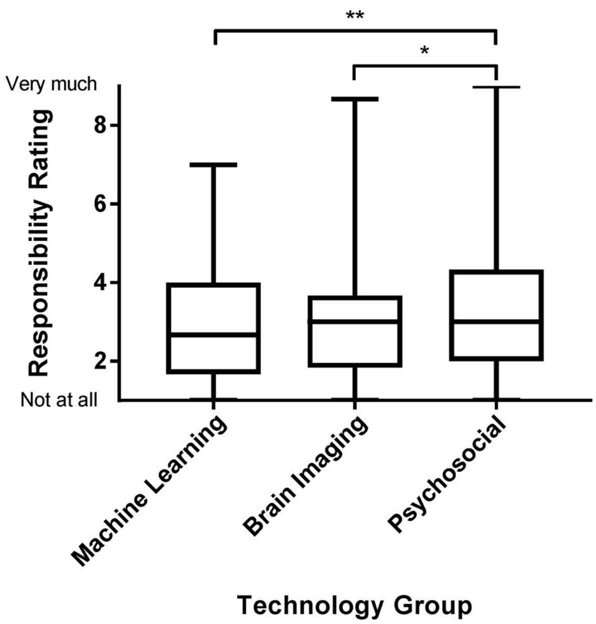

Figure 1. Personal responsibility beliefs scores by technology group. Participants provided a rating using a scale that ranged from 1 to 9, with higher numbers indicating more attributed personal responsibility. The box plot indicates the interquartile range of the data points, with the median indicated as a horizontal line. Whiskers indicate the range (minimum and maximum of individual data points). Graphs visualize the center, spread and overall range of the data (* $p < 0.05$; ** $p \leq 0.01$).

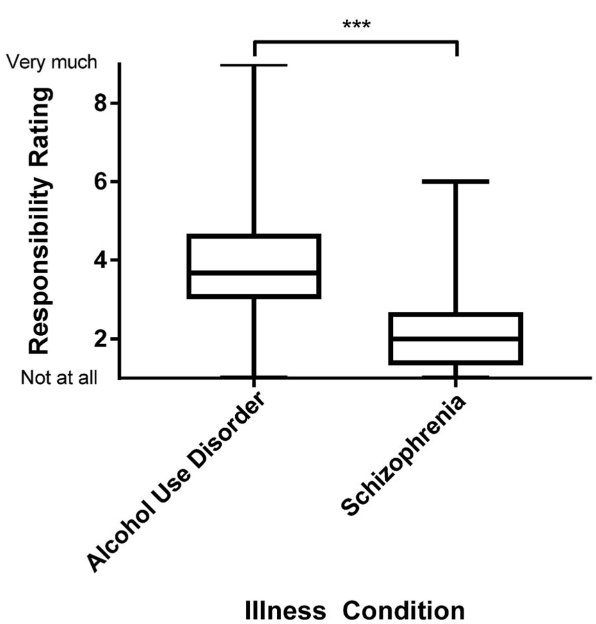

Figure 2. Personal responsibility beliefs scores by illness condition. Participants provided a rating using a scale that ranged from 1 to 9, with higher numbers indicating more attributed personal responsibility. The box plot indicates the interquartile range of the data points, with the median indicated as a horizontal line. Whiskers indicate the range (minimum and maximum of individual data points). Graphs visualize the center, spread and overall range of the data (*** $p \leq 0.001$).

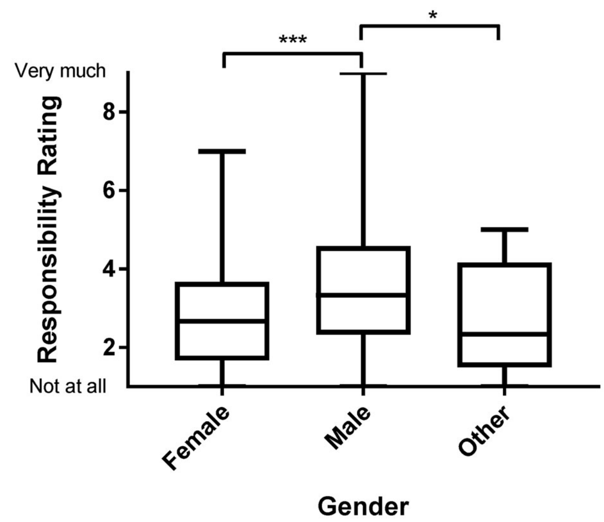

Figure 3. Personal responsibility beliefs scores by participant gender. Other refers to non-binary, two-spirit. Participants provided a rating using a scale that ranged from 1 to 9, with higher numbers indicating more attributed personal responsibility. The box plot indicates the interquartile range of the data points, with the median indicated as a horizontal line. Whiskers indicate the range (minimum and maximum of individual data points). Graphs visualize the center, spread and overall range of the data (* $p < 0.05$; ** $p \leq 0.001$).

We found that exposure to the ML vignette decreased participants' levels of anger toward Jane but had the detrimental effect of increasing fear, relative to the psychosocial vignette. Additionally, exposure to the brain imaging vignette was associated with higher reported feelings of pity relative to both ML and psychosocial vignettes, respectively. Our results also suggest that exposure to the psychosocial vignette increased healthcare professionals' perception that people are somewhat personally responsible for developing their condition. When compared to both brain imaging and ML vignettes, healthcare professionals reading the psychosocial language attributed greater personal responsibility to the character of Jane. This could be in part because such assessments draw heavily upon patient self-report and speculation on the relative weights of family history, circumstances, and environmental interactions.

Predictive technologies might have been perceived as being more objective than the psychosocial assessment. Accordingly, efforts to predict MHSUD with perceived objective tools such as brain imaging or ML apps may reinforce ideas of (neuro)biological essentialism (Haslam and Ernst 2002), which consider conditions such as mental health and substance use disorders as serious, unalterable, and not under personal control; identity-determining pathologies that are treatable but not necessarily recoverable (Kvaale,

Table 5. Multinomial logistic regression predicting Technology group with Stigma subscales.

Contrastive manipulation[a]		Significance	Odds ratio	95% CI Lower	95% CI Upper
Machine learning app	Pity	0.14	1.21	0.94	1.57
	Anger	0.02*	0.45	0.24	0.86
	Fear	0.03*	1.86	1.05	3.29
	Helping	0.52	0.94	0.78	1.13
	Coercion-Segregation	0.57	0.87	0.53	1.42
Brain imaging	Pity	0.05†	1.30	1	1.69
	Anger	0.69	0.88	0.47	1.66
	Fear	0.17	0.58	0.27	1.27
	Helping	0.58	1.06	0.87	1.29
	Coercion-Segregation	0.51	1.21	0.68	2.16

[a]The reference category is the Psychosocial Vignette.
*$p < 0.05$.
†Marginal significance.

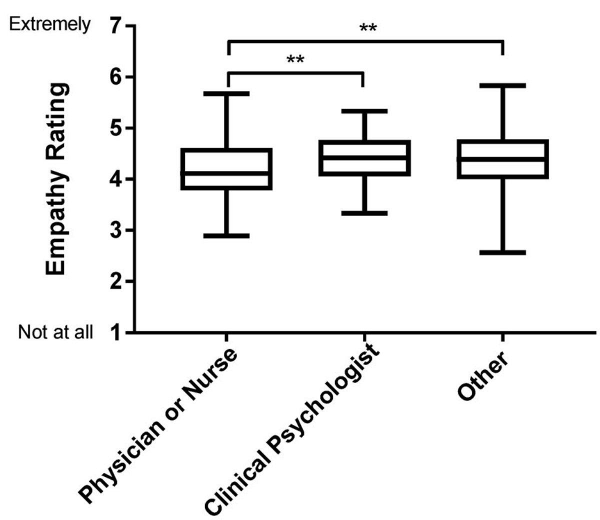

Figure 4. Empathy scores by participant profession. Participants provided a rating using a scale that ranged from 1 to 7, with higher numbers indicating more empathy. The box plot indicates the interquartile range of the data points, with the median indicated as a horizontal line. Whiskers indicate the range (minimum and maximum of individual data points). Graphs visualize the center, spread and overall range of the data (**$p \leq 0.01$).

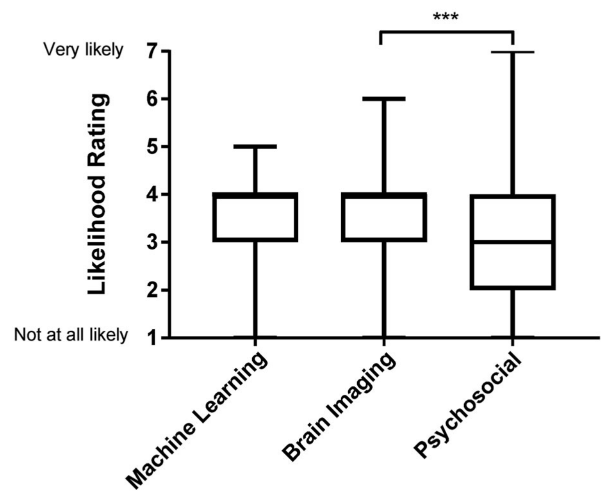

Figure 5. Prediction question 1 by technology group. The question asked, "how likely is it that Jane will develop her future illness condition?" Participants provided a rating using a scale that ranged from 1 to 7, with higher numbers indicating degree of likelihood that Jane is more likely to develop her future illness condition. The box plot indicates the interquartile range of the data points, with the median indicated as a horizontal line. Whiskers indicate the range (minimum and maximum of individual data points). Graphs visualize the center, spread and overall range of the data (***$p \leq 0.01$).

Gottdiener, and Haslam 2013; Haslam and Kvaale 2015; Loughman and Haslam 2018). Predictive technologies that are perceived as being objective may reduce aspects of stigma related to personal responsibility, but it may also inadvertently intensify aspects of stigma such as fear.

The perceptions about the accuracy and reliability of the tools to predict future illness varied. While there are no established brain imaging and ML applications in psychiatric practice, brain imaging was generally thought to be the most accurate and reliable prediction method; however, participants gave it a low accuracy and reliability score. Clinical psychologists were the least confident in the accuracy of the technologies described in the vignettes. This may be due to their increased knowledge of MHSUD compared to other professionals who do not specialize in mental health. This group may have skewed the results given their professional epistemic commitments to understanding MHSUD as primarily biological, and their familiarity with the current sensitivity and specificity limitations of technologies such as brain imaging and ML to predict future mental illness states.

We also found an effect of participant demographics. Males tended to assign more personal

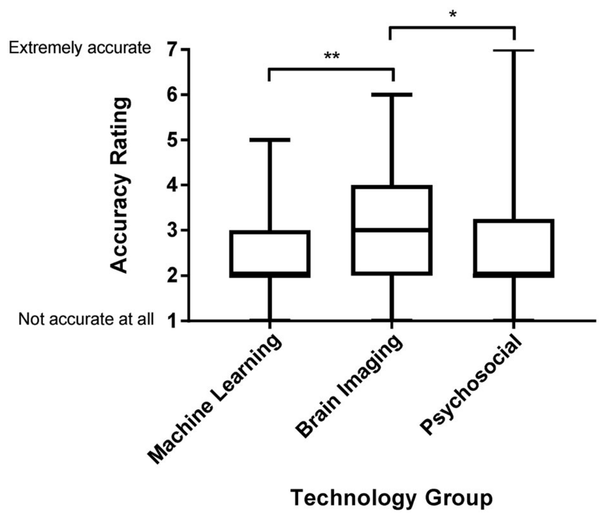

Figure 6. Prediction question 2 by technology group. The question asked, "how accurate are the clinical tools described in the vignette?" Participants provided a rating using a scale that ranged from 1 to 7, with higher numbers indicating more accuracy. The box plot indicates the interquartile range of the data points, with the median indicated as a horizontal line. Whiskers indicate the range (minimum and maximum of individual data points). Graphs visualize the center, spread and overall range of the data (*$p < 0.05$; **$p \leq 0.01$).

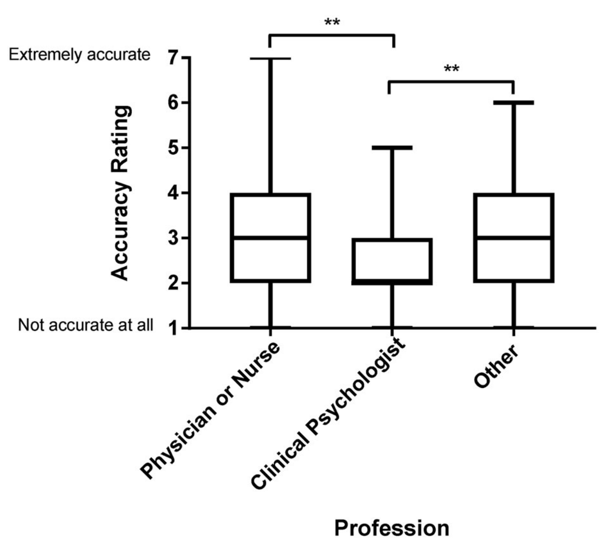

Figure 7. Prediction question 2 by participant profession. The question asked, "how accurate are the clinical tools described in the vignette?" Participants provided a rating using a scale that ranged from 1 to 7, with higher numbers indicating more accuracy. The box plot indicates the interquartile range of the data points, with the median indicated as a horizontal line. Whiskers indicate the range (minimum and maximum of individual data points). Graphs visualize the center, spread and overall range of the data (**$p \leq 0.01$).

responsibility to Jane compared to females and nonbinary participants, which may have played a role in the degree to which attitudes about stigma were captured, as the sample was primarily female. Furthermore, physicians and nurses were less empathetic toward Jane compared to other health professions. There may have also been subtle cultural differences that affected our results, given that most participants resided in Canada, rather than the US.

Participants who were randomized to the AUD vignette assigned Jane higher levels of personal responsibility than the participants who were randomized to the schizophrenia vignette. This finding is consistent with dominant historical perspectives about addiction being a moral condition–a failure of willpower or a social problem–despite many public campaigns to change this narrative toward medicalization (Dackis and O'Brien 2005).

Many of the results had small to medium effect sizes ($0.24 - 0.47$ Cohen's d). Future research can help clarify the clinical meaning and generalizability of these findings. However, this study may be considered proof of concept that a minimal experimental manipulation can activate preconceptions about technology and illness sufficient to influence the responses of healthcare professional participants.

Limitations

Firstly, our results may be influenced by *social desirability bias*, a tendency for participants to respond to questions in a manner that they view as socially acceptable and underreport information that they view as socially undesirable (Krumpal 2013). Participants were healthcare professionals and may have felt pressure to report high levels of empathy and compassion toward Jane—especially since she was concerned about possibly developing schizophrenia or an AUD—and to avoid reporting stigmatizing responses. Our results may also be influenced by the *hypothetical bias*, which occurs when individuals report what they would do hypothetically and not necessarily what they would do in reality (Hensher, Rose, and Greene 2015). While there are active research programs describing ML apps and brain imaging in the precise ways we described, these predictive technologies have not yet been integrated into clinical settings. However, while the hypothetical bias poses limitations, it is also a strength. Surveying the attitudes of healthcare professionals–stakeholders with relevant expertise–before neuroimaging and AI/ML is implemented clinically allows for consideration of their attitudes to be included in, but not definitive of, the development of future health-related policy (Savulescu, Kahane, and Gyngell 2019). Finally, our study aimed to focus on healthcare professionals, and we did not set out to do a comparison between this group and other publics such as the general population. This comparison would provide a useful area of future research.

CONCLUSIONS

Our study found that exposure to descriptions of predictive technologies such as a ML app and brain imaging increases specific aspects of stigma and social distance and reduces others. Neuroimaging and AI/ML research have made important strides toward improving the potential prediction, diagnosis, and treatment of MHSUD, but much of the research is in early stages. Unintended ethical considerations may arise not only from the use of the technologies in practice but also how the technologies shape how society understands, judges, governs, and (re)configures notions of disease and normality. The potential clinical implementation of AI/ML and brain imaging technologies may influence not only the therapeutic relationship, but also clinical decision-making if they are perceived to have epistemic superiority over more traditional clinical methods that rely on patient self-report, such as psychosocial assessments (McCradden, Hui, and Buchman 2022). The anticipated clinical application of these technologies may reinforce simplistic essentialist views about MHSUD that may intensify specific aspects of stigma and social distance. Future research can explore a range of relevant stakeholders and stakeholder judgments on the potential use of predictive technologies in MHSUD and how it influences stigma.

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