Deceptively Simple yet Profoundly Impactful: Text Messaging Interventions to Support Health

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Abstract

This paper examines the development and impact of Text Message Interventions (TMIs) on health behaviors. Initially, it outlines the historical progress in research and the variety of funding from US government agencies. A narrative review follows, highlighting the effectiveness of TMIs in key health areas such as physical activity, diet and weight loss, mental health, and substance use, based on published meta-analyses. The discussion then shifts to crucial design elements, including communication strategies, psychological foundations, behavior change tactics, and advanced functionalities. Additionally, the paper delves into the emergence of chatbots and the potential for Large Language Models (LLMs) to improve user interaction. While TMIs have demonstrated significant potential, challenges in widespread implementation remain, primarily due to the absence of a dedicated commercial platform, privacy and security concerns with SMS technology, and difficulties integrating with Electronic Health Records (EHR) systems. Solutions to these obstacles are proposed to facilitate the broader application of TMIs. The paper aims to provide valuable insights for researchers and practitioners to fully utilize TMIs, with the overarching objective of improving health outcomes and reducing disparities in healthcare access, thereby effectively transitioning from theoretical exploration to meaningful, real-world health interventions.

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Abstract

This paper examines the use of Text Message Interventions (TMIs) for health-related behavioral support. It first outlines the historical progress in TMI research publications and the variety of funding from US government agencies. A narrative review follows, highlighting the effectiveness of TMIs in key health areas such as physical activity, diet and weight loss, mental health, and substance use, based on published meta-analyses. It then outlines advantages of text messaging compared to other digital modalities including the real-time capability to collect information and deliver micro-doses of intervention support. Crucial design elements are offered to optimize effectiveness and longitudinal engagement across communication strategies, psychological foundations, behavior change tactics. We then discuss advanced functionalities, such as the potential for generative Artificial Intelligence to improve user interaction. Finally, major challenges to implementation are highlighted, including the absence of a dedicated commercial platform, privacy and security concerns with SMS technology, difficulties integrating with medical informatics systems, and concern about user engagement. Proposed solutions aim to facilitate the broader application and effectiveness of TMIs. Our hope is that these insights can assist researchers and practitioners in utilizing TMIs to improve health outcomes and reducing disparities.

1. Introduction

Text Message Interventions (TMIs), which use short message service (SMS) platform on smartphones to communicate, have emerged as a significant tool in the landscape of digital health, bridging the expanding gap between healthcare provider constraints and patient needs. While deceptively simple in design, TMIs are grounded in a sophisticated blend of communication strategies, psychological insights, and technological advances, all of which have been shown to positively shape health behaviors. This paper aims to provide a comprehensive overview of the TMIs' trajectory, distilling the evidence of their impact, discussing the critical elements of successful interventions, and exploring future directions for research and application.

Our examination begins with a look back at the emergence and evolution of TMIs, starting from the early 2000s when digital communication first showed promise for supporting health behavior change. We highlight the broad scope of funding from US government agencies and the expanding research in this field. A narrative review then spotlights the success of TMIs across critical health domains—physical activity, diet and weight loss, mental health, and substance use—drawing from recent meta-analyses. We explore the specific aspects of TMIs that contribute to their effectiveness with a focus on the real-time capability of TMIs to collect information and deliver micro-doses of intervention support.

We then discuss crucial TMI design considerations across categories of communication strategies, psychological underpinnings, behavior change techniques, and enhanced functionalities. We also identify key unanswered questions that future research needs to address. We then discuss the evolution of TMIs from rule-based systems (e.g. branching algorithms) to generative Artificial Intelligence (AI) systems. We focus on recent advancements in Large Language Models (LLMs), which present new opportunities for enhancing the interactivity and personalization of TMIs, promising to elevate the user experience and engagement further.

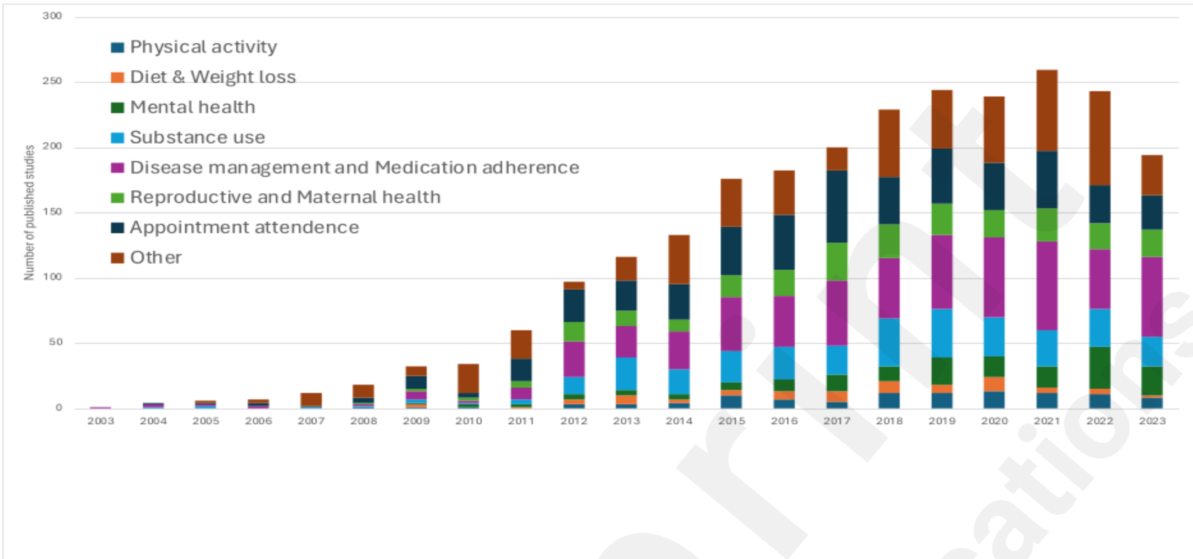
Finally, we discuss existing TMI implementation challenges including transitioning TMIs from research prototypes to widely implemented health interventions including the absence of a centralized platform for dissemination akin to app stores, legal and ethical concerns around data security and patient privacy, and the intricacies of integrating TMIs with existing Electronic Health Record (EHR) systems. We then offer suggestions for overcoming such barriers by combining innovation in technology development, policy formulation, and practice implementation.

Our goal is to equip researchers, healthcare practitioners, and policymakers with the knowledge to effectively use TMIs, aiming to improve health outcomes and reduce healthcare access and quality disparities. By offering a thorough analysis and forward-looking perspective, this paper contributes to the broader conversation on TMIs' role in health promotion and disease prevention.

2. Growth of TMI scholarship and funding

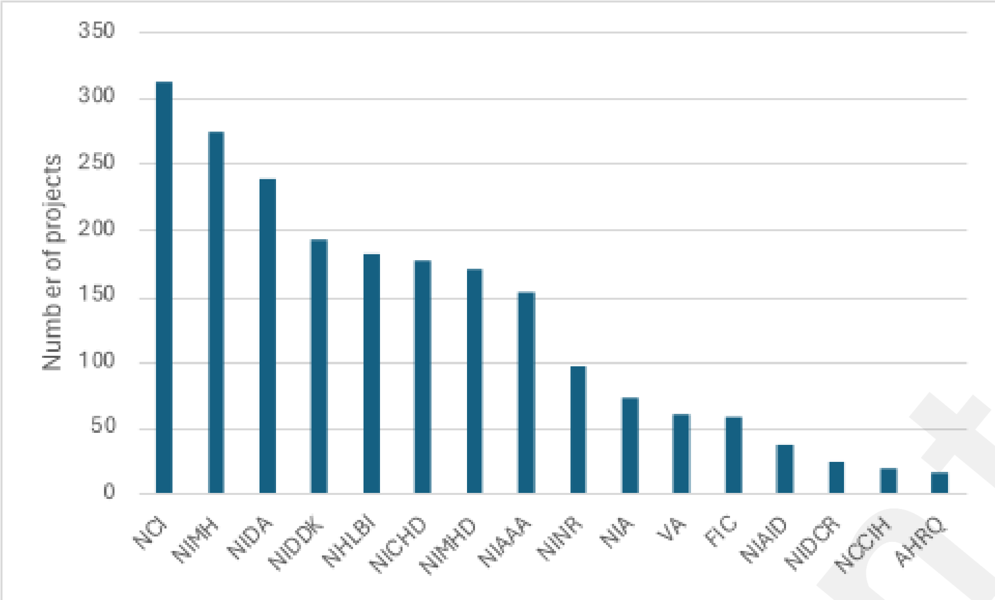
To identify peer-reviewed publications of TMIs across key health-related categories, we conducted a comprehensive search on PubMed. This search included categories such as physical activity, diet and weight loss, mental health, substance use, disease management and medication adherence, reproductive and maternal health, appointment attendance, and other relevant topics. See Supplemental Materials for PubMed search terms. As shown in **Figure 1**, the history of TMIs for behavioral support starts in the early 2000s and appears to peak in 2021 with over 250 peer-reviewed papers that year. The data shows growth across key health-related categories. The most substantial growth was observed in the "Disease management and Medication adherence" category, underscoring the perceived efficacy and value of TMIs in addressing daily health-related behaviors. While the number of studies in some categories, such as physical activity and diet and weight loss, has remained relatively low, there has been a consistent increase in research on mental health, substance use, reproductive and maternal health, and appointment attendance using TMIs. Conversely, the relatively slower increase in research within physical activity and diet and weight loss may reflect the complexities of influencing lifestyle behaviors through digital means alone or possibly the saturation of research in these areas.

Figure 1: Number of published peer-reviewed studies of TMIs by Health-related Categories and Year



To identify US national funding trends for TMI projects, we queried the National Institutes of Health (NIH) Reporter website (https://reporter.nih.gov/) using search terms “text message AND intervention”. In **Figure 2**, we illustrate the diversity of TMI projects from 2007 to 2023 from the top 16 divisions. The National Cancer Institute (NCI) leads with 312 projects, followed by the National Institute of Mental Health (NIMH) with 274 projects and the National Institute on Drug Abuse (NIDA) with 239 projects. Other notable institutes include the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK), the National Heart, Lung, and Blood Institute (NHLBI), the Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD), and the National Institute on Minority Health and Health Disparities (NIMHD), all administering over 170 projects each.

Figure 2: US governmental funding for TMIs across Institutes



Legend: NCI: National Cancer Institute; NIMH: National Institute of Mental Health; NIDA: National Institute on Drug Abuse; NIDDK: National Institute of Diabetes and Digestive and Kidney Diseases; NHLBI: National Heart, Lung, and Blood Institute; NICHD: Eunice Kennedy Shriver National Institute of Child Health and Human Development; NIMHD: National Institute on Minority Health and Health Disparities; NIAAA: National Institute on Alcohol Abuse and Alcoholism; NINR: National Institute of Nursing Research; NIA: National Institute on Aging; VA: Veterans Affairs; FIC: Fogarty International Centerl; NIAID: National Institute of Allergy and Infectious Diseases; NIDCR: National Institute of Dental and Craniofacial Research; NCCIH: National Center for Complementary and Integrative Health; AHRQ: Agency for Healthcare Research and Quality.

The major themes of NCI funding for TMIs to date include smoking cessation for specific groups like pregnant women, cancer screening for cervical and colorectal cancers in underserved areas, improving adherence to cancer treatments, and cancer prevention such as HPV vaccination. The NIMH has focused on TMIs for post-psychiatric emergency care, HIV-related health behaviors, and mental health condition monitoring. The NIDA has targeted funding at managing substance use disorders, emphasizing treatment engagement and recovery support. The NIDDK funded TMIs aimed at diabetes management, obesity prevention, and kidney disease care. The NHLBI invested in TMIs for medication adherence in sickle cell disease, hypertension and asthma management, lifestyle modifications to reduce cardiovascular risk. Lastly, the NIMHD supported a wide array of TMIs addressing health disparities, including efforts to enhance cancer screening attendance, obesity prevention in Hispanic women, health optimization in taxi drivers, workplace inclusion, physical activity in African American cancer survivors, sugary beverage reduction, maximizing

COVID-19 vaccination uptake, and smoking cessation among immigrant populations.

3. Narrative review of TMIs across key health-related categories

In this section, we review recent meta-analyses on the impact of TMIs within key health areas, pinpointing components that bolster intervention efficacy. Our analysis specifically targets peer-reviewed research published after the foundational reviews by Head et al.[1] in 2013, Hall et al.[2] in 2015, and Armanasco et al.[3] in 2017. Head and colleagues analyzed nineteen studies involving 5,958 participants and determined that TMIs across various health promotion contexts achieved an average effect size of 0.33 (95% CI: 0.27, 0.39). Hall et al.'s broader examination found a consistent pattern of positive impacts from TMIs on diabetes self-management, physical activity, weight loss, smoking cessation, and medication adherence. Armanasco's assessment of the sustained impact of seven TMIs post-intervention revealed a modest yet meaningful overall maintenance effect of d=0.17 (95% CI: 0.03, 0.31), underscoring the enduring benefits of TMIs beyond active engagement periods.

3.a. Physical Activity

In 2020, Smith et al.[4] conducted a meta-analysis of ten TMIs aimed at enhancing physical activity and found a significant increase in objectively measured steps per day post-intervention among participants receiving TMIs, with an effect size of Cohen's d=0.38 (95% CI=0.19, 0.58). The analysis indicated that TMIs incorporating multiple components, tailored messages, and those targeted at medical populations tended to yield larger, though not statistically significant, effect sizes compared to simpler TMIs. Additionally, the study revealed that TMIs featuring personalized messages were potentially more effective in promoting physical activity than those using generic text messages (Cohen’s d= 0.39 vs. 0.25). Similarly, interventions that combined text messaging with other intervention components were more effective than text-only TMIs (Cohen’s d =0.37 vs. 0.27).

3.b. Diet, and Weight Loss

In 2015, Siopis et al.[5] conducted a meta-analysis of six studies of TMIs targeting weight loss, finding that participants in TMI programs lost significantly more weight (2.17 kg; 95% CI: -3.41, -0.93) than those in control groups over 8 to 12 weeks. The design of these TMIs varied considerably, with intervention lengths ranging from 1 to 24 months and text messaging frequencies varying from daily to bi-weekly. In 2020, Skinner et al.[6] analyzed twelve weight loss interventions involving 1,977 participants and observed a mean weight loss difference of -2.28 kg (95% CI: -3.17, -1.36) favoring the TMI groups. Among studies focusing on maintaining weight loss involving 3,728 participants, the mean difference in weight change was -0.68 kg (95% CI: -1.31, -0.05) favoring TMIs. For post-intervention follow-ups, the effect was -0.57 kg (95% CI: -1.67, 0.53), suggesting sustained TMI benefits. These variations in weight loss outcomes were not clearly associated with specific intervention characteristics such as duration, text messaging frequency, theoretical basis, interactivity, or personalization. In 2020, Partridge et al.[7] reviewed eight studies targeting adolescents (767 participants), finding that TMIs led to reductions in Body Mass Index ranging from 1.3% to 4.5% compared to controls by the end of follow-up. These studies exhibited diversity in TMI intensity, duration, content, and behavioral strategies employed, underscoring the heterogeneity within TMI research on weight loss and management.

3.c. Mental Health

Within the domain of mental health, most TMIs tested have been focused on depression. In 2019, Senanayake et al.[8] conducted a meta-analysis of seven trials (845 patients: 664 adults and 181 adolescents) finding that the standardized mean reduction in depression scores for TMIs was 0.23 (95% CI: -0.02, 0.48). In 2020, Cox et al.[9] examined seven TMIs (1,918 participants) where pooled analysis found non-significant differences in depressive symptom scores between TMI and control groups (mean= −0.27; 95% CI, −0.54, 0.01). Reductions in depression were greater when text message content targeted mental well-being, mood improvement, and cognitive behavioral therapy and when the message frequency was ⩾2 times per week. Evidence for other mental health issues remains less robustly studied. In 2020, D’Arcey et al.[10] performed a systematic review of fifteen studies focused on patients with schizophrenia. Although effect sizes were not presented, they comment that most TMIs demonstrated positive effects on dimensions of engagement such as medication adherence, clinic attendance, and therapeutic alliance.

3.d. Substance Use

Within the domain of substance use, the most studied behavioral foci for TMIs is smoking cessation. In 2016, Scott-Sheldon et al.[11] conducted a meta-analysis evaluating the effectiveness of TMIs on smoking cessation, analyzing twenty-two interventions with 15,593 participants from ten countries. The analysis revealed that individuals who received TMIs were significantly more likely to quit smoking compared to control groups, as evidenced by various smoking abstinence measures including 7-day point prevalence (odds ratio [OR]=1.38, 95% CI=1.22, 1.55) and continuous abstinence (OR=1.63, 95% CI=1.19, 2.24). In 2023, Zhou et al.[12] focused on young adults aged 16 to 30 and found, across seven studies, that TMIs were effective in promoting 7-day point prevalence abstinence with a risk ratio (RR) of 1.83 (95% CI 1.34-2.48).

Following smoking, alcohol misuse is the next most common substance addressed by TMIs. Bendtsen et al.[13], in 2021, performed a meta-analysis of twenty-six trials (7,376 participants) examining TMIs and found a significant decrease in alcohol consumption among intervention groups compared to controls (Hedges' g = 0.17, 95% CI: 0.10, 0.23). Subgroup analyses indicated more substantial effects for TMIs that used personalized messages (g = 0.25), had a high frequency of messaging (g = 0.24), and were grounded in behavioral theories (g = 0.22).

3.e. Medication Adherence

In 2016 Thakkar et al.[14], conducted a meta-analysis of sixteen trials testing TMIs on medication adherence in chronic disease involving 2742 participants. The findings indicate that TMIs significantly enhanced medication adherence (OR=2.11; 95% CI, 1.52, 2.93). Notably, the effectiveness of TMIs did not vary based on the duration of the intervention, the type of chronic disease targeted, or specific features of the text messages such as personalization, two-way communication, or the frequency of messages sent.

Several special populations have been the focus of meta-analyses for medication adherence TMIs. HIV in Adolescents: A systematic review by Mehra et al.[15] in 2021 included seven studies with a total of 987 participants, where sample sizes ranged from 14 to 332. Five of these studies demonstrated a positive impact of TMIs in improving adherence. The pooled mean difference between the intervention and the control group was 0.05 (95% CI: -0.08 to 0.17). Serious Mental Illness: In 2022, Simon et al.[16] analyzed nine unique trials involving 937 participants. The durations of these studies varied from 30 days to 18 months, with text message frequency ranging from twice a week to twelve times a day. Seven of these studies reported statistically significant improvements in medication adherence and at least one clinical outcome. Vascular disease: In 2017, Adler et al.[17] examined seven randomized trials testing TMIs for participants with established arterial occlusive events in 1310 participants. Although heterogeneity precluded meta-analyses, 6 out of 7 trials showed a significant effect size on medication adherence across a range of definitions.

3.f. Summary

This narrative review highlights the substantial and growing evidence base for the effectiveness of TMIs across a range of health behaviors and outcomes. Meta-analyses consistently demonstrate small to moderate positive effects of TMIs on physical activity, diet and weight loss, mental health, substance use (particularly smoking and alcohol), and medication adherence. There is also emerging evidence for the benefits of TMIs in special populations such as adolescents and individuals with serious mental illness. However, the optimal design features of TMIs (e.g., frequency, duration, personalization) vary across studies and health domains, suggesting the need for further research to identify the most effective intervention components for specific behaviors and populations. Additionally, more studies are needed to assess the long-term maintenance of effects and the potential for TMIs to help older adults. Despite these limitations, the evidence to date supports the use of TMIs as effective in promoting health behavior change and improving clinical outcomes.

4. What Makes TMIs Uniquely Useful?

TMIs continue to be a powerful tool for health behavior support due to their widespread use and unique functioning as a communication tool. One key reason is that SMS remains a highly preferred form of communication. In a national sample of 1,019 adults across the US and Canada in 2023, 70% of people reported that texting is the fastest way to reach them, 74% read every text they receive, and 62% read texts within a few minutes [18]. Another key advantage of SMS is its efficacy in collecting longitudinal and contextual information from individuals and delivering micro-doses of intervention support. SMS functions as a "push" technology, delivering messages directly to individuals without any effort on their part [19], which has been shown to be a powerful engagement tool [20]. This contrasts with other digital communication modalities, such as email or web-based messaging, which require users to proactively check for messages. In contrast to SMS, smartphone app notifications can be turned off, and wearable technologies are not consistently worn [21].

The real-time data collection aspect of TMIs provides unique insights into the mechanisms of behavior change. Historically, behavioral intervention studies used sparse measurements taken immediately before and after the delivery of an intervention to examine mediators of distal behavior change. [22]. This approach has constrained our ability to identify the dynamic and non-linear processes through which behavior change likely occurs [23]. Text messaging allows for low-barrier monitoring of participants, capturing detailed, time-stamped information about their behaviors, emotions, and environmental contexts. This results in a richer dataset compared to traditional methods, which often rely on retrospective self-reports prone to recall bia [24]. Examples of dynamic models of behavior change facilitated by the longitudinal data collected as part of two-way TMIs [24], [25] have begun to offer new insights into behavior change mechanisms.

In summary, the real-time ability to collect information and deliver micro-doses of intervention support is the secret superpower of TMIs. For researchers, it offers a unique opportunity to explore the intricate time-dependencies between various precursors and health behaviors, enhancing our understanding of behavior change mechanisms. For users, it provides immediate, context-relevant support, fostering sustained engagement and promoting long-term health behavior change.

5. Key TMI Design Considerations

In this section, we review concepts to consider when designing TMIs, focusing on communication strategies, psychological theories, behavior change strategies, and adjunctive functionality. We summarize current best practices based on existing research and/or personal experience and highlight important open questions and areas where knowledge remains limited or where special consideration should be made. **Table 1** outlines these features and open questions. Understanding current best practices for design features and gaps in knowledge are crucial for developers seeking to create effective, engaging, and evidence-based TMIs.

5.a. Communication Strategies

One key reason why TMIs are so effective for relationship-building is their ability to simulate a human-like dialogue. The way in which information is conveyed, the tone of the messages, and the timing and frequency of delivery can all have a significant impact on user engagement, motivation, and ultimately, behavior change outcomes. This section explores several key communication strategies in TMI design, including onboarding, embodiment, personalization, timing, intensity, and duration. By examining current best practices and identifying open questions in each of these areas, we aim to shed light on the critical role of communication in creating engaging, persuasive, and effective TMIs.

<u>Onboarding</u>: Clear communication during the onboarding process can help set expectations, build rapport, and increase motivation for engagement with the TMI. Defining expectations is the first critical design component of a well-functioning TMI and should include at minimum conveying information about TMI intensity and duration. If the TMI operates independently of other onboarding

processes (e.g. in-person enrollment), additional baseline information is necessary to allow personalization and tailoring should also be captured. Embodiment: Identifying the program as originating from a credible source can enhance trust and engagement[26]. Regarding transparency, one major open question is whether and how TMI designers should disclose that the program is automated[27], explicitly reminding users that there is no human provenance.

Personalization: Personalizing messages with user characteristics like name is likely to contribute to engagement[28]. By using natural language, TMIs can create a sense of warmth, empathy, and personalization that resonates with users. Beyond this, there remains unknowns as to how personalization such as cohort-specific identifiers impact engagement and effectiveness. It is however crucial for TMIs to avoid labelling someone as having a disease or condition[29], which can lead to the internalization of negative stereotypes and self-stigma, which can erode self-esteem and motivation to engage in healthy behaviors[30].

Timing: For many behaviors, knowing when to interact with users may be as crucial as knowing what to do. Research on habit formation and context-dependent learning[31] suggests that behaviors are strongly influenced by the contexts and cues in which they occur. By delivering interventions at specific moments and in specific contexts, it may be possible to interrupt impending undesired habits or promote the formation of positive habits. However, identifying when these critical moments are likely to occur presents a significant challenge. Some behaviors may exhibit predictable patterns at the population level, such as increased sedentary behavior during the workday or decreased medication adherence on weekends. Other behaviors, however, may show high within-person variability, making it more challenging to predict when an individual will need support. Depending on the behavior and the necessity to control the timing of messages, consideration could be made to allow users to set their own preferred times for receiving messages.

Intensity (Dose): The key to optimizing TMI intensity is to provide sufficient support and guidance to promote behavior change while avoiding overwhelming or burdening the individual. The optimal messaging frequency may vary depending on the nature of the target behavior and its temporal dynamics. For behaviors that occur at short intervals, such as smoking or snacking, more frequent interactions may be necessary to provide timely support and reinforcement. In contrast, for behaviors that occur at longer time scales, such as physical activity or medication adherence, a more spaced-out cadence of messaging may be appropriate. However, it is important to recognize that simply increasing the intensity of messaging, particularly for challenging or complex behaviors, may not always lead to better outcomes[32]. In fact, this approach could backfire by overwhelming or frustrating users, leading to disengagement or even reactance[33]. An open question is how to taper the frequency or intensity of messages over time to gradually transfer responsibility for behavior change from the intervention to the individual. Another related question is how often, for frequent behaviors, one must interact to be effective.

<u>Duration</u>: As with all behavioral interventions, key considerations for TMIs include how long it must run to be effective. Research suggests that it takes an average of 66 days for a new behavior to become automatic, but this can vary widely depending on the complexity of the behavior and individual differences[34]. There is also evidence that duration of engagement with TMIs does not necessarily translate to more favorable outcomes[35], [36] . In our experience, the relationship between TMI engagement and effectiveness is U-shaped: individuals who show the greatest effects either use the program the least (indicating they have adopted the behavior and don't need the support) or the most (indicating commitment to behavior adoption struggle). A fixed duration may be appropriate for interventions targeting short-term goals or behaviors with a clear endpoint, such as completing a vaccination schedule or recovering from surgery. However, for interventions targeting complex, long-term behavior changes, such as adopting a healthy diet or increasing physical activity, a more flexible and individualized approach may be necessary.

5.b. Psychological Theories

The incorporation of psychological theories into the design of TMIs has been a topic of growing interest. The meta-analysis by Head et al.[1] and the systematic review by Hall et al.[2], both found that TMIs based on theory were significantly more effective in promoting health behaviors than those not based on theory. Several specific theories have been commonly used in the design of TMIs. The Transtheoretical Model (TTM)[37], which posits that individuals move through distinct stages of change when modifying health behaviors, has been successfully applied in TMIs for physical activity and smoking cessation[38]. Social Cognitive Theory (SCT)[39], which emphasizes the interplay between personal, behavioral, and environmental factors in shaping behavior, has also been frequently used in TMIs for various health behaviors[38]. Other theories that have informed TMI design include the Health Belief Model (HBM)[40], which focuses on individuals' perceptions of health risks and benefits, and the Theory of Planned Behavior (TPB)[41], which emphasizes the role of attitudes, subjective norms, and perceived behavioral control in shaping intentions and behaviors[42].

While the evidence supports the use of these traditional theories in TMI design, some researchers have argued that existing theories may need to be adapted or integrated to better suit the unique context of mobile interventions[43]. For example, theories could be updated and adapted to take into account for the dynamic and interactive nature of how behaviors play out in the real world, as well as the potential for real-time interventions to adapt to those time- and context-dependent needs[44]. For example, mathematical equations informed by control theory[45] could be used to make predictions at a given timepoint for a given individual based on prior data from that individual to tailor some aspect of intervention content. Testing of such dynamical models is in the early stages[46], [47] and thus it remains unknown whether the complexity pays off in requisite effects.

5.c. Behavior Change Techniques

Self-monitoring, goal-setting/action planning, and feedback are three key behavior change techniques (BCTs) that have been widely incorporated into behavioral interventions in general[22], [48] and digital interventions (including TMIs) specifically[49].

Self-monitoring: Many behaviors, especially when they become habitual, are below the level of conscious recognition[50]. The act of self-monitoring itself can raise awareness of one's behavior and motivate change. TMIs offer a convenient and accessible platform for prompting and assisting individuals in bringing behaviors, emotions, desires to awareness. This can involve prompting individuals to reflect prior to a given behavior (to raise awareness of motives and expectancies) or following a behavior (to promote active reflection). It can also have varying levels of specificity, from simply prompting a reflection on a behavior (e.g., "Think about how exercising made you feel?") to requesting specific data (e.g., "Please reply with the number of steps you took today."). The frequency and format of self-monitoring prompts should be tailored to individual preferences and needs weighed against program requirements for tailoring. An open question remains how to identify individuals who experience outsized negative affect due to the increased self-focused attention due to self-monitoring[51].

Goal-setting and action planning are closely related BCTs that assist behavior change[52]. A meta-analysis of 141 studies testing 384 effect sizes (16,523 participants) found a positive unique effect of goal setting across a range of behaviors (d = .34 (95% CI .28, .41])[53]. TMIs should ideally be designed with SMART (Specific, Measurable, Achievable, Relevant, and Time-bound) goals[31]. Relatedly, action planning should ideally involve the concept of implementation intentions: the more specific someone can be with the when, where, and how the goal will be achieved, the more likely it will be accomplished[54]. TMIs can provide templates or examples to help users develop effective goals and action plans and can send reminders or prompts to encourage adherence to the plans. An open question remains how best to support autonomy in self-determined goals[55] while pushing individuals who may not be intrinsically motivated toward progress.

Performance feedback: The principles of cybernetics and control theory[45] suggest that feedback operates as part of a closed-loop system, wherein individuals compare their current behavior to their goals and adjust their actions accordingly. TMIs can leverage this feedback loop by providing regular, timely feedback and encouraging users to reflect on their progress and adjust as needed.

Feedback can help individuals gauge their progress, identify areas for improvement, and adjust their strategies as needed. In TMIs, behavioral feedback can be descriptive (e.g., "You walked an average of 8,000 steps per day this week.") or evaluative (e.g., "Great job! You exceeded your goal of 7,000 steps per day this week!"). The frequency, tone, and format of feedback messages can be tailored to individual preferences and needs to maximize engagement and effectiveness. One open question is how best to balance the need for providing regular feedback with the risk of overwhelming or discouraging participants. Another open question is how to avoid behavioral disengagement[56] when an individual exhibits persistent goal failures.

5.d. Enhanced functionalities

<u>Human Helpers:</u> Automated systems for delivering TMIs offer several advantages, including scalability and reproducibility. However, a key limitation of automated TMIs is their inability to provide supportive accountability that can be crucial for patient engagement and support[57]. To address this, researchers have explored incorporating human helpers, such as healthcare professionals, significant others, and peers, into TMIs.

One early example of incorporating professionals into TMIs was a study by Rodgers et al.,[58] which evaluated a smoking cessation program where participants received personalized text messages from a team of counselors. The counselors used a web-based interface to monitor participant progress and tailor the content and timing of messages based on individual needs. To capitalize on the strengths of both human and automated approaches, some TMIs have adopted a hybrid model. Aguilera et al.[59] evaluated a hybrid TMI for depression that used an automated system to send daily mood-tracking prompts and self-management tips while also allowing participants to request additional support from a mental health coach via text message. This hybrid approach aimed to strike a balance between the efficiency of automation and the benefits of human interaction.

Dyadic TMIs, which involve significant others, have been studied primarily in adolescent populations, addressing conditions such as asthma[60], diabetes[61], and mental health[62]. In adult populations, dyadic TMIs have been explored for promoting physical activity[63]. Best practices for implementing dyadic TMIs include identifying key social support networks, providing training and guidance to human helpers, facilitating communication between users and helpers via text messaging, and tailoring the involvement of helpers to individual needs and preferences. However, several open questions remain regarding the optimal roles and responsibilities of different types of human helpers, strategies for ensuring the quality and consistency of support, and approaches to addressing potential risks and challenges, such as breaches of confidentiality or inconsistent support. Future research should aim to address these questions to further optimize the integration of human support into TMIs.

Multi-platform Integration: There is evidence that using multiple modes of digital communication (i.e. combining text messaging with other digital communication platforms, such as web pages or mobile apps) can enhance health behavior change[64]. Best practices include ensuring that the text messaging component complements and enhances the functionality of other platforms, providing clear guidance on navigating between platforms, and using data from multiple sources to inform personalization. For example, there are many self-report behavioral instruments composed of more than a few questions that would be tedious if deployed through text messaging. Also there are forms of feedback such as interactive graphs that require other digital modalities. There remain open questions around the optimal combination and sequencing of communication channels, the challenges of developing and maintaining multi-platform interventions that can communicate with one another, and challenges determining which component(s) are necessary for effectiveness.

Integration with Sensors and Connected Devices: Integrating text messaging with data from body-worn and/or ambient sensors presents an opportunity to deliver more personalized and context-aware support. For example, studies have found promising results when using a TMI integrated with activity monitors[65], weight scales[66], physiological monitors (e.g. blood glucose[67], blood pressure[68]) and location (GPS) monitoring[69]. It is certain that the use of wearable sensors[70] and ambient environmental sensors[71] will play a larger role in health monitoring and behavioral interventions. Open questions remain regarding the most effective types of sensors for different health behaviors, the level of certainty needed for inferred behaviors, the development of precise and personalized behavior change models, the optimal algorithms for triggering interventions or support, and the ethical and social implications of using sensor data.

6. Future Opportunities: Large Language Models as TMI Conversational Agents

To date, TMIs have primarily utilized rule-based systems that process simple client inputs through branching algorithms to generate pre-written text responses. For example, a system might compare a reported alcohol consumption quantity against a preset threshold to trigger specific messages about drinking behavior. Although efforts to enhance interactivity through conversational agents like chatbots have shown promise in promoting behavior change across various domains[72]including for mental health[73] and substance[74] use[75], these systems often lack the adaptability required for deep therapeutic engagement.

6.a. LLMs as Therapeutic Conversational Agents

The advent of large language models (LLMs)[76] marks a potentially transformative advancement in conducting automated therapeutic conversations. LLMs, such as OpenAI's Generative Pretrained Transformer (ChatGPT), are deep learning models trained on extensive textual data capable of understanding the context and relationships between words and generating responsive, novel text that is coherent and contextually appropriate[77]. These models can be fine-tuned post-training for specific tasks or domains, enhancing their adaptability for diverse applications[78] including psychotherapy[79]. Emerging studies highlight LLMs' capabilities in areas such as emotional awareness[80], social awareness[81], empathy[82], creativity[83], and reasoning[84]. Preliminary findings suggest that ChatGPT can engage positively in therapeutic conversations[85], actively listen, provide validation, and suggest coping strategies[86]. Trials comparing rule-based and generative counseling are still in early stages[87].

6.b. Training LLMs

When developing LLM-based TMIs for health behavior support, researchers are advised to prioritize pre-training with domain-specific datasets to guarantee that the LLM produces accurate and relevant responses. This essential step involves compiling a diverse dataset, including successful TMIs' text libraries, contributions from human experts, counseling manuals, and psychological theories. These types of datasets should be used to familiarize the LLM with effective language patterns, intervention strategies, and the appropriate tone for health behavior change. The training process should be carefully customized to stress the significance of clarity, empathy, and motivational encouragement, which are crucial for impactful health communication. Additionally, the integration of both pre-formed and real-time responses is crucial, as real-time LLM-generated content can offer a dynamic conversational experience, while pre-formed replies ensure consistency and accuracy for sensitive topics.

6.c. Addressing Unpredictability of LLMs

Due to their generative nature, LLM-based conversations can vary in quality and appropriateness. We suggest several key strategies to minimize untoward communication events. The first line of defense involves **LLM Guardrails**[88]—custom configurations within the LLM that prevent the generation of harmful or inappropriate content, including filters for sensitive topics and checks for alignment with therapeutic best practices. The second strategy is to incorporate a **Human-in-the-Loop System**[89], where a trained research team member reviews all messages and can edit and/or clarify any undesired message. These techniques ensures that LLM-based text messaging interventions are both effective in promoting health behaviors and adhere to high standards of quality and ethical practice.

7. Future Challenges: Bridging TMIs from Research to Real-World Application

Currently, several text message interventions are available to the US public, offering evidence-based support across various health domains. Notable examples include Text4baby.org, which provides maternal health information, VEText, which offers appointment reminders to US veterans, and Smokefree.gov, which offers smoking cessation support. While these programs demonstrate the efficacy of TMIs, they are primarily accessible through government and foundation channels, underscoring the need for enhanced and centralized dissemination methods.

TMIs face several key challenges in transitioning from research environments to widespread real-world implementation and effectiveness. Unlike apps, which benefit from commercial platforms like app stores facilitating consumer access and enabling monetization, TMIs lack a similar marketplace. This gap restricts commercial innovation and the potential for broader adoption. Furthermore, health systems, ideally positioned to leverage TMIs for enhancing patient engagement, encounter barriers due to outdated legal apprehensions regarding the security of text message communication. Concerns about the potential for unauthorized access to sensitive patient data and the technical difficulties of integrating SMS functionalities with existing health informatics systems further complicate implementation efforts, often requiring significant technological investment. Finally, there is the concern that outside the context of a controlled trial, TMI effectiveness will be hampered by low longitudinal user engagement.

To address these challenges and foster the adoption of TMIs, several strategies are proposed. Firstly, establishing a dedicated commercial portal for TMIs could mirror the app store model, offering a platform for users to access evidence-based interventions. This would not only enhance visibility but also stimulate commercial interest and development. Secondly, adopting standardized informed consent procedures would enable patients to opt into TMIs knowingly and willingly, mitigating legal and ethical concerns. Additionally, formulating comprehensive policies and guidelines for digital communication within health systems can promote consistency, compliance, and confidence in the security of text message exchanges. Examples of health systems successfully implementing TMIs in routine healthcare are however growing. For example, Bressman et al.[90] reported on the implementation of a 30-day post-discharge intervention using automated texting to supplement the standard of care within a single primary care practice within Penn

Medicine. They found adjusted odds ratio (aOR) for an ED visit was 0.77 (95% CI, 0.45-1.30) and for a readmission was 0.45 (95% CI, 0.23-0.86). Educating healthcare providers on the value and utility of TMIs could prompt them to prescribe these interventions as part of a treatment plan, much like any conventional medication. Finally, we believe that engagement with TMIs can be optimized through thoughtful design focused on matching user need with support provision. For example, we have found that for TMIs of longer duration, voluntary vacations or breaks from TMIs could reduce attrition[91] and accommodate self-determination[92].

8. Conclusion

In this paper, we have attempted to capture the essence of TMIs, recognizing their fundamental yet often underestimated role in shaping health behaviors. Their apparent simplicity masks a capacity for delivering health interventions that are both nuanced and highly personalized, effectively transmitting information, offering support, and bridging gaps in healthcare services. The true power of text messaging emerges through its steady and subtle influence over time rather than through immediate, dramatic effects.

From the initial tests in the early 2000s to a peak of scholarly activity in the early 2020s, TMIs have demonstrated a broad spectrum of application across critical health behaviors and outcomes, underscored by a steady growth in both academic interest and funding. The narrative review further solidifies the evidence base for TMIs, showcasing their effectiveness in promoting physical activity, aiding weight loss, supporting mental health, reducing substance use, and enhancing medication adherence, with nuanced effects across diverse populations and health domains. We posit that this broad and consistent effectiveness is largely due to the ongoing widespread use of SMS to communicate and unique functioning of SMS as a communication tool.

The exploration of TMIs' key features reveals a delicate balance between technological advancement and human-centric design principles, underscoring the importance of personalization, timing, intensity, and the integration of psychological theories. These considerations are pivotal in designing TMIs that not only engage users but also instigate meaningful behavioral change. The emergence of generate AI presents an exciting frontier, promising to enrich TMIs with more natural and adaptive conversational capabilities, provided that ethical standards and quality assurance mechanisms are rigorously maintained.

Despite all this support and promise, the commercialization of TMIs, their integration into healthcare systems, and engagement outside controlled studies remain ongoing challenges. However, the potential of TMIs to bridge the communication gap between patients and providers is immense. With strategic emphasis on developing a marketplace, patient consent procedures, policy development, medical education, and optimizing user engagement, TMIs could revolutionize healthcare delivery, enhancing patient engagement and support across the continuum of care.

As we navigate the future of health communication, the insights garnered from two decades of TMI research illuminate the path forward, highlighting the need for continued innovation, integration, and interdisciplinary collaboration. As different messaging platforms arise, such as WhatsApp, Facebook Messenger, WeChat, and Snapchat, existing evidence from SMS-based TMIs can inform design. By harnessing the simplicity, adaptability, and depth of TMIs, we can continue to shape the landscapes of health behavior and support, making strides toward improved health outcomes and reduced disparities in the years to come.

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Table 1:

	Feature	Known	Unknown
Communication Strategies	Onboarding	Set expectations for user, including intensity, duration, what can be responded to in real time & what cannot	How much baseline information to capture to allow tailoring and personalization?
	Embodiment	Identifying program with professional affiliation and/or credible source.	Is there an ethical obligation to remind users they are communicating with automated computer program?
	Personalization	Personalize messages based on individual characteristics, such as name.	Tension between age-specific text lingo vs. professionalism.
	Timing	Determine the optimal timing of messages based on the user's daily routines, preferences, and the target behavior or health condition	What are the most effective strategies for determining the optimal timing of messages for different health behaviors, user characteristics, and intervention goals?
		Consider the user's time zone and sleep schedule when scheduling messages to avoid sending them at inappropriate or disruptive times	What are the trade-offs between highly personalized timing (e.g., based on individual schedules) and more standardized timing (e.g., based on general population norms), and how can these be balanced in the intervention design?
		Allow users to customize or adjust the timing of messages based on their individual needs and preferences.	How can the timing of messages be dynamically adapted based on the user's changing needs, preferences, and contexts over time?
	Intensity	Determine the optimal frequency of messages based on the health behavior, intervention goals, and participant preferences.	What is the optimal frequency of messages for different health behaviors, populations, and intervention durations?
		Consider using higher frequency messaging during critical periods (e.g., at the beginning of the intervention or during challenging times)	How can the frequency of messages be personalized based on individual participant characteristics and engagement patterns?
		Allow participants to adjust the frequency of messages based on their needs and preferences.	What are the best practices for managing message fatigue and maintaining participant engagement over time?
		Ensure that the frequency of messages does not	

		become overwhelming or lead to message fatigue. Use data analytics to monitor engagement and adjust frequency accordingly.	
	Duration	Determine the appropriate duration of the intervention based on the complexity of the target behavior, the goals of the intervention, and the needs of the target population. Ensure that the intervention is long enough to support the formation of new habits and the maintenance of behavior change over time Plan for the gradual tapering or fading of intervention intensity to promote self-sufficiency and prevent relapse. Consider offering booster sessions or periodic check-ins to reinforce skills and maintain motivation after the initial intervention period.	What is the optimal duration of text message interventions for different health behaviors, populations, and settings, and how can this be determined empirically? How can intervention duration be personalized based on participant characteristics, preferences, and response to treatment, while still maintaining a standardized protocol? What are the most effective strategies for promoting long-term maintenance of behavior change after the initial intervention period?

Psychological theories		Select evidence-based psychological theories that are relevant to the target health behavior and population (e.g., Health Belief Model, Theory of Planned Behavior, Social Cognitive Theory, Self-Determination Theory) Incorporate key constructs from the selected theories into the intervention design, such as self-efficacy, social support, and motivation.	What is the optimal way to translate psychological theories into effective text message interventions? How can multiple theories be integrated into a coherent intervention design?

		Consider using a combination of theories to address different aspects of behavior change.	What is the role of emergent theories (e.g., Just-in-Time Adaptive Interventions) in optimizing text message interventions?

Behavior change techniques	Self-monitoring	Encourage participants to regularly track their health behaviors by providing simple and user-friendly tools for self-monitoring,	How can self-monitoring be made more accessible and engaging for individuals with low health literacy or limited access to technology?
		Tailor the frequency and timing of self-monitoring prompts based on participant preferences and adherence patterns.	How can self-monitoring be sustained over the long term, and what are the best strategies for preventing participant burnout?
		Emphasize the importance of consistent and accurate self-monitoring for behavior change and goal achievement.	What are the most effective ways to integrate self-monitoring data from multiple sources (e.g., text messages, wearable devices, electronic health records) to provide comprehensive feedback and support?
		Consider using gamification techniques to make self-monitoring more engaging and rewarding.	
	Goals setting & action planning	assist participants in setting specific, measurable, achievable, relevant, and time-bound (SMART) goals aligned with their health behavior objectives.	What is the optimal balance between participant autonomy and intervention guidance in setting and monitoring goals?
		Break down long-term goals into smaller, actionable steps (i.e., action planning) that can be easily monitored and achieved through text message support.	How can text message interventions be designed to help participants overcome common barriers to goal achievement, such as time constraints, lack of resources, or competing priorities?
		Provide regular prompts and reminders to monitor goal progress and encourage participants to report their	What is the role of habit formation and automaticity in sustaining goal-directed behaviors, and how can text message interventions support

		accomplishments. Adapt goals and action plans based on participant progress and feedback.	these processes? What are the potential unintended consequences of goal setting and monitoring (e.g., feelings of failure or guilt), and how can these be mitigated through text message support?
	Feedback	Offer personalized feedback and encouragement based on goal progress, celebrating successes and providing support during setbacks. Provide timely, specific, and actionable feedback on participants' reported behaviors, such as progress towards goals, adherence to recommended actions, or trends over time. Use a combination of positive reinforcement (e.g., praise for successes) and constructive feedback (e.g., suggestions for improvement) to maintain motivation and engagement. Offer feedback in a non-judgmental and supportive tone, emphasizing the participant's efforts and progress.	How can text message interventions balance the need for providing regular feedback with the risk of overwhelming or discouraging participants? What is the role of machine learning and adaptive algorithms in generating personalized and context-aware feedback messages? How can the effectiveness of different feedback strategies be evaluated and compared across text message intervention designs and health behavior domains? What are the potential unintended consequences of providing feedback on behavior (e.g., increased anxiety or self-criticism), and how can these be mitigated through supportive messaging and resources?

functionality	Human helpers	Identify key social support networks and human resources that can enhance the effectiveness of text messaging interventions, such as family members, healthcare providers, peer support groups, and	What are the optimal roles and responsibilities of different types of human helpers in supporting text messaging interventions, and how can these be defined and communicated effectively?

		research staff.	
		Use text messaging to facilitate communication and coordination between users and their human helpers, such as sharing progress updates, requesting support, or scheduling appointments.	How can human helpers be trained and motivated to provide high-quality, consistent, and empathetic support to users, particularly over long periods of time?
		Tailor the involvement of human helpers to the user's individual needs, preferences, and social context, and allow for flexibility and adaptability over time.	What are the potential risks and challenges of involving human helpers in text messaging interventions, such as breaches of confidentiality, boundary violations, or inconsistent support, and how can these be mitigated?
	Multi-platform	Consider integrating text messaging with other digital health platforms, such as web pages or mobile apps, to provide a comprehensive and consistent user experience.	How can data from multiple platforms be effectively integrated and analyzed to provide a holistic view of user engagement and progress?
		Ensure that the text messaging component complements and enhances the functionality of other platforms, rather than duplicating or conflicting with them.	What are the technical, logistical, and financial challenges of developing and maintaining a multi-platform intervention, and how can these be addressed?
		Provide clear guidance to users on how to navigate between different platforms and access the full range of intervention features	
	Sensor integration	Explore opportunities to integrate text messaging with data from body-worn sensors (e.g., Fitbits), ambient sensors (e.g., in the home or car), and connected devices (e.g., Amazon Alexa) to provide more personalized and context-aware support.	What types of sensors and connected devices are most effective and acceptable for different health behaviors and populations, and how can these be seamlessly integrated with text messaging?
		Use sensor data to trigger	How can sensor data be used

		just-in-time adaptive interventions (JITAIs) delivered via text message, based on the user's current state and context.	to develop more precise and personalized models of behavior change, and what are the implications for intervention design?
		Ensure that the integration of sensor data is transparent, secure, and aligned with user preferences and expectations.	How can the validity, reliability, and meaningfulness of sensor data be ensured, and what are the implications for intervention fidelity and effectiveness?

Supplemental Files

1. PubMed search terms:
   A. Physical activity: ("Text Messaging"[Mesh] OR "text messag*" OR "SMS" OR "short message service" OR "text-based" OR "texting") AND "text"[Ti] AND (intervention* OR trial OR study) AND ("physical activity" OR "physical activities" OR exercise* OR "physical fitness" OR "physical endurance" OR "physical exertion" OR "physical performance" OR "physically active" OR "activity") AND "activity"[Ti]
   B. Diet & Weight Loss: Text Messaging[Mesh] OR "text messag*" OR "SMS" OR "short message service" OR "text-based" OR "texting") AND "text"[Ti] AND (intervention* OR trial OR study) AND ("diet"[Ti] OR "weight"[Ti])
   C. Mental Health: "Text Messaging"[Mesh] OR "text messag*" OR "SMS" OR "short message service" OR "text-based" OR "texting") AND "text"[Ti] AND (intervention* OR trial OR study) AND ("mental"[Ti] OR "depress*"[Ti] OR "anxiety"[Ti] OR "schiz*"[Ti] OR "bipolar"[Ti] OR "suicid*"[Ti])
   D. Substance Use: "Text Messaging"[Mesh] OR "text messag*" OR "SMS" OR "short message service" OR "text-based" OR "texting") AND "text"[Ti] AND (intervention* OR trial OR study) AND ("alcohol"[Ti] OR "substance"[Ti] OR "cannabis"[Ti] OR "cocaine"[Ti] OR "cigare*"[Ti] OR "tobacco*"[Ti] OR "smok*"[Ti] OR "opioid"[Ti] OR "heroin"[Ti]"))
   E. "Text Messaging"[Mesh] OR "text messag*" OR "SMS" OR "short message service" OR "text-based" OR "texting") AND "text"[Ti] AND (intervention* OR trial OR study) AND ("medication"[Ti] OR "disease"[Ti] OR "diabet*"[Ti] OR "hypertension"[Ti] OR "heart"[Ti] OR "asthma"[Ti] OR "arthritis"[Ti] OR "skin"[Ti] OR "pain"[Ti] OR "HIV"[Ti] OR "kidney"[Ti] OR "heart"[Ti] OR "stroke"[Ti] OR "COPD"[Ti] OR "cancer"[Ti] OR "liver"[Ti] OR "Parkins*"[Ti] OR "dement*[Ti])))
   F. Reproductive & Maternal Health: ("Text Messaging"[Mesh] OR "text messag*" OR "SMS" OR "short message service" OR "text-based" OR "texting") AND "text"[Ti] AND (intervention* OR trial OR study) AND ("maternal health"[Ti] OR "reproductive health"[Ti] OR "breastfeed*"[Ti] OR "breast feed*"[Ti] OR "infant feeding"[Ti] OR "lactation"[Ti] OR "condom*"[Ti] OR "contraceptive*"[Ti] OR "birth control"[Ti] OR "family planning"[Ti] OR "safe sex"[Ti] OR "safer sex"[Ti] OR "sexual health"[Ti] OR "sexually transmitted"[Ti] OR "STI"[Ti] OR "STD"[Ti] OR "HIV"[Ti] OR "AIDS"[Ti] OR "pregnancy"[Ti] OR "prenatal"[Ti] OR "antenatal"[Ti] OR "postnatal"[Ti] OR "postpartum"[Ti] OR "obstetric*"[Ti] OR "gynecolog*"[Ti] OR "women's health"[Ti])
   G. Other: ("Text Messaging"[Mesh] OR "text messag*" OR "SMS" OR "short message service" OR "text-based" OR "texting") AND "text"[Ti] AND (intervention* OR trial OR study)