Real-time Assessment of Dialogue in Motivational Interviewing (ReadMI)

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Structured Abstract

Purpose: Motivational interviewing (MI) is an evidence-based, patient-centered approach to interaction with patients focused on eliciting from patients their own motivations to make healthy behavior changes. However, the approach is not utilized by many health professionals due to insufficient training, so that an ineffective tendency to simply educate patients prevails. The objective of this research was to further develop and test our Real-time Assessment of Dialogue in Motivational Interviewing (ReadMI) system to help make MI training more efficient.

Scope: ReadMI makes use of the latest advances in deep-learning-based speech recognition, natural language processing (NLP), and mobile and cloud computing technologies to enable automatic and instantaneous MI training assessment and analysis. In real time, metrics are produced to provide feedback on behavioral components of MI, including percentage of time the provider is speaking, use of open- and closed-ended questions, and use of reflective statements.

Methods: After additional refinement of the ReadMI tool, a randomized controlled trial (RCT) was conducted with 83 medical residents and 125 medical students. Control group learners received only subjective feedback for their performance in a MI role play, prior to conducting a second role play, whereas intervention condition learners received both subjective feedback and ReadMI.

Results: Learners in both conditions improved their MI skills, but those in the intervention condition used significantly more open-ended and fewer closed-ended questions in the second role play.

Key Words: motivational interviewing, artificial intelligence, medical education, patient engagement

Purpose

Motivational interviewing (MI) is an evidence-based, brief interventional approach found to be effective in eliciting patient motivation to make positive health behavior changes.[1] Patient health behavior is a critical aspect of effect chronic disease prevention and management, so effective patient engagement and activation through the use of MI is an important skill for healthcare professionals. However, due to limited and ineffective training, MI is under-utilized. This project aims to transform training in motivational interviewing (MI) with a software-based solution that analyzes practitioner responses and gives immediate feedback on how to improve MI skills with at-risk patients. Our innovative MI training program is intended to advance the skill development of physicians and other healthcare professionals in their use of the MI approach with patients.

We have developed a software-based MI training program, “Real-time Assessment of Dialogue in Motivational Interviewing” (ReadMI), making use of deep-learning-based speech recognition and natural language processing, implemented through mobile-cloud computing technologies to produce a spectrum of MI-relevant metrics. This human-artificial intelligence (AI) teaming helps reduce the cognitive load on a training facilitator, such that while ReadMI produces feedback on specific skills, the facilitator can give more attention to the overall quality and content of the conversation between a provider and patient/client. The metrics produced by ReadMI include: provider versus patient talking time, the number of open- and closed-ended questions used, the use of reflective statements, and the use of 0-10 scales (for rating importance, readiness, confidence, etc.). This research aimed to perfect and test the ReadMI training system.

Scope

One of the major public health and medical challenges in the United States is the management of chronic illness, as 60% of adults have at least one chronic condition and over 40% have more than one.[2,3] Patients' active engagement in their own care is crucial, as effective management of chronic illnesses depends more on the behavior of the patient than what the medical professional can contribute.[4-6] When management plans are tailored to the patient's goals and priorities,[7-9] higher levels of patient activation are associated with better adherence and improved health outcomes.[10-13]

Motivational interviewing (MI) is an evidence-based, brief interventional approach that has been demonstrated to be highly effective in increasing patient activation.[14,15] MI is a patient-focused conversation between the provider and the patient that reinforces the patient's motivation to make positive changes in any targeted health behavior. MI involves exploration of the patient's normal and natural ambivalences.[16-18] Providers focus on being compassionate and nonjudgmental to help patients express their perspective on behavioral change and take responsibility for their choices. The MI approach was originally developed for use in treating individuals with substance misuse, and continues to be emphasized in that arena.[19] Screening, Brief Intervention, and Referral to Treatment (SBIRT) is an integrated, evidence-based approach aimed at delivering early intervention for drug and alcohol misuse in medical settings and has been demonstrated to be effective in reducing illicit drug (including opioid) use.[20-23] The Brief Intervention component of SBIRT is an application of MI. MI can be effectively taught to medical students, residents, and practicing physicians,[24,25] yet this patient-centered approach tends to be underutilized due to limited and ineffective training.[26]

The MI approach can be difficult to teach as the natural inclination of physicians and other healthcare clinicians is to take a directive role by educating and instructing the patient with steps to improve health.[27,28] However, knowledge itself, if not combined with substantial motivation, rarely leads to behavior change. MI involves eliciting from the patient their own reasons for making a change, rather than the clinician debating with and/or trying to convince the patient to change (i.e., the spirit of motivational interviewing).[29] During MI training, providers learn to talk less, listen more, use reflective statements, and ask open-ended questions. Real-time feedback on these skills is advantageous in this learning process.

Methods

The central hypothesis for this research was that ReadMI will produce significantly better MI performance than traditional MI training. The two primary objectives with the project were to: 1) refine the ReadMI training tool so that 95% accuracy was achieved for provider-vs-patient conversation time, number of open- and closed-ended questions, number of reflective statements, and use of a change ruler (0-10 scales); 2) conduct a randomized controlled trial (RCT) with medical students and residents to determine the potential benefit of adding ReadMI feedback to MI training. While ReadMI was originally developed for in-person use, the COVID-19 pandemic prompted adaptation for virtual use, so that the RCT was conducted using the online platform Jitsi.[30] Both studies were given an exemption by the institutional review board (IRB) of Wright State University, Dayton, OH, as the projects involved research on the effectiveness of an instructional technique in normal educational practice.

Study One. Transcripts from 48 interviews conducted by medical residents with a simulated patient were obtained and analyzed with the ReadMI tool. The context for these interviews was a motivational interviewing training module for Internal Medicine and Family Medicine residents. These training modules typically include approximately 70% Internal Medicine residents and 30% Family Medicine residents, and equal numbers of males and females. MI metrics produced by the ReadMI app were examined to identify relationships between physician-speaking time and other MI metrics, such as the number of open- and closed-ended questions, number of reflective statements, and use of the change ruler. In addition, five MI training facilitators read the transcripts created by the ReadMI app and rated physician responses as closed-ended, open-ended, reflective, scale (i.e., change-ruler), or none (when the physician's response was neither closed-ended, open-ended, reflective, nor used a change-ruler).

Interrater reliability statistics were conducted to determine the accuracy of the ReadMI app's analysis of physician responses. Pearson *r* correlation analyses were conducted to examine relationships between physician-speaking time and the number of open- and closed-ended questions, number of reflective statements, and use of the change ruler. To examine interrater agreement among the five raters and the ReadMI app, a Fleiss' Kappa statistic was computed along with the percent agreement. Fleiss' Kappa is used as index of agreement between more than two raters and when the ratings are categorical. An intraclass correlation coefficient (ICC) and 95% confidence intervals (CI) were computed to examine agreement among the five raters and the ReadMI ratings for the frequency of categories selected. All data were analyzed using R (R Foundation for Statistical Computing, Vienna, Austria) and IBM SPSS Statistics software (Version 25; IBM Corp., Armonk, NY, USA) and p values < .05 were regarded as statistically significant.

Additionally, using transcripts from 88 role-play sessions (two medical students with one playing to role of doctor and the other playing the role of the patient) obtained in previous MI training, analyses were completed to further assess the extent to which ReadMI classification of provider utterances are consistent with the classification done by two MI trainers.

Study Two. Third-year medical students (N = 125) doing their required third-year Family Medicine Clerkship participated in the RCT. There were approximately 15-16 students for each of eight rotations. These eight Family Medicine clerkship cohorts were randomly assigned to an Intervention condition or a Control condition. Students in both conditions received subjective feedback from the facilitators after a first role-play. However, in the Intervention condition, feedback included metrics produced by ReadMI, so that knowledge of the ReadMI metrics from the first role-play could be incorporated into the subsequent role-play. In the Control condition, ReadMI metrics were provided to the students only after all four role-plays had been completed, so that these metrics would not influence performance in the second set of role-plays. The Motivational Interviewing Knowledge Test (MIKT) was completed by students prior to and subsequent the MI practice sessions and was used to statistically control for MI knowledge in our analyses.[31] The MIKT contains 22 questions, and the number of questions correct was summed to create a score.

A total of 83 medical residents (Internal Medicine, Family Medicine, Pediatrics) also participated in the RCT in a separate training module. This module consisted of four weekly sessions over the course of a four-week rotation. A similar randomization procedure was followed in which rotations, rather than individual residents, were randomized to condition. Similar to the process with medical students, intervention condition residents received ReadMI metrics along with subjective feedback after practice interviews, whereas those in the control condition receive subjective feedback alone. For both conditions, ReadMI metrics were obtained for the “final” (week four) interviews. Residents also completed the MIKT prior to and subsequent to the MI training module.

Means and standard deviations were calculated for continuous variables and frequencies and percentages for categorical variables. To examine differences in the ReadMI metrics and MIKT scores between the intervention and control groups for each session and between sessions, independent and paired t-tests were conducted. To assess changes in the ReadMI metrics between the sessions and group status, a series of mixed models were developed with group, time, and group-by-time interaction entered into the model. A linear mixed model (LMM) was used for doctor speak time and percentage of open questions. A LMM is an extension of the linear regression model where the data are assumed to follow a normal distribution and fixed and random effects are allowed. LMMs can account for multiple data points and can handle missing data over time. Subject-specific random intercepts and slopes were used to account for correlation due to having repeated observations.[32] A generalized linear mixed model (GLMM), with a negative binomial distribution and a log link was used for the open-ended questions, closed-ended questions, total questions, reflections, scale, and ratio metrics. A GLMM was used due to the non-normal data and the repeated measures per individual. A random intercepts model was used to account for the random variation between individuals.[31] Adjusted means were calculated and compared using a Tukey's adjustment. All data were analyzed using SAS version 9.4 (Cary, NC), and p-values <.05 were regarded as statistically significant. Because of the differences in training format for residents and medical students, data were analyzed separately for these two groups of study participants.

Results

Study One. Table 1 presents the overall Kappa and the Kappa for the type-of-question rating given for each line (n = 313) of provider speech from 48 transcripts by the five human raters and the ReadMI app. Interpretation of the Kappa is as follows: <0 is no agreement, 0.01-0.20 is none to slight agreement, 0.21-0.40 is fair agreement, 0.41-0.60 is moderate agreement, 0.61-0.80 is substantial agreement, and 0.81-1.00 is almost perfect agreement. Overall, the Kappa among the five raters and the ReadMI app was .502 (percent agreement = 33.3%) ($p < .0001$), suggesting moderate agreement. The largest Kappa was for use of the change ruler (Kappa = .793; percent agreement = 40.2%; $p < .0001$), suggesting substantial agreement among the five human raters and the ReadMI app, followed by identification of open questions (Kappa = .596; percent agreement = 36.2%; $p < .0001$), suggesting moderate agreement. Least agreement was found for reflective statements. For each type of question/statement, the frequency of ratings were summed for each rater. An intraclass correlation coefficient (ICC) was computed to assess agreement among the frequencies. The ICC among the five human raters and the ReadMI app was .828 (95% CI = .569 - .977). Thus, the ReadMI app analyzed and rated the type of question/statement as well as the human raters.

Table 1. Kappa Statistics Overall and by Type of Question/Statement		
	Kappa Statistic (% agreement)	p-value
Overall (with 5 raters and ReadMI app)	.502 (33.3)	<.0001
Type of Question/Statement (5 human raters and ReadMI)		
Open-ended question	.596 (36.2)	<.0001
Closed-ended question	.428 (27.0)	<.0001
Reflective statement	.351 (20.3)	<.0001
Use of Change Ruler	.793 (40.2)	<.0001
None (Physician just talking)	.472 (33.1)	<.0001

Additional analyses were completed to further assess the extent to which ReadMI classification of provider utterances are consistent with the classification done by two MI trainers using transcripts from 88 role-play sessions (two medical students with one playing to role of doctor and the other playing the role of the patient) containing 2821 clinician utterances from the "doctor role." Table 2 below presents the overall Kappa and the Kappa for the type-of-question rating given for each clinician utterance by the two human raters and the ReadMI app. The largest Kappa was for use of the change ruler (Kappa = .772), suggesting substantial agreement among the two human raters and the ReadMI app.

Table 2. Kappa statistics for ReadMI– Expert Instructor Agreement			
	Agreement	**Cohen's kappa Statistic**	**Interpretation of the Cohen's kappa**
Open-ended question	88.5%	.721	Substantial agreement
Closed-ended question	92.0%	.629	Substantial agreement
Reflective statement	80.7%	.480	Moderate agreement
Use of Change Ruler	98.7%	.772	Substantial agreement
None (Physician just talking)	86.3%	.683	Substantial agreement

Study Two. Table 3 presents the ReadMI metrics among the medical student participants during the first two sessions and by group status. Overall, there were decreases in the average percent of time the doctor spoke (48.2% in role-play #1 versus 41.8% in role-play #2; $t = 4.5$; $p < .0001$) and increases in the percent of questions that were open questions (62.0% in role-play #1 and 69.0% in role-play #2; $t = -2.67$; $p = .008$). For the first role-plays, there were several differences in the ReadMI metrics between the control and intervention groups, with the control group speaking longer (50.4 versus 46.1; $t = 2.1$; $p = .04$), having more closed questions (5.2 versus 3.4; $t = 3.9$; $p = .0002$), and having a lower percentage of questions being open (55.0% versus 68.0%; $t = -3.7$; $p = .0003$) compared to the intervention group. For the second role-plays, the intervention group had a significantly higher percentage of questions that were open (75.0% versus 63.0%; $t = -3.55$; $p = .0005$), a lower number of closed questions (2.8 versus 5.0; $t = 4.6$; $p < .0001$), lower total number of questions (11.3 versus 13.1; $t = 2.5$; $p = .02$), and a higher ratio of open to closed questions (4.8 versus 2.5; $t = -3.7$; $p = .0004$) compared to the control group.

There were no significant group-by-time interactions for the ReadMI metrics in the mixed models. However, for the percent of questions that were open, there was an overall difference between the two groups with the intervention group having a higher adjusted mean percentage compared to the control group (71.3% versus 60.5%; difference = 10.8%; t = -3.61; adjusted p = .0005), and there was an overall increase from role-play #1 to role-play #2 (61.9% versus 69.9%; difference = -8.0%; t = -4.35; adjusted p <.0001) (data not shown).

Table 3. READMI Metrics among Medical Student Participants (N = 125)

	Total (n = 125)		Intervention (n = 65)		Control (n = 60)	
	Session 1	Session 2	Session 1	Session 2	Session 1	Session 2
	Mean (sd)	Mean (sd)	Mean (sd)	Mean (sd)	Mean (sd)	Mean (sd)
Doctor Speak Time	48.2 (11.3)[a]	41.8 (11.0)[a]	46.1 (11.2)[b]	40.1 (10.0)	50.4 (11.1)[b]	43.5 (11.8)
Open Questions	6.8 (3.2)[a]	8.3 (3.6)[a]	7.0 (3.1)	8.5 (4.1)	6.6 (3.3)	8.1 (3.0)
Closed Questions	4.3 (2.8)	3.9 (2.9)	3.4 (2.4)[b]	2.8 (2.3)[c]	5.2 (2.9)[b]	5.0 (3.1)[c]
Total Questions	10.9 (4.4)[a]	12.2 (4.3)[a]	10.2 (4.1)	11.3 (4.4)[c]	11.6 (4.6)	13.1 (4.0)[c]
Reflections	6.1 (3.5)	6.5 (3.5)	4.6 (3.5)[b]	5.0 (3.4)[c]	7.8 (2.6)[b]	8.1 (2.7)[c]
Scale	0.7 (0.8)	0.7 (0.7)	0.8 (0.9)	0.8 (0.6)	0.7 (0.7)	0.6 (0.7)
Ratio of Open to Closed Questions	2.6 (2.7)[a]	3.7 (3.6)[a]	3.2 (3.1)[b]	4.8 (4.1)[c]	1.9 (2.0)[b]	2.5 (2.5)[c]
Ratio of Reflection Questions	0.6 (0.4)	0.6 (0.4)	0.5 (0.4)[b]	0.5 (0.4)[c]	0.8 (0.5)[b]	0.7 (0.3)[c]
Percent of Open Questions	62.0 (20.0)[a]	69.0 (20.0)[a]	68.0 (20.0)[b]	75.0 (20.0)[c]	55.0 (19.0)[b]	63.0 (17.0)[c]

[a]Denotes significant differences (p<.05) between sessions 1 and 2 overall
[b]Denotes significant differences between groups during session 1
[c]Denotes significant differences between groups during session 2

For the resident portion of the RCT, there were 83 residents with READMI metrics data recorded. Of those, 64.2% were in the intervention group. The results are aggregated over the four-week time period. Overall, the mean percentage of time the doctor spoke was 45.2% ± 10.8, the average number of open questions was 5.4 ± 3.4, and the average number of reflective statements was 5.8 ± 3.5. Although not significant, the intervention group had a lower average amount of time the doctor spoke (43.4 versus 47.2), but a higher average number of open questions (5.8 versus 4.8).

Table 4. READMI Metrics by Intervention Group Status for Resident Participants (N = 83)						
	Total (n = 83)	**Intervention (n = 52)**	**Control (n =31)**	**t**	**df**	**p**
	Mean (sd)	**Mean (sd)**	**Mean (sd)**			
Doctor Speaking Time (percentage of time)	45.2 (10.8)	43.4 (10.4)	47.2 (11.1)	1.4	61	.17
Open Questions	5.4 (3.4)	5.8 (3.5)	4.8 (3.0)	-1.3	81	.20
Closed Questions	5.0 (3.2)	4.8 (3.1)	5.3 (3.3)	0.7	81	.52
Total Questions	10.4 (5.1)	10.6 (4.8)	10.1 (5.5)	-0.4	81	.66
Reflective Statements	5.8 (3.5)	5.7 (3.3)	6.1 (3.9)	0.5	81	.61
Scale	0.3 (0.6)	0.3 (0.6)	0.3 (0.5)	-0.1	81	.89
Ratio of Open to Close Questions	1.6 (1.9)	1.8 (2.2)	1.3 (1.3)	-1.3	81	.14
Ratio of Reflective Statement to Questions	0.7 (0.6)	0.7 (0.6)	0.6 (0.5)	-0.2	81	.87
Df = degrees of freedom						

While ReadMI metrics measure skill, the MIKT measures knowledge. Students had a slightly higher number of questions correctly answered compared to residents (16.04 versus 15.08; difference = 0.96; t = 2.29; p = .02). When comparing the scores between those in the intervention group and those in the control group, the intervention group had a non-significant increase in scores (14.65 versus 15.13; t = -0.69; p = .49) while the control group had a non-significant decrease in scores (15.64 versus 14.55; t = 1.71; p = .12). Among medical students, the intervention group had significantly higher scores compared to the control group (16.6 versus 15.5; p = .03).

Discussion and Conclusions. Our research demonstrates how artificial intelligence can be utilized both for measurement of MI skills and as an instructional aid in training. Improvement in the behavioral skills components of MI can be quantified, and reveal improvement from one role play to the next. Not surprisingly, students and residents in both the control and intervention conditions in our RCT improved from their first to their second role play. However the addition of ReadMI metrics to the feedback provided to students in the intervention group was advantageous to a statistically significant degree with respect to the doctor talking less and using a greater proportion of open-ended questions. It should be also noted that even if the addition of ReadMI metrics to feedback does not lead to statistically significant improvements in performance beyond that attained with subjective feedback from training facilitators, the ReadMI tool proved to be valuable in measuring important communication skills and served to quantify change in performance.

Our ReadMI tool allows for real-time quantitative feedback for learners being trained in the MI approach, without the facilitator needing to track performance on specific communication metrics. This represents a reduction in the cognitive load on the training facilitator so that the facilitator can focus on and provide feedback about the qualitative aspects of the interview. This is an important step forward in MI training, so that this important patient-centered approach can be effectively taught in a time-efficient manner.

Training in MI can be a time-consuming endeavor, both for a training facilitator and for a learner, and available time for such learning can be quite limited in the training of health professionals. The use of ReadMI can make MI training more manageable and engaging, and is intended to contribute to wider use of the MI approach. Health professionals who have learned to incorporate the MI approach into their interaction with patients are better equipped to facilitate the patient engagement and activation that are crucial in effective chronic disease prevention and management.

List of Publications and Products

Publications

Vasoya MM, Shivakumar A, Pappu S, Murphy CP, Pei Y, Bricker DA, Wilson JF, Castle A, Hershberger PJ. ReadMI: An innovative app to support training in motivational interviewing. J Grad Med Ed. 2019;11:344-6. doi.org/10.4300/JGME-D-18-00839.1

Hershberger PJ, Pei Y, Bricker DA, Crawford TN, Shivakumar A, Vasoya M, Medaramitta R, Rechtin M, Bositty A, Wilson JF. Advancing motivational interviewing training with artificial intelligence: ReadMI. Adv Med Educ Pract. 2021;12:613–8, PMC8186935.

Paper submitted for publication

Hershberger PJ, Pei Y, Bricker DA, Crawford TN, Shivakumar A, Castle A, Conway K, Medaramitta R, Rechtin M, Wilson JF. Motivational interviewing skills practice enhanced with artificial intelligence: ReadMI.

Presentations

Castle A, Rechtin M, Drouet G, Grisham A, Shivakumar A, Pei Y, Conway K, Bricker D, & Hershberger P. (2022, January). Using artificial intelligence to assist with motivational interviewing training. Presentation at the 2022 STFM Conference on Medical Student Education (Virtual).

Rechtin M, Vasoya M, Shivakumar A, Pei Y, Bricker D, Wilson J, Crawford T, Hershberger P. (2020, November). Real Time Assessment of Dialogue in Motivational Interviewing (ReadMI): Metrics for Training. Presentation at the Annual Meeting of the Association of American Medical Colleges (AAMC), Washington, DC.

Trademark, Copyright

Wright State University is in the process of applying for a trademark for the “ReadMI” name and a copyright for the ReadMI product. Wright State is in early licensing discussions with a company to commercialize ReadMI.

References

1. Miller WR, Rollnick S. Motivational interviewing: Helping people change. New York: Guilford, 2013.
2. Buttorff C, Ruder T, Bauman M. Multiple chronic conditions in the United States. Santa Monica, CA: Rand Corporation. 2017, https://www.rand.org/pubs/tools/TL221.html.
3. Benjamin RM. Multiple chronic conditions: a public health challenge. Public Health Rep. 2010; 125:626-7, PMC2924996.
4. Kaplan, RM. Behavior change and reducing health disparities. Prev Med. 2014 Apr 26. pii: S0091-7435(14)00145-5. doi: 10.1016/j.ypmed.2014.04.014. [Epub ahead of print]
5. Hershberger PJ, Bricker DA. Who determines physician effectiveness? JAMA. 2014; 312:2613-4, PMID 25317546.
6. Conway K, Hershberger PJ, Bricker DA, Castle A. Flipped exam room. J Med Ed Curricular Devel. 2020;7:1-5, PMC7768865.
7. Ivey SL, Shortell SM, Rodriguez HP, Wang YE. Patient engagement in ACO practices and patient-reported outcomes among adults with co-occurring chronic disease and mental health conditions. Med Care. 2018; 56:551-6, PMC6170192.
8. Simmons LA, Wolever RQ, Bechard EM, Snyderman R. Patient engagement as a risk factor in personalized health care: a systematic review of the literature on chronic disease. Genome Med. 2014; 6:1-13, PMC4064309.
9. Burton RA, Zuckerman S, Haber SG, Keyes V. Patient-centered medical home activities associated with low Medicare spending and utilization. Ann Fam Med. 2020; 18:503-10, PMC7708292.
10. Greene J, Hibbard JH, Sacks R, Overton V, Parrotta CD. When patient activation levels change, health outcomes and costs change, too. Health Aff (Millwood). 2015; 34:431–7, PMID 25732493.

11. Hibbard JH, Mahoney ER, Stock R, Tusler M. Do increases in patient activation result in improved self-management behaviors? Health Serv Res. 2007; 42:1443–63, PMC1955271.

12. Shortell SM, Poon BY, Ramsay PP, et al. A multilevel analysis of patient engagement and patient-reported outcomes in primary care practices of accountable care organizations. J Gen Intern Med. 2017; 32:640–7, PMC5442008.

13. Hibbard JH, Greene J, Sacks RM, Overton V, Parrotta C. Improving population health management strategies: Identifying patients who are more likely to be users of avoidable costly care and those more likely to develop a new chronic disease. Health Serv Res. 2017; 52:1297-1309, PMC5517668.

14. Lundahl B, Moleni T, Burke BL, et al. Motivational interviewing in medical care settings: a systematic review and meta-analysis of randomized controlled trials. Patient Educ Couns. 2013; 93:157–68, PMID 24001658.

15. VanBuskirk KA, Wetherell JL. Motivational interviewing with primary care populations: A systematic review and meta-analysis. J Behav Med. 2014;37:768-80. doi: 10.1007/s10865-013-9527-4

16. Zomahoun HTV, Guenette L, Gregoire JP, et al. Effectiveness of motivational interviewing interventions on medication adherence in adults with chronic diseases: A systematic review and meta-analysis. Int J Epidemiol. 2017;46:589-602. doi: 10.1093/ije/dyw273

17. Linden A, Butterworth SW, Prochaska JO. Motivational interviewing-based health coaching as a chronic care intervention. J Eval Clin Pract. 2010;16:166-74, PMID 20367828.

18. Palacio A, Garay D, Langer B, Taylor J, Wood BA, Tamariz L. Motivational Interviewing improves medication adherence: A systematic review and meta-analysis. J Gen Intern Med. 2016; 31:929–40, PMC4945560.

19. Miller WR. Motivational interviewing with problem drinkers. Behav Psychotherapy. 1983;11:147–72.
20. Babor TF, McRee BG, Kassebaum PA, Grimaldi PL, Ahmed K, Bray J. Screening, Brief Intervention, and Referral to Treatment (SBIRT): Toward a public health approach to the management of substance abuse. Subst Abus. 2007; 28, (3): 7-30. PMID: 18077300
21. Hill KP, Rice LS, Connery HS, Weiss RD. Diagnosing and tracking opioid dependence. J Fam Pract. 2012; 61(10): 588-597.
22. Bonhomme J, Shim RS, Gooden R, Tyus D, Rust G. Opioid addiction and abuse in primary care practice: A comparison of methadone and buprenorphine as treatment options. JAMA. 2012;104(0):342-350. PMC4039205
23. D'Onofrio G, O'Connor PG, Pantalon MV, Chawarski MC, Busch SH, Owens PH, Bernstein SL, Fiellin DA. Emergency Department–initiated buprenorphine/naloxone treatment for opioid dependence: A randomized clinical trial. JAMA. 2015;313(16):1636–1644. PMC4527523
24. Kaltman S, Tankersley A. Teaching motivational interviewing to medical students: A systematic review. Acad Med. 2020;95:458-69. doi: 10.1097/ACM.0000000000003011
25. Gecht-Silver M, Lee D, Ehrlich-Jones L, Bristow M. Evaluation of motivational interviewing training for third-year medical students. Fam Med. 2016;48:132-35. PMID: 26950785
26. Hall K, Staiger PK, Simpson A, Best D, Lubman DI. After 30 years of dissemination, have we achieved sustained practice change in motivational interviewing? Addiction. 2015;111:1144-50, PMID 26216706.
27. Noordman J, van der Weijden T, van Dulmen S. Communication-related behavior change techniques used in face-to-face lifestyle interventions in primary care: a systematic review of the literature. Patient Educ Couns. 2012;89:227–44.

28. Werner JJ, Lawson PJ, Panaite V, Step MM, Flocke SA. Comparing primary care physicians' smoking cessation counseling techniques to motivational interviewing. J Addict Med. 2013;7:139-42. doi:10.1097/ADM.0b013e3182879cc5
29. Douaihy A, Kelly TM, Gold MA, editors. 2016. Motivational interviewing: a guide for medical trainees. New York (NY): Oxford University Press.
30. Jitsi. An open-source multiplatform voice, videoconferencing and instant messaging platform [Internet]. 8x8; [cited 2021 Jan]. Available from: https://jitsi.org/.
31. Moyers TB, Martin T, Christopher P. Motivational interviewing knowledge test. Albuquerque, NM: Center on Alcoholism, Substance Abuse, and Addictions, University of New Mexico. Retrieved from: https://casaa.unm.edu/download/ELICIT/MI%20Knowledge%20Test.pdf
32. Brown H, Prescott R. Applied mixed models in medicine (3rd ed.). Hoboken, NJ: John Wiley & Sons, 2015.