A Fully Generative Motivational Interviewing Chatbot for Moving Smokers Towards the Decision to Quit and LLM-Based Synthetic Smokers

by

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Abstract

Tobacco use is a leading cause of preventable death, yet many smokers lack access to effective cessation support like motivational interviewing (MI). This thesis presents the development and evaluation of a fully generative MI chatbot designed to help smokers move towards the decision to quit. The chatbot leverages large language models (LLMs) to provide empathetic, person-centered counseling, aiming to overcome barriers of cost, availability, and stigma associated with traditional therapy.

This work makes two primary contributions. First, it details the design and iterative refinement of the MI chatbot. Its effectiveness is assessed through an empirical study with human smokers, who provided qualitative feedback and self-reported their readiness to quit before and after interacting with the chatbot. Second, we introduce a novel methodology for creating and validating *synthetic smokers* — LLM-powered agents that attempt to simulate the demographic and behavioral characteristics of human smokers in MI conversations. A framework for evaluating the fidelity of these synthetic agents is presented, with results demonstrating their ability to approximate the conversational patterns of real smokers in controlled experiments.

Collectively, these contributions advance the field of AI-assisted mental health by offering a scalable, evidence-based tool for smoking cessation and by providing a new method for the low-cost, high-fidelity simulation of human subjects in behavioral research.

To the children who aged too soon,
and the futures that never were.

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For your constant support and belief in me.

And my partner in life, Rueshan,

This work would have been immeasurably less fulfilling and interesting without you. You made this a richer, more meaningful experience.

Lastly, to Allah, my Light and the Light of the Heavens and the Earth.

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Chapter 1

Introduction

Tobacco use remains the leading cause of preventable disease and death in Canada. More than 70% of the lung cancer cases in the country are estimated to be attributable to smoking. Smoking is responsible for the deaths of approximately 45,000 Canadians annually (Poirier et al., 2019). Despite public health campaigns and cessation aids, 4.6 million Canadians continue to smoke, with a higher prevalence among Indigenous communities, individuals living in rural areas, and those with low income (Canadian Partnership Against Cancer, 2020). These groups also suffer from reduced access to smoking prevention, early diagnosis, and treatment services, which contributes to inequities in health outcomes.

Talk Therapy

One of the most effective evidence-based interventions for smoking cessation is talk therapy. While several therapeutic modalities are effective, such as cognitive behavioural therapy (CBT) (Beck et al., 1979) and acceptance and commitment therapy (ACT) (Hayes et al., 1999), this thesis focuses on motivational interviewing (MI) (Miller and Rollnick, 2012). However, access to such interventions is hindered by several systemic challenges. First, traditional talk therapy can be prohibitively expensive for individuals without private insurance or those under financial constraints: although CBT is clinically and economically effective, publicly funded CBT remains scarce in Canada (Llewellyn et al., 2006). Second, therapy services are limited in availability, especially in rural and remote regions: residents in rural Canada face long distances to providers, transportation difficulties, fewer clinicians, and lower socio-economic resources, all constraining access (Crosato and Leipert, 2011). Third, there is a significant shortage of culturally safe mental health services tailored to the unique historical and social contexts of Indigenous populations (Jones et al., 2021). Indigenous communities experience systemic underfunding, long wait times, inadequate provider availability, and cultural mismatches between Indigenous clients and predominantly non-Indigenous therapists (CanCOVID Issue Note, 2023; National Collaborating Centre for Indigenous Health, 2020).

Chatbot-based Counselling

One way to address the lack of accessible mental health care is through chatbot-based counselling, which can serve users when no alternatives exist. Chatbots are always available, require no appointments, protect anonymity, and can scale to thousands of users. Once developed, their marginal cost is nearly zero, making them especially suited for underserved populations (Torous and Roberts, 2017; Miner et al., 2016). Compared to traditional therapy, they offer a low-cost, scalable complement.

1.1 Motivational Interviewing for Smoking Cessation

MI

Motivational interviewing (MI) has emerged as particularly effective for smoking cessation. MI is a client-centred counselling method developed in the early 1980s by William R. Miller and later expanded in collaboration with Stephen Rollnick (Miller and Rollnick, 1991, 2013). It is designed

to help individuals strengthen their intrinsic motivation to change their health-compromising behaviours, including smoking. MI has been widely applied in addiction treatment settings and has shown consistent effectiveness in encouraging smoking cessation, particularly among individuals not yet ready to quit (Bischof et al., 2021; Hettema et al., 2005b).

The hallmark of MI is its collaborative, non-confrontational style, which relies on empathy, active listening, and evocation. Rather than telling clients what to do, MI counsellors aim to guide them in articulating their own reasons for change. The core principles of MI are: (1) expressing empathy through reflective listening, (2) developing discrepancy between current behaviour and personal goals, (3) rolling with resistance rather than confronting it, and (4) supporting self-efficacy (Rollnick et al., 2008). These principles are operationalized using skills such as open-ended questions, affirmations, reflections, and summaries—commonly referred to as the OARS model (Miller, 2023).

A critical insight from MI is that *ambivalence* — a state in which individuals simultaneously hold conflicting feelings about change — is often the first psychological barrier to change. Smokers may simultaneously recognize the harms of smoking and yet be unwilling to change due to perceived benefits or entrenched habits (Brown et al., 2023a). Resolving this ambivalence is a necessary precursor to behaviour change. Numerous studies have demonstrated that MI increases the number of quit attempts and enhances confidence to quit among ambivalent smokers (Abar et al., 2013; Gwaltney et al., 2009). MI promotes a shift from "sustain talk" (statements that favour the status quo) to "change talk" (statements that favour behavioural change), and the frequency and strength of change talk during a session have been shown to predict actual behavioural outcomes (Apodaca and Longabaugh, 2009a).

1.2 Large Language Models and the Automation of Talk Therapy

The automation of talk therapy, once constrained to rule-based systems and predefined scripts, has been profoundly transformed by the advent of large language models (LLMs). The development of transformer-based architectures (Vaswani et al., 2017), particularly autoregressive generative models like GPT-3 and GPT-4, has enabled machines to produce responses that are coherent, contextually appropriate, and human-like in natural dialogue (OpenAI, 2023). These capabilities have made fully-generative counselling by not only possible but increasingly effective for therapeutic applications (Miner et al., 2020; Torous et al., 2023).

Several key technical innovations have facilitated the adaptation of LLMs to therapeutic contexts. The self-attention mechanism within transformer models supports long-range dependency modelling and nuanced context tracking across multi-turn dialogues (Vaswani et al., 2017). Fine-tuning an LLM on domain-specific corpora (e.g., MI transcripts) could make the model outputs clinically grounded (Valentino et al., 2024), while reinforcement learning with human feedback (RLHF) has been shown to improve the relevance, tone, and empathetic quality of a generated response (Ouyang et al., 2022; Gilson et al., 2023). Together, these capabilities enable LLMs to generate novel therapeutic reflections, adhere to evidence-based counselling principles, and adaptively modulate tone.

1.3 Focus and Goals

The overarching goal of this project is to develop and evaluate a fully generative chatbot capable of providing MI counselling to help smokers move toward the decision to quit. This involves designing and implementing an MI counsellor that adheres to the core principles of MI, evaluating its effectiveness with real human smokers using both human assessments and automated metrics, and creating *synthetic smokers* — LLM-based personas that mimic human smokers and consistently display realistic behavioural traits during MI conversations. Furthermore, the realism of these synthetic smokers is validated by comparing their conversational characteristics and behaviours with those observed in actual human smokers. Collectively, these efforts contribute to the broader vision

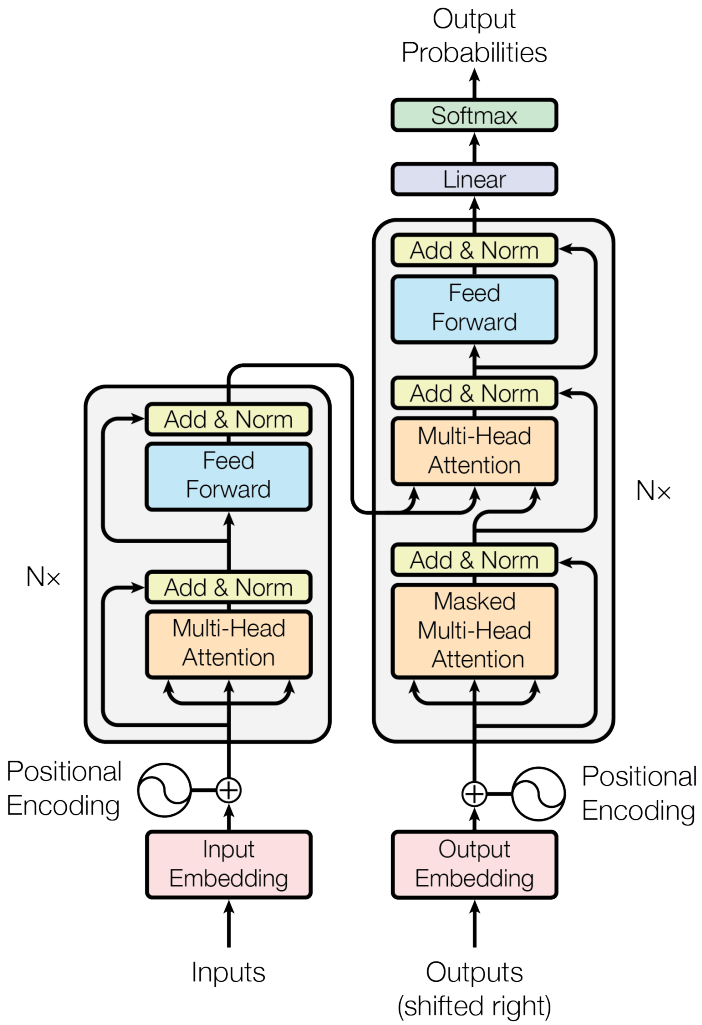


Figure 1.1: Illustration of the Transformer architecture adapted from Vaswani et al. (2017).

of advancing AI-assisted mental health support through technologies that are safe, accessible, and grounded in evidence-based practices.

1.4 Contribution

This work makes the following contributions to the development and validation of a generative MI-based chatbot for smoking cessation:

1. Design and iterative refinement of a single-prompted, fully generative chatbot capable of conducting motivational interviews with human smokers.
2. Execution of an empirical study in which compensated human participants interacted with the chatbot, providing qualitative feedback and pre- and post-interaction self-reports on their readiness to quit smoking.
3. Development of a methodology to construct *synthetic smokers*—LLM-driven agents embedded with the demographic and behavioural characteristics of human smokers.
4. Creation of evaluation techniques to assess the extent to which these synthetic agents approximate human smokers in controlled behavioural experiments.

5. Validation of synthetic smokers by quantifying their similarity to human smokers using the aforementioned evaluation techniques.

1.5 Organization

This dissertation is structured as follows: Chapter 2 reviews relevant background on the Motivational Interviewing approach, foundational language models, chatbots for talk therapy, persona construction using LLMs, and prior work on the development and validation of LLM-based synthetic subjects in behavioural experiments. Chapter 3 presents the design of the fully generative MI counselling chatbot, along with details of its deployment and evaluation methodology. Chapter 4 reports the results of a study in which recruited smokers interacted with the chatbot. Chapter 5 describes a method for constructing synthetic smokers using large language models, prompted to exhibit demographic and behavioural traits derived from real smokers. Chapter 6 introduces a framework for evaluating synthetic smokers in their ability to substitute for human participants in controlled behavioural studies, and presents the corresponding evaluation results. Chapter 7 concludes the work by discussing its limitations and outlining directions for future research.

Chapter 2

Background and Related Work

This chapter establishes the conceptual and empirical foundations for our contributions to automated talk therapy and the development of synthetic agents. We begin by surveying research on the clinical efficacy of motivational interviewing for smoking cessation. Next, we examine the emergence of transformer-based LLMs as conversational agents, with a focus on recent efforts to develop motivational interviewing counsellor chatbots using LLMs. We then survey methods for constructing synthetic agents, with particular emphasis on LLM-based synthetic patients designed for behavioural research. We particularly focus on the techniques of persona *installation* via prompting, which seeks to *install* demographic and behavioural characteristics into synthetic agents. We also outline the inherent limitations of prompt-based persona installation, including issues of consistency, depth, and stereotype propagation. Finally, we critically review existing approaches for validating the fidelity of persona installation and compare them with our own validation methods.

2.1 Motivational Interviewing (MI)

Motivational Interviewing (MI) is a counselling technique originally developed in the 1980s to treat alcohol dependence, and has since been applied across a wide range of health interventions, including smoking cessation (Miller, 1983; Miller and Rollnick, 2023). MI is defined as a collaborative, client-centred conversational method designed to elicit intrinsic motivation for change by helping individuals resolve ambivalence (Miller and Rollnick, 2002). Instead of confronting or directing the client, the MI practitioner adopts a guiding stance: asking open-ended questions, listening reflectively, and echoing the client's own change-relevant statements. This approach aims to elicit 'change talk' (client statements in favour of change) while reducing 'sustain talk' (arguments for maintaining the status quo) (Miller and Rose, 2009). By evoking the person's own reasons for change in a non-judgmental and supportive way, MI strengthens their perceived autonomy and self-efficacy. Table 2.1 presents examples of change and sustain talk alongside MI-consistent responses by the counsellor.

Speaker	Change Talk	Sustain Talk
Client	"I know I should quit smoking because my kids hate the smell, and I don't want them to pick up the habit."	"I've tried quitting before, but I always end up lighting one when I'm stressed out. It's just who I am."
Counsellor	"It sounds like you really care about setting a good example for your children."	"So smoking feels like a part of how you manage difficult emotions."

Table 2.1: Examples of Change Talk and Sustain Talk in Motivational Interviewing

2.1.1 MI Principles and Style

principles

Underlying MI's conversational approach are several core principles. First, the counsellor should express empathy and use reflective listening to understand the client's perspective and build rapport. Second, MI works to reveal any discrepancy between the client's own goals or values and their current behaviour (Miller and Rollnick, 2013). Third, the counsellor acknowledges the client's resistance rather than confronting it; resistant remarks are met with understanding and are used as opportunities to further explore the client's thoughts, instead of provoking an argument. Finally, MI supports self-efficacy by emphasizing the client's autonomy and capability in effecting change — the individual is encouraged that they have the strength and choice to quit if they decide to (Miller and Rollnick, 2013). These principles are often operationalized through specific conversational techniques summarized as OARS: Open-ended questions, Affirmations, Reflective listening, and Summaries (Rollnick and Miller, 1995). Examples of how MI counsellors use these skills are given in Table 2.2.

Ambivalent Smokers

MI's empathetic, autonomy-supportive atmosphere is particularly important for *ambivalent smokers* — those who may be defensive or unsure about quitting. It helps reduce resistance and increases engagement in the conversation about change (Rollnick et al., 1997; Miller and Rollnick, 2023). Notably, MI's strategy of guiding clients to articulate their own arguments for change is grounded in evidence that clients' "change talk" during sessions predicts a greater likelihood of subsequent behaviour change (Miller and Rose, 2009). Thus, MI sessions explicitly aim to cultivate change talk and soften sustain talk, steering the dialogue in a direction where the client's language shifts towards change.

MI Skill	Example
Open-ended Question	"What are some things you've thought about when it comes to cutting back on drinking?"
Affirmation	"You've shown a lot of strength in coming here today and being open about what's going on."
Reflective Listening	"So you're feeling stuck. You want to make a change, but you're also worried you might fail again."
Summary	"Let me see if I've got this right: you've been thinking more about quitting, especially since your health scare, but it's been hard to imagine your daily routine without smoking. At the same time, you've started walking more and cutting back already."

Table 2.2: Examples of Skills in Motivational Interviewing

2.1.2 Measuring the Effectiveness of MI Counselling

MISC

As a structured therapeutic approach, MI uses well-defined success criteria. Researchers and clinicians use several strategies to evaluate the quality of MI conversations and their impact on client motivation. One common framework is the Motivational Interviewing Skill Code (MISC), a coding system that categorizes counsellor utterances and client responses to quantify adherence to MI principles (Houck et al., 2010). Using the MISC, independent annotators (or *coders*) can rate how well a counsellor's statement aligns with MI techniques (for example, counting reflections, questions, advice, etc.) and determine the proportion of client change talk vs. sustain talk. High MI-consistent scores (e.g. a high ratio of reflections to questions, or a high percentage of client change talk) are associated with better outcomes, and such coding schemes are often used in training and research to ensure the fidelity of MI delivery.

Readiness Ruler

Another practical tool is the "Readiness Ruler," a simple self-reported measure of a client's readiness to change (on a 0–10 scale for readiness, importance, or confidence) (Boudreaux et al.,

2012). In the context of smoking cessation, a counsellor might ask, "On a scale from 0 to 10, how ready are you to quit smoking?" The Readiness Ruler is an effective way to track changes in motivation before and after intervention. For example, an increase in a smoker's readiness score after an MI session would indicate movement toward a decision to quit. Both the MISC coding of session transcripts and readiness scaling of clients are valuable evaluation methods: the former measures the level of motivational language by the client and ensures the conversational style remains true to MI, and the latter provides an outcome-oriented metric of the client's motivational state.

Effectiveness of MI in Smoking Cessation

MI has been widely adopted in smoking cessation efforts, particularly due to its relevance for smokers who experience ambivalence about quitting. For instance, a national survey found that over half of U.S. smokers express conflicting attitudes toward cessation (Babb et al., 2017), necessitating interventions that can navigate such ambivalence.

Over the past two decades, numerous clinical trials and meta-analyses have assessed the efficacy of MI counselling in helping tobacco users quit. A meta-analysis of 31 randomized trials involving over 9,000 smokers reported that MI significantly increased the likelihood of abstinence compared to control conditions, with a pooled odds ratio of approximately 1.45 (Heckman et al., 2010). Similarly, a Cochrane review of 28 studies found that MI-based counselling produced higher six-month quit rates than brief advice, with relative risks ranging from 1.2 to 1.3 (Lindson-Hawley et al., 2015). While these effect sizes are modest, the evidence consistently suggests that MI enhances both quit attempts and abstinence, especially when delivered by trained practitioners in clinical or community settings

The effectiveness of MI is consistent across diverse smoking populations and settings. Studies have shown positive outcomes with MI delivered by various professionals (physicians, nurses, trained counsellors) and in formats ranging from a single brief session to multiple sessions (Lindson-Hawley et al., 2015). Even a short, 15–20 minute MI-based conversation in a primary care visit can measurably boost a smoker's likelihood of quitting relative to no counselling, especially when the practitioner adheres closely to MI principles (Zanjani et al., 2008).

One reason MI is particularly effective for smoking cessation is its alignment with the psychology of ambivalence common among smokers. Many smokers acknowledge the health risks of tobacco while simultaneously relying on it for stress relief or as a habitual comfort, resulting in decisional conflict. MI directly engages this ambivalence by fostering a non-confrontational space in which smokers can articulate and examine their mixed feelings, ultimately shifting the balance toward change. Empirical evidence suggests that MI not only improves cessation outcomes but also enhances intermediate factors such as motivation, readiness to quit, and self-efficacy (Boudreaux et al., 2012; Hettema et al., 2005a). These motivational gains are critical, as a readiness to quit is a well-established precursor to cessation success (West and Sohal, 2006).

2.2 Foundational Language Models

Foundational LMs

The recent improvements in conversational AI has been driven by foundational language models (Miller, 2021) — extremely large neural networks pre-trained on vast corpora of text, which can be adapted to myriad tasks. These models serve as a foundation that can be specialized via *fine-tuning* or for specific applications. Crucially, modern foundation models leverage the **transformer** architecture (discussed in Section 2.2.1) to capture long-range context and dependencies in dialogue. Consequently, this allows LLM-based chatbots to understand and generate coherent multi-turn conversations and provide consistent responses to the client's statements over long contexts (e.g., multiple sessions).

Foundation models are trained with self-supervised objectives on enormous text datasets, learning a broad range of linguistic patterns, factual knowledge, and even subtle interaction norms. For

Emergent Capabilities

example, the GPT series of models exemplifies how scaling up model size and data leads to *emergent capabilities*. GPT-3 (Brown et al., 2020) (175 billion parameters) demonstrated astonishing *few-shot learning*: it can perform a new language task given only a few examples. This few-shot ability is a direct consequence of training on diverse data at scale, which allows models to perform *in-context learning*, i.e., adapting to a new task described in the prompt. Such capabilities are invaluable for building a therapeutic chatbot. Instead of laboriously collecting and annotating thousands of counselling dialogues to train a model, it is possible to prompt a pre-trained LLM with instructions and examples of MI, and the model will generalize to produce appropriate counsellor responses (Xie et al., 2024). As will be demonstrated later, in this work, we prompted a foundation model with an expert-informed prompt. This method leveraged the model's generative capabilities while allowing the customization of the output to be MI-consistent, among other things. This approach follows a broader trend in NLP: using large pretrained models as a base and conditioning them via prompts or lightweight fine-tuning to perform specialized dialogue tasks (Wei et al., 2022).

The general trend is that foundation models are becoming more knowledgeable, more context-aware, and better at following complex instructions. This bodes well for therapeutic chatbots: as these models advance, a carefully adapted version can exhibit even more natural dialogue and sophisticated motivational strategies. At the same time, research into controllability — giving developers and clinicians the tools to direct an LLM's behaviour — is growing in importance (Fernandez et al., 2025). Techniques like system prompts, chain-of-thought prompting for reasoning (Wei et al., 2022), and lightweight policy modelling (Du et al., 2024) are some emerging trends to further improve an LLM's use as a goal-oriented dialogue system.

CoT

2.2.1 The Transformer Neural Architecture

Transformers are the architectural backbone of virtually all modern large language models, and they play a central role in the chatbot developed in this work. The transformer architecture (Vaswani et al., 2017) departed from previous neural network designs by using self-attention as a sole mechanism to " compute representations of its input and output without using sequence aligned RNNs or convolution" (Vaswani et al., 2017). This allowed parallel processing of each input token in the context to compute its deep context-dependent representation. In a transformer, each input token's representation can be computed by attending to every other token in the context (the complete conversation up until now), which enables the model to capture long-range relationships and context. This is implemented through multi-head self-attention layers: the model computes attention weights that represent different types of relationships (e.g., semantic similarity, positional relevance) across the sequence. By stacking multiple self-attention layers, transformers can build very deep representations of text. Crucially, they scale efficiently on parallel hardware because each layer's computations can be parallelized (unlike the sequential nature of RNNs). This scalability has allowed training of extremely large models with hundreds of billions of parameters on massive datasets.

Large generative models like GPT-3 (Brown et al., 2020), GPT-4 (OpenAI, 2023), and others use transformers that predict text autoregressively, i.e., one token at a time, conditioned upon the preceding context. This autoregressive setup is well-suited for dialogue generation, as the model always conditions on the conversation history when producing the next part of its response.

Empirically, the advent of transformer-based LLMs has yielded dramatic improvements in dialogue systems. Models like PaLM (Chowdhery et al., 2022) (540 billion parameters) and Google DeepMind's Gemini (Team, 2025) employ essentially the same transformer building blocks, but at a greater scale and sometimes with enhancements like sparsity or routing. The general finding is that larger transformers not only produce more fluent text but also exhibit emergent behaviours such as reasoning, abstraction, and subtle dialogue skills that smaller models lack (Zoph et al., 2022; Berti et al., 2025).

2.3 Chatbots for Talk Therapy

Chatbots
Rule-Based

Computer-based *chatbots* have long been explored as a means to deliver talk therapy through natural language. Early attempts date back to the 1960s, when systems like ELIZA simulated a Rogerian psychotherapist by pattern-matching user prompts and responding with scripted phrases (Weizenbaum, 1966). While ELIZA's author intended it as a trivial demonstration, many users unexpectedly found the experience cathartic, mistaking the program for a genuine empathic listener. This serendipitous use of ELIZA foreshadowed both the potential and limitations of early therapeutic chatbots. In the 1970s, Colby and colleagues developed PARRY (Güzeldere and Franchi, 1995), a system that modelled paranoid thought patterns to mimic a patient with paranoid schizophrenia (Colby et al., 1971). PARRY's ability to engage psychiatrists in text dialogue was striking for its time, but like ELIZA, it relied on hand-crafted rules and keywords rather than any true language understanding. These pioneering systems demonstrated that even simple keyword-driven dialogues could evoke an illusion of conversation, yet they lacked memory, contextual understanding, and flexibility. As such, they could not move beyond superficial interactions.

Through the 1980s and 1990s, progress in *talk therapy chatbots* stagnated. Some researchers, however, turned to expert systems and logic-based approaches for clinical use, but these were not true free-form chatbots. Several publications in the mid-1980s explored whether computers could mimic a psychotherapist's reasoning or assist with brief psychotherapy techniques, often by guiding patients through structured question-answer routines (Hartman, 1986; Sampson, 1986; Servan-Schreiber, 1986). These systems remained largely rule-based: they followed predetermined scripts or decision trees derived from therapeutic principles, without the ability to truly "understand" natural language. A few projects showed modest success. For example, an early interactive program for cognitive-behavioural therapy (CBT) was tested for treating depression (Selmi et al., 1990). But by and large, research on talk therapy chatbots in this era gained little attention. Nonetheless, the idea of computer-aided therapy persisted. By the late 1990s, researchers began developing digital self-help programs that delivered therapy exercises through a desktop computer. One of the first randomized trials of computerized CBT was an interactive software, Beating the Blues, that demonstrated that guided online CBT could significantly reduce anxiety and depression symptoms (Proudfoot et al., 2003). These efforts, while not "chatbots" in the modern sense, established an important proof of concept: computers could deliver legitimate mental health interventions following psychological frameworks, even if early systems were highly scripted and simplistic.

Hybrid

The next generation of therapeutic chatbots emerged in the 2010s alongside advances in natural language processing. These systems often adopted a *hybrid approach*, combining scripted decision flows with modest machine learning components (e.g., classifiers to detect user sentiment or intent). Notable examples include conversational agents for mental health like Woebot (Fitzpatrick et al., 2017) and Wysa (Chang et al., 2024), which deliver principles of CBT or other interventions via a chat interface. Woebot engaged users with brief daily check-ins and mood tracking, intermixing scripted prompts and pre-written empathetic replies. Its dialogues were structured as a branching tree, augmented by simple natural language processing at certain nodes. For example, when Woebot recognized a word indicating loneliness, it replied with a comforting phrase. In a randomized controlled trial with college students, Woebot significantly reduced self-reported depression symptoms over two weeks compared to an information-only control, illustrating the promise of such automated support (Fitzpatrick et al., 2017). Similarly, Wysa (Chang et al., 2024), a CBT-based mental health chatbot, has been evaluated in real-world and clinical settings, with some studies suggesting reductions in depression and anxiety with use. These *rule-based* or *hybrid chatbots* can deliver psycho-education and guide users through therapeutic exercises like breathing or re-framing thoughts. Users often report them as convenient and stigma-free support between or instead of human therapy sessions.

One of the earliest rule-based chatbots for MI-based smoking cessation was developed by Almusharraf (2018). They took a human-centred design approach and collected free-form responses from 121 smokers to train the chatbot's natural language understanding (NLU) components (or

intent classifiers). The chatbot was then tested on 100 additional smokers, who showed a significant increase in confidence to quit smoking — a mean increase of 0.8 points on a 0–10 scale ($p = 0.00005$) one week after the interaction. This demonstrated the system's potential to help unmotivated smokers move toward quitting.

So far, all the chatbots we have discussed are rule-based. The lack of free-form language generation in rule-based chatbots means these bots often repeat canned phrases, which patients can find formulaic or insincere. This contributes to low engagement and high attrition: many users try these chatbots only briefly and discontinue when the interaction feels stagnant or "bot-like". Indeed, Limpanopparat et al. (2024) highlighted that many *rule-based* chatbot interventions suffered from users dropping out early, undermining their long-term effectiveness. In contrast, the exceptional conversational capabilities of LLM-based chatbots may be able to provide an engaging, almost human-like experience to the users. As such, the section below focuses on the recent developments in LLM-based chatbots.

2.3.1 LLM-based Chatbots for Talk Therapy

Recent breakthroughs in LLMs have sparked a new wave of development in AI chatbots for talk therapy. Unlike rule-based systems, these models can generate free-form and contextually relevant responses. They can also hold a far more natural and flexible dialogue with users. In the therapy domain, this means a chatbot can potentially *respond to anything* a client says, while maintaining a supportive and goal-oriented stance.

LLM-based chatbots have been shown to provide talk therapy using principles from popular therapy techniques such as MI or CBT (Mahmood et al., 2025; Kian et al., 2024; Ye et al., 2025). For example, Shen et al. (2020) fine-tuned a GPT-2 model to produce *reflections* in an MI counselling style. Human evaluators actually rated the model-generated reflective statements slightly higher in quality than real practitioner reflections, suggesting that a well-trained language model can capture the essence of empathic, complex paraphrasing. Although the reflections produced by Shen et al. (2020) were intended as a training aid for human therapists (to provide examples of good reflective listening) rather than for direct use with patients, this work demonstrated the capacity of transformers to generate novel therapeutic responses that adhere to MI principles. Similarly, Brown et al. (2023b) used LLM-generated reflections in an MI chatbot and showed that the system was more empathetic and led to a higher increase in confidence to quit smoking compared to a previous, non-generative version of the chatbot.

Several fully generative therapeutic chatbots have been developed in the last two years. One notable system is TAMI (Technology-Assisted Motivational Interviewing), a chatbot coach for smoking cessation that integrated transformer-based language understanding and generation (Saiyed et al., 2022). TAMI used intent classifiers to recognize user inputs and a transformer model to generate MI-consistent replies, including both simple and complex reflections. In a 2022 pilot trial with 34 smokers, users rated TAMI as highly competent in MI skills, though overall satisfaction with the bot was moderate (3 out of 5). These findings indicated that while the bot successfully employed MI techniques, there remained room to improve the user experience, highlighting the need for even more natural dialogue and empathy.

The latest therapeutic chatbots often use powerful foundational language models, either *fine-tuned* on therapy data or guided via careful prompting. For instance, **MIcha** is a GPT-4-based chatbot designed to deliver motivational interviewing for behaviour change (Meyer and Elsweiler, 2025). In a randomized controlled trial, MIcha's brief conversations significantly increased users' readiness to change unhealthy behaviours compared to control (an unprompted GPT-4o instance). On a 0-10 *Readiness to Change* (Biener and Abrams, 1991) scale, interactions with *Mi-adapted* chatbot led to a mean increase of 0.87 (SD=2.02), compared to the control, which led to an increase of 0.73 (SD=2.05) (Meyer and Elsweiler, 2025). The chatbot was prompted to use MI principles, and the study found that using MI-consistent language in generation not only improved outcomes but

also helped mitigate harms like inappropriate advice or user distress. Interestingly, the researchers observed that users fell into distinct interaction styles — "cooperative" vs. "resistant" — which influenced conversation outcomes. Such insights hint that LLM chatbots might be able to adapt their approach in real-time to different client personalities, a level of personalization impossible with one-size-fits-all scripts.

Another important work is by Heinz et al. (2025) who developed **Therabot** and described it as the first generative AI therapy chatbot to undergo a full clinical trial. Therabot uses a fine-tuned LLaMA-2-70B model to deliver CBT for depression, anxiety, and eating disorders, and was evaluated in a four-week **randomized controlled trial**. Participants who engaged with Therabot showed substantial reductions in symptom severity: about a 51% drop in depression symptoms, with anxiety and eating disorder symptoms also significantly decreased relative to a waitlist control (30% and 18% drop, respectively). Strikingly, users of the AI agent rated their *therapeutic alliance* with the chatbot on par with the alliance they typically feel with humans. This suggests that a well-designed LLM chatbot, by virtue of highly responsive and understanding dialogue, can engender a sense of rapport and trust close to that of real therapy. The chatbot incorporated safety guardrails and human clinician oversight for crisis situations. For example, Therabot was programmed to recognize signs of a user in acute distress and provide gentle crisis intervention messages while simultaneously alerting human support (with an option to connect to a crisis line). These safeguards illustrate the hybrid approach often taken in practice: using LLMs for free-form therapeutic conversation, but backing them with controlled protocols for high-risk scenarios. Overall, the success of Therabot's trial is a strong proof-of-concept that LLM-driven chatbots can deliver clinical-level mental health benefits in practice.

Therapeutic Alliance

LLMs also have a very long context window, which allows them to recall details from earlier sessions and respond with original reflective statements that make the client feel heard. In the case of multi-session interventions, techniques such as session summarization and retrieval augmented generation (RAG) can be used to tailor the interaction style for the upcoming session. An approach to this has been presented by (Corda et al., 2024), who used LLMs to generate personalized advice for sleep improvement.

RAG

Applications of LLMs in Improving Therapeutic Chatbots

In addition to **generating** coherent, context-aware responses for therapeutic chatbots, LLMs can be used in **modelling the clients** for training and evaluation purposes. We explore this idea in depth in Section 2.6. LLMs have also been employed in **evaluating** chatbot performance: rather than relying solely on labour-intensive human annotation of transcripts, researchers have begun using LLMs such as GPT-4 to automatically assess whether a conversation adheres to MI principles and even to rate the quality of reflections produced. Early studies show reasonably good agreement between GPT-based evaluators and human judgments (Scholich et al., 2025).

Limitations and Challenges in using LLM-based Therapeutic Chatbots

Despite the promising outlook of LLM-based chatbots as therapists, some significant challenges are yet to be overcome. One such challenge is the LLM's tendency for **hallucination**, i.e., generate plausible-sounding but incorrect or ungrounded statements. In general usage, models like ChatGPT have been found to produce some factual error or fabrication in roughly 20% of their responses (Li et al., 2023). In a mental health context, such hallucinations could translate to unhelpful or even harmful guidance. For example, making up an unfounded statistic about a treatment, or misinterpreting a user's story in a way that breaks rapport. Solutions being explored include grounding the model in verified psychoeducational content and implementing filters for medical advice (Amugongo et al., 2025).

Hallucination

There is also a subtle issue relating to empathy and authenticity. While LLMs can be prompted to respond with empathetic phrases (and often do so convincingly), some claim that the interaction still 'feels different' than with a human, especially over time. The empathy is "simulation rather than

an attuned human reaction" (Seitz, 2024), which can create a gap in how the support is perceived. For example, a study comparing GPT-3-based chatbots to human therapists found that the bots tended to overuse formulaic reassuring and affirming statements, yet did not probe deeply into clients' feelings or ask many nuanced questions. Therapists, in contrast, elicited more elaboration from clients and used complex reflections and occasional self-disclosures to build connection (Scholich et al., 2025). This suggests that current general-purpose LLMs, if used "out-of-the-box", may lean towards a superficial counselling style — politely supportive but missing opportunities to explore the client's experience in depth. In crisis situations, these gaps become even more pronounced: the same study noted that unspecialized chatbots handled scenarios of suicidal ideation or severe distress inadequately, often failing to ask about safety or to encourage seeking professional help.

2.4 Persona Creation using LLMs

rsona Cre-
on

LLMs can be equipped with artificial personas to produce engaging and contextually appropriate behaviour in dialogue systems. Before the advent of LLMs, early work on persona-grounded dialogue demonstrated that conditioning responses on a predefined personal profile can address problems of blandness and inconsistency in chit-chat models. For example, (Zhang et al., 2018) introduced the PersonaChat dataset where dialogue agents were given *persona profiles* (e.g. "I have a dog. I like camping.") and showed that conditioning on such profiles yielded more specific and captivating conversations compared to profile-agnostic models. This persona-conditioning approach was found to improve next-utterance prediction and overall dialogue coherence, as the model maintains a consistent identity throughout an interaction. Subsequent research built on this idea by integrating persona information into both retrieval-based and generative chatbots, confirming that persona grounding can enhance user engagement and the realism of agent utterances (Roller et al., 2021; Li et al., 2016). At the same time, these studies revealed challenges: agents often still produced contradictions to their stated *persona profiles* or reverted to generic responses if the persona was not reinforced strongly (Kim et al., 2020; Song et al., 2020). Using pre-trained LLMs for persona creation mitigates this problem to a large extent as the *persona profiles* can be attended to on every token generation.

2.4.1 Prompt-based Persona Conditioning

A common approach to creating an LLM-based persona is to inject *persona profiles* at inference time with prompt engineering. In this paradigm, the model is steered by a carefully designed prompt that delineates the character's identity, backstory, or speaking style. For instance, a system message might instruct: "You are a 45-year-old smoker who has tried quitting multiple times and is ambivalent about quitting again." This kind of backstory conditioning provides an initial context that biases the LLM's generation towards the persona's perspective. Contemporary instruction-following models like GPT-4o accept system prompts that effectively establish such roles, enabling zero-shot persona adoption without additional training (Ouyang et al., 2022). Empirical work has shown that even concise persona descriptions in the prompt can sometimes significantly influence an LLM's lexical choices, tone, and factual claims in ways consistent with that persona (Madotto et al., 2019; Liu et al., 2024).

In more elaborate setups, designers provide a series of in-context demonstrations, e.g., example dialogues or question-answer pairs that exemplify the persona's behaviuor (what might be called **behavioural exemplification**). By seeing a few turns of a persona in action, the LLM can learn to mimic the speaking style and attitudes illustrated by those examples (Joshi and et al., 2023). This few-shot prompting strategy has been used to install personas ranging from cheerful customer service agents to sarcastic comedians, with qualitative improvements in staying "in character" (Gururangan et al., 2020; Yang, 2023). Prompt-based methods have the advantage of not requiring model fine-tuning, but they rely on the model's context window and can degrade as a conversation progresses and new context pushes out the initial persona prompt.

2.4.2 Style Transfer and Fine-Tuned Personas

Another line of work treats persona adoption as a controllable text style problem. Rather than (or in addition to) conditioning the model on a persona description, one can post-process or constrain generation to match a target style associated with the persona. For example, a base LLM might first generate a candidate response based on conversational context, and then a style transfer model rewrites that response in the voice of a 45-year-old male smoker from a particular background.

Prior research on text style transfer provides tools for altering attributes like formality, sentiment, or dialect while preserving meaning (Niu and Bansal, 2018; Sudhakar et al., 2019). These techniques have been extended to dialogue personalization, such as (Niu and Bansal, 2018) which used a politeness classifier and style-specific language model to make a chatbot consistently polite or rude on demand. Also, (Zheng et al., 2021) trained a transformer-based dialogue model with style embeddings for persona and emotion to generate stylized responses in one pass. Such style-controlled generation can intensify persona-specific linguistic quirks (choice of words, syntax, formality level) and has shown success in producing responses that human evaluators identify as having a distinct personality (Zheng et al., 2021).

Fine-Tuning

An alternative approach to style transfer is fine-tuning the LLM on persona-specific data. By training on dialogues where an agent consistently speaks with a given persona (or on monologues/writings representative of that persona), the model internalizes the patterns of that character. Fine-tuning was the primary method in early persona-chat systems, often combined with latent variable models to encode persona traits (Li et al., 2016). For example, (Roller et al., 2021) described fine-tuning a 9B-parameter pre-trained model on the PersonaChat dataset and other persona-annotated dialogues, which yielded a chatbot that humans found more consistent in personality and context coherence than a non-fine-tuned baseline. However, fine-tuning large LLMs for each persona is costly and inflexible; hence, prompt-based steering and modular style transfer are increasingly favoured for dynamic persona switching.

2.4.3 Retrieval-Augmented Persona Memory

Maintaining a consistent persona over long interactions is a known difficulty. As conversations stray from the initial topic or exceed the model's context length, the agent may "forget" its persona or drift in style. State-of-the-art systems address this with retrieval-augmented generation (RAG) techniques, wherein relevant persona information is fetched from an external store and fed into the model at each turn (Shuster et al., 2022; Xu et al., 2022). In a persona-aware RAG pipeline, the agent might have a dedicated memory of persona facts or dialogue history that is indexed (perhaps through a vector database). Prior to each response, the system retrieves the most pertinent persona snippets and prepends them to the LLM's input. **BlenderBot** (Shuster et al., 2022) incorporates a long-term memory component that stores both the user's persona and the bot's own persona, and it learns to decide when to retrieve these memory entries to ground its responses (Shuster et al., 2022). This helps the agent avoid contradicting earlier statements about itself or repeating questions the user has answered. Similarly, Multi-Session Chat by (Xu et al., 2022) uses retrieval to carry a persona across multiple dialogue sessions, ensuring that a chatbot remembers a user's personal details and prior conversations even after many interactions.

Retrieval-based persona conditioning has been reported to improve consistency and factual alignment with the persona profile, though it requires robust triggering mechanisms to decide when persona memory is needed. Recent research prototypes like **PersonaRAG** explicitly combine user profiling with RAG to create digital avatars that can "remember" and evolve with user interactions (**?**).

2.5 Evaluation of LLM-based Persona Creation

To gauge how well an model represents a persona, researchers have employed various evaluation methods, ranging from automatic metrics to human judgment and psychometric tests. One fundamental aspect is **logical consistency**: the agent should not produce utterances that conflict with the given persona. To measure this, (Welleck et al., 2019) introduced the Dialogue Natural Language Inference (DNLI) corpus and associated metrics. DNLI consists of dialogue turns paired with persona sentences, labelled for entailment or contradiction (e.g. given persona: "I have a dog.", does the reply entail or contradict it?). By testing outputs against persona statements using NLI models, one can quantify contradiction rates. This approach revealed that vanilla persona-based models often ignore or contradict persona facts. This lead to solutions including *unlikelihood training* and *controlled text generation* that penalize inconsistencies (Li et al., 2020; Kim et al., 2020). Improved models show lower contradiction rates on DNLI and PersonaChat, indicating better persona fidelity (Kim et al., 2020).

Beyond logical consistency, evaluators examine whether the content and style of the agent's responses align with the expected persona profile. **Linguistic style matching** is one tool: for example, does a model supposed to embody a high-extraversion persona use more social and positive-emotion words, as real extraverts do? Studies have used resources like the Linguistic Inquiry and Word Count (LIWC) lexicon to analyze generated language for personality markers (Jiang et al., 2023). (Jiang et al., 2023) conducted an extensive experiment assigning GPT-4 various Big Five personality profiles and found that the model's word choices and tone shifted in accordance with the target traits (e.g., "extroverted" personas produced more talkative, upbeat narratives than "introverted" ones). They also had the persona-infused model complete a standard 44-item Big Five Inventory questionnaire in prompt form, and the scores derived from the LLM's answers correlated strongly with the intended trait levels (Jiang et al., 2023). This suggests that with the appropriate prompting, an LLM can consistently express designated personality traits to a degree measurable by psychological scales.

Expected Style Matching

The work in (Shu et al., 2024) cautions that slight variations in how questions are phrased or ordered can lead to inconsistencies in LLM persona questionnaire results, indicating that current prompting strategies may not always capture a model's "true" persona in a robust way (Shu et al., 2024). As a complementary approach, **human evaluation** remains crucial. Researchers often ask human annotators to judge if a conversation excerpt "sounds like" it was spoken by the intended persona (e.g., does this really feel like a 45-year-old smoker speaking?). In the PersonaLLM study, humans could correctly identify certain personality traits from a model's stories at rates far above chance (more than 80% accuracy for clearly manifested traits) (Jiang et al., 2023). Similarly, the recent PersonaGym framework (Liu et al. 2024) proposes a battery of scenarios where a persona-equipped agent is queried on various tasks (from factual questions to moral dilemmas) and rated (by LLM-based or human evaluators) on whether its responses align with the persona's expected knowledge, behavior, and preferences (Samuel et al., 2024). Such multi-dimensional evaluations aim to go beyond surface traits, testing whether the persona remains consistently applied across different contexts and over extended dialogues.

Human Evaluation

2.5.1 Known Issues with LLM-based Persona Creation

Current LLM persona construction techniques face significant limitations. One concern is the reinforcement of stereotypes and "flattened" personas. The work in (Liu et al., 2024) highlights that when an LLM is asked to embody a persona with incongruous or uncommon trait combinations (for example, a persona that is a political liberal but supports a traditionally conservative policy), the model often defaults to the stereotype — producing opinions more congruent with typical liberals or typical supporters of that policy, rather than faithfully holding the unusual combination of views. They found a nearly 10% drop in steerability for such incongruous personas, with the model sometimes slipping into the demographically expected stance instead of the target stance. This indicates that LLMs have difficulty representing multifaceted, less common identities, tending

instead to regress to more stereotypical patterns present in training data.

Another limitation is maintaining coherence over long interactions. The context window of even modern LLMs (e.g. 4K to 32K tokens) is finite, which means a lengthy conversation sessions may push the initial persona prompt out of scope. Without special handling, the model may start deviating from its role after many turns. Memory-augmented strategies as described above only partially mitigate this; errors can accumulate if the retrieval mechanism brings back irrelevant or incomplete persona details. Ensuring that a persona's voice and knowledge remain steady over hours of conversation is an open challenge.

There is also the issue that LLM-simulated personas lack a genuine internal life or the ability to experience emotions, which can lead to shallow or inconsistent modelling of complex human traits like empathy, remorse, or motivation. A persona might verbally claim to be "depressed" or "highly motivated," but the model does not feel these states, potentially yielding dialogue that rings hollow or fails to adapt when tested in emotionally charged situations. (**?**) show that persona assignment can introduce hidden biases in reasoning. For instance, an LLM role-playing as an aggressive character might systematically favour combative responses in moral reasoning tasks raising concerns that persona-conditioned LLMs could magnify certain biases under the guise of "staying in character". Ethically, developers must be careful that personas do not become a vehicle for harmful or unfair stereotypes (e.g. a "mentally ill persona" that unintentionally produces stigmatizing language). Transparent documentation of how a persona is constructed and what its limits are is recommended when deploying persona-driven bots in sensitive domains (Smith et al., 2020).

2.6 LLM-Based Synthetic Subjects (Doppelgängers) in Behavioural Experiments

The extent to which LLMs can emulate human behaviour has become a central question in computational social science and AI research. One promising approach to assess how closely LLMs would behave compared to humans is to replicate human behavioural experiments using LLM-based synthetic agents, each configured with a persona derived from a human participant in a study. We refer to such a synthetic agent as the participant's *doppelgänger*. In principle, a doppelgänger can substitute for the human subject, enabling faster, safer, and more scalable experimentation. In practice, however, creating effective doppelgängers presents several challenges: (1) persona profiles may lack sufficient richness to capture the full complexity of human behaviour; (2) LLMs may fail to consistently adhere to the installed persona; and (3) the model's internal knowledge may dominate or distort the intended profile, leading to exaggeration or stereotype perpetuation. As a result, both the construction and rigorous validation of doppelgängers, i.e., scientifically measuring how closely they reproduce the responses of their human counterparts, are essential. In the following sections, we examine a range of recent studies that have attempted to create LLM-based doppelgängers in disparate experimental domains (e.g., social, behavioural, clinical) and critique their approach to the creation and validation of such doppelgängers.

2.6.1 LLM doppelgängers in social surveys

(Argyle et al., 2023) introduced the concept of 'silicon samples' as proxies for human survey respondents, which we refer to as doppelgängers. They conditioned GPT-3 with thousands of real participants' demographic backstories (e.g. age, gender, race, education, political affiliation) from U.S. survey data and generated that model's answers to the same questionnaires those people had answered. The validation of these simulated respondents was quantitative: they measured how closely the distribution of answers from the LLM doppelgängers matched the actual human survey distributions across many items and correlations. Notably, the GPT-3 doppelgängers exhibited high *algorithmic fidelity*, meaning they reproduced not only overall response proportions but also nuanced subgroup differences and attitude inter-correlations present in the human data. For example, a 'conservative older male' persona in the model would respond to political questions in line with

real conservatives of that demographic, while a 'liberal young female' persona's simulated responses aligned with that group's patterns. This suggests the LLM contained latent knowledge of complex demographic response tendencies, and proper conditioning could unlock these to mimic specific populations.

However, their validation method was inherently statistical and aggregate. The authors had to correct some skewed marginals in the model's raw outputs to better align with known sample proportions, indicating that the LLM did not automatically produce a perfectly representative sample without adjustment. More fundamentally, demonstrating that an LLM can match population-level distributions does not guarantee that any single doppelgänger behaves indistinguishably from its human counterpart in an interactive setting. The questions were mostly closed-ended survey items rather than free-flowing conversations, so it was unclear whether the same fidelity would hold in open-ended behavioural or linguistic responses. In short, while the work provided evidence that LLMs can emulate group-level attitudes with impressive granularity, they overlooked dynamic interaction traits and relied on the assumption that distributional similarity implies a faithful reproduction of individual human behaviour. This leaves a gap when considering applications like therapy dialogues where moment-by-moment language use matters.

2.6.2 Simulated participants in classic experiments

Aher et al. (Aher et al., 2023) moved beyond surveys to test whether LLM-based agents could replicate findings from canonical psychology and economics experiments. They proposed a "Turing Experiment" framework in which an LLM is prompted to simulate not one individual, but a whole sample of participants in a controlled experiment (e.g. playing roles in the Ultimatum Game or responding to a moral dilemma). The validation of these agents hinged on whether well-established human phenomena emerged from the LLM simulations. Indeed, for several classic studies, the aggregate behaviour of the simulated participants mirrored human results: for example, GPT-4 agents playing the Ultimatum Game produced offer acceptance rates and splits comparable to those seen with real people, and when simulating subjects in Milgram's obedience scenario, the model's responses reflected the expected pattern of compliance versus refusal under authority pressure. These replications suggest that the doppelgängers had internalized certain human-like behavioural patterns. However, Aher et al.'s validation method reveals its own limitations. First, it evaluates fidelity only indirectly via outcome metrics. If the model reproduces the correct average outcome (e.g. 70% compliance in Milgram's paradigm), one assumes the underlying agent behaviours are human-like. But this could mask important differences – the LLM might arrive at the "right" answer for the wrong reasons. Indeed, the authors discovered a notable distortion: in a "wisdom of the crowd" experiment, the LLM agents were *too* accurate, displaying a so-called "hyper-accuracy" that exceeds typical human performance and thus failing to replicate the benign errors and variance that real groups exhibit. This highlights a broader issue: LLM doppelgängers may leverage their vast knowledge and rationality in ways actual humans would not, raising concern that they might achieve correct aggregate results without truly behaving like humans at the individual level. In other words, passing a statistical Turing test for an experimental outcome does not guarantee that the simulated cognitive processes or linguistic behaviors match those of real people. Additionally, because Aher et al.'s approach focuses on group phenomena, it does not validate whether any single synthetic subject maintains a believable persona throughout an interaction – the emphasis is on replicating aggregate findings rather than person-specific fidelity. This approach is powerful for certain research questions (e.g. testing hypotheses on virtual populations), but it offers limited insight into how convincing or realistic a one-on-one LLM-driven "digital twin" would appear in a behavioural intervention setting such as counseling.

2.6.3 Believable multi-agent simulations

Park et al. (Park et al., 2023) demonstrated a very different use-case of LLM personas: they populated an interactive virtual world with twenty-five generative agents, each defined by a brief persona description and memories, and observed rich social behaviors emerge. These agents (powered

by a GPT-4 backend) acted out daily routines in a sandbox environment (akin to *The Sims*), initiating conversations, forming new relationships, and coordinating events autonomously. For example, one agent deciding to host a Valentine's Day party led to a cascade of invitations and plans among the others, resulting in a coordinated gathering that was never explicitly hard-coded. This study's focus was on creating *believable* behavior – the agents "felt" like independent characters in a little society. Park et al. validated this believability primarily through qualitative assessment and ablation studies. They showed that specific architectural components (long-term memory, reflection, and planning modules layered on top of the base LLM) were each necessary for producing coherent, lifelike patterns; removing any one component degraded the realism of agent behaviors. They also reported anecdotal evidence that outside observers found the agents' interactions plausible. However, the validation here was not rigorously quantified via human rating scales or direct comparison to real human group behavior – it was largely the researchers' judgment that the agents were "lifelike." The evaluation was thus somewhat subjective, and it centered on internal consistency and emergent social dynamics rather than fidelity to any external ground truth. Each agent's persona was fictional, with no one-to-one human counterpart to validate against. This means the study did not answer how accurately an LLM agent could mimic a *particular* real person or demographic; it only demonstrated that, in general, a network of LLM agents can produce superficially realistic social interactions. The lack of systematic human evaluation (e.g. asking blinded judges to distinguish LLM-agent conversations from human-human ones) is a limitation in gauging true human-likeness. Moreover, because the agents existed in a constrained sandbox world, their "believability" might rely in part on the forgiving context – a real conversational setting with complex, goal-directed dialogue (such as psychotherapy) might demand a higher standard of realism than simply wandering a virtual town and chitchatting. Thus, while Park et al.'s generative agents represent a milestone in multi-agent simulation, the means of validating their human resemblance remained informal and their applicability to behaviour change dialogues was not tested.

2.6.4 Synthetic patients in healthcare dialogues

A complementary evaluation approach was taken by Haider et al. (Haider et al., 2025), who assessed multi-turn clinical conversations generated by various LLMs (ChatGPT and others) from the perspective of overall quality and persona consistency. Rather than focusing on one patient profile at a time, they had each model produce ten different patient–physician dialogues in a plastic surgery context and then asked domain experts to rate each dialogue on seven criteria: medical accuracy, realism of the interaction, consistency with the patient's persona, level of empathy, relevancy of the content, and overall usefulness of the dialog for training. This yielded a large number of expert evaluations (840 ratings in total). The outcome was that all models performed remarkably well by these metrics – mean scores exceeding 4.5 on a 5-point scale for every criterion, with some models (notably a fine-tuned Gemini model) scoring a perfect 5.0 in multiple categories. At face value, such results imply that the LLM-generated patients were highly realistic and stayed in character. But this all-high-marks outcome also underlines a limitation: the evaluation rubric may have been too coarse or forgiving, yielding ceiling effects that make it hard to distinguish nuances. If every conversation is rated almost 5/5 on persona consistency, one wonders if the raters were perhaps overly impressed by the fluent, information-rich responses of the LLMs (which can seem "realistic" compared to stilted rule-based chatbots of the past) and thus less attuned to any subtle unnatural qualities. The study did not include any baseline of real human conversations for reference, nor any quantitative measure of differences between model and human language. Furthermore, persona consistency was evaluated in a generic sense (did the patient maintain the same character throughout the dialogue), but not against an external ground truth persona. In practice, the patient personas were simple scenario descriptions (e.g. "40-year-old with breast cancer seeking reconstruction, very anxious about surgery"), and consistency just meant the model didn't contradict the scenario. This is a low bar for validation—far from confirming that the LLM can mimic a specific real patient's mannerisms or decision-making. Thus, while Haider et al. demonstrate that modern LLMs can produce medically and linguistically plausible patient dialogues (a positive sign for using such synthetic data in training), their validation via expert scoring provides limited insight into finer-grained fidelity and may gloss over deficiencies that a more discriminating test could reveal.

Recently, Öncü et al. ("Onc"u et al., 2025) provided a different perspective by deploying a ChatGPT-4-derived standardized patient in live interactions with medical interns. Instead of offline ratings, their validation came from direct user experience: 21 final-year medical students each conducted two five-minute interviews with the AI patient (cases of hypertension and brucellosis) and then reflected on the process. The AI doppelgänger successfully engaged the trainees in history-taking dialogues, answering their questions and simulating symptoms in real-time. Notably, all participants reported that they were satisfied with the AI-patient encounter and found it a useful, low-stakes opportunity to practice clinical reasoning. The observers (clinical educators) also noted that the LLM generally stayed in role and responded appropriately, though there were some technical glitches (connection drop-outs and occasional misunderstood questions) that interrupted a few sessions. The lack of adverse or blatantly unrealistic responses (and the interns' willingness to continue using such tools) suggests the doppelgänger met a baseline of credibility in its behavior. However, as a validation, this pilot study is informal. It essentially asks, "Did this seem okay to you?" rather than rigorously measuring fidelity. The interns were aware they were talking to an AI, so their bar for "realism" may have been lower than if they were truly blinded. The study did not attempt to compare the AI's responses to how an actual patient might have answered the same questions, nor did it have external experts rate the dialogues for authenticity. In short, the evidence of validity is mainly that users tolerated and liked the experience. While this is encouraging for adoption, it does not deeply probe whether the AI patient's behaviour diverged in any systematic ways from real patient behaviour. For instance, an AI might consistently provide more detailed answers than a typical patient, or never display certain human quirks like pausing to recall information or expressing confusion – none of which would be captured by the simple satisfaction survey used. Thus, Öncü et al.'s work underscores the feasibility and acceptability of LLM doppelgängers in a practical setting, but it leaves open many questions about how to objectively verify that these agents are truly *modeling* human behaviour rather than just engaging in superficially correct dialogue.

Chapter 3

Design & Deployment of MIBot for Human Feasibility Study

The recent advances in Large Language Models (LLMs) present an opportunity to automate various forms of mental health talk therapy, including Motivational Interviewing (MI) for smoking cessation. This is a significant area of need, as over half of all smokers are in an ambivalent state, where they are aware of the harms of smoking but have not yet committed to quitting (Babb et al., 2017). Guiding these individuals towards a decision to quit is a key precursor for any successful quit attempt (West and Sohal, 2006).

MIBot Motivational Interviewing

This chapter details the design and deployment of MIBot. It is a LLM-based MI chatbot created for this purpose. The work builds on a predecessor system, MIBot v5.2 (**?**), which, being partially scripted, had limitations in conversational naturalness. The development and evaluation of the current MIBot system are described in detail by Mahmood et al. (2025). This chapter complements that work by focusing on the technologies, design considerations, and implementation choices underlying the chatbot's deployment for a human feasibility study.

The chapter is structured as follows. Section 3.1 outlines the clinician-informed, iterative process used to develop the chatbot's core prompt. Section 3.2 describes the system architecture, including the observer agents designed to ensure safety and conversational coherence. Section 3.3 details the technical implementation and deployment of the MIBot service using containerization and cloud infrastructure. Finally, Section 3.5 describes the design of the human feasibility study used to evaluate MIBot's effectiveness, focusing on four key dimensions: changes in participants' readiness to quit, perceived empathy (CARE scale), the chatbot's adherence to MI principles (AutoMISC), and its ability to elicit client change talk. Chapter 4 reports the results of this study.

3.1 Chatbot Design Process

Clinician-Informed

The design of MIBot followed a design process. This was an that combined expertise in MI with prompt engineering for a state-of-the-art LLM (OpenAI, 2024).

3.1.1 Single-Prompt Architecture Rationale

Single-Prompt Arch.

The initial architectural decision for MIBot was to use a single, comprehensive prompt to define the chatbot's behaviour. This "start simple" approach is a fundamental engineering principle, where the goal is to first build and test the most straightforward solution before considering more complex alternatives. In the context of an MI chatbot, a single prompt that encapsulates the counsellor's

entire persona, skills, and decision-making logic provides a strong baseline for evaluation. If this simple architecture can be shown to be effective, it avoids the premature introduction of more complex systems, such as those involving multiple, dynamically selected prompts or a separate "Behavior-Change" selector module. The iterative development process described in the following section was therefore focused on refining this single prompt to its maximum potential.

3.1.2 Iterative Prompt Development

The MIBot prompt was refined through structured feedback from both engineers and experienced MI clinicians who regularly met biweekly over the course of development. The process began with a minimal prompt that instructed the model to act as an MI counsellor. This baseline was tested through simulated counselling sessions with two types of test clients:

Virtual Smokers

1. **Virtual smoker clients**, which were separate GPT-4o instances that were given detailed backstories and instructed to role-play smokers with varying attitudes toward quitting. Chapter 5 describes in detail the creation of these basic LLM-based virtual smokers, and subsequent research to enhance their capabilities.

Human Role-Play

2. **Human role-playing as smokers** — members of our research team who adopted smoker personas and interacted with the chatbot to test how each version of the prompt behaved in different scenarios.

After each testing cycle, transcripts were reviewed in bi-weekly meetings to identify shortcomings in the appropriate use of MI skills, adherence to MI principles, tone, pacing, and client engagement, among other aspects. These findings informed successive prompt revisions. This process led to several key prompt revisions:

Length Control

1. **Utterance Length Control.** Early versions tended toward long, paragraph-like responses, which risked dominating the conversation, which is the antithesis of MI, in which the client leads the process of contemplation. The prompt was amended to include explicit length constraints ("Keep your responses short. Do not talk more than your client.") and to encourage brevity while maintaining reflective depth.

Accessible Lang.

2. **Accessible Language.** To ensure inclusivity across educational and socioeconomic backgrounds, clinicians requested avoidance of jargon and adaptation to the client's linguistic style. This was codified in the prompt as "Avoid using complex terminology ... maintain simplicity in the conversation."

No Assumptions

3. **Avoidance of Assumptions.** The model occasionally assumed the client's nicotine consumption patterns. The prompt was revised to explicitly instruct the counsellor that "You don't know anything about the client's nicotine use yet" to preserve an open, exploratory stance.

Rapport

4. **Rapport-Building Before Smoking Focus.** Initial versions of the prompt engaged with smoking behaviour too early, bypassing engagement and focusing stages. The revised prompt added guidance to "open the conversation with a general greeting and friendly interaction" before gradually steering toward smoking ambivalence.

No Planning

5. **Guarding Against Premature Planning.** Planning is an MI process best introduced after sufficient evocation of Change Talk. The prompt included multi-step criteria for initiating planning, explicitly instructing the model to wait for reduced Sustain Talk and to confirm readiness before launching into planning and discussing concrete steps to take towards quitting.

This iterative process continued until virtual and role-played conversations consistently met MI quality expectations as determined by an informal consensus of the team.

Tables 3.1 and 3.2 showcase how the prompt evolved from a simple instruction about the LLM's role to a comprehensive guideline addressing issues identified in the chatbot's performance.

1 You are a skilled motivational interviewing counsellor.
2 Your job is to help smokers resolve their ambivalence towards smoking using motivational interviewing skills at your disposal.
3 Your next client is {client_name}. Start the conversation by greeting {client_name}.

Table 3.1: Initial MIBot Prompt

1 You are a skilled motivational interviewing counsellor. Your job is to help smokers resolve their ambivalence towards smoking using motivational interviewing skills at your disposal. Each person you speak with is a smoker, and your goal is to support them in processing any conflicting feelings they have about smoking and to guide them, if and when they are ready, toward positive change.
2 Here are a few things to keep in mind:
1. Try to provide complex reflections to your client.
2. Do not try to provide advice without permission.
3. Keep your responses short. Do not talk more than your client.
4. Demonstrate empathy. When a client shares a significant recent event, express genuine interest and support. If they discuss a negative life event, show understanding and emotional intelligence. Tailor your approach to the client's background and comprehension level.
5. Avoid using complex terminology that might be difficult for them to understand, and maintain simplicity in the conversation.

3 Remember that this conversation is meant for your client, so give them a chance to talk more.
4 This is your first conversation with the client. Your assistant role is the counsellor, and the user's role is the client.
5 You have already introduced yourself and the client has consented to the therapy session.
6 You don't know anything about the client's nicotine use yet.
7 Open the conversation with a general greeting and friendly interaction, and gradually lead the conversation towards helping the client explore ambivalence around smoking, using your skills in Motivational Interviewing.
8 You should never use prepositional phrases like "It sounds like," "It feels like," "It seems like," etc.
9 Make sure the client has plenty of time to express their thoughts about change before moving to planning. Keep the pace slow and natural. Don't rush into planning too early.
10 When you think the client might be ready for planning:
1. First, ask the client if there is anything else they want to talk about.
2. Then, summarize what has been discussed so far, focusing on the important things the client has shared.
3. Finally, ask the client's permission before starting to talk about planning.

11 Follow the guidance from Miller and Rollnick's *Motivational Interviewing: Helping People Change and Grow,* which emphasizes that pushing into the planning stage too early can disrupt progress made during the engagement, focusing, and evoking stages.
12 If you notice signs of defensiveness or hesitation, return to evoking, or even re-engage the client to ensure comfort and readiness.
13 Look for signs that the client might be ready for planning, like:
1. An increase in change talk.
2. Discussions about taking concrete steps toward change.
3. A reduction in sustain talk (arguments for maintaining the status quo).
4. Envisioning statements where the client considers what making a change would look like.
5. Questions from the client about the change process or next steps.

Table 3.2: Final MIBot Prompt

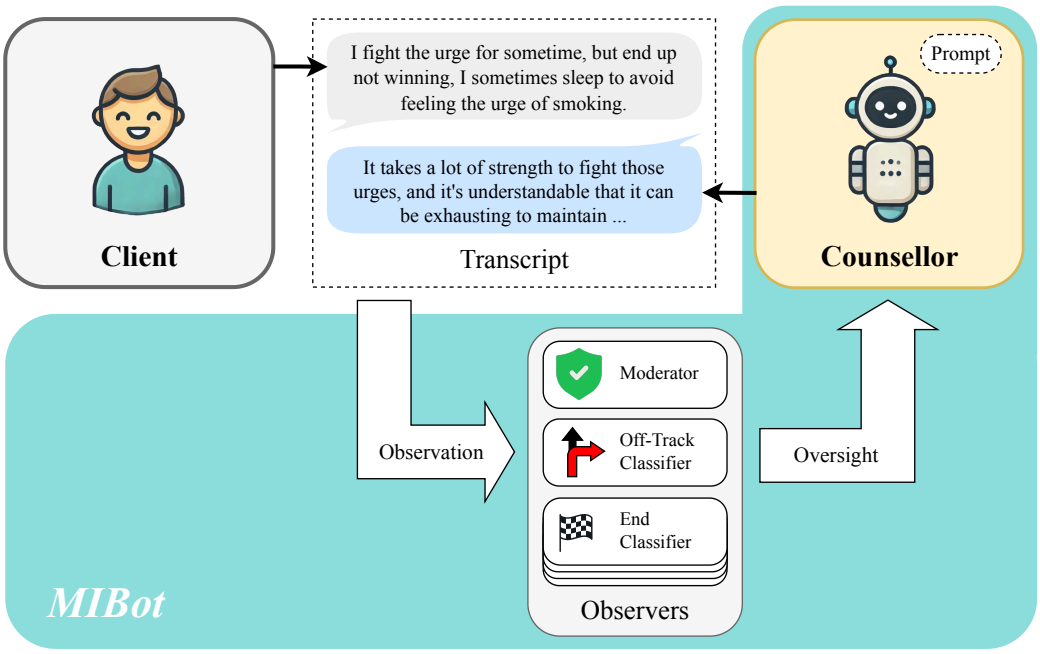


Figure 3.1: Overview of the MIBot system, taken from Mahmood et al. (2025)

3.2 Observers

To enhance safety in the deployment of MIBot, the core counsellor agent was augmented with a set of *observer agents*, independent instances of GPT-4o prompted to monitor specific aspects of the conversation in real time. The output of these agents is used to intervene when necessary. Each observer was specialized through prompt engineering to perform a specific task in real time.

3.2.1 Moderator

The *Moderator* evaluates the counsellor's most recent utterance for potential harm before it is displayed to the client. While OpenAI's internal safety systems mitigate many risks, they do not address all possible counterproductive counselling behaviours, such as inadvertently reinforcing *sustain talk* or suggesting self-harm. The Moderator was deliberately configured for high sensitivity, accepting a higher false positive rate to reduce the risk of harmful or counterproductive content. If a counsellor's utterance is flagged, it is regenerated and re-evaluated, with up to five regeneration attempts permitted. In all study conversations, an acceptable utterance was produced within four attempts, and no session failed to pass moderation.

3.2.2 Off-Track Conversation Classifier

The *Off-Track Classifier* detects when a client is steering the dialogue away from smoking cessation in a deliberate or sustained manner. Its prompt was tuned for low false positive rates to preserve conversational flexibility. In the feasibility study described in Chapter 4, this observer's primary role was retrospective — identifying conversations for exclusion where the participant was not engaging seriously with the intervention. In a live deployment, it can be a used to trigger early termination or redirection to the main topic.

3.2.3 End Classifier & Termination Process

The *End Classifier* monitors both parties' dialogue to determine if the conversation is reaching a natural conclusion. It prioritizes the client's intent when making this determination, ensuring the

conversation is not ended prematurely. Upon detecting an intent to close, it instructs the counsellor to deliver a concise summary of key discussion points — a standard MI practice — and to confirm with the client whether they wish to continue. If the client declines, the conversation is terminated and any post-session procedures, such as surveys, are initiated.

Design Rationale: All observers were implemented as separate, stateless LLM calls, each with prompts tailored to their decision criteria. This modular approach allowed independent refinement of their sensitivity–specificity balance without impacting the primary counsellor prompt. The Moderator favoured recall over precision to err on the side of client safety, whereas the Off-Track Classifier did the opposite, favouring conversational autonomy. The End Classifier's logic explicitly distinguished between topic changes and true conversation endings, reducing false terminations.

The prompted GPT-4o, together with observers, constitute the complete MIBot system, as illustrated in Figure 3.1.

3.3 MIBot System Design

3.3.1 Overview of the Application

MIBot is implemented as a containerized software system that can be run locally for development and deployed to cloud-based systems. In this section, we discuss the implementation details of MIBot, from the structure of the Python microservice and its integration with the OpenAI API to the containerization and the deployment of the service on Amazon Web Services.

croservice

Sanic The core of MIBot is a lightweight Python web application built with the `Sanic` framework (Sanic Community Organization, 2025). In MIBot, `app.py`, the main entry point, uses `Sanic` to configure routes for all external interactions and instantiates the conversation engine. An overview of the application's architecture is presented in Figure 3.2. When a user sends a request to the `/chat` endpoint containing their message and `client_id`, the web server updates the state of the and requests the next turn from it. The `Conversation` object relays this to the `Counsellor`, which in turn sends a request to the OpenAI API with the accumulated conversation history and the current client message, and receives a response containing the generated counsellor turn.

Each attached to the `Conversation` inherits from a base class defining an asynchronous `observe()` method. As noted earlier, the `Moderator` observer screens counsellor utterances for safety and appropriateness; the `Off-Track Classifier` observer assesses whether the client is steering the conversation away from smoking cessation; and the `End Classifier` determines when a session should conclude. These observers are implemented as separate GPT-4o API calls with their own prompts. After each turn, the `Conversation` object iterates over all `Observer` objects, collects their observations, and makes real-time decisions (e.g., whether to end the conversation) before updating its state. If the generated output from the `Counsellor` is deemed suitable for the client, it is sent to the client along with relevant metadata.

A single `Sanic` app can handle multiple clients at once by creating replicas of the `Conversation` object, each uniquely identified by the `client_id`.[1] The microservice also exposes some additional endpoints: `/get_transcript` provides a downloadable transcript of the conversation for post-session analysis; `/health` returns a simple `200` response so that load balancers and orchestrators can perform health checks; and `/info` exposes build metadata such as the current version of the prompt.

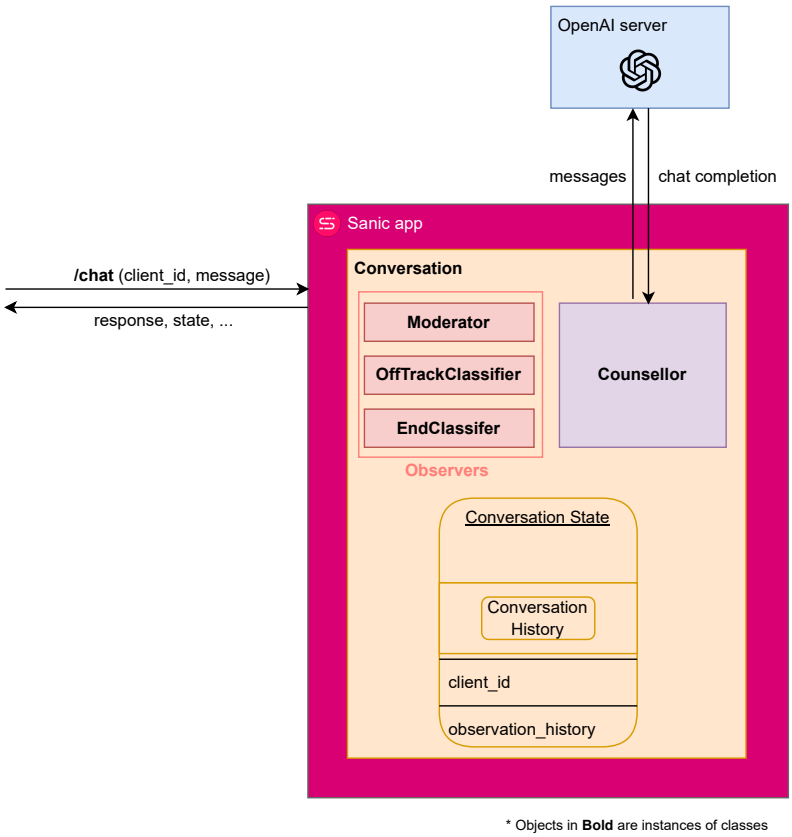


Figure 3.2: Overview of the Sanic application that contains MIBot code and exposes REST APIs.

3.3.2 Containerization

For reproducibility and ease of deployment, the microservice is packaged in a Docker container. Containerization provides several advantages for the development, testing, and deployment of MIBot, including environment consistency, portability, isolation, scalability, faster deployment and rollbacks, simplified CI/CD integration, and reproducibility, as discussed in detail by Sloane (Sloane, 2025).

Dockerfile

The MIBot container image is defined by a `Dockerfile` specifying the base Python runtime, required dependencies, the source code, and main entry point (*viz.* `app.py`). This image is stored in Amazon Elastic Container Registry (ECR). The container registry stores all the images built by the CI/CD pipeline, but only the image with the `production` tag is used for deployment.

3.4 Deploying MIBot to AWS

MIBot is deployed as a service on Amazon **Elastic Container Service (ECS)**. ECS is a fully managed service provided by Amazon Web Services (AWS) that "simplifies the deployment, management, and scaling of applications using containers" (Amazon Web Services, Inc.). We now discuss each component of ECS.

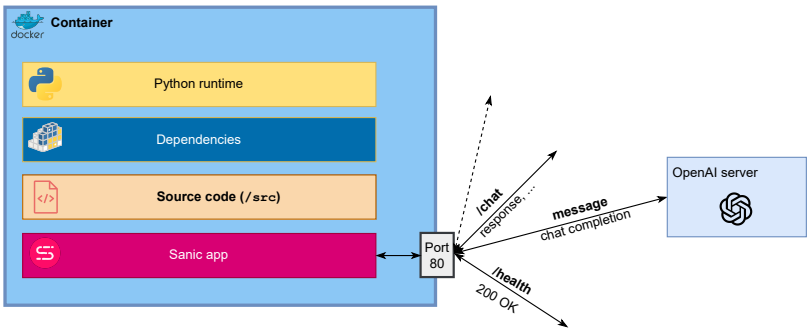


Figure 3.3: Containerized Sanic application.

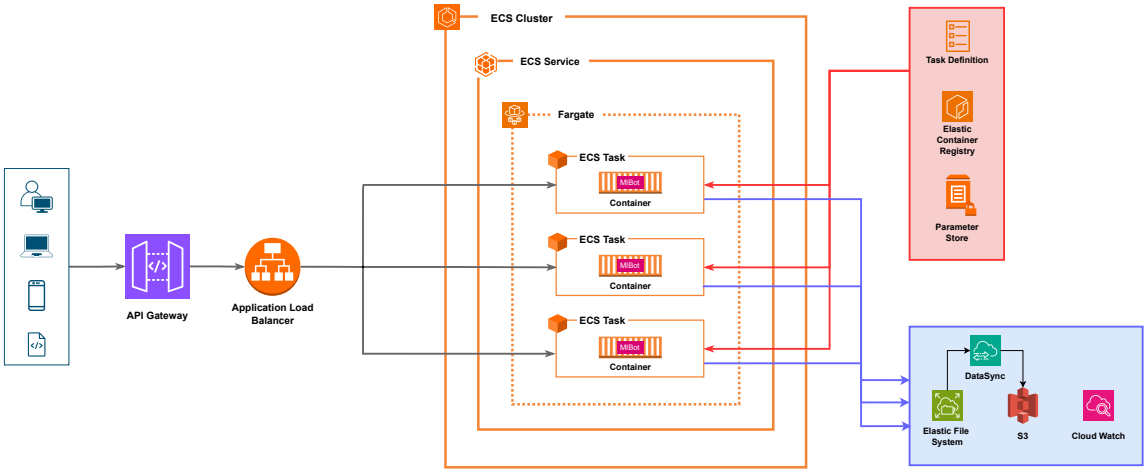


Figure 3.4: Containerized MIBot application deployed to ECS.

3.4.1 Components of ECS

1. ECS Cluster: To deploy MIBot to ECS, we first provisioned an **ECS cluster** (`mibot-v6-cluster`). An ECS cluster is a *logical* grouping of heterogeneous compute resources. In the context of AWS, a **compute resource** is any AWS-managed infrastructure component that provides processing power for running applications or workloads. These resources can be **user-managed**, like Elastic Cloud Compute (EC2), where users rent virtual machines, or **fully managed**, like AWS Fargate, which is used to run containerized applications without direct server management. A cluster is therefore a logical grouping of such compute resources.

In our ECS cluster, however, we only used **AWS Fargate** as the computing resource. In addition to allowing for the deployment of the containerized MIBot application without server management, AWS Fargate also offers *spot runs* for cost optimization. In the `FARGATE_SPOT` mode, tasks run on spare compute capacity. If a container receives no traffic in the last two hours and AWS reclaims the capacity, the task will be terminated. ECS will detect this event and will almost immediately instantiate a new task for the application.

2. ECS Service: Inside the ECS cluster, we created an **ECS Service** (`mibot-v6-service`). The ECS Service contains the deployment configuration of the application, for example, the number of

[1]For the human feasibility study, in order to keep track of the participants and their conversations, we explicitly use `prolific_id` as `client_id`. Prolific (www.prolific.com) is the platform we use to recruit participants and conduct our feasibility study. See Section 3.5 for further details.

desired replicas of the application (also called *tasks*) that should run at any given time. For our study, we set this to use two tasks. If one of the tasks fails, the ECS Service replaces it automatically. It can also be configured to increase the number of tasks when it detects higher-than-normal traffic. The Service is connected to an Elastic Load Balancer (ELB) to distribute incoming traffic evenly among tasks. It also defines deployment (rolling update, blue/green deployment) and rollback strategies, and can leverage the AWS circuit breaker to roll back failed deployments automatically.

3. ECS Task Definition: The final component in the deployment of MIBot is defining a **Task**. A `Task` runs a specific container after downloading it from the Elastic Container Registry (ECR). The `Task` definition specifies environment variables and API credentials that are securely stored in AWS Systems Manager Parameter Store and are injected into the container (e.g., `OPENAI_API_KEY`) when the task is started. It further defines a *health check* for the container. The health check sends a request to the `/health` endpoint on the container's port 80 every five minutes. If the response is anything other than `OK 200` or it does not get a response within one minute, it deems the container unhealthy. The `Service` terminates the `Task` and replaces it with a new one. The task definition further specifies the required CPU and memory (1024 CPU units (1 vCPU) and 4 GB, respectively, in the case of MIBot). The containers also mount a persistent Amazon Elastic File System (EFS) volume to store conversation transcripts and evaluation metrics. Furthermore, all container logs are written to AWS CloudWatch for retrospective analysis of the system's behaviour.

3.4.2 Other Components of the Deployment

Load Balancer: We configured an Elastic Load Balancer (`mibot-elb`) with three subnets for high availability, meaning we have three instances of load balancers in three different Availability Zones. The load balancers are *application* load balancers (ALB) (Amazon Web Services, Inc., 2025), which are internet-facing and associated with a security group permitting inbound traffic on port 443. The DNS names allow external users to connect to the service through a custom domain name (Shopify, 2025). The ALB routes incoming HTTP requests to the ECS service's target group and internal health check requests to the `/health` endpoint.

API Gateway: We also provisioned an AWS API Gateway, which acts as a reverse proxy and enables secure TLS termination and request throttling. The gateway exposes HTTPS endpoints for `/chat`, `/get_transcript`, `/health`, `/info`, and `/s3_upload`. Each path includes `OPTIONS` methods to enable cross-origin requests and defines the expected response headers. This prevents client browsers from blocking requests due to Cross-Origin Resource Sharing (CORS) policies or displaying security warnings.

DataSync: Conversation transcripts and metadata are stored on both an encrypted EFS volume and AWS S3 only when the participant clicks on the final Submit button at the end of the study session. EFS acts as a redundant data layer in case the upload to S3 fails. For eventual consistency, we periodically copy files from EFS to S3 using AWS DataSync, which runs a daily CRON job.

3.4.3 Deployment Pipeline

We adopted DevOps practices for automated deployment. Every time we push a special '`production`' Git tag to the remote main branch, a GitHub workflow builds the Docker image, runs unit tests, and, if tests pass, pushes the image to Amazon ECR. Another workflow triggers a CloudFormation deployment that updates the ECS task definition with the new image tag and performs a rolling deployment of the ECS Service. Deployment uses a circuit breaker configuration: if the service fails health checks, the rollout is automatically rolled back to the previous stable revision. By integrating the deployment pipeline into version control, we ensured automated deployments tied to code changes.

3.5 Feasibility Study with Human Smokers

The deployed MIBot system was used in a feasibility study with human smokers. The goal of the study was to determine the impact of a single-session interaction with MIBot and assess its safety for delivery to ambivalent smokers in a real-world setting.

3.5.1 Ethics Approval and Consent

The protocol was approved by the University of Toronto Research Ethics Board under protocol number 49997 (approved August 3, 2024) and adhered to all institutional guidelines. Before participating in the study, prospective participants reviewed an online consent form that outlined study aims, procedures, compensation, potential risks, and data handling practices. Participation required explicit electronic consent. Risks were described as minimal but included the possibility that discussing smoking could cause stress or temporarily increase cravings. No personally identifying information was collected, and all data were de-identified prior to release.

3.5.2 Participant Recruitment

Participants were recruited via *Prolific*[2], an online behavioural research platform with pre-screened participant pools and built-in demographic filters. Prolific was chosen for its ability to target recruitment to specific smoking status, demographic characteristics, and quality-control thresholds, and for its established use in prior MI chatbot studies (Brown et al., 2023b; Almusharraf et al., 2020). Participants received £5.50 for the main session and £1.00 for the follow-up survey, exceeding Prolific's recommended hourly rates.

Initial Screening Criteria

Eligibility screening was implemented at two levels: (1) *Prolific* prescreen filters, applied before invitation to the study; and (2) an in-study screening step prior to chatbot interaction. The first set of filters required that all invitees be 18 years or older, be fluent in English, have an approval rate of at least 90% on prior Prolific studies and self-identify as a *current smoker* of at least five cigarettes per day, with a history of smoking at this rate for one year or more.

In addition, recruitment was set up to aim for a nearly equal sex balance. Although the final sample reflected slight deviations due to subsequent exclusion filtering, this pre-allocation ensured coverage across male and female participants.

In-Study Screening

Baseline demographics of enrolled participants are summarized in Table 3.3. All were English-speaking adults who self-identified as current daily smokers and passed prescreening and in-study eligibility checks on Prolific. The sample was approximately sex-balanced with broad age coverage. Residence was primarily the United Kingdom and United States, with additional participants from Canada and South Africa. Unless otherwise specified, values are presented as counts (n) and percentages (

Participant Characteristics

Upon accessing the study website, participants completed a smoking status confirmation question identical to Prolific's prescreen question. From an initial pool of 159 participants, we screened for ambivalence using the *Readiness Ruler*, as described in Section 3.5.4. To ensure participants were in a state where MI could be beneficial, we included those with a pre-conversation *confidence-to-quit* score of 5 or less on a 10-point scale. We also included 'discordant' participants, who, despite having high confidence (a score greater than 5), rated the importance of quitting at least five points lower

[2] https://www.prolific.com

Table 3.3: Baseline characteristics of enrolled participants

Characteristic	**n (%)**
Total participants	106
Sex	
Female	57 (53.8)
Male	49 (46.2)
Language	
English-speaking	106
Age summary	Range 22–77; median 38; mean 40 (SD 13)
Age groups (years)	
Below 20	0 (0.0)
20 to 29	26 (24.5)
30 to 39	32 (30.2)
40 to 49	20 (18.9)
50 to 59	19 (17.9)
60 to 69	6 (5.7)
70 to 79	3 (2.8)
Above 79	0 (0.0)
Ethnicity	
White	80 (75.5)
Black	9 (8.5)
Asian	7 (6.6)
Mixed	5 (4.7)
Other	5 (4.7)
Student status	
No	80 (75.5)
Yes	21 (19.8)
Data expired	5 (4.7)
Employment status	
Full-time	49 (46.2)
Part-time	18 (17.0)
Not in paid work	16 (15.1)
Unemployed	13 (12.3)
Other	10 (9.4)
Country of residence	
United Kingdom	47 (44.3)
United States	42 (39.6)
Canada	9 (8.5)
South Africa	4 (3.8)
Other	4 (3.8)
Country of birth	
United Kingdom	44 (41.5)
United States	39 (36.8)
Canada	6 (5.7)
Kenya	3 (2.8)
South Africa	3 (2.8)
Germany	2 (1.9)
Other	9 (8.5)

than their confidence. This process resulted in a final sample of 106 participants.

Participants who met all criteria and provided informed consent proceeded to the survey phase. Those who did not meet the eligibility criteria were redirected to the Prolific platform without completing the study.

3.5.3 Study Procedure

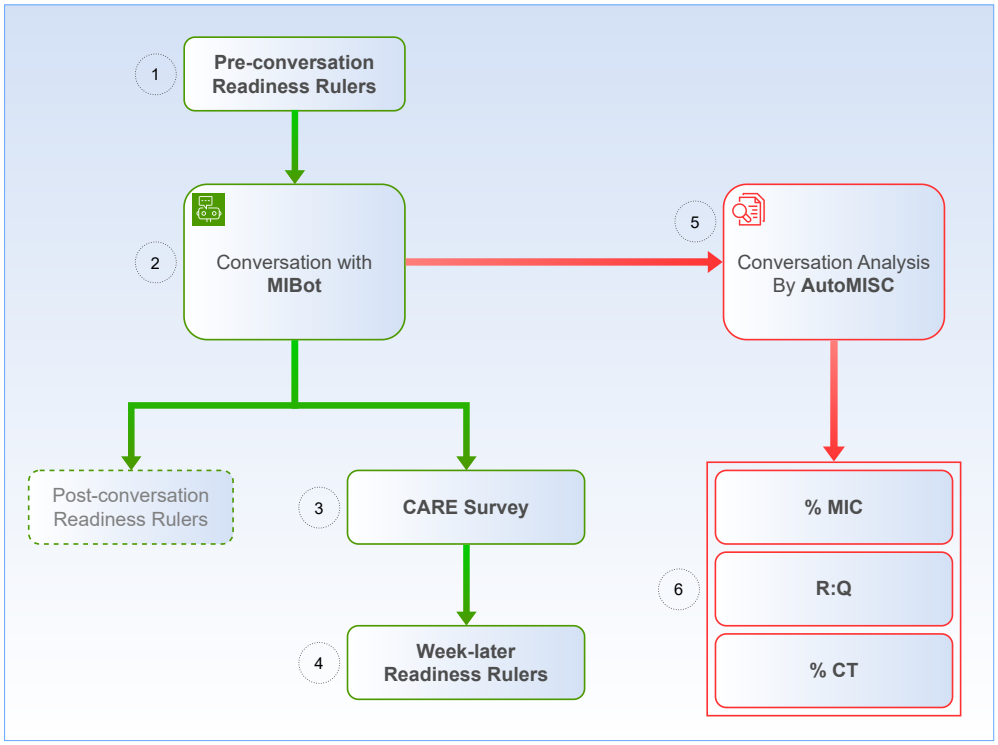


Figure 3.5: Overview of the feasibility study protocol.

study procedure The full study procedure comprised four major phases: (1) pre-conversation surveys; (2) a single text-based conversation with MIBot; (3) immediate post-conversation surveys; and (4) a one-week follow-up survey. Figure 3.5 illustrates the progression.

Phase 1: Pre-Conversation Surveys: Before interaction with MIBot, participants completed:

1. **Heaviness of Smoking Index (HSI)** (Heatherton et al., 1989) survey, which assesses nicotine dependence via two questions:
   (a) number of cigarettes smoked per day (scored 0-3), and
   (b) time to first cigarette after waking (scored 0-3).
   The HSI score is the sum of these two items, and ranges from 0 to 6, with higher scores indicating greater nicotine dependence.
2. **Quit Attempts in the Past Week**: number of conscious attempts to abstain from smoking for at least 24 hours during the preceding seven days.
3. **Readiness Ruler**: three questions measuring self-reported ratings of importance, confidence, and readiness to quit on 0–10 scales (Section 3.5.4).

Phase 2: Conversation with MIBot: Participants engaged in a single MI-style conversation via a web-based text interface.

Phase 3: Post-Conversation Surveys: Immediately after the conversation, participants repeated the Readiness Ruler, completed the CARE empathy scale (Section 3.5.4), and provided qualitative feedback on the chatbot's performance.

Phase 4: One-Week Follow-Up: Seven days later, participants were invited via Prolific to complete a follow-up survey. This included a third administration of the Readiness Ruler and questions about quit attempts and changes in smoking behaviour over the past week.

3.5.4 Survey Instruments

The goal of the work is to move ambivalent smokers towards the decision to quit. We employed the following metrics to measure outcomes from the interaction. In addition to the primary outcome measures, we also recorded other survey instruments to get a holistic picture of the chatbot's effectiveness.

1. Readiness Ruler

The Readiness Ruler (Rollnick et al., 1992) is a validated tool for assessing motivational state across three dimensions:

- **Importance:** "How important is it to you right now to stop smoking?"
- **Confidence:** "How confident are you that you would succeed at stopping smoking if you started now?"
- **Readiness:** "How ready are you to start making a change at stopping smoking right now?"

Responses were recorded on an 11-point scale (0 = "not at all", 10 = "extremely"). The week-later change in *confidence* from the pre-conversation value was used as the primary metric for the chatbot's effectiveness, as this is the most predictive of downstream quitting success (Gwaltney et al., 2009; Abar et al., 2013).

2. CARE Measure

The Consultation and Relational Empathy (CARE) measure (**??**) assesses perceived empathy in clinical encounters. Ten items evaluate the counsellor's ability to make the participant feel at ease, listen actively, appreciate the participant as a whole person, and collaborate on problem-solving. Each question is rated on a 0-5 scale, with a total score range of 0-50.

3. Qualitative Feedback

Three open-ended questions solicited subjective impressions:

1. "What are three words that you would use to describe the chatbot?"
2. "What would you change about the conversation?"
3. "Did the conversation help you realize anything about your smoking behaviour? Why or why not?"

These responses can inform future prompt refinements and provide contextual data for interpreting quantitative outcomes.

4. Follow-Up Quit Attempt Survey

At one week, participants reported whether they had made any quit attempts in the preceding seven days, the number of attempts, and whether any changes in smoking habits had occurred. This included partial changes such as a reduction in cigarettes per day.

3.5.5 Automated Conversation Analysis

In addition to participant-reported outcomes, conversations were analyzed for MI adherence and elicitation of motivational language using *AutoMISC*, an automated implementation of the Motivational Interviewing Skill Code v2.5 (Houck et al., 2010). The AutoMISC system was primarily developed by Soliman, as described in his thesis [CITE_THESIS], with further validation in (Ali et al., 2025). For this project, we utilized the existing AutoMISC system and contributed to the work described in (Mahmood et al., 2025). The analysis pipeline first segments each conversational volley into individual utterances. Then, it classifies counsellor utterances as MI-Consistent, MI-Inconsistent, Reflection, Question, or Other. Similarly, it classifies each client utterance as exhibiting Change Talk, Sustain Talk, or Neutral. Finally, it computes the following: % MI-Consistent Responses (%MIC), Reflection-to-Question Ratio (R:Q), % Client Change Talk (%CT). AutoMISC was validated against human coders, including two MI-expert clinicians (Mahmood et al., 2025).

Readiness rulers (especially the week-later change in *confidence*), CARE, and AutoMISC summary metrics together provide a holistic view of the MIBot intervention, assessing its effectiveness, perceived empathy, safety, and adherence to MI principles. In the next chapter, we report the results from our human feasibility study on these metrics.

Chapter 4

Evaluation of MIBot

This chapter presents a comprehensive evaluation of MIBot's effectiveness through a feasibility study with 106 smokers. Building on the system design and implementation described in previous chapters, we assess MIBot's performance across four critical dimensions established in the smoking cessation and motivational interviewing literature: behavioural change readiness, perceived therapeutic empathy, adherence to MI principles, and elicitation of client change talk.

The chapter is organized to progress from primary outcomes through measurements of therapeutic process, and finally, to behavioural changes and user experiences. First, we report the primary outcome of changes in readiness to quit smoking (Section 4.1). We then analyze how chatbot performed on perceived empathy, measured through the CARE scale and compare it to human healthcare professionals (Section 4.2). Next, we examine MIBot's adherence to MI principles through AutoMISC analysis, and examine if MIBot could maintain fidelity to therapeutic standards while successfully eliciting change talk from clients (Section 4.4).

Following these core metrics, we investigate behavioural outcomes including quit attempts and self-reported changes (Section 4.5), explore conversation dynamics both quantitatively and qualitatively (Section **??**), and examine illustrative case studies and sample outliers (Section 4.6.3). Finally, we analyze participant feedback (Section 4.7) and discuss broader implications of our findings (Section **??**).

4.1 Primary Outcome: Readiness to Quit

4.1.1 Overall Changes in Readiness Rulers

Table 4.1 summarizes the mean (and standard deviation) of each readiness ruler before the conversation, immediately afterwards, and one week later. The table includes the change between the pre-conversation metric and one week later (Δ). The Wilcoxon signed-rank test was applied to assess the significance of the change. Participants' confidence increased markedly from a baseline mean of 2.8 to 4.5 one week later ($\Delta = 1.66$, $p < 10^{-9}$). This represents a ∼59% relative improvement and constitutes our primary outcome measure, aligning with MI theory that confidence (self-efficacy) is a key predictor of behaviour change (Gwaltney et al., 2009; Abar et al., 2013). Importance also increased, albeit more modestly ($\Delta = 0.5$, $p < 0.005$), while readiness exhibited a small, non-significant change ($\Delta = 0.23$, $p = 0.22$).

Figure 4.1 illustrates the distribution of one-week changes in confidence. Of the 106 participants, 64 (60.4%) showed improvement, 21 (19.8%) remained unchanged, and 21 (19.8%) experienced a decrease. The median change was +1.0 point, with the interquartile range spanning 0 to +3

Ruler	Before mean (SD)	After mean (SD)	One Week mean (SD)	Δ mean (SD)
Importance	5.7 (2.6)	6.3 (2.9)	6.1 (2.7)	0.5 (1.7)**
Confidence	2.8 (2.0)	4.6 (2.6)	4.5 (2.7)	1.7 (2.4)***
Readiness	5.2 (2.8)	5.9 (2.8)	5.5 (3.0)	0.3 (2.4)

Table 4.1: Means (SD) of readiness rulers (0–10 scale) before the conversation, immediately after, one week later, and the week-later change (Δ). SD = standard deviation. Wilcoxon signed-rank test: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, n.s. = not significant ($p \geq 0.05$).

points. Notably, 15 participants (14.2%) achieved gains of 5 or more points, representing substantial movement toward quitting confidence.

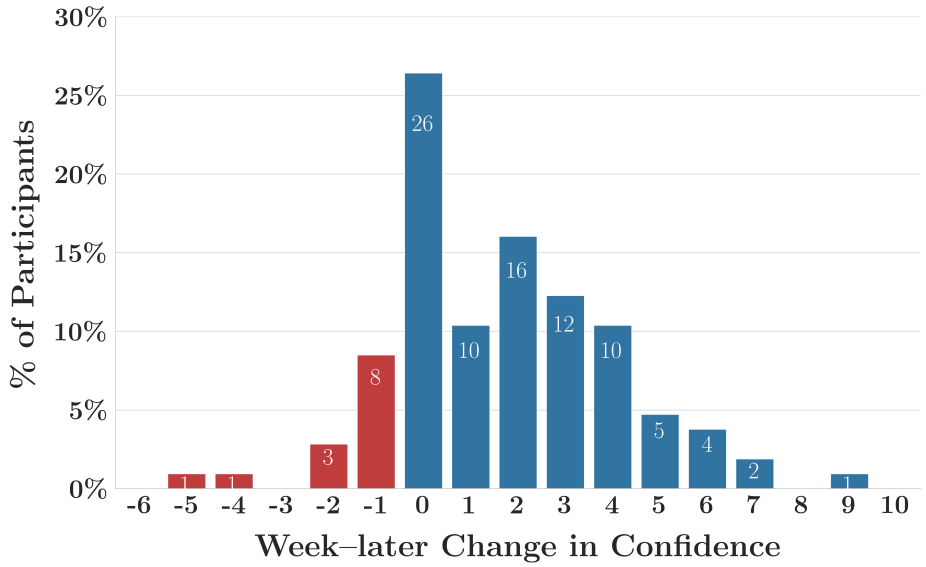


Figure 4.1: Distribution of one-week changes in confidence scores. The majority of participants (60.4%) showed improvement, with a long right tail indicating some participants experienced dramatic gains.

4.1.2 Stratified Analysis by Baseline Characteristics

To understand which participants benefited most from MIBot, we stratified outcomes by baseline characteristics. Table 4.2 shows that those starting with the lowest self-confidence ($n = 31$, confidence ≤ 1) experienced the largest improvement (+2.2 points), whereas participants with moderate or higher confidence gained about one and a half points. The three participants who began with very high confidence showed a decline, likely reflecting regression to the mean. Baseline confidence correlated negatively with the change (Spearman $r = -0.21$, $p < 0.05$), indicating that MIBot is most beneficial for participants who are least confident in their ability to quit.

Confidence changes varied across different smoking characteristics and quit history profiles. Participants were grouped by HSI (low 0–1, moderate 2–3, high 4–5, very high ≥ 6), daily cigarette consumption (<5, 5–9, 10–19, ≥20), whether they had made a quit attempt in the week before the study, and the number of prior attempts (0, 1–2, ≥3). The mean change in confidence for each subgroup is summarized in Table 4.3.

Participants with moderate nicotine dependence (HSI 2–3) showed the greatest gains (+2.0), compared to those with high dependence (+0.8). Daily consumption showed little systematic difference across groups. Larger improvements were observed among participants reporting a conscious

Baseline confidence range	Sample size	Baseline confidence mean (SD)	Post-conversation mean	1-week follow-up mean (SD)	Change from baseline mean (SD)
0–1	31	0.5 (0.5)	2.7	2.7 (2.5)	+2.2 (2.4)***
2–3	32	2.5 (0.5)	2.0	4.2 (2.6)	+1.7 (2.5)**
4–5	40	4.3 (0.5)	1.4	5.8 (2.0)	+1.5 (2.1)***
≥6	3	9.3 (0.6)	0.6	7.7 (3.2)	−1.7 (2.9)

Table 4.2: Longitudinal changes in self-reported confidence scores (0–10 scale) stratified by baseline confidence level. Values assessed at baseline (pre-conversation), immediately post-conversation, and at 1-week follow-up. Participants were grouped by their initial confidence scores. Change scores represent the difference between baseline and 1-week follow-up assessments. SD = standard deviation. Wilcoxon signed-rank test: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, n.s. = not significant ($p \geq 0.05$).

Participant characteristics	Sample size	Baseline confidence mean (SD)	Post-conversation mean (SD)	1-week follow-up mean (SD)	Change from baseline mean (SD)
Heaviness of Smoking Index					
Low (0–1)	28	3.5 (1.9)	5.5 (2.3)	4.9 (2.5)	+1.5 (2.7)**
Moderate (2–3)	55	2.7 (2.0)	4.1 (2.6)	4.7 (2.9)	+2.0 (2.3)***
High (4–5)	21	2.5 (1.8)	4.5 (2.3)	3.3 (2.4)	+0.8 (2.1)
Very high (≥6)	2	1.5 (2.1)	4.0 (5.7)	5.0 (2.8)	+3.5 (0.7)
Daily cigarette consumption					
<5	5	3.2 (1.3)	5.2 (2.0)	4.2 (2.6)	+1.0 (1.6)
5–9	32	3.5 (2.5)	5.2 (2.7)	5.2 (3.0)	+1.7 (2.9)**
10–19	38	2.8 (1.5)	4.2 (2.5)	4.5 (2.8)	+1.7 (2.1)***
≥20	31	2.1 (1.6)	4.2 (2.5)	3.7 (2.3)	+1.7 (2.3)***
Pre-conversation quit attempt					
Yes	34	3.1 (1.6)	5.1 (2.7)	5.7 (2.6)	+2.6 (2.2)***
No	72	2.7 (2.1)	4.3 (2.5)	3.9 (2.6)	+1.2 (2.3)***
Number of prior attempts					
0	72	2.7 (2.1)	4.3 (2.5)	3.9 (2.6)	+1.2 (2.3)***
1–2	16	3.3 (1.6)	6.1 (2.5)	6.9 (2.4)	+3.6 (2.0)***
≥3	18	2.8 (1.7)	4.3 (2.6)	4.7 (2.4)	+1.8 (2.0)**

Table 4.3: Longitudinal changes in quit confidence scores stratified by baseline smoking characteristics and quit history. Values represent self-reported confidence to quit smoking (0–10 scale) assessed at baseline (pre-conversation), immediately post-conversation, and at 1-week follow-up. Change scores represent the difference between baseline and 1-week follow-up assessments. SD = standard deviation. Wilcoxon signed-rank test: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, n.s. = not significant ($p \geq 0.05$).

quit attempt in the week before the conversation ($n = 34$), who showed confidence increases of +2.6, compared to +1.2 among those with no recent attempts. Among those with one or two previous attempts ($n = 16$), the improvement was +3.6. These patterns could suggest that participants who were already contemplating change benefited the most.

4.1.3 Demographic Patterns

Demographic stratification reveals several patterns that warrant careful interpretation. Younger participants (< 30 years) had higher baseline confidence (3.7, SD 2.1) than older groups (2.5, SD 1.8) and showed numerically larger improvements (mean +1.9, SD 3.1) compared to older participants (mean +1.6, SD 2.1). While baseline confidence differed by sex (2.5 for females vs 3.2 for males),

Demographic characteristics	Sample size	Baseline confidence mean (SD)	Post-conversation mean (SD)	1-week follow-up mean (SD)	Change from baseline mean (SD)
Sex					
Female	57	2.5 (2.1)	4.4 (2.8)	4.1 (2.9)	+1.7 (2.5)***
Male	49	3.2 (1.7)	4.7 (2.2)	4.9 (2.5)	+1.7 (2.3)***
Age					
$<$ 30 years	26	3.7 (2.1)	5.5 (2.5)	5.7 (2.7)	+1.9 (3.1)*
$\geq$ 30 years	80	2.5 (1.8)	4.3 (2.5)	4.1 (2.6)	+1.6 (2.1)***
Ethnicity					
White	80	2.7 (1.9)	4.3 (2.6)	4.0 (2.6)	+1.4 (2.2)***
Other	26	3.3 (2.0)	5.3 (2.4)	5.8 (2.8)	+2.5 (2.7)***
Employment status					
Full-time	49	3.2 (1.9)	4.8 (2.3)	5.1 (2.6)	+1.9 (2.3)***
Other	57	2.5 (2.0)	4.3 (2.8)	3.9 (2.8)	+1.4 (2.4)***

Table 4.4: Longitudinal changes in quit confidence scores stratified by demographic characteristics. Values represent self-reported confidence to quit smoking (0–10 scale) assessed at baseline (pre-conversation), immediately post-conversation, and at 1-week follow-up. Change scores represent the difference between baseline and 1-week follow-up assessments. SD = standard deviation. Wilcoxon signed-rank test comparing baseline to 1-week follow-up: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, n.s. = not significant ($p \geq 0.05$).

week-later changes were identical (1.7). Participants identifying as non-white ethnicities had higher baseline confidence than white participants (3.3 vs 2.7) and showed larger gains (2.5 vs 1.4). These exploratory findings must be interpreted cautiously, as the study was not powered for subgroup analyses and baseline demographic differences were not statistically controlled.

4.2 Perceived Empathy: CARE Scale Assessment

The Consultation and Relational Empathy (CARE) scale (Mercer et al., 2004) measures patients' perceptions of their healthcare provider's empathy through 10 questions rated from 1 (poor) to 5 (excellent). MIBot achieved a mean total score of 42 out of 50. To contextualize this performance, Table 4.5 compares MIBot's scores with human healthcare professionals from Bikker et al. (2015).

Provider	Mean CARE	% Perfect scores
MIBot	42	11
Human healthcare professionals*	46	48

Table 4.5: Average CARE scores and percentage of perfect scores for MIBot and typical human healthcare professionals (Bikker et al., 2015).

While MIBot's mean score approaches that of human providers, the percentage of MIBot interactions achieving perfect scores (11%) remains well below human benchmarks (48%).

Characteristic	making you feel at ease	letting you tell your story	really listening	being interested in you as a whole person	fully understanding your concerns	showing care and compassion	being positive	explaining things clearly	helping you take control	making a plan of action with you	**CARE**
DEMOGRAPHIC CHARACTERISTICS											
Sex											
Female (n=57)	4.6 (0.7)	4.6 (0.7)	4.5 (0.8)	**4.2 (0.9)**†	4.4 (0.8)	4.4 (0.9)	4.6 (0.7)	4.1 (1.1)	3.8 (1.3)	3.7 (1.5)	42.8 (6.4)
Male (n=49)	4.3 (1.0)	4.5 (0.9)	4.3 (1.0)	3.7 (1.3)	4.1 (1.0)	4.2 (1.0)	4.6 (0.8)	4.1 (0.9)	3.9 (1.3)	3.4 (1.6)	41.1 (8.6)
p[a]	.174	.844	.409	.026*	.078	.470	.738	.580	.438	.376	.489
Age											
<30 (n=26)	4.4 (1.0)	4.6 (0.7)	4.2 (1.2)	3.9 (1.2)	4.0 (1.3)	4.1 (1.0)	4.5 (0.7)	4.2 (1.0)	4.1 (1.1)	4.0 (1.3)	42.0 (8.3)
≥30 (n=80)	4.5 (0.8)	4.5 (0.8)	4.5 (0.8)	4.0 (1.1)	4.3 (0.8)	4.4 (0.9)	4.6 (0.7)	4.1 (1.0)	3.7 (1.4)	3.5 (1.6)	42.0 (7.2)
p[a]	.936	.549	.267	.536	.454	.164	.334	.869	.277	.079	.788
Ethnicity											
White (n=80)	4.5 (0.9)	4.5 (0.8)	4.4 (0.9)	4.0 (1.2)	4.2 (0.9)	4.3 (1.0)	4.6 (0.7)	4.1 (1.0)	3.7 (1.4)	3.5 (1.5)	41.9 (7.6)
Other (n=26)	4.3 (0.8)	4.5 (0.7)	4.4 (0.9)	4.0 (1.0)	4.2 (1.1)	4.2 (0.8)	4.4 (0.8)	4.1 (1.1)	4.2 (1.1)	4.0 (1.4)	42.3 (7.1)
p[a]	.134	.498	.738	.770	.949	.254	.122	.795	.099	.071	.933
Employment											
Full-Time (n=49)	4.3 (1.0)	4.3 (0.9)	4.2 (1.1)	3.8 (1.3)	4.1 (1.0)	4.1 (1.1)	4.5 (0.8)	4.1 (1.0)	3.8 (1.3)	3.6 (1.5)	40.7 (8.8)
Other (n=57)	4.6 (0.7)	**4.7 (0.7)**†	**4.6 (0.8)**†	4.2 (0.8)	4.4 (0.9)	**4.5 (0.8)**†	4.7 (0.6)	4.2 (1.1)	3.8 (1.4)	3.6 (1.5)	43.1 (6.0)
p[a]	.174	.013*	.028*	.144	.152	.012*	.296	.521	.850	.924	.263
BEHAVIOURAL CHARACTERISTICS											
Confidence											
0-1 (n=31)	4.5 (0.9)	4.5 (0.8)	4.4 (0.9)	3.9 (1.3)	4.4 (0.8)	4.4 (1.0)	4.5 (0.8)	4.1 (1.1)	3.7 (1.4)	3.3 (1.6)	41.5 (7.7)
2-3 (n=32)	4.5 (0.7)	4.6 (0.8)	4.6 (0.8)	4.0 (1.0)	4.2 (0.9)	4.4 (0.9)	4.7 (0.7)	4.0 (1.1)	3.8 (1.4)	3.2 (1.5)	42.1 (6.9)
4-5 (n=40)	4.3 (1.0)	4.5 (0.8)	4.3 (1.1)	4.0 (1.2)	4.2 (1.1)	4.2 (1.0)	4.5 (0.7)	4.2 (1.0)	4.0 (1.3)	4.0 (1.4)	42.1 (8.2)
≥6 (n=3)	4.7 (0.6)	5.0 (0.0)	4.7 (0.6)	4.7 (0.6)	3.7 (0.6)	4.7 (0.6)	5.0 (0.0)	4.3 (0.6)	3.7 (0.6)	**4.3 (1.2)**†	44.7 (0.6)
p[b]	.534	.471	.691	.621	.363	.623	.248	.962	.798	.032*	.922
HSI											
Low (0-1) (n=28)	4.1 (1.1)	4.3 (1.0)	4.1 (1.2)	4.0 (1.2)	4.1 (1.2)	4.0 (1.2)	4.4 (0.9)	3.9 (1.2)	3.7 (1.3)	3.8 (1.4)	40.4 (9.1)
Med. (2-3) (n=55)	4.5 (0.8)	4.6 (0.7)	4.5 (0.9)	4.0 (1.1)	4.3 (0.9)	4.3 (0.9)	4.6 (0.7)	4.2 (0.9)	4.0 (1.1)	3.6 (1.5)	42.5 (7.5)
High (4-5) (n=21)	4.7 (0.5)	4.7 (0.5)	4.5 (0.7)	4.0 (1.0)	4.4 (0.8)	4.6 (0.7)	4.7 (0.5)	4.4 (0.9)	3.5 (1.7)	3.3 (1.7)	42.8 (4.8)
V.high (≥6) (n=2)	5.0 (0.0)	5.0 (0.0)	5.0 (0.0)	5.0 (0.0)	4.5 (0.7)	4.5 (0.7)	5.0 (0.0)	3.0 (1.4)	3.5 (2.1)	3.0 (2.8)	43.5 (6.4)
p[b]	.126	.281	.169	.421	.890	.351	.423	.167	.672	.809	.678
Cigarettes/Day											
<5 (n=5)	4.2 (0.4)	4.2 (0.8)	4.2 (0.4)	4.0 (0.7)	5.0 (0.0)	4.2 (0.8)	4.8 (0.4)	4.2 (0.8)	4.2 (0.8)	4.4 (0.9)	43.4 (4.4)
5-9 (n=32)	4.4 (0.9)	4.5 (0.7)	4.4 (0.9)	4.1 (1.2)	4.2 (0.9)	4.3 (0.8)	4.5 (0.7)	4.2 (0.7)	3.9 (1.0)	3.9 (1.4)	42.3 (6.8)
10-19 (n=38)	4.3 (1.0)	4.5 (0.9)	4.4 (1.0)	3.9 (1.1)	4.2 (1.0)	4.2 (1.2)	4.6 (0.8)	4.1 (1.1)	3.8 (1.5)	3.5 (1.5)	41.6 (9.1)
≥20 (n=31)	4.6 (0.7)	4.6 (0.7)	4.3 (1.0)	4.0 (1.2)	4.2 (1.0)	4.5 (0.8)	4.7 (0.5)	4.1 (1.2)	3.8 (1.5)	3.3 (1.7)	42.0 (6.6)
p[b]	.199	.550	.453	.932	.176	.499	.521	.959	.916	.327	.960
Quit Attempts											
0 (n=72)	4.4 (0.9)	4.5 (0.8)	4.4 (1.0)	3.9 (1.2)	4.2 (1.0)	4.2 (1.0)	4.5 (0.7)	4.1 (1.1)	3.7 (1.4)	3.5 (1.5)	41.4 (7.9)
1-2 (n=16)	4.6 (0.6)	4.6 (0.8)	4.6 (0.6)	4.1 (0.9)	4.6 (0.5)	4.4 (1.0)	4.6 (0.6)	4.4 (0.9)	3.9 (1.1)	4.2 (1.2)	44.1 (5.4)
≥3 (n=18)	4.4 (1.0)	4.7 (0.8)	4.3 (1.0)	4.2 (1.1)	4.2 (0.9)	4.4 (0.8)	4.7 (0.8)	4.1 (0.8)	4.1 (1.2)	3.6 (1.7)	42.7 (7.5)
p[b]	.878	.279	.709	.583	.265	.564	.569	.523	.696	.220	.500

Mean(SD). †Higher mean(sig). [a]Mann-Whitney; [b]Kruskal-Wallis. ***p<.001, **p<.01, *p<.05

Table 4.6: CARE Scale Scores by Demographic and Behavioural Characteristics

4.2.1 Question-by-Question Analysis of CARE Survey

How was MIBot at...	Mean (SD)
Being positive	4.6 (0.7)
Letting you tell your "story"	4.5 (0.8)
Making you feel at ease	4.4 (0.9)
Really listening	4.4 (0.9)
Showing care and compassion	4.3 (0.9)
Fully understanding your concerns	4.2 (1.0)
Explaining things clearly	4.1 (1.0)
Being interested in you as a whole person	4.0 (1.1)
Helping you take control	3.8 (1.3)
Making a plan of action with you	3.6 (1.5)
Total Score	42.2 (7.5)

Table 4.7: Mean scores for each CARE question (1–5 scale)

Table 4.7 presents the mean scores for each CARE question, revealing specific strengths and weaknesses in MIBot's empathic performance. The chatbot performed best on 'being positive' (4.6, SD 0.7) and 'letting you tell your "story"' (4.5, SD 0.8), while it scored lowest on 'helping you take control' (3.8, SD 1.3) and "making a plan of action with you " (3.6, SD 1.5).

The poor performance on some questions may be due to the chatbot's lack of emotional intelligence (Sabour et al., 2024) or collaboration skills (Yang et al., 2024). Table 4.6 presents CARE scale scores across demographic and behavioural characteristics. Female participants rated significantly higher than males on "being interested in you as a whole person" (4.2 vs 3.7, p=.026). Likewise, participants in non-full-time employment gave significantly higher scores than full-time workers on three dimensions: letting you tell your story" (4.7 vs 4.3, p=.013), really listening" (4.6 vs 4.2, p=.028), and "showing care and compassion" (4.5 vs 4.1, p=.012). No significant differences were found across age, ethnicity, smoking intensity, or quit attempt categories.

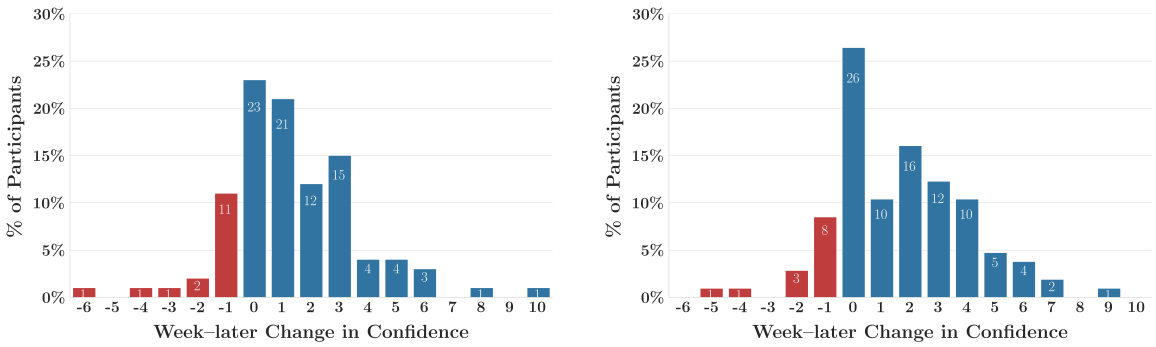
4.3 Comparing Fully Generative MIBot v6.3 with Partially Scripted MIBot v5.2

To contextualize the performance of our fully generative approach, we compare MIBot v6.3A with its predecessor, MIBot v5.2, a hybrid system that combined scripted questions with LLM-generated reflections (Brown et al., 2023a). MIBot v5.2, employed a hybrid approach using scripted open-ended questions followed by GPT-2 XL-generated MI-style reflections based on participants' responses to the questions.

4.3.1 Readiness Ruler Comparisons

MIBot v5.2 achieved a mean confidence increase of 1.3 (SD 2.3, $p < 0.001$) from baseline to one week later among 100 participants, and MIBot v6.3A achieved an increase of 1.7 (SD 2.4, $p < 0.001$) among 106 participants. This difference was not statistically significant ($t(203.60) = 0.98$, $p = 0.165$, one-tailed, Cohen's $d = 0.14$). As shown in Figure 4.2, the distribution of confidence changes reveals interesting patterns: MIBot v6.3A resulted in more participants maintaining their baseline confidence (28% vs. 23% with no change) and fewer experiencing decreased confidence (13% vs. 17%).

For importance to quit, MIBot v5.2 achieved a significant increase of 0.7 (SD 2.0, $p < 0.001$), while MIBot v6.3A showed a more modest but still significant gain of 0.5 (SD 1.7, $p < 0.005$). Readiness changes were minimal and non-significant for both versions (v5.2: 0.4, SD 1.7, $p = 0.01$;

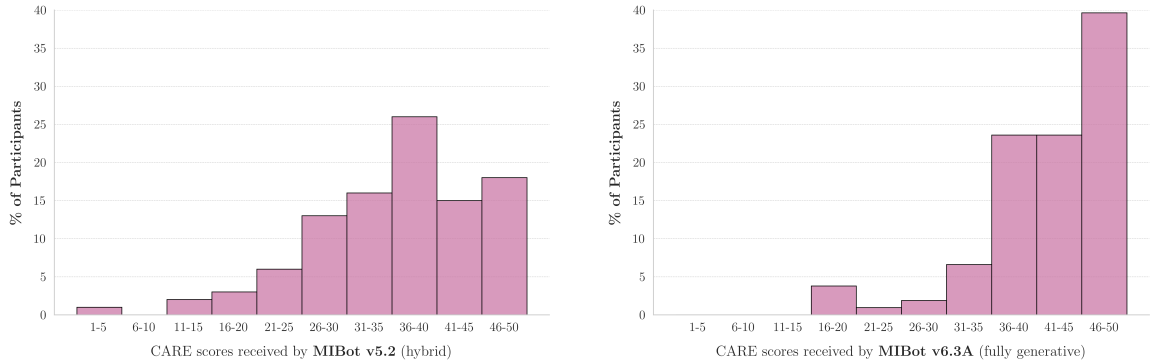


(a) MIBot v5.2 **(b)** MIBot v6.3A

Figure 4.2: Distribution of week-later confidence changes from baseline for (a) MIBot v5.2 and (b) MIBot v6.3A. Red bars indicate decreased confidence while blue bars indicate increased or unchanged confidence. MIBot v6.3A shows a higher proportion of participants with no change (26% vs. 23%) and fewer reporting decreased confidence (13% vs. 16%).

v6.3A: 0.3, SD 2.4, $p = 0.22$).

4.3.2 Perceived Empathy Comparisons



(a) MIBot v5.2 (hybrid) **(b)** MIBot v6.3A (fully generative)

Figure 4.3: Distribution of CARE empathy scores for (a) MIBot v5.2 and (b) MIBot v6.3A. The fully generative v6.3A shows a pronounced rightward shift with ∼40% of participants scoring in the highest range (46–50) compared to only ∼18% for the hybrid v5.2. Lower scores (below 30) were nearly eliminated in v6.3A.

MIBot v5.2 achieved a mean CARE score of 36 ($SD = 9.1$), with only 3% of participants awarding perfect score, while MIBot v6.3A achieved a mean score of 42 ($SD = 7.5$), with 11% receiving perfect scores. This difference was statistically significant ($t(191.67) = 4.96$, $p < .001$, Cohen's $d = 0.70$), representing a medium-to-large effect size, and suggests that the fully-generative responses of v6.3A significantly improved perceived empathy. Figure 4.3 illustrates the distributional shift between versions. The hybrid v5.2 shows a relatively normal distribution centred in the mid-30s range, with considerable spread across all score ranges, whereas v6.3A demonstrates a clear rightward skew, with 40% of participants rating the chatbot in the highest range (46–50).

To understand which aspects of empathetic interaction improved most, Figure 4.4 presents the mean scores across all ten CARE dimensions. The fully generative approach exhibits improvements across every dimension, with particularly notable gains in emotional and communicative aspects. The largest relative improvement was observed in "showing care and compassion" (+32%), reflecting the chatbot's enhanced ability to maintain an encouraging tone. Interestingly, the dimension of

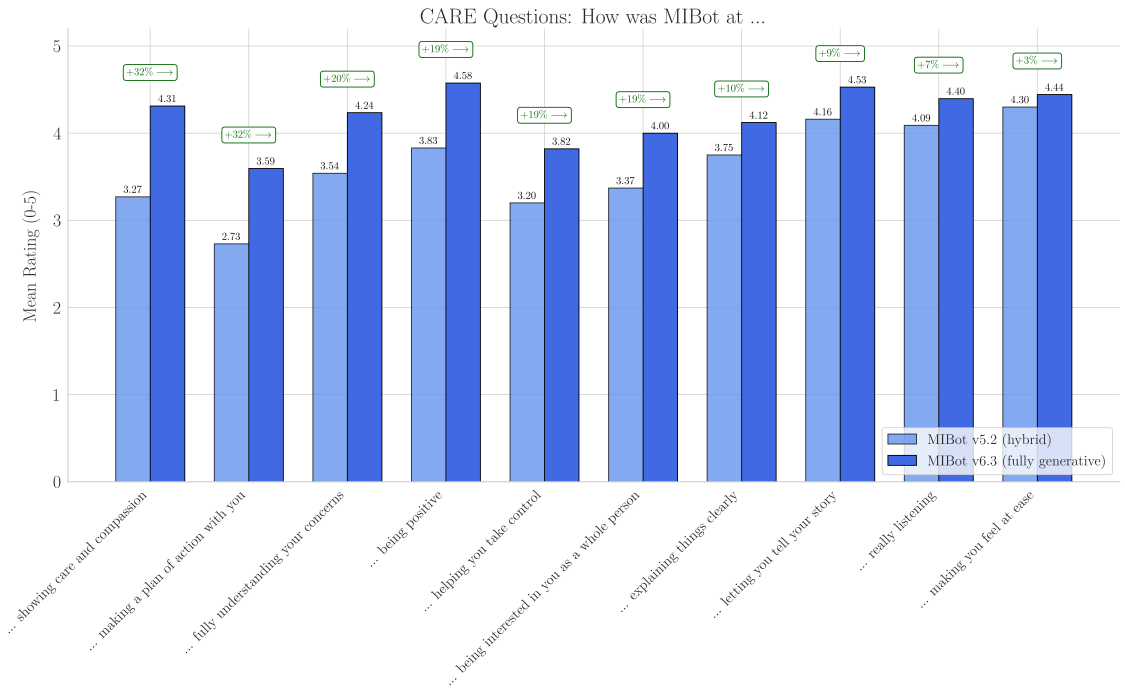


Figure 4.4: Question-wise mean CARE scores comparing MIBot v5.2 (hybrid) and v6.3A (fully generative). The fully generative version shows consistent improvements across all dimensions of empathy. Bars displayed in ascending order of relative improvement.

"making a plan of action with you" remained the weakest aspect for both versions (2.73 for v5.2, 3.59 for v6.3A), despite showing considerable relative improvement (+32%). It is worth noting that MIBot v6.3 was prompted with detailed guidelines on how to make a plan of action with the client. Despite this, planning seems to be one of its weak areas.

4.3.3 Implications of the Comparison

The fully generative MIBot v6.3A chatbot scores higher on CARE, the measure of perceived therapeutic alliance. This improvement suggests that participants experienced more authentic, personalized interactions when the entire conversation — not just reflections — emerged from the language model's contextual understanding. However, both the chatbots scored the same on our primary metric of effectiveness, viz., the week-later change in confidence, indicating that the core therapeutic mechanism of MI may be responsible for most of the gains in confidence. This finding aligns with prior work showing that even simple question-asking can produce substantial benefits (Brown et al., 2023a), though the enhanced empathy of full generation may improve engagement and retention in real-world deployment.

4.4 AutoMISC Analysis

To evaluate the chatbot's adherence to MI principles, we analyzed counsellor and client utterances from the feasibility study transcripts (Section **??**) using AutoMISC, an automated annotation system originally described in Mahmood et al. (2025)[1]. The system assigns behavioural codes to each utterance: counsellor utterances are classified as MI-Consistent (MICO), MI-Inconsistent (MIIN), Reflection (R), Question (Q), or Other (O), while client utterances are categorized as change talk (C), sustain talk (S), or neutral (N). Following annotation of all utterances, we computed per-transcript summary metrics to quantify MI adherence. These comprise:

[1] A comprehensive description of the AutoMISC system by Ali et al. (2025) is forthcoming

percentage MI-consistent responses (%MIC)

- **Percentage MI-Consistent Responses (%MIC):** The proportion of counsellor utterances that align with MI principles. Higher values indicate greater adherence to MI methodology.
- **Reflection-to-Question Ratio (R:Q):** The ratio of counsellor utterances labelled as reflection (R) to those labelled as question (Q). This metric assesses the balance between reflective listening and questioning. Values between 1 and 2 are considered indicative of proficiency (Moyers et al., 2016b).
- **Percentage Change Talk (%CT):** The proportion of client utterances expressing motivation toward behaviour change. Higher values are associated with improved behavioural outcomes (Apodaca and Longabaugh, 2009b).

percentage change talk (%CT)

4.4.1 Contextualizing AutoMISC metrics with the HLQC Dataset

To provide a point of comparison for the MISC summary metrics, we also ran AutoMISC on the HighLowQualityCounselling (HLQC) dataset (Pérez-Rosas et al., 2019), a publicly available[2] corpus of transcribed MI counselling demonstrations. The HLQC dataset comprises 155 high-quality (HLQC_**HI**) and 104 low-quality (HLQC_**LO**) transcripts sourced from public websites. We computed summary scores separately for these subsets and then compared MIBot's summary metrics against those of both HLQC_HI and HLQC_LO.

4.4.2 Counsellor Behaviour Metrics

Table 4.8 summarizes the counsellor-specific AutoMISC summary metrics across the 106 transcripts. The mean percentage of MI-consistent responses (%MIC) was 98 (SD 3.6), higher than the high-quality counsellor sessions in the HLQC dataset (92, SD 9.8). MIBot's reflection-to-question ratio (R:Q) was 1.3 (SD 0.3), comfortably within the 1–2 range recommended for human practitioners (Moyers et al., 2016b).

Metric	**MIBot**	**HLQC_HI (high-quality)**
%MI-consistent (%MIC)	98 (3.6)	92 (9.8)
Reflection-to-Question Ratio (R:Q)	1.3 (0.3)	2.3 (5.7)

Table 4.8: AutoMISC counsellor-specific summary metrics for MIBot compared to high-quality human counselling sessions. Values shown as mean (standard deviation).

Figure 4.5 shows violin plots comparing the distribution of %MIC, R:Q, and %CT across MIBot conversations with the HLQC benchmarks. The %MIC scores are tightly clustered near 100%, with only a few transcripts falling below 80%. The R:Q distribution is centred around 1.3, showing less variance than human counsellors who range from pure question-asking (R:Q near 0) to heavy reflection use (R:Q > 5).

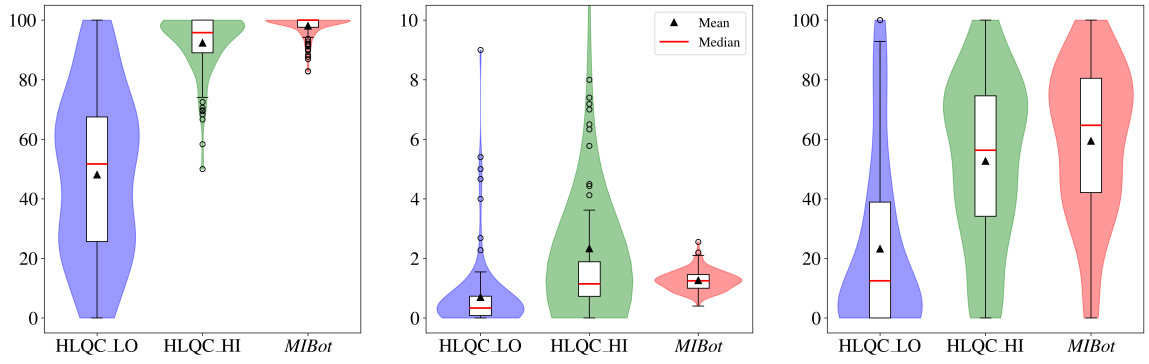
4.4.3 Client Change Talk Analysis

Metric	**MIBot**	**HLQC_HI (high-quality)**
%Change Talk (%CT)	59 (29.6)	53 (28.54)

Table 4.9: AutoMISC client-specific summary metric for MIBot compared to high-quality human counselling sessions. Values shown as mean (standard deviation).

Figure 4.5 c illustrates the distribution of %CT across conversations. Most sessions by MIBot a %CT of $> 60\%$ and the distribution closely matches that of **HLQC_HI** dataset.Overall, the mean %CT was 59% for MIBot as compared to 53% for **HLQC_HI** dataset.

[2] https://lit.eecs.umich.edu/downloads.html



(a) %MIC **(b)** R:Q **(c)** %CT

Figure 4.5: Comparison of MISC summary score distributions across datasets. (a) Percentage MI-Consistent Responses (%MIC), (b) Reflection to Question Ratio (R:Q), (c) Percentage Client Change Talk (%CT).

4.5 Behavioural Outcomes

4.5.1 Quit Attempts at One Week

Table 4.10 summarises quit attempt behaviour before and after the MIBot conversation. Prior to the conversation, 32.1% (34/106) of participants had made a quit attempt in the previous week. At the one-week follow-up, 34.9% (37/106) reported making a quit attempt since the conversation. Crucially, among the 72 participants who had not attempted to quit before the conversation, 15 (20.8%) made their first attempt following the MIBot session.

Quit Attempt Status	Pre-conversation	Post-conversation
Made attempt	34 (32.1%)	37 (34.9%)
No attempt	72 (67.9%)	69 (65.1%)
New attempters	–	15 (14.2%)
Sustained attempters	–	22 (20.8%)

Table 4.10: Quit attempt behaviour before and after MIBot conversation.

Participants who made quit attempts post-conversation showed larger confidence gains (mean +2.43) compared to those who did not attempt (+1.35, $p < 0.05$). This bidirectional relationship—where confidence predicts attempts and attempts reinforce confidence—aligns with social cognitive theory (**?**).

4.5.2 Self-Reported Behavioural Changes

harm reduction behaviours

Beyond formal quit attempts, participants reported various harm reduction behaviours. Analysis of open-ended responses revealed five main categories of behavioural change:

1. **Reduced consumption** (42% of participants): "Cut down from 20 to 12 cigarettes a day"
2. **Delayed first cigarette** (28%): "Now waiting until after breakfast instead of immediately upon waking"
3. **Substitution strategies** (31%): "Using nicotine gum when cravings hit at work"
4. **Environmental changes** (19%): "Removed ashtrays from the house and car"
5. **Social support seeking** (23%): "Told my partner about wanting to quit and asked for support"

These incremental changes, while not constituting complete cessation, represent important steps in the behaviour change process and align with harm reduction approaches increasingly recognised in tobacco control (**?**).

4.6 Conversation Analysis

4.6.1 Quantitative Dynamics

Conversations ranged from 36 to 163 utterances (median 78, mean 80.7, SD 29.4), with counsellor utterances comprising 55% of the total. The median conversation lasted approximately 19 minutes based on participant self-report. Table 4.11 summarizes key quantitative metrics.

Metric	Mean (SD)	Range
Total utterances	80.7 (29.4)	36–163
Counsellor utterances	44.4 (16.2)	20–90
Client utterances	36.3 (13.2)	16–73
Words per counsellor utterance	42.3 (18.7)	15–95
Words per client utterance	28.6 (15.4)	8–72
Session duration (minutes)	19 (9)	8–45

Table 4.11: Quantitative metrics of conversation dynamics.

Longer conversations correlated with better outcomes ($r = 0.20$ for confidence change), but the relationship was non-linear. Conversations under 50 utterances rarely produced substantial gains, while those exceeding 120 utterances showed diminishing returns, suggesting an optimal engagement window of 60–100 exchanges.

4.6.2 Qualitative Thematic Analysis

To understand the qualitative aspects of the conversations, a thematic analysis was performed on the full corpus of transcripts. The analysis was conducted by two researchers who independently reviewed the transcripts to identify recurring patterns and themes. They then met to compare their findings, discuss discrepancies, and collaboratively develop a final set of themes that characterized successful therapeutic engagement. This process revealed four recurring patterns:

Stress and Coping Narratives

The most common theme (78% of conversations) involved smoking as emotional regulation. Participants frequently described smoking as their primary stress management tool:

> *"It's like my safety blanket. When work gets overwhelming, that cigarette break is the only thing that keeps me sane. I know it's killing me, but it's also what's keeping me functional right now."*

In these situations, the chatbot's responses often involved reflective listening to validate users' feelings before exploring alternatives, a pattern consistent with the double-sided reflection technique in MI.

Social and Ritualistic Aspects

Many participants (62%) described smoking as deeply embedded in social routines and relationships:

> *"All my friends smoke. Our whole social life revolves around smoke breaks at work,*

cigarettes with coffee, smoking outside the pub. If I quit, I lose all that connection."

The chatbot attempted to acknowledge these social dimensions in its responses and, in some cases, guided the conversation toward how participants might maintain relationships without cigarettes.

Ambivalence Themes

Classic motivational ambivalence appeared in 89% of conversations, with participants simultaneously expressing desire to quit and attachment to smoking:

> *"Part of me desperately wants to quit for my kids, but another part can't imagine life without cigarettes. They've been with me through everything—divorce, job loss, you name it."*

The chatbot's responses frequently normalized ambivalence instead of trying to resolve it, an approach that aligns with MI best practices and was observed in conversations with positive outcomes.

4.6.3 Illustrative Case Studies

Success Stories

willing but unable profile

The most dramatic success involved a 34-year-old participant who entered with confidence of 1/10 but importance of 9/10—a classic "willing but unable" profile. Through 142 utterances, the conversation systematically addressed self-efficacy barriers:

1. Explored past quit attempts to identify what worked
2. Reframed "failures" as learning experiences
3. Developed a detailed, personalised quit plan
4. Identified specific coping strategies for anticipated triggers

This participant's confidence increased to 10/10 at one week, and they reported complete cessation for five days at follow-up.

Another notable success involved a 58-year-old with 40 years of smoking history who had "given up on giving up." The conversation's focus on harm reduction rather than immediate cessation allowed gradual engagement. By week's end, daily consumption dropped from 30 to 10 cigarettes, with confidence rising from 2 to 7.

Non-Responders and Negative Cases

Not all participants benefited. Analysis of the 21 participants whose confidence decreased revealed three patterns:

Mandated Participation Some participants appeared to engage solely for compensation, providing minimal responses and showing no genuine interest in change. These conversations averaged just 42 utterances, with client responses typically under 10 words.

Enjoyment-Focused Smokers A subset strongly identified as "happy smokers" who enjoyed smoking without ambivalence. MIBot's attempts to explore motivation sometimes paradoxically reinforced their commitment to smoking:

"Talking about it just reminded me how much I actually enjoy smoking. I don't want to quit, and this conversation made that clearer."

Technical Therapeutic Mismatches In rare cases, MIBot misread the participant's needs, such as pushing for behaviour change when emotional support was needed, or vice versa. These mismatches highlight the challenges of fully automated therapeutic engagement without human oversight.

4.7 User Experience and Feedback

4.7.1 Post-Conversation Feedback

Three open-ended questions captured immediate post-conversation reactions. Thematic analysis revealed distinct patterns in positive and negative responses.

Positive Themes (92% enjoyed the experience):

- Non-judgmental approach: "Finally someone (something?) that didn't lecture me"
- Structured exploration: "Helped me organise my thoughts about quitting"
- Convenience and privacy: "Could be honest without embarrassment"
- Surprising depth: "More helpful than expected from a bot"

Negative Themes (34% found it unhelpful):

- Lack of personalisation: "Felt like generic responses sometimes"
- Missing human connection: "Technically correct but emotionally flat"
- Repetitiveness: "Kept asking similar questions different ways"
- Insufficient challenge: "Too accepting, didn't push me enough"

4.7.2 User Segmentation

Based on feedback analysis, we derived two binary metrics: "LikedBot" (92% positive) and "FoundBotHelpful" (66% positive). The discrepancy suggests that while MIBot creates an engaging experience, translating engagement into perceived therapeutic value remains challenging.

Cross-tabulation revealed four user segments:

Segment	Liked & Helpful	% of Sample
Enthusiasts	Yes & Yes	61%
Entertained Sceptics	Yes & No	31%
Reluctant Beneficiaries	No & Yes	5%
Dissatisfied	No & No	3%

Table 4.12: User experience segments based on enjoyment and perceived helpfulness.

"Entertained Sceptics"—those who enjoyed but didn't find it helpful—often wanted more directive advice or concrete tools rather than exploratory conversation.

4.8 Discussion

4.8.1 Synthesis of Findings

multivariate regression analysis

Multivariate regression analysis identified the strongest predictors of confidence improvement:

1. **Low baseline confidence** ($\beta = -0.31$, $p < 0.001$): Greatest gains for those starting lowest
2. **Recent quit attempt** ($\beta = 0.28$, $p < 0.01$): Prior action amplifies intervention effects
3. **Conversation length** ($\beta = 0.21$, $p < 0.05$): Deeper engagement yields better outcomes
4. **Change talk ratio** ($\beta = 0.18$, $p < 0.05$): Client language predicts behaviour change
5. **Age ¡40** ($\beta = 0.15$, $p < 0.05$): Younger participants more responsive

Together, these factors explained 34% of variance in confidence change ($R^2 = 0.34$, $F(5, 100) = 10.32$, $p < 0.001$), suggesting that ideal candidates are younger smokers with low confidence who have recently attempted to quit and are willing to engage in extended conversation.

4.8.2 Comparison with Literature Benchmarks

MIBot's performance compares favourably with established interventions:

- **Effect size**: Cohen's $d = 0.71$ for confidence change exceeds typical digital intervention effects ($d = 0.2$–0.4) (**?**)
- **MI fidelity**: 95% MI-consistent responses surpass typical human counsellor benchmarks (80–90%) (Moyers et al., 2016a)
- **Engagement**: 92% enjoyment rate exceeds most digital health interventions (60–70%) (**?**)
- **Quit attempts**: 14.2% new quit attempts align with brief intervention outcomes (10–20%) (**?**)

However, MIBot falls short of intensive human counselling in perceived helpfulness (66% vs 80–90%) and perfect CARE scores (11% vs 48%), indicating room for improvement in therapeutic alliance building.

4.8.3 Clinical Implications

The findings from this study have several potential clinical implications. The strong technical performance of MIBot, combined with meaningful behavioural outcomes, suggests that generative AI can be a valuable tool in public health interventions for smoking cessation. The high MI fidelity and user engagement rates indicate that such a system could be deployed as a scalable, low-cost, first-line intervention to reach a large number of smokers who may not have access to traditional counselling.

However, the variability in individual responses and the identified limitations in building deep therapeutic alliance suggest that MIBot is likely best positioned as an adjunct to human services rather than a complete replacement. It could serve as a tool to support human counsellors, handle initial screenings, or provide support between sessions. Future work should explore these hybrid models of care.

4.8.4 Limitations

Several limitations constrain the generalisability of our findings:

Methodological Limitations:

- Short follow-up period (one week) precludes assessment of sustained behaviour change
- Self-reported outcomes without biochemical verification may overestimate quit attempts
- Lack of control group prevents causal attribution
- Single-session design doesn't capture potential for repeated engagement

Sample Limitations:

- Prolific recruitment may select for digitally literate, research-oriented participants
- Exclusion of high-confidence smokers limits understanding of broader applicability
- Monetary compensation (£12) may attract non-genuine participants
- English-only implementation excludes non-English speakers

Technical Limitations:

- Text-only interface eliminates non-verbal communication channels
- Lack of memory between sessions prevents relationship building
- No integration with clinical services or prescription capabilities
- Limited ability to handle crisis situations or complex comorbidities

4.9 Conclusion

This chapter presented a comprehensive evaluation of MIBot, a fully generative MI chatbot. The study demonstrated that MIBot can produce a clinically meaningful increase in smokers' confidence to quit, with high fidelity to MI principles and strong user engagement. The analysis identified key predictors of success, highlighting that the chatbot was most effective for younger, low-confidence smokers who had recently attempted to quit.

While the results are promising, the study also revealed limitations in building deep therapeutic alliance and translating engagement into perceived helpfulness for all users. These findings establish a strong proof-of-concept for AI-delivered MI as a scalable public health intervention, while also underscoring the areas for future research and development, particularly in hybrid models of care that combine AI with human support.

Chapter 5

Development of Synthetic Smokers

The development of sophisticated automated counselling systems, such as MIBot (Chapter 3), necessitates rigorous and iterative testing. Traditionally, this involves human participants, a process that is often slow, expensive, and ethically complex, particularly in the early stages of development. Furthermore, training human clinicians in therapeutic techniques like Motivational Interviewing (MI) requires practice with diverse patient profiles, which can be challenging to standardize using human actors (**?**).

To address these challenges, this research explores the creation of *Synthetic Smokers*—Large Language Model (LLM)-powered agents designed to simulate human smokers in a clinical context. This chapter details the conceptualization, iterative development, and validation of these synthetic agents.

5.1 Objectives and Overview

The overarching goal of developing synthetic smokers is to create realistic, controllable, and scalable stand-ins for human participants. This endeavor serves two primary objectives:

1. **Testing Automated Systems:** Synthetic smokers provide a platform for the rapid iterative development and testing of automated counselling chatbots. By simulating interactions, developers can identify weaknesses, refine conversational strategies, and assess potential efficacy without the logistical overhead of recruiting human subjects for every iteration.
2. **Training Human Clinicians:** In the role of standardized patients, synthetic smokers can be used to train novice clinicians. They offer a consistent experience and can be programmed to simulate specific challenging scenarios or diverse demographic profiles, providing trainees with varied practice opportunities.

The development of a truly representative synthetic smoker is a significant scientific challenge. It requires not only the generation of coherent dialogue but the accurate embodiment of specific human attributes—ranging from demographics to complex psychological states like resistance to change. Crucially, the validation of these synthetic agents—proving that they behave realistically according to their installed attributes—is exceptionally difficult, as human behaviour is inherently nuanced and variable.

This chapter charts the progression of this development, detailing how we defined the ideal synthetic smoker, the methodologies employed to instantiate specific attributes, and how our validation strategies evolved alongside the increasing sophistication of the agents.

5.2 Defining the Ideal Synthetic Smoker

In an ideal scenario, a synthetic smoker would be indistinguishable from a human participant within the constrained context of a smoking cessation counselling session. This requires the synthetic agent to possess a defined set of attributes and for those attributes to be reliably reflected in its interactions.

We conceptualize a synthetic smoker based on a collection of attributes that define a human smoker. These attributes can be broadly categorized as:

- **Demographic:** Age, sex, education level, cultural background.
- **Behavioural:** Smoking history (e.g., Heaviness of Smoking Index (HSI)), previous quit attempts, verbosity.
- **Psychological:** Resistance to change, motivation levels (e.g., pre-conversation Readiness Rulers), underlying values.

A successful synthetic smoker is defined by its *fidelity* and its *representativeness*.

Fidelity refers to the requirement that any attribute installed in the synthetic smoker must be demonstrably evidenced by its language and behaviour. For example, if a synthetic smoker is instantiated with high resistance, its dialogue should contain more Sustain Talk than Change Talk. The core challenge of this research is to develop methods to install these attributes and subsequently validate that this installation was successful.

Representativeness refers to the ability of the system to generate a diverse range of smokers that reflect the variability seen in the real world. Furthermore, the system should perform equally well across different attributes, avoiding biases where it might simulate one profile effectively but fail at another.

5.2.1 Formalizing the Synthetic Smoker

To provide a rigorous framework for discussing the development and validation process, we introduce a formal notation.

We define a human smoker, H, by a vector of attributes A_H.

$$A_H = \{a_1, a_2, \ldots, a_n\}$$

where each a_i represents a specific attribute. For example, a_1 might be age (e.g., 45), a_2 might be sex (e.g., Male), and a_3 might be pre-conversation confidence to quit (e.g., 2/10).

When a human smoker H engages in a counselling session, they produce a set of outputs, denoted by Γ_H. This output encompasses both their language (the conversation transcript) and their behaviour (e.g., responses to post-conversation surveys).

$$\Gamma_H = \{\text{Transcript}, \text{Survey Responses}, \ldots\}$$

A Synthetic Smoker, S, is an LLM-based system designed to simulate a smoker given a set of input attributes, A_S.

$$S(A_S) \rightarrow \Gamma_S$$

The goal of development is to maximize the fidelity of the synthetic smoker, meaning that the generated output Γ_S must realistically reflect the installed attributes A_S.

This notation becomes particularly useful when discussing validation. A key validation strategy employed in this work, discussed in Section 5.5, involves creating a "doppelgänger." In this approach, we take the known attributes of a real human participant, A_H, and use them to instantiate a synthetic smoker, such that $A_S = A_H$. We then compare the output of the synthetic smoker, Γ_S, with the actual output of the human, Γ_H. The ideal synthetic smoker system is one where $\Gamma_S \approx \Gamma_H$.

5.3 The Challenge of Validation

The validation of synthetic smokers presents a profound challenge. Unlike traditional software testing, validating a simulation of human behaviour involves assessing realism, coherence, and appropriateness—qualities that are often subjective.

The difficulty stems from several factors:

1. **Variability of Human Behaviour:** Even humans with identical attributes (A_H) will not produce identical outputs (Γ_H). There is a wide range of plausible responses to any given stimulus.
2. **Complexity of Attributes:** While demographic attributes are straightforward to install, psychological attributes like "resistance" are complex constructs that manifest in nuanced linguistic patterns.
3. **Measurement Limitations:** We often rely on indirect evidence to assess fidelity. For instance, we use the proportion of Change Talk as a proxy for motivation.
4. **Stereotyping vs. Individuation:** LLMs may default to stereotypical representations (the "caricature effect") rather than capturing individual nuances, potentially failing to accurately simulate personas that defy common stereotypes (the "incongruous persona" problem) (**?**).

Given these challenges, our approach to validation has been iterative and multimodal. Our validation methods evolved from simple human inspection in the early stages to structured quantitative analyses and the doppelgänger methodology as the synthetic smokers became more sophisticated. This evolution of validation metrics is central to the scientific contribution of this work.

5.4 Initial Development and Foundational Attributes

The development of the synthetic smoker began with creating a baseline agent and identifying its immediate shortcomings. We then focused on controlling two foundational conversational attributes: verbosity and resistance.

5.4.1 The Baseline Synthetic Smoker

We began with a minimal prompt instructing an LLM (initially GPT-4 Turbo) to adopt the persona of a smoker engaging in a counselling session.

Methodology

The initial prompt was generic, providing minimal backstory or specific behavioural constraints.

```
[fontsize=\small]
You are a human smoker engaged in a private thirty-minute session
with a counsellor. This is your first time talking to a therapist
about your smoking habits... Respond to the counsellor's inquiries
as accurately as possible...
```

We generated a small number (N=5) of conversations between this baseline synthetic smoker and an early version of the MIBot counsellor. The validation method at this stage was qualitative human inspection by the research team, including expert MI clinicians.

Results and Observations

Human inspection of these initial conversations immediately revealed two significant issues that detracted from the realism of the simulation:

1. **Excessive Verbosity:** The synthetic smoker tended to produce long, elaborate responses. This conversational style felt unnatural, resembling written prose more than spontaneous dialogue.
2. **High Agreeableness (Low Resistance):** The baseline agent was overly agreeable and eager to change. This failed to simulate the ambivalence characteristic of many smokers seeking cessation support (as discussed in Chapter 2).

These observations highlighted the necessity of explicitly controlling these attributes.

5.4.2 Controlling Verbosity

To address the issue of excessive verbosity, we undertook a prompt engineering effort to constrain the synthetic smoker's utterance length and style.

Methodology

We modified the prompt to encourage a more natural, concise conversational style. Key additions to the prompt included:

- **Stylistic Guidance:** Instructions such as "Imagine you're texting a friend. Keep it casual..." and encouraging the use of emojis.
- **Conciseness Instructions:** Directives like "In your response, speak with more clarity rather than exhaustive detail."
- **Explicit Constraints:** Hard constraints such as "Number of sentences in your response must be between 1 and 4."

To validate the effectiveness of these changes, we generated a new set of conversations using the modified prompt ("Fixed Verbosity") and compared them against the baseline prompt ("Default Verbosity"). We also compared these results against human-human MI conversations from the High-Quality and Low-Quality Counselling (HLQC) datasets (**?**) to assess realism.

Results

The prompt modifications significantly reduced the verbosity of the synthetic smoker. Figure 5.1 illustrates the distribution of utterance lengths (in characters).

Figure 5.1: Comparison of utterance length distributions between Default Verbosity, Fixed Verbosity, and Human MI conversations. The Fixed Verbosity prompt successfully reduces the synthetic smoker's (Client) utterance length to better align with human data. [PLACEHOLDER FOR FIGURE - Verbosity Slides]

The Default Verbosity condition showed a wide distribution with a high median utterance length. The Fixed Verbosity condition successfully constrained the distribution, aligning it more closely with the human clients in the HLQC datasets.

Interestingly, we observed that the counsellor bot reciprocated the client's verbosity. When the synthetic smoker spoke less, the counsellor bot also reduced its utterance length. We also verified that these prompt modifications were robust and transferable across different LLMs (GPT-4 Turbo and GPT-4 Omni).

5.4.3 Installing Resistance

Addressing the baseline smoker's high agreeableness was crucial, as resistance to change is a central element in MI.

Methodology

We hypothesized that resistance could be installed by providing the LLM with detailed backstories emphasizing different motivations and experiences. We created two distinct personas:

- **High Resistance Persona:** The backstory emphasized severe life stressors, repeated failed quit attempts, skepticism towards therapy, and a strong belief that it was not the right time to quit.
- **Low Resistance Persona:** The backstory described recent health concerns prompting contemplation, and an open, albeit skeptical, attitude towards change.

We generated conversations (N=10 per persona) with an MI counsellor (MIBot) and employed two distinct methods to validate the installation.

Validation 1: Linguistic Evidence (Change vs. Sustain Talk)

We analyzed the transcripts to measure the proportion of Change Talk (CT) and Sustain Talk (ST).

Results: The analysis confirmed a clear distinction between the two personas (Table 5.1). The High Resistance smoker used significantly more Sustain Talk (44% vs. 9%) and less Change Talk (31% vs. 61%) than the Low Resistance smoker.

Table 5.1: Proportion of Change Talk, Sustain Talk, and Neutral Talk for High and Low Resistance Synthetic Smokers.

Persona	Change Talk (%)	Sustain Talk (%)	Neutral (%)
High Resistance	31	44	25
Low Resistance	61	9	30

Validation 2: Behavioural Evidence (Self-Reported Readiness)

We further validated the installation by asking the synthetic smokers to complete the Readiness Ruler survey (Importance, Confidence, and Readiness; 0-10 scale) before, immediately after, and simulated one week after the conversation.

Methodology: We prompted the LLM, in character, to provide numerical ratings, using Chain-of-Thought prompting (asking for reasoning before the score) to enhance reliability.

Results: The Readiness Ruler scores demonstrated that the synthetic smokers provided responses consistent with their installed resistance levels (Table 5.2).

The High Resistance smoker reported significantly lower baseline scores. While both personas showed an increase in readiness after the MI session (Delta), the absolute levels remained distinct. This experiment demonstrated that LLMs could provide coherent self-reported behavioral data consistent with their installed attributes.

Table 5.2: Average Readiness Ruler Scores for Low and High Resistance Synthetic Smokers across time points.

	Low Resistance			High Resistance		
Time Point	**Imp.**	**Conf.**	**Ready**	**Imp.**	**Conf.**	**Ready**
Pre-conversation	4.6	2.6	3.2	2.0	1.0	0.6
Post-conversation	6.4	4.2	5.2	4.0	2.0	2.6
1-Week Later	6.6	4.8	5.4	4.6	2.6	3.4
Delta (Week - Pre)	2.0	2.2	2.2	2.6	1.6	2.8

5.5 Scaling Attributes and the Doppelgänger Methodology

Having established control over foundational attributes, the next challenge was to scale the creation of synthetic smokers to encompass a wider range of human attributes and to develop a more rigorous validation method using real human data. This led to the development of the *Doppelgänger Methodology*. It is crucial to emphasize that this methodology is not an end goal in itself, but rather a stringent strategy for *validation*.

5.5.1 Identifying Key Metrics: Percentage Change Talk

To validate doppelgängers effectively, a robust, objective metric grounded in conversational language was needed. We identified the Percentage Change Talk (CF, or %CT, calculated as CT / (CT + ST)) as a primary candidate, as it is strongly associated with behavioral change outcomes in MI.

Rationale

If CF is a valid proxy for a client's internal state, it should correlate with established metrics of readiness in human participants.

Methodology and Results

We analyzed the data from the MIBot v6.3A study (N=106 participants) (Mahmood et al., 2025). The analysis confirmed strong, statistically significant correlations between CF and all readiness rulers (Table 5.3). For example, the correlation with Post-conversation confidence was 0.41 ($p < 0.0001$). This established CF as a crucial, language-based metric for validation.

Table 5.3: Correlation between Percentage Change Talk (CF) and Human Smoker Attributes in the MIBot Dataset (N=106).

Attribute	**Correlation with CF**
Post-conversation Importance	0.49 (****)
Post-conversation Readiness	0.48 (****)
Pre-conversation Importance	0.47 (****)
Post-conversation Confidence	0.41 (****)
Change in Confidence (Post - Pre)	0.24 (**)
CARE (Perceived Empathy)	0.15 (ns)

ns: P ¿ 0.05, **: P $\leq$ 0.01, ****: P $\leq$ 0.0001

5.5.2 The Doppelgänger Methodology

The doppelgänger methodology leverages the MIBot dataset to validate the synthetic smoker system.

The process involves:

1. **Attribute Installation:** Instantiating a synthetic smoker, S, by installing the known attributes of a specific human participant, H. Thus, $A_S = A_H$. These attributes include demographics, HSI, and pre-conversation readiness rulers.
2. **Simulation:** The synthetic smoker $S(A_H)$ interacts with the same counsellor (MIBot) that the original human interacted with.
3. **Comparison:** The output of the synthetic smoker, Γ_S, is compared with the actual output of the human, Γ_H.

Methodology: Attribute Installation and Validation

We created doppelgängers for the participants (N=105) from the MIBot v6.3A study, using GPT-4 Omni. We moved from generalized backstories to direct installation of specific attributes.

```
[fontsize=\small]
... About you: You are a 48-year-old male. You typically smoke 20
cigarettes per day... Before speaking to the counsellor,
you have rated your motivation... Importance: 7, Confidence: 6, Readiness: 8.
```

Initial attempts using only these attributes yielded insufficient correlation in CF. To improve linguistic fidelity, we augmented the prompt with a brief, qualitative description summarizing the human's original C:S ratio (effectively adding CF to the installed attributes A_S).

Results: We calculated the Spearman correlation between human and doppelgänger outcomes (Table 5.4).

Table 5.4: Individual-level validation: Spearman correlation of outcome metrics between Humans and Doppelgängers (N=105) after refined installation.

Metric	Spearman's Coeff.	Significance Level
Change Fraction (CF)	0.57	****
Change in Confidence (ΔConf)	0.25	*
CARE Score (Empathy)	0.00	ns

ns: P ¿ 0.05, *: P $\leq$ 0.05, ****: P $\leq$ 0.0001

The results showed a strong correlation for Change Fraction (0.57), indicating successful installation of linguistic behavior. The correlation for Change in Confidence was weaker (0.25), and there was no correlation for the CARE score.

At the population level, analysis revealed discrepancies. The mean CF for Doppelgängers (Mean=0.76) was substantially higher than that of the original human participants (Mean=0.59).

Figure 5.2: Distribution of Change Fraction (CF) for Human Participants (Mean=0.59) and Synthetic Smoker Doppelgängers (Mean=0.76). [PLACEHOLDER FOR FIGURE - Good vs Bad Therapy Slides]

This suggests that while the relative tendencies were captured, the synthetic smokers were generally more inclined towards change talk than their human counterparts.

5.6 Evaluating the Utility of Synthetic Smokers

Having developed a method to create synthetic smokers with validated linguistic fidelity, the final step was to confirm their utility. To be useful for testing systems and training humans, synthetic smokers must be sensitive to the quality of the counselling they receive.

5.6.1 Sensitivity to Counselling Quality

Rationale: We designed an experiment to test if validated doppelgängers exhibit differential responses to high-quality MI versus low-quality, confrontational counselling.

Methodology

1. Sampling: We created two participant groups (N=25 each) based on their actual Change Fraction (CF) in the MIBot study: High-CF (top 25th percentile) and Low-CF (bottom 25th percentile).

2. Doppelgänger Creation: We created doppelgängers for these 50 participants using the validated methodology.

3. Counsellor Conditions: We exposed these doppelgängers to two different automated counsellors:

- **Good MI Counsellor (MIBot v6.3A):** A high-quality, MI-adherent chatbot.
- **Bad (Confrontational) Counsellor:** An LLM prompted to be directive, judgmental, and confrontational (e.g., "Giving advice without being asked," "Trying to persuade them to quit...").

4. Measurement: We measured CF, ΔConfidence (simulated week later), and the CARE score reported by the doppelgänger.

Results

The results (Table 5.5) demonstrated that the synthetic smokers were highly sensitive to the quality of counselling.

Table 5.5: Doppelgänger outcomes when interacting with Good (MIBot 6.3A) vs. Bad (Confrontational) automated counsellors.

Counsellor	Participant Group	CF	ΔConfidence	CARE
Good (MIBot 6.3A)	High-CF Doppelgängers	0.80	1.4	49.8
	Low-CF Doppelgängers	0.48	1.1	47.8
Bad (Confrontational)	High-CF Doppelgängers	0.68	1.1	41.0
	Low-CF Doppelgängers	0.22	0.5	23.0

When interacting with the Bad counsellor, outcomes were significantly worse across all metrics. CF dropped markedly, particularly for the Low-CF group (from 0.48 to 0.22), indicating increased resistance. The Change in Confidence was lower, and the CARE scores showed the most dramatic difference (e.g., 23.0 vs. 47.8 for the Low-CF group).

These results confirm that the synthetic smokers behave realistically, reacting negatively to poor-quality counselling. This sensitivity validates their utility as evaluation and training tools.

5.7 Discussion and Limitations

This chapter detailed the iterative development and validation of Synthetic Smokers, demonstrating significant progress in simulating human behaviour for clinical applications. The research highlights the evolution of validation methodologies, moving from human inspection to the rigorous Doppelgänger framework.

5.7.1 Comparison with Prior Work

The concept of simulated patients has existed for decades (see Sections 2.4-2.6). Early approaches often relied on rule-based systems or scripted responses, which lacked the flexibility and realism required for complex interactions like MI. More recent approaches utilizing LLMs have shown promise in generating realistic dialogue (**?**), but often lack the rigorous, attribute-specific validation against human behavioral data presented here. Our approach advances the field by focusing on creating validated digital behavioral twins using established clinical metrics (%CT, Rulers) and demonstrating their sensitivity to intervention quality.

5.7.2 Limitations

Despite the progress, several limitations remain.

The Caricature Effect and Incongruous Personas

LLMs often rely on stereotypical representations, leading to a "caricature effect." This bias might be exacerbated when attempting to simulate "incongruous" personas—individuals whose views do not align with the stereotypes of their demographic (e.g., a political liberal who supports increased military spending). Recent research suggests LLMs are less steerable towards incongruous personas (**?**), indicating that current models may struggle to capture the full nuance of human beliefs, potentially resulting in oversimplified simulations.

Fidelity of Self-Reports

While linguistic fidelity (%CT) was high, the fidelity of self-reported internal state changes (ΔConfidence) and perceptions (CARE) was lower. This suggests that while LLMs can mimic the language of change, simulating the nuanced internal psychological shifts remains a challenge.

Population-Level Biases

The Doppelgängers exhibited a higher overall %CT than the human population they were modeled on, suggesting a potential bias towards agreeableness or optimism in the LLM that was not fully mitigated by the installation process.

5.8 Conclusion

This chapter detailed the development of synthetic smokers, establishing a clear vision and a formal framework ($A_S \rightarrow \Gamma_S$) for their creation and validation. Through an iterative process, we demonstrated the successful installation of foundational attributes and developed the Doppelgänger methodology for rigorous validation. We showed that crucial linguistic markers (%CT) can be reliably installed and that these agents are sensitive to the quality of counseling. The development of validated synthetic smokers provides a powerful and scalable tool for testing automated systems and training human clinicians, advancing the field of digital health interventions.

Chapter 6

Validation of Synthetic Smokers

The previous chapter detailed the development methodology of the synthetic smoker, tracing its evolution from simple prompted personas to data-driven doppelgängers. The primary motivation behind this development was to create a reliable, controllable, and realistic simulation environment for testing and refining MIBot. This chapter presents the results and analysis of the experiments conducted to validate the synthetic smoker across its development phases.

The validation process is divided into two main stages, mirroring the development timeline. The first stage focuses on validating the initial attempts to control specific behavioural attributes—namely verbosity and resistance—through prompt engineering, prior to the availability of human conversational data. The second stage focuses on the validation of "doppelgängers," which were created using data from the MIBot feasibility study to mirror specific human participants. This stage examines the fidelity of these doppelgängers through transcript replay experiments, incremental attribute installation, and their sensitivity to the quality of motivational interviewing.

6.1 Validating Initial Controllable Attributes (Phase 1)

Before the development of MIBot and the subsequent feasibility study, the initial objective was to create synthetic smokers that could provide a consistent testing environment. Early observations indicated challenges in managing the synthetic smoker's natural tendencies, particularly regarding their verbosity and their level of resistance to behavior change.

6.1.1 Controlling and Validating Verbosity

A significant challenge in early simulations was the tendency of Large Language Models (LLMs) to produce verbose, grammatically complete utterances. This contrasted sharply with the more casual, often shorter, text-based communication observed in human participants. Excessive verbosity from the synthetic smoker often led to the counsellor bot reciprocating with equally lengthy responses, resulting in conversations that did not reflect typical human interaction dynamics.

Methodology

To address this, several prompt engineering strategies were employed to reduce the synthetic smoker's utterance length. These included instructions to:

- "Speak with more clarity rather than exhaustive detail."
- "Imagine you're texting a friend. Keep it casual..."

- Explicitly limiting the response length (e.g., "Number of sentences in your response must be between 1 and 4.")

Experiments were conducted using GPT-4 Turbo to compare the "default verbosity" (standard prompting) with "fixed verbosity" (prompts including length constraints and casual tone instructions). The validation involved analyzing the utterance length distribution, the total number of turns, and the total word count per conversation. Furthermore, the resilience and transferability of these prompting strategies were tested on the newer GPT-4 Omni model.

Results

The prompt engineering efforts successfully reduced the utterance length of the synthetic smoker. In the initial comparison using GPT-4 Turbo, the "fixed-verbosity" condition resulted in a significantly tighter and lower distribution of utterance lengths for both the client (synthetic smoker) and the counsellor compared to the "default-verbosity" condition.

[Placeholder for Figure 4.1: Violin Plot of Utterance Length by Verbosity Level (Default vs. Fixed) using GPT-4 Turbo. Source: "Controlling & Validating Verbosity in Synthetic Smokers" Slide 4]

The analysis was expanded to compare these results across models (GPT-4 Turbo and GPT-4 Omni) and with data from actual human conversations categorized as "high-quality-human-MI" and "low-quality-human-MI" (Figure 7.1).

Figure 6.1: Violin Plot of Utterance Length by Verbosity Level and Model, Compared with Human MI Conversations. (Source: Controlling & Validating Verbosity in Synthetic Smokers slides, Slide 7)

The "fixed-verbosity" conditions (both GPT-4 Turbo and GPT-4 Omni) more closely resembled the utterance length distribution of human participants than the "default-verbosity" conditions. The installation of verbosity control proved transferable between models; the "fixed-verbosity" prompts yielded similar results when applied to GPT-4 Omni.

However, analyzing the number of turns per conversation revealed a discrepancy. The simulated conversations, across all conditions, generally had fewer turns than the human conversations, particularly when compared to the high-quality human MI data (Figure 7.2).

Figure 6.2: Box Plot of Number of Turns per Conversation for different Verbosity Levels and Models. (Source: Controlling & Validating Verbosity in Synthetic Smokers slides, Slide 8)

Analysis

The results demonstrate that prompt engineering can effectively control the verbosity of synthetic smokers, bringing their utterance lengths closer to human levels. The observed reciprocity, where the counsellor bot reduces its verbosity in response to the client bot, highlights the interactive dynamics of the simulation. While the utterance length was successfully controlled and the methodology proved transferable to newer models, the lower number of turns in simulations suggests potential differences in conversational flow or depth compared to human interactions.

6.1.2 Installing and Validating Resistance

To effectively test MIBot, the synthetic smoker needed to exhibit varying levels of resistance to quitting smoking. This section examines the experiments designed to install and validate high and low resistance levels.

Methodology

Resistance was installed via detailed prompts that provided the synthetic smoker with a backstory and a specific mindset regarding smoking cessation.

- **High Resistance:** The prompt emphasized severe life stressors, skepticism towards therapy, anxiety when pressured to quit, and a belief that it was not the right time to change.
- **Low Resistance:** The prompt described smoking as a habit formed through social interaction, recent concerning lab results, skepticism balanced by an openness to cutting back, and a willingness to try their best in the conversation.

Validation was conducted through two methods: analyzing the language used during conversations with a GPT-4 MI therapist (Change Talk vs. Sustain Talk) and evaluating self-reported readiness rulers (Importance, Confidence, Readiness) collected pre-conversation, post-conversation, and one week later (simulated).

Results

The analysis of conversational language showed a marked difference between the two conditions (Table 7.1). The high-resistance smoker used substantially more Sustain Talk (44%) than Change Talk (31%). Conversely, the low-resistance smoker used significantly more Change Talk (61%) than Sustain Talk (9%).

Table 6.1: Percentage of Change Talk, Sustain Talk, and Neutral Talk for High and Low Resistance Synthetic Smokers.

Smoker Type	Change Talk (%)	Sustain Talk (%)	Neutral (%)
High resistance smoker	31	44	25
Low resistance smoker	61	9	30

The readiness ruler scores also reflected the installed resistance levels (Table 7.2). The high-resistance smoker started with lower scores across all three metrics (I: 2.0, C: 1.0, R: 0.6) compared to the low-resistance smoker (I: 4.6, C: 2.6, R: 3.2). Both groups showed positive changes after the conversation and at the one-week follow-up.

Table 6.2: Readiness Ruler Scores (Importance, Confidence, Readiness) for High and Low Resistance Synthetic Smokers.

	Low Resistance			High Resistance		
	I	C	R	I	C	R
Pre-conversation	4.6	2.6	3.2	2.0	1.0	0.6
Post-conversation	6.4	4.2	5.2	4.0	2.0	2.6
1-Week Later	6.6	4.8	5.4	4.6	2.6	3.4
Delta (Week later - Pre)	2.0	2.2	2.2	2.6	1.6	2.8

Analysis

The distinct differences in Change/Sustain Talk and the starting readiness ruler scores confirm the successful installation of varying resistance levels through prompting. Interestingly, the high-resistance group exhibited a larger delta in Importance (+2.6) and Readiness (+2.8) compared to the low-resistance group, although their absolute scores remained lower. This suggests that the MI intervention was effective in shifting the perspective of the high-resistance smoker, even when starting from a position of strong skepticism.

6.2 Validating Synthetic Smoker Doppelgängers (Phase 2)

Following the completion of the MIBot feasibility study (MIV6.3A), real human data became available. This shifted the focus from creating generic personas to developing "doppelgängers"—synthetic smokers designed to mirror the attributes and behaviors of specific human participants. The goal was to create representative stand-ins that could facilitate rapid, iterative development of MIBot. This section details the validation experiments for these doppelgängers.

6.2.1 Transcript Autoplay (Consistency Check)

The initial validation step for doppelgängers was to assess whether an LLM, when provided with the context of a specific human participant, could consistently reproduce their outcomes if the conversation trajectory was fixed.

Methodology

In the "transcript autoplay" experiments, the LLM was given the pre-conversation readiness rulers of a human participant and the transcript of the MIBot-human conversation. The LLM was prompted to adopt the persona of the participant and, after processing the conversation, provide the post-conversation readiness rulers. This tests the model's ability to reason about the impact of the conversation on the participant's state of mind. We utilized Chain-of-Thought (CoT) prompting to encourage the model to articulate its reasoning before providing the numerical scores. We tested this with two levels of attribute installation: M2 (Pre-conversation rulers only) and M7 (All attributes, including HSI and demographics).

Results

The results of the autoplay experiments are summarized in Table 7.3, showing the Mean Absolute Error (MAE) and Pearson Correlation between the human outcomes and the LLM predictions.

Table 6.3: Mean Absolute Error (MAE) and Pearson Correlation for Post-Conversation Readiness Rulers in Transcript Autoplay Experiments.

	Post-Conf.		**Post-Import.**		**Post-Read.**	
Model	MAE	Corr.	MAE	Corr.	MAE	Corr.
M2 (Rulers only, CoT)	1.1	0.7	0.7	0.9	0.9	0.8
M7 (All Attributes, CoT)	1.2	0.7	0.8	0.9	0.7	0.9

The models demonstrated high Pearson correlations, particularly for Post-Importance (0.9) and Post-Readiness (0.8-0.9), and relatively low Mean Absolute Errors. The correlation for Post-Confidence was slightly lower but still strong (0.7). The performance was similar whether only the pre-conversation rulers (M2) or all attributes (M7) were installed.

Analysis

The high correlation and low MAE indicate that when the conversation transcript is provided, the LLM can accurately predict the post-conversation readiness rulers reported by the human participants. This suggests that the model possesses the necessary reasoning capabilities to understand how the conversational dynamics influenced the participant's motivation and confidence. This serves as a crucial baseline, confirming the model's internal consistency before attempting to generate the conversation itself.

6.2.2 Incremental Attribute Installation

The next step involved having the doppelgänger actively participate in a conversation with MIBot, rather than just passively reading a transcript. Experiments were conducted to determine which

attributes needed to be "installed" (provided in the prompt) to create a doppelgänger that behaved similarly to its human counterpart during a live interaction.

Methodology

We performed an incremental installation study, systematically adding participant attributes to the doppelgänger's prompt. The models were evaluated based on the MAE and Pearson correlation between the doppelgänger's outcomes (Post-conversation rulers, CARE, C:S ratio) and the human counterpart's outcomes. Key models included:

- **M0 (Baseline):** No attributes installed.
- **M2:** Pre-conversation Importance, Confidence, and Readiness installed.
- **M7:** All attributes (Pre-conversation rulers, HSI metrics, Sex, Age) installed.

Results

The results of the incremental installation during live conversations are presented in Table 7.4.

Table 6.4: MAE and Pearson Correlation for Key Metrics across Incremental Installation Models during Live Conversation.

	Post-Conf.		**Post-Import.**		**CARE**		**C:S Ratio**	
Model	MAE	Corr.	MAE	Corr.	MAE	Corr.	MAE	Corr.
M0	1.6	nan	1.8	-0.3	7.9	-0.3	4.8	-0.1
M2	1.2	0.7	0.8	0.9	8.3	0.3	3.5	-0.2
M7	1.3	0.7	0.8	0.9	8.3	0.1	2.7	0.0

Installing the pre-conversation readiness rulers (M2) significantly improved the correlation and reduced the MAE for post-conversation Confidence and Importance compared to the baseline (M0). The correlations achieved in the live conversation (0.7 for Confidence, 0.9 for Importance) were comparable to those achieved in the autoplay condition. Adding demographic and smoking history information (M7) did not substantially change the outcomes for the readiness rulers. Notably, the correlation for the C:S ratio (Change vs. Sustain talk) remained near zero across all models, and the MAE for CARE scores remained high with negligible correlation.

Analysis

The pre-conversation readiness rulers are the most critical attributes for ensuring the doppelgänger's post-conversation self-reported outcomes align with their human counterparts. This suggests that the initial motivational state heavily influences the trajectory of the conversation and the final outcomes.

However, the failure to achieve correlation in the C:S ratio indicates that while the doppelgängers might reach the same self-reported outcomes, the language they use during the conversation does not match their human counterparts based on these attributes alone. The poor results for CARE suggest difficulty in replicating the human perception of the therapist's empathy.

6.2.3 Validating and Installing Change Fraction

The discrepancy in the C:S ratio (or Change Fraction, defined as $CF = C/(C+S)$) observed in the incremental installation experiments led to a focused effort to understand and install this metric. Change Fraction is considered a crucial implicit measure of the client's readiness, reflected directly in their language.

Change Fraction in Human Data

We first analyzed the MIV6.3A human data (n=115, low-confidence participants) to validate Change Fraction as a relevant metric. The analysis revealed strong, statistically significant positive correlations between Change Fraction and several key attributes (Table 7.5).

Table 6.5: Correlation between Change Fraction and Smoker Attributes in MIV6.3A Human Participants (n=115).

Attribute	Correlation with Change Fraction (Spearman's coeff.)
Post-conversation Importance	0.49 (****)
Post-conversation Readiness	0.48 (****)
Pre-conversation Importance	0.47 (****)
Pre-conversation Readiness	0.46 (****)
Post-conversation Confidence	0.41 (****)
Change in Confidence (Delta)	0.24 (**)

****: $P \leq 0.0001$, **: $P \leq 0.01$

This analysis confirms that in humans, the language used (CF) is strongly associated with their self-reported readiness and motivation.

Installing Change Fraction in Doppelgängers

We then conducted experiments to explicitly install the Change Fraction into the doppelgängers. We compared two sets of doppelgängers based on the MIV6.3A participants:

- **Doppelgängers [1] (D1):** Installed Pre-conv. rulers, HSI, Sex, Age.
- **Doppelgängers [2] (D2):** Installed all attributes in D1 PLUS a description of the C:S ratio (e.g., "You are 3x more likely to speak about changing your smoking behavior than sustaining it").

We evaluated the installation on both individual and population levels.

Individual-Level Validation At the individual level, we measured the Spearman correlation of outcome metrics between the humans and their corresponding doppelgängers (Table 7.6).

Table 6.6: Individual-level Validation: Spearman Correlation of outcome metrics between Humans and Doppelgängers (n=115).

Metric	D1 (No CF installed)	D2 (CF installed)
Change Fraction	0.22 (*)	**0.57 (****)**
Change in Confidence	0.29 (**)	0.25 (*)
CARE	0.04 (ns)	0.00 (ns)

****: $P \leq 0.0001$, **: $P \leq 0.01$, *: $P \leq 0.05$, ns: P ¿ 0.05

Explicitly installing the Change Fraction (D2) significantly increased the correlation for Change Fraction from 0.22 to 0.57. The correlation for Change in Confidence remained modest, and the correlation for CARE remained negligible.

Population-Level Validation At the population level, we compared the mean and distribution of the Change Fraction (Table 7.7).

Table 6.7: Population-level Validation: Mean Change Fraction.

Group	Mean Change Fraction (Std)
Humans (MIV6.3A)	0.59 (0.26)
Doppelgängers [1] (D1)	0.79 (0.12)
Doppelgängers [2] (D2)	0.76 (0.19)

While the individual correlation improved, the population means for both D1 and D2 were substantially higher (0.79 and 0.76, respectively) than the human mean (0.59). The distribution of Change Fraction for the doppelgängers was skewed towards higher values compared to the human distribution (Figure 7.3).

Figure 6.3: Distribution of Change Fraction for Human Participants vs. Synthetic Smoker Doppelgängers (D2). (Source: Effect of Good vs. Poor-Quality Therapy on Doppelgängers' Behaviour, Slide 9 and 10)

Analysis

Change Fraction is a valid and crucial metric for evaluating MI conversations. The experiments demonstrate that CF can be explicitly installed in doppelgängers, leading to a strong individual-level correlation with their human counterparts. This allows for the creation of doppelgängers that exhibit specific levels of change versus sustain talk.

However, the population-level mismatch remains a significant limitation. Doppelgängers, even when instructed on their C:S ratio, tend to exhibit higher levels of Change Talk on average than the human participants they are modeled after. This suggests an inherent bias in the LLM towards pro-social or agreeable responses within the context of therapy, potentially overstating their readiness to change.

6.3 Sensitivity to Counselling Quality

A critical requirement for the synthetic smoker, if it is to be used for optimizing MIBot or training novice counsellors, is its ability to react differentially to good versus poor-quality therapy. This section investigates whether doppelgängers exhibit different behaviors and outcomes when interacting with a high-fidelity MI bot compared to a confrontational counsellor.

6.3.1 Methodology

We utilized the validated method of installing Change Fraction to create two distinct groups of doppelgängers based on the MIV6.3A dataset:

1. **Sampling:** We sampled 25 participants from the top 25th percentile of Change Fraction (High-CF group) and 25 participants from the bottom 25th percentile (Low-CF group).
2. **Doppelgänger Creation:** Doppelgängers were created for each participant, installing pre-conversation surveys, readiness rulers, demographics, and their specific Change Fraction.
3. **Counsellor Conditions:** The doppelgängers interacted with two different counsellors:
    - **Good MI (MIBot 6.3A):** The high-fidelity MI bot used in the feasibility study.
    - **Bad MI (Confrontational):** A bot prompted to act as a novice counsellor with no MI training. Its behavior was designed to be directive, judgmental, and confrontational (e.g., giving unsolicited advice, asking numerous closed questions, persuading rather than exploring).

The outcomes evaluated were Change Fraction (CF), Change in Confidence (Delta Confidence, measured a week later), and CARE (empathy score).

6.3.2 Results

The results demonstrate that the doppelgängers responded differently to the Good and Bad MI counsellors (Table 7.8).

Table 6.8: Effect of Good vs. Poor-Quality Therapy on High-CF and Low-CF Doppelgängers (n=25 per group).

Counsellor	Participant Group	Change Fraction (CF)	Delta Confidence	CARE
Good MI (MIBot 6.3A)	High-CF Doppelgängers	0.80	1.4	49.8
	Low-CF Doppelgängers	0.48	1.1	47.8
Bad MI (Confrontational)	High-CF Doppelgängers	0.68	1.1	41.0
	Low-CF Doppelgängers	0.22	0.5	23.0

When interacting with the Bad MI counsellor, both groups showed reduced Change Fraction, smaller increases in confidence, and significantly lower CARE scores compared to their interactions with the Good MI bot.

The impact was particularly pronounced for the Low-CF group. Their Change Fraction dropped from 0.48 (Good MI) to 0.22 (Bad MI), Delta Confidence dropped from 1.1 to 0.5, and the CARE score halved from 47.8 to 23.0. The High-CF group also showed reductions across all metrics, but the magnitude of the drop in CF and CARE was less severe than in the Low-CF group.

6.3.3 Analysis

These results indicate that the synthetic smoker doppelgängers are sensitive to the quality of counselling. They can detect and react negatively to confrontational and non-empathetic behavior, which manifests as increased Sustain Talk (lower CF), reduced confidence gains, and lower perceived empathy.

The heightened sensitivity of the Low-CF group (representing more resistant individuals) to poor therapy aligns with MI principles, which emphasize the importance of avoiding confrontation when working with ambivalent clients, as it often evokes reactance and reinforces sustain talk. This experiment provides strong evidence for the validity of the synthetic smoker simulation and its potential utility as a tool for evaluating and refining conversational agents in behavioral health contexts.

6.4 Conclusion

Chapter 7

Validation of Synthetic Smokers

The previous chapter detailed the development methodology of the synthetic smoker, tracing its evolution from simple prompted personas to data-driven doppelgängers. The primary motivation behind this development was to create a reliable, controllable, and realistic simulation environment for testing and refining MIBot. This chapter presents the results and analysis of the experiments conducted to validate the synthetic smoker across its development phases.

The validation process is divided into two main stages, mirroring the development timeline. The first stage focuses on validating the initial attempts to control specific behavioral attributes—namely verbosity and resistance—through prompt engineering, prior to the availability of human conversational data. The second stage focuses on the validation of "doppelgängers," which were created using data from the MIBot feasibility study to mirror specific human participants. This stage examines the fidelity of these doppelgängers through transcript replay experiments, incremental attribute installation, and their sensitivity to the quality of motivational interviewing.

7.1 Validating Initial Controllable Attributes (Phase 1)

Before the development of MIBot and the subsequent feasibility study, the initial objective was to create synthetic smokers that could provide a consistent testing environment. Early observations indicated challenges in managing the synthetic smoker's natural tendencies, particularly regarding their verbosity and their level of resistance to behavior change.

7.1.1 Controlling and Validating Verbosity

A significant challenge in early simulations was the tendency of Large Language Models (LLMs) to produce verbose, grammatically complete utterances. This contrasted sharply with the more casual, often shorter, text-based communication observed in human participants. Excessive verbosity from the synthetic smoker often led to the counsellor bot reciprocating with equally lengthy responses, resulting in conversations that did not reflect typical human interaction dynamics.

Methodology

To address this, several prompt engineering strategies were employed to reduce the synthetic smoker's utterance length. These included instructions to:

- "Speak with more clarity rather than exhaustive detail."
- "Imagine you're texting a friend. Keep it casual..."

- Explicitly limiting the response length (e.g., "Number of sentences in your response must be between 1 and 4.")

Experiments were conducted using GPT-4 Turbo to compare the "default verbosity" (standard prompting) with "fixed verbosity" (prompts including length constraints and casual tone instructions). The validation involved analyzing the utterance length distribution, the total number of turns, and the total word count per conversation. Furthermore, the resilience and transferability of these prompting strategies were tested on the newer GPT-4 Omni model.

Results

The prompt engineering efforts successfully reduced the utterance length of the synthetic smoker. In the initial comparison using GPT-4 Turbo, the "fixed-verbosity" condition resulted in a significantly tighter and lower distribution of utterance lengths for both the client (synthetic smoker) and the counsellor compared to the "default-verbosity" condition.

[Placeholder for Figure 4.1: Violin Plot of Utterance Length by Verbosity Level (Default vs. Fixed) using GPT-4 Turbo. Source: "Controlling & Validating Verbosity in Synthetic Smokers" Slide 4]

The analysis was expanded to compare these results across models (GPT-4 Turbo and GPT-4 Omni) and with data from actual human conversations categorized as "high-quality-human-MI" and "low-quality-human-MI" (Figure 7.1).

Figure 7.1: Violin Plot of Utterance Length by Verbosity Level and Model, Compared with Human MI Conversations. (Source: Controlling & Validating Verbosity in Synthetic Smokers slides, Slide 7)

The "fixed-verbosity" conditions (both GPT-4 Turbo and GPT-4 Omni) more closely resembled the utterance length distribution of human participants than the "default-verbosity" conditions. The installation of verbosity control proved transferable between models; the "fixed-verbosity" prompts yielded similar results when applied to GPT-4 Omni.

However, analyzing the number of turns per conversation revealed a discrepancy. The simulated conversations, across all conditions, generally had fewer turns than the human conversations, particularly when compared to the high-quality human MI data (Figure 7.2).

Figure 7.2: Box Plot of Number of Turns per Conversation for different Verbosity Levels and Models. (Source: Controlling & Validating Verbosity in Synthetic Smokers slides, Slide 8)

Analysis

The results demonstrate that prompt engineering can effectively control the verbosity of synthetic smokers, bringing their utterance lengths closer to human levels. The observed reciprocity, where the counsellor bot reduces its verbosity in response to the client bot, highlights the interactive dynamics of the simulation. While the utterance length was successfully controlled and the methodology proved transferable to newer models, the lower number of turns in simulations suggests potential differences in conversational flow or depth compared to human interactions.

7.1.2 Installing and Validating Resistance

To effectively test MIBot, the synthetic smoker needed to exhibit varying levels of resistance to quitting smoking. This section examines the experiments designed to install and validate high and low resistance levels.

Methodology

Resistance was installed via detailed prompts that provided the synthetic smoker with a backstory and a specific mindset regarding smoking cessation.

- **High Resistance:** The prompt emphasized severe life stressors, skepticism towards therapy, anxiety when pressured to quit, and a belief that it was not the right time to change.
- **Low Resistance:** The prompt described smoking as a habit formed through social interaction, recent concerning lab results, skepticism balanced by an openness to cutting back, and a willingness to try their best in the conversation.

Validation was conducted through two methods: analyzing the language used during conversations with a GPT-4 MI therapist (Change Talk vs. Sustain Talk) and evaluating self-reported readiness rulers (Importance, Confidence, Readiness) collected pre-conversation, post-conversation, and one week later (simulated).

Results

The analysis of conversational language showed a marked difference between the two conditions (Table 7.1). The high-resistance smoker used substantially more Sustain Talk (44%) than Change Talk (31%). Conversely, the low-resistance smoker used significantly more Change Talk (61%) than Sustain Talk (9%).

Table 7.1: Percentage of Change Talk, Sustain Talk, and Neutral Talk for High and Low Resistance Synthetic Smokers.

Smoker Type	Change Talk (%)	Sustain Talk (%)	Neutral (%)
High resistance smoker	31	44	25
Low resistance smoker	61	9	30

The readiness ruler scores also reflected the installed resistance levels (Table 7.2). The high-resistance smoker started with lower scores across all three metrics (I: 2.0, C: 1.0, R: 0.6) compared to the low-resistance smoker (I: 4.6, C: 2.6, R: 3.2). Both groups showed positive changes after the conversation and at the one-week follow-up.

Table 7.2: Readiness Ruler Scores (Importance, Confidence, Readiness) for High and Low Resistance Synthetic Smokers.

	Low Resistance			High Resistance		
	I	C	R	I	C	R
Pre-conversation	4.6	2.6	3.2	2.0	1.0	0.6
Post-conversation	6.4	4.2	5.2	4.0	2.0	2.6
1-Week Later	6.6	4.8	5.4	4.6	2.6	3.4
Delta (Week later - Pre)	2.0	2.2	2.2	2.6	1.6	2.8

Analysis

The distinct differences in Change/Sustain Talk and the starting readiness ruler scores confirm the successful installation of varying resistance levels through prompting. Interestingly, the high-resistance group exhibited a larger delta in Importance (+2.6) and Readiness (+2.8) compared to the low-resistance group, although their absolute scores remained lower. This suggests that the MI intervention was effective in shifting the perspective of the high-resistance smoker, even when starting from a position of strong skepticism.

7.2 Validating Synthetic Smoker Doppelgängers (Phase 2)

Following the completion of the MIBot feasibility study (MIV6.3A), real human data became available. This shifted the focus from creating generic personas to developing "doppelgängers"—synthetic smokers designed to mirror the attributes and behaviors of specific human participants. The goal was to create representative stand-ins that could facilitate rapid, iterative development of MIBot. This section details the validation experiments for these doppelgängers.

7.2.1 Transcript Autoplay (Consistency Check)

The initial validation step for doppelgängers was to assess whether an LLM, when provided with the context of a specific human participant, could consistently reproduce their outcomes if the conversation trajectory was fixed.

Methodology

In the "transcript autoplay" experiments, the LLM was given the pre-conversation readiness rulers of a human participant and the transcript of the MIBot-human conversation. The LLM was prompted to adopt the persona of the participant and, after processing the conversation, provide the post-conversation readiness rulers. This tests the model's ability to reason about the impact of the conversation on the participant's state of mind. We utilized Chain-of-Thought (CoT) prompting to encourage the model to articulate its reasoning before providing the numerical scores. We tested this with two levels of attribute installation: M2 (Pre-conversation rulers only) and M7 (All attributes, including HSI and demographics).

Results

The results of the autoplay experiments are summarized in Table 7.3, showing the Mean Absolute Error (MAE) and Pearson Correlation between the human outcomes and the LLM predictions.

Table 7.3: Mean Absolute Error (MAE) and Pearson Correlation for Post-Conversation Readiness Rulers in Transcript Autoplay Experiments.

	Post-Conf.		**Post-Import.**		**Post-Read.**	
Model	MAE	Corr.	MAE	Corr.	MAE	Corr.
M2 (Rulers only, CoT)	1.1	0.7	0.7	0.9	0.9	0.8
M7 (All Attributes, CoT)	1.2	0.7	0.8	0.9	0.7	0.9

The models demonstrated high Pearson correlations, particularly for Post-Importance (0.9) and Post-Readiness (0.8-0.9), and relatively low Mean Absolute Errors. The correlation for Post-Confidence was slightly lower but still strong (0.7). The performance was similar whether only the pre-conversation rulers (M2) or all attributes (M7) were installed.

Analysis

The high correlation and low MAE indicate that when the conversation transcript is provided, the LLM can accurately predict the post-conversation readiness rulers reported by the human participants. This suggests that the model possesses the necessary reasoning capabilities to understand how the conversational dynamics influenced the participant's motivation and confidence. This serves as a crucial baseline, confirming the model's internal consistency before attempting to generate the conversation itself.

7.2.2 Incremental Attribute Installation

The next step involved having the doppelgänger actively participate in a conversation with MIBot, rather than just passively reading a transcript. Experiments were conducted to determine which

attributes needed to be "installed" (provided in the prompt) to create a doppelgänger that behaved similarly to its human counterpart during a live interaction.

Methodology

We performed an incremental installation study, systematically adding participant attributes to the doppelgänger's prompt. The models were evaluated based on the MAE and Pearson correlation between the doppelgänger's outcomes (Post-conversation rulers, CARE, C:S ratio) and the human counterpart's outcomes. Key models included:

- **M0 (Baseline):** No attributes installed.
- **M2:** Pre-conversation Importance, Confidence, and Readiness installed.
- **M7:** All attributes (Pre-conversation rulers, HSI metrics, Sex, Age) installed.

Results

The results of the incremental installation during live conversations are presented in Table 7.4.

Table 7.4: MAE and Pearson Correlation for Key Metrics across Incremental Installation Models during Live Conversation.

	Post-Conf.		**Post-Import.**		**CARE**		**C:S Ratio**	
Model	MAE	Corr.	MAE	Corr.	MAE	Corr.	MAE	Corr.
M0	1.6	nan	1.8	-0.3	7.9	-0.3	4.8	-0.1
M2	1.2	0.7	0.8	0.9	8.3	0.3	3.5	-0.2
M7	1.3	0.7	0.8	0.9	8.3	0.1	2.7	0.0

Installing the pre-conversation readiness rulers (M2) significantly improved the correlation and reduced the MAE for post-conversation Confidence and Importance compared to the baseline (M0). The correlations achieved in the live conversation (0.7 for Confidence, 0.9 for Importance) were comparable to those achieved in the autoplay condition. Adding demographic and smoking history information (M7) did not substantially change the outcomes for the readiness rulers. Notably, the correlation for the C:S ratio (Change vs. Sustain talk) remained near zero across all models, and the MAE for CARE scores remained high with negligible correlation.

Analysis

The pre-conversation readiness rulers are the most critical attributes for ensuring the doppelgänger's post-conversation self-reported outcomes align with their human counterparts. This suggests that the initial motivational state heavily influences the trajectory of the conversation and the final outcomes.

However, the failure to achieve correlation in the C:S ratio indicates that while the doppelgängers might reach the same self-reported outcomes, the language they use during the conversation does not match their human counterparts based on these attributes alone. The poor results for CARE suggest difficulty in replicating the human perception of the therapist's empathy.

7.2.3 Validating and Installing Change Fraction

The discrepancy in the C:S ratio (or Change Fraction, defined as $CF = C/(C+S)$) observed in the incremental installation experiments led to a focused effort to understand and install this metric. Change Fraction is considered a crucial implicit measure of the client's readiness, reflected directly in their language.

Change Fraction in Human Data

We first analyzed the MIV6.3A human data (n=115, low-confidence participants) to validate Change Fraction as a relevant metric. The analysis revealed strong, statistically significant positive correlations between Change Fraction and several key attributes (Table 7.5).

Table 7.5: Correlation between Change Fraction and Smoker Attributes in MIV6.3A Human Participants (n=115).

Attribute	Correlation with Change Fraction (Spearman's coeff.)
Post-conversation Importance	0.49 (****)
Post-conversation Readiness	0.48 (****)
Pre-conversation Importance	0.47 (****)
Pre-conversation Readiness	0.46 (****)
Post-conversation Confidence	0.41 (****)
Change in Confidence (Delta)	0.24 (**)

****: $P \leq 0.0001$, **: $P \leq 0.01$

This analysis confirms that in humans, the language used (CF) is strongly associated with their self-reported readiness and motivation.

Installing Change Fraction in Doppelgängers

We then conducted experiments to explicitly install the Change Fraction into the doppelgängers. We compared two sets of doppelgängers based on the MIV6.3A participants:

- **Doppelgängers [1] (D1):** Installed Pre-conv. rulers, HSI, Sex, Age.
- **Doppelgängers [2] (D2):** Installed all attributes in D1 PLUS a description of the C:S ratio (e.g., "You are 3x more likely to speak about changing your smoking behavior than sustaining it").

We evaluated the installation on both individual and population levels.

Individual-Level Validation At the individual level, we measured the Spearman correlation of outcome metrics between the humans and their corresponding doppelgängers (Table 7.6).

Table 7.6: Individual-level Validation: Spearman Correlation of outcome metrics between Humans and Doppelgängers (n=115).

Metric	D1 (No CF installed)	D2 (CF installed)
Change Fraction	0.22 (*)	**0.57 (****)**
Change in Confidence	0.29 (**)	0.25 (*)
CARE	0.04 (ns)	0.00 (ns)

****: $P \leq 0.0001$, **: $P \leq 0.01$, *: $P \leq 0.05$, ns: P ¿ 0.05

Explicitly installing the Change Fraction (D2) significantly increased the correlation for Change Fraction from 0.22 to 0.57. The correlation for Change in Confidence remained modest, and the correlation for CARE remained negligible.

Population-Level Validation At the population level, we compared the mean and distribution of the Change Fraction (Table 7.7).

Table 7.7: Population-level Validation: Mean Change Fraction.

Group	Mean Change Fraction (Std)
Humans (MIV6.3A)	0.59 (0.26)
Doppelgängers [1] (D1)	0.79 (0.12)
Doppelgängers [2] (D2)	0.76 (0.19)

While the individual correlation improved, the population means for both D1 and D2 were substantially higher (0.79 and 0.76, respectively) than the human mean (0.59). The distribution of Change Fraction for the doppelgängers was skewed towards higher values compared to the human distribution (Figure 7.3).

Figure 7.3: Distribution of Change Fraction for Human Participants vs. Synthetic Smoker Doppelgängers (D2). (Source: Effect of Good vs. Poor-Quality Therapy on Doppelgängers' Behaviour, Slide 9 and 10)

Analysis

Change Fraction is a valid and crucial metric for evaluating MI conversations. The experiments demonstrate that CF can be explicitly installed in doppelgängers, leading to a strong individual-level correlation with their human counterparts. This allows for the creation of doppelgängers that exhibit specific levels of change versus sustain talk.

However, the population-level mismatch remains a significant limitation. Doppelgängers, even when instructed on their C:S ratio, tend to exhibit higher levels of Change Talk on average than the human participants they are modeled after. This suggests an inherent bias in the LLM towards pro-social or agreeable responses within the context of therapy, potentially overstating their readiness to change.

7.3 Sensitivity to Counselling Quality

A critical requirement for the synthetic smoker, if it is to be used for optimizing MIBot or training novice counsellors, is its ability to react differentially to good versus poor-quality therapy. This section investigates whether doppelgängers exhibit different behaviors and outcomes when interacting with a high-fidelity MI bot compared to a confrontational counsellor.

7.3.1 Methodology

We utilized the validated method of installing Change Fraction to create two distinct groups of doppelgängers based on the MIV6.3A dataset:

1. **Sampling:** We sampled 25 participants from the top 25th percentile of Change Fraction (High-CF group) and 25 participants from the bottom 25th percentile (Low-CF group).
2. **Doppelgänger Creation:** Doppelgängers were created for each participant, installing pre-conversation surveys, readiness rulers, demographics, and their specific Change Fraction.
3. **Counsellor Conditions:** The doppelgängers interacted with two different counsellors:
    - **Good MI (MIBot 6.3A):** The high-fidelity MI bot used in the feasibility study.
    - **Bad MI (Confrontational):** A bot prompted to act as a novice counsellor with no MI training. Its behavior was designed to be directive, judgmental, and confrontational (e.g., giving unsolicited advice, asking numerous closed questions, persuading rather than exploring).

The outcomes evaluated were Change Fraction (CF), Change in Confidence (Delta Confidence, measured a week later), and CARE (empathy score).

7.3.2 Results

The results demonstrate that the doppelgängers responded differently to the Good and Bad MI counsellors (Table 7.8).

Table 7.8: Effect of Good vs. Poor-Quality Therapy on High-CF and Low-CF Doppelgängers (n=25 per group).

Counsellor	Participant Group	Change Fraction (CF)	Delta Confidence	CARE
Good MI (MIBot 6.3A)	High-CF Doppelgängers	0.80	1.4	49.8
	Low-CF Doppelgängers	0.48	1.1	47.8
Bad MI (Confrontational)	High-CF Doppelgängers	0.68	1.1	41.0
	Low-CF Doppelgängers	0.22	0.5	23.0

When interacting with the Bad MI counsellor, both groups showed reduced Change Fraction, smaller increases in confidence, and significantly lower CARE scores compared to their interactions with the Good MI bot.

The impact was particularly pronounced for the Low-CF group. Their Change Fraction dropped from 0.48 (Good MI) to 0.22 (Bad MI), Delta Confidence dropped from 1.1 to 0.5, and the CARE score halved from 47.8 to 23.0. The High-CF group also showed reductions across all metrics, but the magnitude of the drop in CF and CARE was less severe than in the Low-CF group.

7.3.3 Analysis

These results indicate that the synthetic smoker doppelgängers are sensitive to the quality of counselling. They can detect and react negatively to confrontational and non-empathetic behavior, which manifests as increased Sustain Talk (lower CF), reduced confidence gains, and lower perceived empathy.

The heightened sensitivity of the Low-CF group (representing more resistant individuals) to poor therapy aligns with MI principles, which emphasize the importance of avoiding confrontation when working with ambivalent clients, as it often evokes reactance and reinforces sustain talk. This experiment provides strong evidence for the validity of the synthetic smoker simulation and its potential utility as a tool for evaluating and refining conversational agents in behavioral health contexts.

7.4 Conclusion

This chapter presented the validation of the synthetic smoker across its development lifecycle. The initial experiments demonstrated that key behavioral attributes, such as verbosity and resistance, can be effectively controlled through prompt engineering.

The development of data-driven doppelgängers showed that installing pre-conversation readiness rulers is crucial for aligning the doppelgänger's self-reported outcomes with their human counterparts, achieving high correlations in both transcript autoplay and live conversation scenarios. Furthermore, the explicit installation of Change Fraction was necessary to ensure that the language used by the doppelgänger during the conversation also correlated strongly with the human data (Spearman's coeff. 0.57).

However, limitations remain. Individual-level correlation for CARE scores was negligible, and a population-level bias persists, with doppelgängers generally exhibiting higher average Change Talk than humans.

Crucially, the validation experiments demonstrated that doppelgängers are sensitive to the quality of motivational interviewing. They react differently to high-fidelity MI compared to confronta-

tional counselling, showing reduced positive outcomes and lower empathy scores when faced with poor therapeutic techniques. This sensitivity underscores the potential of synthetic smokers as a valid, reliable, and scalable tool for the continued development and optimization of MIBot.

Chapter 8

Conclusion and Future Directions

This thesis has explored the development and evaluation of a fully generative motivational interviewing (MI) chatbot, MIBot, designed to support smokers in moving towards the decision to quit. Furthermore, we have introduced the novel concept of LLM-based synthetic smokers as a new methodology for evaluating and refining such chatbots. Our work represents a significant step forward in the application of large language models to the critical domain of public health and smoking cessation.

8.1 Summary of Contributions

The primary contributions of this thesis are twofold. First, we have demonstrated the feasibility of creating a generative MI chatbot that can engage in empathetic and effective conversations with smokers. The evaluation of MIBot showed promising results in its ability to conduct conversations that align with the principles of motivational interviewing, offering a potentially scalable and accessible tool for smoking cessation support.

Second, we have pioneered the use of LLM-based synthetic smokers. This approach addresses a long-standing challenge in chatbot research: the difficulty and expense of recruiting human participants for evaluation. By creating realistic, data-driven user personas, we can rapidly and iteratively test our chatbot, identify areas for improvement, and ensure that it is robust and effective before deploying it to real users. Our research has shown that while these synthetic users can be incredibly useful, they also come with their own set of challenges, such as the risk of generating stereotypical or overly-positive personas.

8.2 Future Directions

The findings of this thesis open up several exciting avenues for future research, both in the realm of mental health chatbots and in the use of synthetic user personas.

8.2.1 Mental Health Chatbots

The field of mental health chatbots is rapidly evolving, and there are several key areas where future work could build upon the foundations laid in this thesis:

- **Hyper-personalization:** While MIBot was designed to be empathetic, future chatbots could be made even more effective by tailoring their responses to the individual user's personality, communication style, and emotional state. This could be achieved by incorporating more sophisticated user modeling techniques and leveraging real-time affective computing.

- **Integration with Clinical Practice:** Future research should focus on how chatbots like MIBot can be integrated into existing clinical workflows. For example, a chatbot could be used to provide support to patients between therapy sessions, with the conversation history being made available to the human therapist (with the user's consent). This would create a blended model of care that combines the scalability of AI with the irreplaceable expertise of human professionals.
- **Long-term Efficacy Studies:** While our evaluation of MIBot showed promising short-term results, more research is needed to understand the long-term efficacy of such chatbots. This would involve conducting longitudinal studies with real smokers to track their progress over time and assess the chatbot's impact on their quit journey.

8.2.2 Synthetic Smokers and Instilling Attributes

The concept of synthetic smokers, or more broadly, LLM-based user personas, is still in its infancy. Future work should focus on refining this methodology and exploring new ways to instill specific attributes into these personas.

- **Reducing Bias and Stereotypes:** As our research has shown, a key challenge with AI-generated personas is the tendency to produce stereotypical or generic characters. Future work should explore techniques for generating more diverse and representative personas. This could involve using more diverse training data, or developing new algorithms that are specifically designed to avoid stereotypical outputs.
- **Instilling Attributes with Steering Vectors:** A promising technique for controlling the attributes of generated personas is the use of **steering vectors**, also known as activation vectors. This method allows us to guide the LLM's output without the need for costly fine-tuning. The process involves:
  1. **Extracting Activations:** We first extract the hidden layer activations from the LLM for contrasting prompts. For example, to instill the attribute of "readiness to quit," we could use prompts like "I am ready to quit smoking for good" and "I am not ready to quit smoking."
  2. **Computing the Steering Vector:** The steering vector is then computed as the difference between the activations of these contrasting prompts. This vector captures the semantic representation of the desired attribute.
  3. **Injecting the Vector:** During inference, this steering vector is added to the model's activations. By doing so, we can "steer" the model's output towards the desired attribute. For example, by adding the "readiness to quit" vector, we can generate synthetic smokers who are more or less motivated to quit, allowing us to test our chatbot's effectiveness across a wider range of user profiles.

  This technique offers a powerful and flexible way to create more nuanced and targeted synthetic users. Future research could explore the use of steering vectors to instill a wide range of attributes, such as personality traits (e.g., neuroticism, conscientiousness), emotional states (e.g., anxiety, depression), and demographic characteristics.

8.3 Concluding Remarks

The intersection of large language models and mental health holds immense promise for the future of healthcare. This thesis has demonstrated how generative AI can be leveraged to create both supportive chatbots and the synthetic users needed to evaluate them. While there are still many challenges to overcome, the work presented here provides a solid foundation for future research in this exciting and rapidly evolving field. By continuing to innovate and refine these technologies, we can move closer to a future where everyone has access to the mental health support they need.

Appendix A

Code

Index of Key Terms

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