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Natural language processing of patient in-session speech to predict brief motivational interviewing alcohol intervention response: an exploratory study

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Abstract

Background: **Motivational interviewing (MI) is a patient-centred, goal-oriented psychotherapy for alcohol use disorder (AUD) and numerous other conditions. While some language patterns have been linked to MI response, less is known about how broader linguistic features, sentiment, and engagement relate to post-intervention drinking. This study used natural language processing to examine these associations and clarify mechanisms through which MI for AUD exerts its effects.**

Methods: **Adults with AUD ($N = 68$) completed a single MI session with structured feedback and discussion of potential drinking changes. Speech transcripts were analysed for change-, emotion-, motivation-, substance-, and health-related words. Sentiment analysis assessed emotional polarity, and engagement was measured by total words spoken. Linear regression models tested associations between linguistic features and drinking outcomes, including drinks/week, percent heavy drinking days (%HDD), and percent drinking days (%DD).**

Results: **Participants showed significant reductions in drinks per week and %DD. Consistent with recent reviews of MI predictors, linguistic analyses found that greater use of change talk and health-related language was associated with more drinks per week at follow-up, whereas greater emotional talk and positive sentiment predicted fewer drinks per week. Health- and substance-related language predicted higher %HDD, while social motivation-related language predicted lower %DD. Term-frequency and multivariate analyses supported these patterns.**

Conclusions: **Via natural language processing of MI speech, linguistic features such as motivational content and sentiment were linked to drinking outcomes. Findings demonstrate the potential of this approach as a scalable, data-driven complement to traditional coding systems, with applications for real-time feedback, clinician training, and personalized interventions.**

Keywords motivational interviewing, alcohol use disorder, natural language processing, linguistic patterns, sentiment analysis, treatment outcomes

Introduction

Motivational interviewing (MI) is a patient-centred, goal-oriented therapeutic approach designed to strengthen an individual's motivation and commitment to change. It was originally developed by Miller and Rollnick (1992) to be grounded in principles of collaboration, evocation, and autonomy; and emphasize empathy and reflective listening to elicit self-motivational statements from clients. Unlike confrontational methods, MI leverages an individual's intrinsic values and desires to foster behaviour change, making it particularly effective for addressing substance use disorders (Miller and Rose 2009, Miller and Rollnick 2013). Through guided conversations, clinicians help clients resolve ambivalence about their substance use behaviour, enhancing their readiness to pursue healthier choices. This dynamic and adaptable approach has gained widespread recognition as a key intervention in the treatment of alcohol use disorder (AUD)

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and other addictive behaviours (Nyamathi et al. 2010, Miller and Rollnick 2013, Hurlocker et al. 2023, Schwenker et al. 2023).

A substantial body of MI process research has focused on client language, particularly the concept of 'change talk,' defined as client statements expressing desire, ability, reasons, and need (DARN) for change, as well as the related construct of commitment language, which reflects the client's intention or decision to change and has been shown to be especially salient when examined in terms of its strength and temporal dynamics (Amrhein et al. 2003). However, recent work has raised important questions about the sufficiency of change talk alone in explaining MI's effectiveness and the consistency of its relationship with treatment outcome. For example, in Magill et al.'s (2014) meta-analysis, no consistent relationship between change talk and drinking outcomes was found, while sustain talk, which reflects language favouring the status quo or opposing change, was negatively associated with the treatment outcome. In another more recently conducted meta-analysis, greater sustain talk related to DARN was associated with increased addictive behaviour at follow-up. Interestingly, change talk were also linked to MI outcomes, but in an unexpected direction (i.e. worse outcome) (Magill et al. 2019). Gaume et al. (2021) reported that change talk predicted alcohol outcomes only when relational quality was high, and therapist MI-consistent skills alone were not predictive. These findings suggest that change talk may function more as a mediator, contingent on relational context, rather than a direct mechanism. Villarosa-Hurlocker et al. (2019) further complicate the picture, focusing on therapist–client interaction patterns without finding direct associations between client change language and alcohol outcomes. Taken together, these studies highlight ongoing debates about MI's mechanisms of action and the inconsistent role of client's change talk. These findings underscore the importance of considering a broader spectrum of client language as a key factor in understanding and facilitating behaviour change, which is supported by models that view MI as an interactive process, involving both technical components (e.g. eliciting change talk) and relational factors (e.g. empathy, collaboration) (Miller and Rose 2009, Moyers et al. 2009).

Traditional coding frameworks have primarily emphasized frequency-based quantification of change and sustain talk. This approach may overlook other meaningful linguistic markers that reflect emotional processing, health concerns, or motivational salience, all of which are central to MI's therapeutic spirit. The current study aims to address this gap by analysing broader in-session linguistic features, including emotional and health-related language, as well as sentiment polarity, the overall positive or negative semantic tone of client language. In doing so, it offers a conceptual expansion of the MI framework, moving beyond the narrow focus on change talk to consider a wider array of client-expressed processes reflective of discrepancy resolution, emotional engagement, and intrinsic motivation.

This also aligns with ongoing efforts in the field of psychotherapy process research to integrate computational tools, including natural language processing (NLP), into the analysis of in-session dialogue. NLP offers scalable and objective methods for parsing large volumes of therapy data, enabling fine-grained analysis of linguistic features linked to therapeutic mechanisms. Prior work in this domain has used NLP to evaluate MI fidelity (Atkins et al. 2014), assess therapist–client interactions (Imel et al. 2014), classify behavioural codes in MI (Tavabi et al. 2021), and compare automated coding strategies (Tanana et al. 2016). Building on these developments, the present study applies NLP methods, specifically term-frequency analysis and sentiment analysis, to explore how various word categories and sentiment polarity predict treatment outcomes in MI.

By incorporating emotional and health-related language, this exploratory study contributes both conceptually and methodologically to MI process research. Conceptually, it complements existing models by examining novel linguistic indicators that may reflect client engagement with key therapeutic mechanisms like emotional salience and health-based discrepancy, and it offers a lexical reconceptualization of in-session language analysis which is fundamentally different from the traditional MI coding systems. Methodologically, it extends recent computational psychotherapy approaches by applying scalable NLP tools to analyse client speech in an MI context. As such, the study speaks to contemporary debates around how best to model the mechanisms of MI and offers new directions for improving intervention fidelity and personalization.

In this context, the current study aimed to explore how linguistic patterns during the MI session relate to changes in drinking behaviour by analysing the frequency of use of specific word categories, sentiment polarity (i.e. the degree to which speech expresses a positive, negative, or neutral emotional semantic content), and engagement measures such as word count and readiness ruler dimensions (i.e. a tool that assesses an individual's importance, confidence, and readiness to change their drinking behaviour). While previous research has emphasized the impact of change and commitment talk on outcomes, this work expands the focus to include emotional, motivational, health-related, and substance use language. In doing so, it offers an empirically grounded expansion of the MI model that integrates linguistic predictors with NLP-based measurement of sentiment, contributing to a more expansive understanding of how MI facilitates behaviour change. Gaining a deeper understanding of these associations may offer valuable insights into the mechanisms of MI and enhance the assessment of intervention efficacy for AUD.

Materials and Methods

Participants

A total of 70 non-treatment-seeking adults, between ages 21 and 55 and diagnosed with AUD, were recruited from the general community in Hamilton, Ontario, Canada. To be eligible, participants needed to (i) have a current diagnosis of AUD and not be in remission, (ii) demonstrate consistently high levels of alcohol consumption over the preceding 3 months, in line with the National Institute on Alcohol Abuse and Alcoholism (NIAAA) guidelines, which specify more than 14 standard drinks per week for males or seven for females, and (iii) be fluent in English. The AUD diagnosis was defined by the presence of at least three DSM-5 symptoms as assessed by trained research personnel. The threshold of three symptoms was set intentionally to exclude marginal clinical diagnoses of AUD. Exclusion criteria included (i) a current substance use disorder other than alcohol, cannabis, or tobacco; (ii) more than weekly recreational drug use other than alcohol, cannabis, or tobacco; and (iii) a history of severe mental health disorders, such as schizophrenia or bipolar disorder. After each study assessment, participants received a $40 gift card. All

Table 1 Sample demographics ($N = 68$).

Variable	Mean (SD)/*N*(%)
Age	33.75 (10.49)
Sex (female)	38 (55.88%)
Race (White European)	55 (82.09%)
Years of education	14.66 (2.69)
Income (median)	$75 000-90 000
AUD symptoms	6.43 (2.44)
Drinks per week	
Baseline	25.66 (15.39)
Follow-up	16.99 (12.82)
% Heavy drinking days	
Baseline	39.02 (26.92)
Follow-up	31.09 (25.74)
% Drinking days	
Baseline	61.50 (23.61)
Follow-up	35.08 (27.93)

participants provided written informed consent, and the study received ethical approval from the Hamilton Integrated Research Ethics Board (protocol #4551). Retention was high; 68 (97%) of participants completed a follow-up session around 7 weeks later. The study sample characteristics are detailed in Table 1. The AUD symptoms shown in Table 1 were measured using the Diagnostic Assessment Research Tool (DART; McCabe et al. 2017, Schneider et al. 2022). This exploratory study utilizes the full AUD sample from a larger neuroimaging study that examines neural activity to predict treatment response (Elsayed et al. 2026, Hargreaves et al. 2025, Syan et al. 2023).

Motivational interviews and clinical diagnosis

Eligibility screening for interested individuals was conducted via telephone interviews or online questionnaires. Participants who met the initial criteria underwent a comprehensive in-person screening session to verify eligibility based on their alcohol consumption patterns. This was followed by two baseline sessions, the first included behavioural assessments and clinical evaluations, while the second included MI interventions.

To assess AUD severity, the DART, a structured clinical interview was administered (McCabe et al. 2017, Schneider et al. 2022). This tool is based on DSM-5 AUD criteria and has recently been validated in an AUD sample (Garber et al. 2024). Participants were asked to reflect on their typical behaviour over the past 3 months to determine the presence of a current AUD. Each DSM-5 criterion endorsed by the participant was assigned one point, with scores of 2–3, 4–5, and 6–11 corresponding to mild, moderate, and severe AUD, respectively.

Alcohol consumption over the previous 28 days was assessed using the 28-day Timeline Follow Back, a clinician-administered tool (Sobell and Sobell 1992). Participants were asked to recall their alcohol intake, providing estimates to the best of their ability in terms of standard drinks (e.g. 5 oz of wine, 12 oz of beer or cider, or 1.5 oz of liquor or distilled spirits). These estimates were used to calculate the number of drinks consumed per week, the percentage of drinking days (%DD; days on which any alcohol was consumed), and the percentage of heavy drinking days (%HDD; defined by the NIAAA as 4+ drinks for women and 5+ drinks for men on any occasion).

The MI sessions were conducted by clinical psychology doctoral trainees (E.L., M.G., and S.K.S.) supervised by a licensed psychologist with expertise in MI (E.M.). The study clinicians followed a structured therapy manual created by a licensed psychologist with expertise in clinical research implementations of MI (J.M.). The manual is provided in Supplementary Material 1. All participants received a single MI session as part of the study protocol that lasted ∼60 min, which was designed to enhance participants' motivation to reduce their alcohol consumption. During the sessions, participants were encouraged to consider the impacts of their alcohol use, with a focus on physical and mental health, finances, personal values, and the consequences of alcohol use on their lives. Based on the participant's preference, the clinician could assist in creating goals and a plan to reduce alcohol consumption, although any participant-preferred outcome was supported. Participants were offered the opportunity to schedule up to three additional follow-up visits with the clinician over the next 3 weeks to discuss any further changes they wished to make in relation to alcohol consumption patterns. Approximately one-quarter of participants opted for these supplementary visits. However, for the purposes of the present study, only text from the first MI session was included. The correlation between the variation in the number of MI sessions administered before the follow-up visit and the reduction of the outcome variables (from baseline to follow-up visit) was examined to account for any potential effects. Alcohol consumption variables (i.e. drinks per week, %DD, and %HDD) were calculated for both the baseline and follow-up visit to quantify any pre-post MI effects. The period between the baseline and follow-up visits varied as a result of scheduling and because the number of MI sessions varied across participants (Mean $\pm$ SD: 6.8 ± 1.2 weeks). MI sessions were audio-recorded and evaluated by at least two raters for overall quality using the Global Rating of Motivational Interviewing Therapist scale (Moyer and Finney 2004) and a protocol adherence checklist (Median: 93.33%; Mean: 88.69%; SD: 8.95%).

Data analysis

Transcription and extraction of participant data

The first step in preprocessing involved transcribing the recorded audio files of the MI sessions. Each interview was transcribed manually by a human transcriber and independently reviewed by another to ensure accuracy. After the interviews were fully transcribed and reviewed, the contributions of the participants were isolated from the transcripts. Each interview transcript was processed to retain only the participant's speech, excluding the clinician's, ensuring the analysis focused solely on participant language relevant to treatment outcomes. The participants' language was converted to lowercase and stemmed (i.e. reduced to their root forms) using the Snowball algorithm to standardize word variations (Bouchet-Valat 2023). Additionally, all numbers were removed to retain only textual data.

Text categorization and term-frequency analysis

Specific word categories were identified in the participant-only textual data, which included 'change talk, emotional talk, commitment/self-efficacy talk', words identifying 'motivation to quit', words identifying 'motivation to drink, health-related' words, and 'substance-related' words. Words belonging to each category are shown in Table 2.

'Change talk' included words such as 'quit, change, stop, break, reduce, and detox'. 'Emotional talk' included words related to emotions, such as 'depression, ashamed, guilty, anxiety, stress, hopeful, and grief'. 'Commitment/self-efficacy talk' included words reflecting confidence and self-discipline, such as 'able, manage, handle, confident, believe, and determined'. Words identifying 'motivation to quit' included three subcategories: 'family' (e.g. 'mother, father, son, daughter'), 'financial' concerns (e.g. 'money, spend, budget'), and 'future aspirations' (e.g. 'success, dreams, career'). Words identifying 'motivation to drink' included terms related to four subcategories: 'coping' (e.g. 'escape, relief, relax'), 'social' aspects (e.g. 'party, friends, gathering'), and 'habitual behaviours' (e.g. 'habit, craving, urge'), and 'situational'-related words (e.g. 'vacation, board, wedding'). 'Health-related' words included 'health, liver, damage, hospital, mental, recovery, disease, and disorder'. 'Substance-related' words included words related to any other substance use other than alcohol, such as 'marijuana', and 'cigarette'. Finally, 'alcohol-related' terms included words like 'beer, drink, wine, and vodka'. For a comprehensive list, refer to Table 2. For each participant's MI session, the frequency of occurrence of each stemmed word within these categories was computed. Category-level frequencies were calculated as the sum of the frequencies of all words in a given category. These frequencies were subsequently used to investigate their association with treatment outcomes recorded at a follow-up visit, including drinks per week, %HDD, and %DD.

The categorization process was conducted iteratively, beginning with an *a priori* list developed by analysts based on theoretical and empirical understanding of MI, substance use behaviour, and participant language (Apodaca et al. 2013, McCallum et al. 2016, Le Berre 2019, Magill and Hallgren 2019, Piquet-Pessôa et al. 2019, Stephenson et al. 2022, AshaRani et al. 2023, Prestigiacomo et al. 2024). This list was then refined through collaborative review by human transcribers and MI-trained clinicians to ensure contextual relevance and alignment with actual participant narratives. In cases where word meaning overlapped across categories (e.g. 'relax' could signify either emotional regulation or stress-related coping), decisions were based on the most contextually appropriate usage as observed in transcripts. This approach allowed the categories to remain sensitive to the nuances of natural language use in MI sessions while still grounded in theoretical constructs.

The categorization of these words, along with their hypothesized relationship to treatment outcomes, was rooted in established theories and supported by prior research on MI. Specifically, research has demonstrated that 'change talk', such as expressions of desire, ability, and reasons to change, is a key predictor of treatment outcomes in MI (Miller and Rose 2009, Magill et al. 2014). Similarly, the strength and in-session timing of commitment language have been associated with improved substance use-related outcomes (Amrhein et al. 2003). Although commitment and self-efficacy language are commonly categorized as subtypes of change talk within Motivational Interviewing Skills Code (MISC)-based coding systems, they were examined separately in the present analysis to explore their distinct lexical contributions, rather than to draw direct equivalence with traditional frequency-based MI process measures. Emotional and health-related language categories were included to reflect broader motivational and psychological processes theorized to underlie MI. Emotional talk may signal affective processing, a critical MI mechanism in which participants explore and express underlying emotional drivers of substance use (Miller and Rollnick 2013, Orsolini 2020). Emotional expression can enhance engagement, strengthen therapeutic alliance, and support self-regulation, all of which are conducive to change (Hasking et al. 2011, Le Berre 2019). Likewise, health-related talk reflects the MI principle of discrepancy, as participants articulate a misalignment between their current behaviours and valued health outcomes. Raising such discrepancy has been shown to increase intrinsic motivation and predict positive outcomes (Apodaca and Longabaugh 2009, Miller and Rose 2009, Gaume et al. 2021).

While the 'motivation to drink' category was informed by the broader literature on drinking motives (Cooper 1994, Kuntsche et al. 2005), it was not mapped directly onto established taxonomies such as the Drinking Motives Questionnaire. This decision was made to capture themes more representative of participants' spontaneous language and to reduce conceptual overlap between categories. For instance, while 'relax' is often considered an enhancement motive in the drinking motives literature, in our dataset it commonly appeared in the context of coping with stress or tension, thus warranting its placement under the Coping subcategory.

Although categories other than change talk have not been directly linked to treatment outcomes in MI, they were selected based on their relevance to motivation in AUD and both empirical and theoretical reasons mentioned above. These categories reflect the intricate relationships between motivation, emotional stability, psychological and physical health, and co-occurring substance use, all of which have been shown to play a critical role in understanding and addressing AUD (Kwako et al. 2019, Le Berre 2019, Esser et al. 2021). In this context, linguistic features such as emotional and health-related word use may serve as proxies for participants' MI-consistent processes like discrepancy resolution, intrinsic motivation, and emotional salience, offering a window into participant engagement and readiness for change (Miller and Rose 2009, Miller and Rollnick 2013, Gaume et al. 2021). The proportion of categorized words in Table 2 relative to the total participant speech corpus is shown in Supplementary Table S16. Although the included words comprise only 2.5%–5% of the total textual data, we believe they represent the most semantically meaningful and thematically relevant portions of the sessions, particularly in relation to treatment outcomes. This is consistent with practices in traditional qualitative thematic analysis, where the central themes often represent only a small proportion of the overall text but capture the core substance of the discourse. It is important to note that these categories are lexical-based and therefore fundamentally different from the semantic categories commonly analysed within traditional coding frameworks; as such, they do not necessarily map onto them directly or perfectly.

Sentiment analysis

Sentiment analysis, an NLP technique, evaluates the emotional semantic content of text by assigning each word a polarity score from -1 (negative) to 1 (positive) based on a predefined lexicon. The overall sentiment value is then calculated by averaging these individual scores, using either lexicon-based methods or machine learning models. In this study, sentiment analysis was performed on the participants' text using the TextBlob library in Python, which determines overall sentiment polarity within

Table 2 List of the investigated words and their corresponding categories.

Change	Emotion	Commitment & self-efficacy	Motivation to quit	Motivation to drink	Health	Substance	Alcohol
quit	depression	able	**Family**	**Coping**	health	smoke	alcohol
change	ashamed	manage	family	coping	liver	joint	beer
stop	guilty	handle	mother	escape	damage	weed	drink
break	embarrassed	confident	father	relief	hangover	marijuana	drunk
reduce	anxiety	believe	son	relax	hospital	cannabis	wine
detox	stress	determined	daughter	comfort	sick	cigarette	bottle
abstain	hopeful	sponsor	brother	calm	headache	opioid	whisky
sober	happy	discipline	sister	numb	mental	cocaine	vodka
	grief	achieve	dad	forget	recovery	heroin	tequila
	lonely	resourceful	mom	pain	disease	vape	gin
	helpless	practice	husband	**Social**	disorder	meth	rum
	scared		wife	social	heart	ecstasy	liquor
	trauma		girlfriend	party	kidney	hallucinogen	booze
	worry		boyfriend	friends	symptoms		shot
	sad		partner	bonding	rehab		cocktail
			child	celebrate	counseling		spirits
			grandparent	gathering	treatment		bar
			aunt	networking	cure		pub
			uncle	**Habitual patterns**	longevity		tavern
			Future Goals	habit	fitness		
			success	routine	exercise		
			dreams	craving	active		
			career	urge	prevent		
			job	**Situational**	abuse		
			education	bored	well-being		
			aspiration	night	weight		
			growth	weekend			
			Financial	vacation			
			money	holiday			
			spend	occasion			
			budget	wedding			
			expenses				
			savings				
			wealth				
			financial				
			cost				
			debt				
			value				

Note. The substance-related category includes words associated with substance use, excluding alcohol-related terms, which are categorized separately.

the −1 to +1 range (Taboada 2016, Loria 2018). Negative values indicate negative sentiment, while positive values reflect positive sentiment. The overall sentiment score, representing the polarity of emotional expression in the participants' responses during the MI sessions, was extracted for each baseline MI transcript. This score was then used to investigate its association with treatment outcomes at the follow-up visit.

Engagement and readiness ruler

To incorporate traditional clinical predictors of treatment outcomes (Apodaca and Longabaugh 2009, Magill et al. 2014), we used the Readiness Ruler (Moyers et al. 2009), a widely used tool in MI that assesses individuals' self-reported readiness, confidence, and importance regarding behaviour change related to their drinking habits. Specifically, readiness measured how prepared individuals felt to change their drinking behaviour, confidence captured their belief in their ability to achieve and sustain change, and importance indicated how critical they perceived the change to be. This tool was administered by the clinicians at the end of the MI session with appropriate clinical engagement. Additionally, the total number of words spoken by the participants during the session was used as a proxy for engagement, with higher word counts interpreted as a sign of greater involvement and active participation in the interview. Engagement, a critical factor in the success of MI, has been linked to improved treatment outcomes through increased interaction (Magill et al. 2014).

Statistical analyses

To confirm that the outcome of interest exhibits significant change over the course of the intervention, paired t-tests were conducted to evaluate within-subject differences between baseline and follow-up measures. This step ensures that the treatment had a measurable effect, thereby validating the outcome variable as a meaningful target for prediction and supporting the relevance of using baseline data to forecast individual treatment response. Subsequently, linear regression models were used to investigate the relationships between these predictors and MI outcomes. For drinks per week at follow-up, we controlled for sex, age, baseline drinks per week, and total number of words spoken by the participant during the session. Similarly, for %DD at the follow-up visit, sex, age, baseline %DD, and total number of words spoken by the client during the session were included as covariates. For %HDD at follow-up, the covariates were sex, age, baseline %HDD, and total number of words spoken by the participant during the session. The total number of words spoken by the participant during the session was included as a covariate to account for overall verbal output, which was found to be significantly correlated with all word categories of interest (see Supplementary Fig. S1). This adjustment ensures that associations with specific language features are not confounded by individual differences in talkativeness. Although %HDD inherently accounts for sex differences through distinct threshold criteria, sex was still included as a covariate to capture any residual differences in drinking patterns and language use, as differences in verbal functioning between males and females have been previously reported (Hirnstein et al. 2023). To isolate the true effect size of the primary variable of interest, uncontaminated by covariates, the ΔR^2 was calculated. This metric represents the difference between the R^2 of a model that includes both the primary variable and covariates and the R^2 of a model containing only the covariates. By subtracting the latter from the former, ΔR^2 quantifies the unique contribution of the primary variable to the model's explanatory power. Additionally, to enhance interpretability and support transparent effect size evaluation, 95% confidence intervals for the ΔR^2 were calculated using 1000 bootstrapping. The same analyses conducted at the category level were repeated at the individual-term level using the same covariates. For transparency, multiple comparisons were corrected using false discover rate (Benjamini and Hochberg 1995), and a premutation-based correction (Edgington 1995). However, given the exploratory nature of this work and the relatively small size, the focus was on the uncorrected *P*-values to avoid type II error inflation. All statistical analyses were conducted in R (version 4.4.2). All premutation and bootstrapping were conducted for 1000 times. All regression models were checked for violations of the statistical assumptions. The normality of all investigated variables was examined and corrected through Cox-Box transformation when needed, see Supplementary Table S1.

To account for the small sample size, a *post hoc* power analyses were conducted using Cohen's framework to estimate power based on the observed effect size and model degrees of freedom (Cohen 2013). For the secondary individual-word analyses, we included only words that appeared in the text corpus more frequently than the sample size. This criterion was applied to ensure that each word was likely used by each individual at least once and to reduce the number of multiple comparisons performed, see Supplementary Table S2. To assess the joint contribution of the investigated linguistic domains, multivariate regression models were fitted in which all word-category measures and sentiment score were entered simultaneously as predictors of alcohol-related outcomes.

Results

Changes in drinking following the brief intervention

The results of the paired samples t-tests conducted to investigate the statistical differences in treatment outcomes between baseline and follow-up revealed a significant reduction in drinks per week ($t = -5.16$, $P < .001$, 95% Cohen's $d = -0.88, -0.36$), and %DD ($t = -6.38$, $P < .001$, 95% Cohen's $d = -1.04, -0.36$). A notable reduction in %HDD was present as well ($t = -2.82$, $P = .006$, 95% Cohen's $d = -0.58, -0.01$). See Fig. 1 for a visualization of the differences in drinking variables between baseline and follow-up visits.

Term- and category-frequency analysis

The analysis of language use in MI sessions revealed significant positive associations between specific linguistic categories and drinking outcomes. For drinks per week, 'change talk' ($\beta = 0.184$, $P = .031$, $R^2 = 0.51$, $\Delta R^2 = 0.162$), 'emotional talk' ($\beta = -0.\ 234$, $P = .021$, $R^2 = 0.402$, $\Delta R^2 = 0.054$), and 'health-related' words ($\beta = 0.\ 103$, $P = .041$, $R^2 = 0.472$, $\Delta R^2 = 0.123$) were significantly associated. For %HDD, frequency of 'health-related' words ($\beta = 0.116$, $P = .034$, $R^2 = 0.487$, $\Delta R^2 = 0.108$) and other substance-related words ($\beta = 0.17$, $P = .01$, $R^2 = 0.513$, $\Delta R^2 = 0.135$) reached statistical significance. For %DD, frequency of motivation to drink related words, driven particularly by the social category was significant ($\beta = -0.371$, $P = .024$, $R^2 = 0.113$, $\Delta R^2 = 0.059$), see Supplementary Tables S3–S5 for the complete results.

At the individual term level, words such as quit ($\beta = 0.246$, $P = .030$, $R^2 = 0.414$, $\Delta R^2 = 0.047$), spend ($\beta = -0.301$, $P = .008$, $R^2 = 0.436$, $\Delta R^2 = 0.069$), and social ($\beta = -0.291$, $P = .025$, $R^2 = 0.417$, $\Delta R^2 = 0.050$) were significantly associated with drinks per week at follow-up. Words such as spend ($\beta = -0.236$, $P = .035$, $R^2 = 0.435$, $\Delta R^2 = 0.042$) and weekend ($\beta = 0.216$, $P = .035$, $R^2 = 0.435$, $\Delta R^2 = 0.042$) were associated with %HDD. The words quit ($\beta = 0.254$, $P = .049$, $R^2 = 0.111$, $\Delta R^2 = 0.056$), stress ($\beta = -0.267$, $P = .044$, $R^2 = 0.115$, $\Delta R^2 = 0.060$), and friend ($\beta = -0.318$, $P = .038$, $R^2 = 0.119$, $\Delta R^2 = 0.064$) were significantly associated with %DD. See Supplementary Tables S7–S9 for the complete results.

Sentiment, engagement, and readiness ruler analysis

The total number of words spoken by participants during the interviews (i.e. engagement) showed no significant association

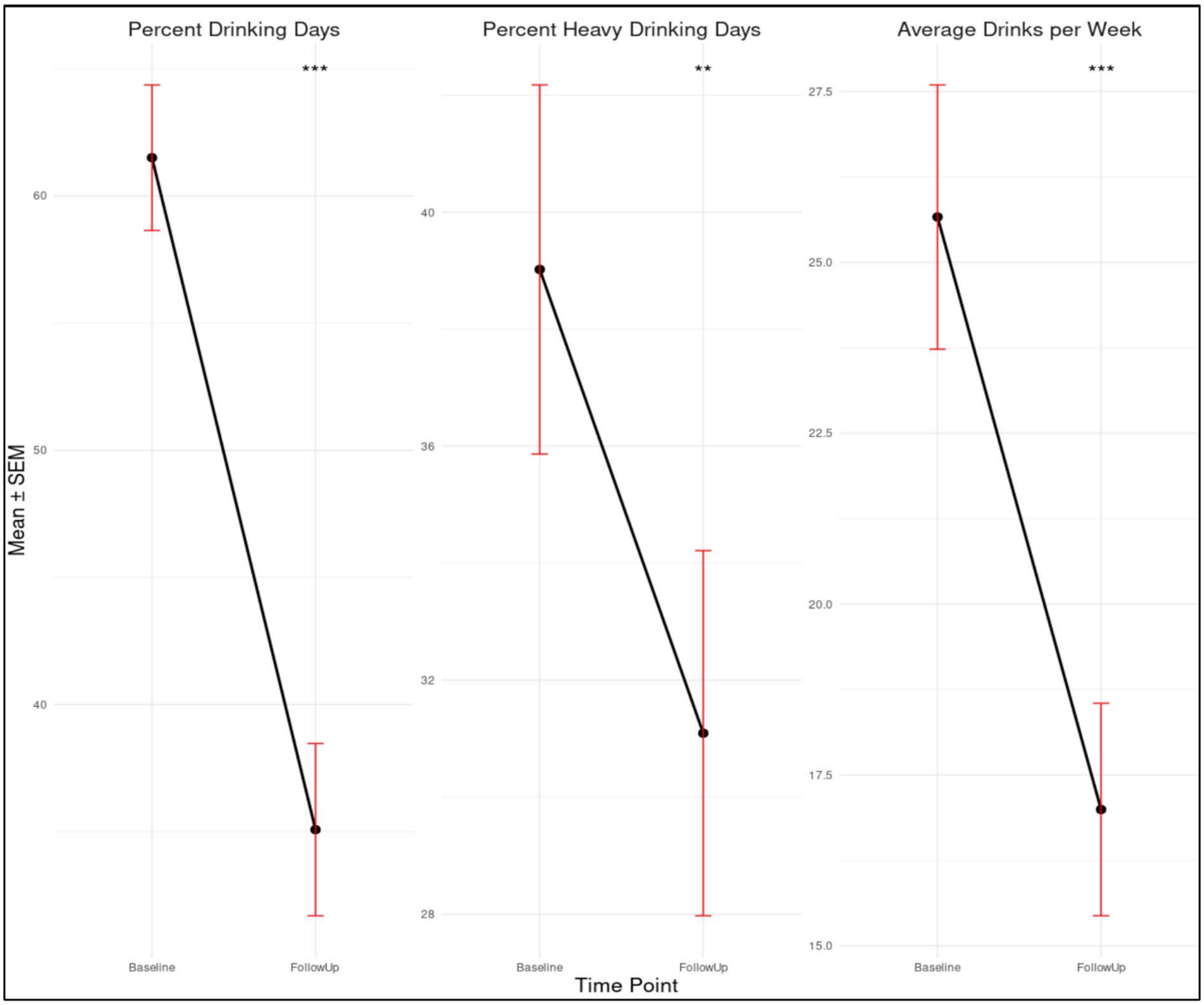

Figure 1 Changes in drinking following the brief intervention from baseline to follow-up visits. Note. The asterisks over the follow-up indicates a statistically significant difference between the two time points (∗∗ donate $P < .01$ and ∗∗∗ donate $P < .001$), while the error bars represent the standard error of the mean.

with the treatment outcome variables. None of the three readiness rulers (i.e. readiness, confidence, and importance) exhibited a significant association with any of the treatment outcome variables.

Sentiment score showed a significant inverse association with drinks per week ($\beta = -0.297$, $P = .003$, $R^2 = 0.435$, $\Delta R^2 = 0.087$), %HDD ($\beta = -0.215$, $P = .014$, $R^2 = 0.511$, $\Delta R^2 = 0.132$), and %DD ($\beta = -0.287$, $P = .046$, $R^2 = 0.146$, $\Delta R^2 = 0.093$). See Supplementary Table S6 for the complete results.

Diagnostic testing results of linear regression assumptions for all the conducted models are presented in Supplementary Tables S10–S15. *Post hoc* power analyses suggest sufficient ability to detect small to medium effects, see Supplementary Tables S3–S9. Variation in the number of MI sessions administered prior to follow-up (i.e. where the outcome variables where collected) was not associated with the reduction of the outcome variables (see Supplementary Table S17).

Multivariate analysis

Multivariate regression models including all linguistic categories and sentiment score simultaneously demonstrated significant overall predictive power for drinks per week and %HDD but not for %DD. The full model significantly predicted drinks per week at 1-month follow-up ($F = 3.86$, $P < .001$), explaining 56.7% of the variance (adjusted $R^2 = 0.42$), and %HDD at 1 month ($F = 3.41$, $P < .001$), accounting for 53.7% of the variance (adjusted $R^2 = 0.38$). In contrast, the multivariate model did not significantly predict %DD ($F = 1.13$, $P = .36$), with limited explained variance ($R^2 = 0.28$; *adjusted* $R^2 = 0.03$).

Discussion

This exploratory study demonstrates that health-related language, change talk, emotional talk, social motivation-related language, and sentiment polarity during MI are meaningfully associated with alcohol use following the intervention among adults with AUD. Specifically, greater use of health-related and change talk was associated with more drinks per week post-intervention, whereas increased emotional talk was linked to fewer drinks per week. Additionally, higher use of health-related and substance-related language was associated with the %HDD, while social motivation to drink-related language was associated with the %DD. Sentiment polarity was inversely related to drinking frequency. However, associations with %HDD were modest, and those with %DD were comparatively weaker.

Some of these findings may appear counterintuitive at first, particularly the association between greater use of health-related language and worse treatment outcomes, and the association between social motivation-related language and better outcomes. However, these patterns may reflect characteristics of the individuals undergoing MI, rather than the mechanistic pathways through which MI operates. For example, individuals with more severe AUD may be more likely to experience health complications and thus refer to health issues more frequently in their speech. Even after adjusting for baseline drinking levels, higher severity may still present a greater challenge for reducing alcohol use, and health-related talk may signal distress or problem awareness rather than readiness to change. By contrast, individuals whose drinking is primarily motivated by social contexts may exhibit a lower severity profile, with more situational and controllable patterns of alcohol use, making reduction more achievable. The negative association between change talk and treatment outcome is perhaps the most counterintuitive; however, this direction has been observed in previous meta-analysis (Magill et al. 2019), and may reflect unresolved ambivalence or verbal expressions of motivation that are not yet accompanied by behavioural commitment. Additionally, a broader propositional or contextual composite may attenuate the observed association between change talk frequency and poorer outcomes (Magill et al. 2014, 2019).

These findings underscore the importance of examining broader linguistic markers to gain a deeper understanding of MI's impact. While these associations between specific linguistic categories and MI treatment outcomes, aside from change talk (Apodaca and Longabaugh 2009, Miller and Rose 2009), have not been previously documented in the research literature, they align with existing theories on motivational reinforcers (Hasking et al. 2011, Barker and Taylor 2014). The inverse relationship between sentiment polarity and treatment outcomes suggests that participants expressing more positive sentiment consumed less alcohol at follow-up, which was also supported by the significant association between the emotional talk category and the drinks per week at the follow-up It may be that greater optimism and emotional resilience reinforce the role of positive emotional expression in behaviour change. Consistent with prior research, positive affect and engagement during therapy are linked to better outcomes (Magill et al. 2014). This finding supports the idea that difficulties in emotional expression can drive impulsive behaviours like substance use (Orsolini 2020). Sentiment analysis, which incorporates the full lexical corpus, may therefore capture broader affective signals than the predefined lexical categories, potentially explaining its stronger associations with outcomes.

The association between other substance-related language and higher %HDD is interesting, as it sheds light on the potential role of broader substance use patterns and polysubstance-related thinking in undermining alcohol reduction efforts (Bailey et al. 2019). This may suggest that individuals who frequently reference other substances during MI sessions are more likely to struggle with higher-risk drinking patterns, possibly due to overlapping behavioural tendencies, shared triggers, or a more entrenched addictive profile (Boileau-Falardeau et al. 2022).

According to MI theory, such emotional congruence and salience can enhance client engagement and strengthen commitment to change (Miller and Rollnick 2013). Linguistic markers of emotion, such as expressions of hope, guilt, or ambivalence, may serve as vehicles for resolving discrepancies between current behaviours and personal values, facilitating behavioural change.

Despite discovering promising associations for future research, limitations in the sentiment analysis method used should be noted. We employed TextBlob, a lexicon-based tool, due to its accessibility and simplicity; however, this method may lack domain specificity and struggle with the nuanced or context-dependent language common in addiction treatment settings. Words such as 'abstain,' 'relapse,' or 'quit' may be misclassified, potentially skewing sentiment scores (Mohammad 2020, Villanueva-Miranda et al. 2025). Future research should consider validating sentiment scores against a manually annotated subset of transcripts or comparing results to those derived from a second sentiment classifier, such as VADER or transformer-based models like RoBERTa (Hutto and Gilbert 2014, Liu et al. 2019).

The lack of significant associations between several investigated variables and treatment outcomes could, in part, be attributed to the limited sample size, which may have constrained statistical power and increased the likelihood of Type II error. However, beyond sample size limitations, it is also possible that some of these variables, while theoretically relevant, may not directly map onto short-term changes in drinking behaviour as measured here. The absence of significant associations between treatment outcomes and Readiness Ruler scores (confidence, importance, and readiness) is particularly noteworthy, given the central role of these measures in MI theory and practice. One potential explanation is that while Readiness Rulers capture explicit, self-reported motivational states, the linguistic features identified in our analysis may reflect more implicit, nuanced dimensions of motivation and emotion that are not consciously accessible or verbally endorsed. In this context, the richer predictive value of implicit language features, compared to explicit ratings, suggests that spontaneous speech may offer a more sensitive index of motivational shifts during MI. An alternative interpretation of the null findings for readiness rulers is that their clinical relevance within MI lies less in the absolute numeric score and more in the clinician's subsequent response. In practice, readiness rulers function as interactional tools intended to elicit elaboration and change talk (e.g. through follow-up questions such as why a client endorsed a given value rather than a lower one), rather than as standalone indicators of motivation. From this perspective, the motivational information conveyed by readiness rulers may be expressed indirectly through ensuing client language, including change talk and other nuanced linguistic markers, rather than through the initial rating itself. Notably, readiness rulers in the present study were administered during the MI session in accordance with the treatment manual, and the timing of their administration relative to subsequent therapeutic dialogue may further limit their utility as static predictors of outcome. Accordingly, the absence of direct associations between readiness ruler scores and drinking outcomes should be interpreted with caution and does not necessarily indicate a lack of motivational relevance within the MI process.

The study's use of word count as a proxy for participant engagement and also warrants further scrutiny. While greater word count may suggest increased involvement or expressiveness, it can also reflect verbosity unrelated to therapeutic engagement, or even emotional dysregulation. In future work, engagement metrics should be complemented by additional indicators such as number of speech turns, dialogue balance, session duration, or clinician-rated engagement (Bijkerk et al. 2022). These multidimensional metrics may provide a more nuanced picture of how clients participate in MI.

This study broadens the scope of MI mechanisms research by analysing relevant linguistic domains alongside traditional 'change and commitment talk'. The inclusion of sentiment analysis, motivational linguistic patterns, and engagement metrics offers new insights into the emotional and motivational factors influencing treatment outcomes. However, it is important to recognize that this study focused solely on the client's speech and therefore omits the inherently dyadic nature of MI. Therapeutic change in MI emerges through a collaborative conversation between the clinician and client (Miller and Rollnick 2013). Future studies should examine both sides of the interaction to better capture the reciprocal processes that influence motivation and commitment. These methodological innovations deepen the understanding of MI's mechanisms and highlight potential new avenues for refining interventions for individuals with AUD. For example, linguistic markers identified in this study, such as higher use of health-related terms or more positive sentiment, could potentially be used in real-time feedback systems to alert clinicians to moments of high or low motivational salience. This could guide therapists toward reinforcing positive language or responding more intentionally to ambivalent statements. In training settings, NLP-based tools might also help clinicians learn to recognize linguistic indicators of client change talk or distress. Moreover, automated session coding using validated language features could serve as a scalable quality assessment method, reducing the need for labour-intensive manual coding.

At the same time, the current approach should be viewed as complementary to, not superior to, established manual coding systems like the MISC (Moyers et al. 2005). While the categories identified here (e.g. emotional talk, health-related terms) were predictive of certain drinking outcomes, it remains unclear whether they offer incremental validity over established codes such as change talk, sustain talk, or commitment language. Additionally, the method by which these categories are inferred is fundamentally different than what is traditionally done in the coding analyses and do not necessarily perfectly map to each other. As such, conclusions about the added value of these linguistic features should be tempered, and future research should directly compare NLP-derived features with existing coding frameworks.

Despite these contributions, the study's small sample size limits the generalizability of findings and constrained the use of advanced analytical methods like machine learning, which are more capable of capturing these linguistic patterns. Another inherent limitation of the analysis is that certain words could reasonably fit into more than one category. For example, the word 'relax' could be associated with both the Emotional talk category, indicating a desired emotional state, and the Coping (a sub-category of motivation to drink) category, reflecting a strategy to manage stress. While we addressed this issue by analysing the contextual use of each word and assigning it to the most contextually appropriate category, this solution is not without drawbacks. It relies on subjective judgment and remains a suboptimal fix. A better solution would be to automate the process by using transformer-based models empowered with a multi-head attention mechanism, which indicates the meaning and context of a word and then categorizes it in vector or lexical space (Vaswani et al. 2017). Unfortunately, such models require massive amount of data that was not available in this study. This limitation highlights a promising direction for future research, developing data-driven, context-sensitive large language models (i.e. transformer-based models) tailored to MI data and clinical use. Additionally, all interpretations presented in this manuscript should be regarded as provisional and interpreted with caution, given the limited effect sizes, the predominance of non-significant findings, and the lack of consistent associations across alcohol-related outcomes; the results are therefore best viewed as hypothesis-generating rather than confirmatory.

As preliminary NLP study on alcohol MI response, the current study provides clear *a priori* hypotheses for future investigations, which will reduce or at least stratify the number of tests. It also provides future investigations with effect sizes for power analyses. Future research should replicate these findings in larger, more diverse samples to improve generalizability. Additionally, more dynamic and longitudinal analytic approaches could reveal the lasting impact of linguistic patterns and sentiment on AUD outcomes. Expanding analyses to include coping strategies, social influences, and clinician responses may provide deeper insight into the mechanisms driving MI effectiveness. It is also critical that future research move beyond lexicon-based NLP and incorporate more advanced approaches, such as contextual word embeddings (e.g. BERT, GPT), which can capture semantic nuance, sarcasm, and domain-specific meanings with greater precision (Vaswani et al. 2017, Devlin et al. 2018, Lee et al. 2020). Such methods could advance the field by offering more accurate, flexible, and generalizable models of therapeutic discourse.

Considered collectively, the findings from the current study demonstrate that linguistic patterns during MI, including health-related language, emotional expression, and motivational markers, are valuable predictors of drinking outcomes in individuals with AUD. By highlighting the nuanced roles of sentiment polarity, emotional talk, and motivational language, this study underscores the potential of linguistic analysis to uncover meaningful insights into MI's mechanisms of effect, markers of success, predictive utility, and therapeutic impact. The practical implications of these findings are manifold. For instance, knowing that certain words (e.g. 'quit') are associated with higher future drinking may encourage clinicians to explore a client's ambivalence more deeply rather than interpreting such statements as unequivocal commitment. These results support the idea that integrating sentiment analysis with established linguistic markers can enhance clinicians' understanding of client engagement and emotional expression, offering new strategies to personalize MI interventions. Future research should replicate these findings in larger samples and build on these exploratory insights by investigating how linguistic patterns interact with contextual factors, such as social support, stress, and treatment readiness, to optimize MI outcomes. Most importantly, this study demonstrates the utility and effectiveness of the NLP techniques in identifying meaningful linguistic patterns linked to drinking outcomes, providing a promising tool for future MI research and clinical practice.

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Supplementary data

Supplementary data are available at *Alcohol and Alcoholism* online.

Conflicts of interest

J.M. is a principal and senior scientist in Beam Diagnostics, Inc., but no Beam products or services were used in this research. No other authors have disclosures.

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Data availability

The transcribed data and code are available pending author and research ethics board reviews.

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