

Convolutional Neural Networks for Automated Health Behavior & Change Talk Evaluation in Technology-Assisted Motivational Interviewing (TAMI) for Tobacco Cessation

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Abstract

Interactions based in Motivational Interviewing (MI) [1], driven by machine learning, may provide an efficient way to evaluate readiness to quit, elicit behavior change preferences, and scalable flexibility to extend reach to more diversified target populations. This study used patient and public sources of conversational data to develop a Technology Assisted Motivational Interviewing chatbot (TAMI), a digital agent employing machine learning models to deliver MI for tobacco cessation. Consistent with the four tasks of MI (engagement, focusing, evocation, and planning), the creation of TAMI involved 1) utilization of existing de-identified datasets to identify specific smoking topics of interest; 2) incorporation of MI-consistent utterances to enhance relational connection to TAMI and elicit language expressing interest in quitting (change talk); 3) instilling change talk recognition and topic classification to guide discussion with TAMI and 4) providing tailored treatment options if indicated. Informed by patient, provider, and public discussions about smoking, TAMI can explore motivation associated with tobacco use, and privately employ interventions to elicit change talk, or accurately evaluate readiness for tobacco cessation. TAMI is also scalable technology, which opens the possibility of having more tools for clinical assessment, delivering MI, and tailoring cessation referrals to underserved populations or those with other target behavior goals.

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Original Manuscript

RUNNING HEAD: TAMI Chatbot

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Technology-Assisted Motivational Interviewing (TAMI) for Tobacco Cessation

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Abstract

Interactions based in Motivational Interviewing (MI) [1], driven by machine learning, may provide an efficient way to evaluate readiness to quit, elicit behavior change preferences, and scalable flexibility to extend reach to more diversified target populations. This study used patient and public sources of conversational data to develop a Technology Assisted Motivational Interviewing chatbot (TAMI), a digital agent employing machine learning models to deliver MI for tobacco cessation. Consistent with the four tasks of MI (engagement, focusing, evocation, and planning), the creation of TAMI involved 1) utilization of existing de-identified datasets to identify specific smoking topics of interest; 2) incorporation of MI-Consistent utterances to enhance relational connection to TAMI and elicit language expressing interest in quitting (change talk); 3) instilling change talk recognition and topic classification to guide discussion with TAMI and 4) providing tailored treatment options if indicated. Informed by patient, provider, and public discussions about smoking, TAMI can explore motivation associated with tobacco use, and privately employ interventions to elicit change talk, or accurately evaluate readiness for tobacco cessation. TAMI is also scalable technology, which opens the possibility of having more tools for clinical assessment, delivering MI, and tailoring cessation referrals to underserved populations or those with other target behavior goals.

Key Words: mHealth, nicotine, motivational interviewing

Introduction

Smoking continues to be a leading cause of preventable morbidity and mortality and an estimated 11.5% of American adults currently smoke [2] and over 480,000 die annually due to smoking-related illness attributable to smoking and second-hand smoke [3 4]. Individuals with low education, low income, and those from under-represented minority groups or residing in rural areas are disproportionately affected [5]. Strong evidence supports a number of evidence-based practices (EBP's) for smoking cessation with the gold standard being the United States Public Health Service's 5A's model in which a medical provider ASKS about smoking, ADVISES cessation, ASSESSES level of readiness, ASSISTS with motivation and/or a plan to quit, and ARRANGES a follow-up appointment. [6 7]. Unfortunately, although most providers ASK and ADVISE, they often fail to ASSESS readiness (39%-63.4% prevalence) and ASSIST patients (38.6%-56.4%) and even more rarely ARRANGE a follow-up (2%-10.4%) [8 9]. Other strategies, such as the abbreviated Ask-Advise-Refer (AAR) and Ask-Advise-Connect (AAC) still require a primary care provider appointment, and neither have a mechanism for assessing or enhancing patient motivation. Other "active referral" approaches that use in-house navigators or counselors to elicit patient cessation preferences and facilitate connections with smoking cessation programs have shown promising results but can be prohibitively expensive in under resourced areas and are most likely unscalable [e.g., 10].

A digital health intervention is particularly well-suited to perform initial patient assessments and basic brief interventions, and could potentially be designed to enhance motivation and tailor cessation referrals [11]. Smartphones have extensive reach into even low-income populations and are increasingly integrated into traditional health care [12 13]. Although smartphone or other digital interventions for smoking cessation are not new, the large majority are unvalidated mobile apps that usually require motivated users and rarely engage patients in a sustained and meaningful way [14]. More advanced, responsive, and tailored digital interventions – such as smart chatbots that empower

patients and support providers are necessary to harness the true promise of digital health as a tool for active (and successful) cessation referrals [15-17]. Chatbot research has shown that patients enjoy interacting with chatbots several times per day [18], develop emotional attachments [19], and show high levels of satisfaction [20] – even preferring the chatbot to a human [21 22]. Even if a digital tool has initial appeal, extended patient engagement is unlikely [23]. Therefore, the style of communication any chatbot uses to discuss smoking is a vital consideration.

Motivational interviewing [MI; 1] may be an appropriate style of communication to engage a patient to discuss his/her smoking and may enhance intrinsic interest in a referral to quit smoking. MI consists of four tasks – engaging the client, focusing on a specific behavior, evocation of the client's own argument for change, and planning behavior change. During evocation, MI is designed to elicit change talk and facilitate behavior change. Change talk (CT) is defined as “any self-expressed language that is an argument for change” [1; p. 159]. In contrast, the opposite of change talk is sustain talk (ST), which is “the person's own arguments for not changing, for sustaining the status quo” (p. 7). Current MI theory [1 24] posits that evoking Change Talk and reducing Sustain Talk increases the likelihood that individuals will change subsequent behavior. Two therapeutic components facilitate this task, a relational component focused on therapist and client factors and a technical component [25 26]. The relational component focuses on the clinical relationship that develops between the therapist and the client over the course of the session (e.g., therapist empathy). The technical component states that specific MI-consistent (MICO) therapist skills (e.g., reflections, affirmations, open-ended questions about the benefits of change) will be associated with specific types of client language; namely, increased CT and decreased ST. In turn, greater CT and decreased ST should lead to desired health behavior outcome. Specifically, a greater proportion of change talk is significantly associated with a reduction in risk behaviors [$r = .16$, $p < .001$; 27]. In several reviews and meta-analyses, MI has been observed as an efficacious intervention for substance abuse behaviors, with small to moderate and variable effects [28-33]. Meta-analyses of in-session MI tasks

indicates the most support for the technical component – which can be readily translated into a digital format - in predicting behavior [34], a finding replicated in subsequent meta-analyses [27 30].

Digital tools incorporating MI skills have been developed for a variety of health behaviors [35 36] A review of 41 studies (Shingleton & Palfai, 2016) examining technology-delivered adaptation of MI found that the majority (32/41) delivered fully automated interventions with no interaction with counselors, and only 5 used real-time synchronous interactions. However, these interactions were with counselors using the technology (e.g., chat room, computer program) in real-time. Since that review, there have been several more advanced, responsive, and tailored digital interventions – such as smart chatbots that empower patients and support providers and “embodied conversational agents” – that are trying to harness the true promise of digital health as a tool for active (and successful) cessation referrals [15 37 38]. Thus, chatbot format may more easily allow for relational components of MI (empathy, collaboration, facilitating self-exploration) while advances in machine learning and artificial intelligence (AI) can improve the delivery of MICO technical skills, thus enhancing the focus and credibility of the MI delivered. For example, one study found that a smoking cessation MI chatbot was able to increase self-efficacy by simply programming the MI chatbot to ask open-ended evocative questions; similarly, programming reflections using Chat GPT in addition to evocative questions improved readiness to quit and perceived empathy of the MI chatbot [36].

A credible chatbot using MI will have to engage the user, focus the interaction on smoking, evoke and recognize change talk and sustain talk, and if interest in quitting is indicated, develop a plan to quit smoking. Therapist MICO skills can effectively evoke both Change and Sustain Talk, highlighting the need to train the chatbot to quickly recognize change language and utilize MICO skills strategically – a level of detail not performed (and possibly not known) in earlier studies. As this occurs, maintaining a conversational focus on smoking is also vital to cultivate internal motivation for change related to that focus which in turn may foster interest in planning to quit.

The aim of the current study was to develop a Technology-Assisted Motivational Interviewing chatbot (TAMI) to assess and enhance patient readiness for smoking cessation, create tailored cessation referrals, and improve treatment initiation. TAMI is a collaborative, client-centered digital tool that can increase intrinsic motivation for smoking cessation and make tailored referrals. The current manuscript details how TAMI was developed using existing clinical and public datasets to incorporate MICO skills to guide the individual through the four tasks of MI. To do so, the research team had to first structure interactions to engage and focus the user on smoking topics. It was important to have TAMI have relational capacity (i.e., be liked by users) and be able to tailor the experience of the user (by pulling in earlier demographic data and remembering prior interactions). Then, automated AI detection of change talk and topic classification were vital to facilitate ongoing evocation of change language regarding smoking cessation. Third, appropriate and tailored resources were to be provided when the user was planning how to quit smoking. In this way, TAMI is a fully automated, text-based conversational agent that uses several core abilities to achieve the goal of promoting cessation treatment initiation.

Methods

Study Design

Expert and user-centered design interviews and focus groups guided the initial “personality” development, interface logic, and flow of a conversational chatbot based on technical motivational interviewing (MI) principles. The prototype was built in four stages. First, in order to build an initial scenario of a discussion about smoking, we identified initial set of intents (topics) and responses. Second, using a library of existing texts (e.g. motivational interviewing transcripts, public Reddit threads) and extending existing statistical models (e.g. word2vec), we built and tested an intent recognition model. Third, we built a statistical model that recognizes and labels change language and degree of its use. Finally, we linked all these efforts together to guide the user through the four tasks of MI (engaging, focusing, evocation, and planning). Specifically, we

implemented initial conversation flow using a decision tree and a database of potential intents and train a statistical decision tree model using existing conversation flows.

The initial construction of TAMI was based on over 450 session transcripts, training codebooks and role play transcripts, and expert input to map basic conversational structures and begin a lexicon of change talk with linked decision-trees driving TAMI's MICO responses. Multiple iterative development rounds with project staff, with the goal of "tripping up" the system and finding misunderstood intents and badly worded responses, taught the chatbot to be more intelligent and more MI-consistent in its responses. Table 1 provides an overview and summary of clinical data used to inform both focusing and evoking components of TAMI.

Engagement One of the challenges of any digital tool is facilitating repeated engagement, which has also been termed a working relationship, connection, or alliance [1]. Therefore, TAMI contacts users on a schedule tailored to their preferences. As a result, users don't have to remember to open an app or do their "homework" as the chatbot will prompt them at optimal (pre-determined) time points throughout the week, engage them in brief conversations, and (at times) recommend activities or other homework that is later reviewed in future conversations. Although a minimum number of contacts can be programmed to occur, patients were able to initiate conversations as much as they like at any time. Users were able to determine what times they preferred being contacted. The default frequency was once a week, although this could be increased by the user. In addition, if a user had decided to quit and received a referral, notifications to re-engage were ceased. Together, these efforts ensured that TAMI engaged the users at appropriate times to have a conversation about smoking.

Focusing. Once the user was engaged, TAMI needed to maintain a clear and consistent direction of the conversation about change towards smoking cessation rather than being sidetracked to other topics. Focusing was conceptualized as having two components: structured, discrete sessions in which the user could discuss his or her smoking specific topics regarding smoking.

Evocation. Once the user was engaged and focused on the session, the challenge was to have TAMI be able to classify the user texts (by topic, change talk and sustain talk) and then respond appropriately using MICO skills that have been demonstrated to evoke further change talk [e.g., double-sided reflections ending on patient change talk; 24]

Planning. Once a user completed a session with TAMI and indicated readiness to quit smoking, TAMI guided them through user preferences for referral and quit-plan elements similar to our prior work [39 40].

Results

Development of Focusing Tssk

Session Structure. As TAMI responded to only the previous user text, without this structure, focus would quickly be lost, and the session could continue infinitely or until abandoned by the user. To this end, session templates were constructed for each of 12 themed sessions that explored topics such as the pros and cons of smoking, benefits of quitting, self-efficacy, and setting a quit date (see Table 2). MI theory informed the development of the structure of sessions, specifically the utilization of MICO skills of open-ended questions, affirmations, and reflections to guide the user through the session. In addition, TAMI incorporated MI strategies such as the readiness ruler and asking key questions (“What do you think you’ll decide to do?”).

Smoking Topics. To identify topics that were relevant to smokers, de-identified text from transcripts of MI and health education sessions addressing smoking from a randomized clinical trial [41] and chats on Facebook regarding smoking and health education [42]. Eighty-one topics related to smoking were extracted from these data sources such as financial costs of smoking, appearance (breath, smell), social triggers (family, friends), healthcare systems and mental health. These topics were then fed into the public REDDIT dataset. When Open Health Network (OHN) ran further analyses through REDDIT data and extracted posts and comments that incorporated those topics. These discussions were then reviewed, and off-topic information removed. This dataset was then

divided into 77 classes in order to develop TAMI topic comprehension.

Development of Evocation Task

Classification. Datasets were machine parsed into utterances, and then the clinical research coding team assessed the presence of change talk within the utterances and identified topic and subtopic classification. Two datasets [43 44] had already reliably coded client language, and the clinical research coding team identified change talk and sustain talk within the other datasets by consensus. TAMI was then able to incorporate data that had already been parsed (divided into discrete utterances) and coded. However, other data that the team accessed had to be put into a format that TAMI could incorporate. This was done in four steps. First, the data was transcribed from audio to written text. This was done manually, as in the case of all received written transcripts, or this process used Otter.io for audio files and formatted appropriately. Second, the data was parsed into utterances. This step was accomplished using natural language process (NLP). Third, the utterances were coded into change and sustain talk by a group of coders trained by the research team [see 45 for details of this process]

TAMI's custom Natural Language Understanding (NLU) model-based approach evaluates utterances using transformer-based classifiers. In addition to topic and change-sustain talk classification, MI interviewing skill-code and question-answer classification were also added (Saiyed et al., 2022). An existing corpus of MI transcripts were used to map conversational structures and to derive machine learning-based classifiers allowing recognition of message intents, client change language content, and decision trees for accurate MICO responses. A large part of reflection and language recognition design for TAMI was to identify topics and change talk from existing clinical motivational interviewing datasets and infuse these with AI engagement. Prototype development started with consultations with MI experts, the research team, and Open Health Network (OHN). OHN received over 20,000 lines of de-identified utterances from the Facebook dataset and a prior RCT with unmotivated community member smokers [41] Using scored and coded transcripts, the

team trained a classifier for each situation.

An existing neural network, word2vec, was used [46] that had been pre-trained on the English language corpus derived from Wikipedia articles. Word2vec represents synonyms and antonyms in the English language without explicit hand-built dictionaries. Word2Vec is used to measure how similar the user-entered text is to sets of texts representing specific topics (e.g. smoking, shortness of breath). A piece of text that meets a certain threshold is seen as expressing that “specific intent.” Having a library of “intents” and associated training text thus allows us to refine and filter the output of a neural network and use it to generate response and switch action paths as needed. The primary challenge of this phase was managing the breadth of potential patient responses, categorizing them correctly, then having TAMI recognize the “topic intent” of person and respond via MICO skills [45].

Response Libraries. Once TAMI was able to classify the text from the user, a MICO response had to be generated. Therefore, a library of reflections and open-ended questions was developed to ensure that the conversation abilities of TAMI were always MI-Consistent. To provide TAMI with even more reflections that could be used to address smoking, our team generated reflections about the 15 topic codes and 77 classes from machine parsed utterances. All reflections were organized into a 77 (classes) by 5 (strong and moderate change talk, neutral, moderate, and strong sustain talk) decision matrix, resulting in 385 possible responses. The matrix was reviewed and edited by clinicians and expert coders. The same approach was used to develop a matrix for open-ended questions.

Identification of change talk. TAMI was trained to identify change talk and sustain talk for tobacco use using a BERT neural network to build a model of CT vs ST in an MI interview context. We trained the neural network on 51000 utterances extracted from 255 de-identified transcripts [43 44]. BERT network recognized CT/ST/follow neutral talk with f-score of 0.82, and severity of CT/ST on a Likert scale with an f-score of 0.75, accuracy comparable to a human coder.

Development of Decision Tree and Matrix. After OHN worked on an NLP model, TAMI chat flow diagrams were developed and the clinician matrix and decision tree were reviewed. A demo reviewed utterance input and return vectors for change and sustain talk, as well as topic classification. The connection of these vectors to the matrices of responses led to the next step of TAMI development in which issues were addressed such as repeated questions by a participant.

Development of Planning Task

Development of Quit Plan. The tailored quit plan is typically comprised of several evidence-based cessation interventions that are selected by the user/participant such as NRT, behavioral counseling, state quit lines, and pharmacotherapy (e.g. varenicline). TAMI assists patients in recalling strategies used in the past and reminds them when additional steps need to be taken such as contacting a prescribing physician or downloading discount coupons to buy nicotine patches. TAMI also encourages the patient to set a quit date and provides tips to increase the likelihood of success such as removing smoking triggers from the home and informing friends and family about the quit date. The full tailored quit plan with relevant links and instructions could be downloaded and printed.

Discussion

We created an evidence-based smart chatbot to educate patients, assess and enhance motivation for cessation, and to eventually tailor cessation referrals based on patient preferences, readiness, and resources. Consistent with the four tasks of MI (engagement, focusing, evocation, and planning), the creation of TAMI involved the utilization of existing patient and public datasets to identify specific smoking topics of interest. As can be seen in the interaction detailed in Table 3, these efforts facilitated the incorporation of MICO prompts to enhance relational connection to TAMI and elicit change talk. Specifically, TAMI was instilled with change talk recognition and topic classification to guide a personal discussion with TAMI about smoking. Furthermore, when indicated TAMI could provide tailored treatment options. In this way, TAMI guided the participants to learn

about their smoking and consider options for smoking cessation.

TAMI was also designed to use compelling and high fidelity MICO skills such as affirmation, emphasizing personal choice and control, asking key questions (“What do you think you’ll decide to do?”) in order to guide the patient through the four tasks of MI – engagement, a focus on smoking, evoking and resolving ambivalence about quitting smoking, and planning for change. TAMI does not require any PCP/clinician involvement, although it allows for and encourages that exploring professional assistance with quitting smoking when developing a quit plan. By combining proven engagement strategies (e.g., targeted incentives, an active chatbot vs passive mobile app) with artificial intelligence and machine learning, TAMI helps to enhance patient motivation and reduce barriers to utilization by tailoring referrals that are provided at just the right time for all patients regardless of their initial level of readiness.

Several strengths and a few limitations to the current study should be noted. First, existing patient transcripts addressing smoking and/or demonstrating high-fidelity MI were available to train the system that recognizes the topic and appropriate response. Using available smoking cessation transcripts from high-fidelity MI ensured TAMI generated responses that may closely resemble a clinician practicing MI and are targeted to smoking cessation. In addition, a team of researchers, computer scientists, and clinicians with MI training created the prototype of TAMI, and further improved its responses. However, TAMI remains a relatively scripted and structured intervention with limited ability to adapt to participant input and questions thus potentially limiting engagement and follow through with the quit plan. Fortunately, since this work was completed, there has been remarkable advances in the development of large language models (LLMs) (e.g., ChatGPT 4.0) that incorporate large amounts of data to craft questions and reflections that are equivalent to human-generated utterances in criteria such as specificity, naturalness, appropriateness and engagement [see 36 47 48]. As a result, next steps for the further development of the TAMI Coach are to effectively graft the structure of TAMI with more advanced LLM’s to create opportunities for enhanced

evocations and strengthening of the participant's personal argument for quitting smoking. This enhancement will be especially important during the evocation component, which was previously limited to scripted reflections and questions pertinent only to the most immediate response by the participant. Specifically, the chatbot may facilitate a more nuanced discussion of the 5R's (relevance, risks, rewards, roadblocks, repetition) for use with smokers who report not being ready (i.e., motivated) to quit [6]. Once these revisions are completed, we plan to assess the feasibility and acceptability (F&A) of a research protocol evaluating the revised TAMI as a digital tool to assess and improve patient readiness for smoking cessation, provide tailored cessation referrals, and promote treatment initiation. Results of the F&A pilot will inform adjustments made to TAMI and/or the research protocol in preparation for a full RCT including comparing TAMI versus enhanced usual care (UC) conditions.

In sum, digital health applications such as TAMI may fill a vital gap in healthcare by facilitating conversations that evoke a personal argument for change – whether relevant to smoking or other health-related behaviors. The overall structure of focused conversations has been guided by decades of therapy process research and the clinician utterances that facilitate these conversations are also well established [e.g., reflections, affirmations, open-ended questions; 27 30]. Although chatbots will likely never fully replace human interactions and guidance, ever-evolving chatbots may be able to initiate the conversation about change on a broad scale and efficiently facilitate movement through a stepped continuum of care ending with professional clinicians who resolve complex ambivalence towards change.

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None of the authors report a conflict of interest.

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Table 1: Data sources used in the development of TAMI

Data Source	Description	Sample Description	Task – Data Extraction
Meacham, et al. [42]	Short textual language about smoking	5416 utterances classified for topic by clinical research coding team	Evocation - Change talk /sustain talk identification
Catley, et al. [41]	Motivational Interviewing and Health Education for smoking	Over 10,000 utterances classified by clinical research coding team	Focusing - Topic classification Evocation - Change talk identification
Reddit	Discussions about 15 smoking topics	17225 utterances	Focusing - Topic Classification
Borsari et al., (2015)	Motivational Interviewing for alcohol use	46301 Utterances parsed by machine and change talk identification by clinical research coding team	Evocation - Change talk identification
Apodaca, et al. [43]	Motivational interviewing for alcohol use	Sessions were reviewed by the clinical research team to influence session theme development	Evocation - Change talk identification

Table 2. MI Session Template Themes

Session	Session theme(s)
1	Rapport-building, exploring the pros and cons of smoking, assessment of readiness using the readiness ladder
2	How quitting smoking would affect your life
3	Tackling a problem related to quitting smoking
4	Discussing and celebrating previous quit attempts
5	Overview of facts related to smoking and smoking cessation
6	Exploring the risks and rewards of smoking
7	Reviewing evidence-based smoking cessation interventions
8	Anticipating obstacles that could get in the way of quitting smoking
9	Imagining life as a non-smoker
10	Reviewing pharmacologic smoking cessation tools
11	How would you advise a friend or family member who wants to quit smoking
12	Reflecting on the past 3 months of the intervention, giving information about how to make a quit plan on the TAMI Coach webapp

Table 3: Sample Smoking Discussion

TAMI Coach (TC): Hey, <Pt name>, got a minute? [Pt clicks on yes]

TC: Is it ok if I check in with you about your smoking? [MICO ; Seeking Collaboraton; Pt clicks ok]

TC: Great. Let's see where we are starting first. Think back over the past week. How many days out of the past 7 have you had a cigarette? [Pt enters 7]

TC: Ok, 7 out of 7 days. On an average day, how many cigarettes did you smoke? [Pt enters 15]

TC: Got it, so an average of 15 cigarettes per day over the past 7 days.

TC: How do you feel about your smoking? (MICO; Open Question, evoking Change Talk or Sustain Talk)

Pt: [Pt types] Maybe it's a bit much but I'm fine (CT/ST).

TC: What makes you think it's a bit too much? [Open Question evoking CT]

Pt: I enjoy smoking but it's expensive and really isn't helping my asthma (ST/CT).

TC: I see, so you like smoking but it is expensive and makes your asthma worse [MICO: Reflection of ST and then CT]

TC. On a scale of 1-10 with 10 indicating more readiness, how ready would you say you are to quit smoking?

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