

Bridging Innovation and Equity: Advancing Public Health Through Just-in-Time Adaptive Interventions

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Annu. Rev. Public Health 2025. 46:43–68

First published as a Review in Advance on December 10, 2024

The *Annual Review of Public Health* is online at publhealth.annualreviews.org

<https://doi.org/10.1146/annurev-publhealth-071723-103909>

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Keywords

digital health, ecological momentary assessments, EMAs, health equity, just-in-time adaptive interventions, JITAIs, mHealth technologies, microrandomized trials, MRTs

Abstract

This review explores the transformative potential of just-in-time adaptive interventions (JITAIs) as a scalable solution for addressing health disparities in underserved populations. JITAIs, delivered via mobile health technologies, could provide personalized, context-aware interventions based on real-time data to address public health challenges such as addiction treatment, chronic disease management, and mental health support. JITAIs can dynamically adjust intervention strategies, enhancing accessibility and engagement for marginalized communities. We highlight the utility of JITAIs in reducing opportunity costs associated with traditional in-person health interventions. Examples from various health domains demonstrate the adaptability of JITAIs in tailoring interventions to meet diverse needs. The review also emphasizes the need for community involvement, robust evaluation frameworks, and ethical considerations in implementing JITAIs, particularly

in low- and middle-income countries. Sustainable funding models and technological innovations are necessary to ensure equitable access and effectively scale these interventions. By bridging the gap between research and practice, JITAIIs could improve health outcomes and reduce disparities in vulnerable populations.

1. INTRODUCTION

The global public health landscape is faced with a complex set of challenges, from chronic issues to emerging threats. Noncommunicable chronic illnesses, such as cardiovascular diseases and obesity, continue to be the major risk factors for morbidity and mortality globally (6, 51). Mental health problems have been amplified, exacerbated by the lingering impacts of the COVID-19 pandemic and societal stressors (86, 126). Infectious diseases endure as a notable threat, with the possibility of imminent or new epidemics demanding vigilance (80, 93). As health disparities and inequities in access to high-quality health care continue to undermine global health efforts, this convergence of challenges emphasizes the need for equitable health care service delivery and innovative solutions.

This review explores the possibility of mobile health (mHealth) technologies (91, 117), with a focus on just-in-time adaptive interventions (JITAIIs), to address some of these pressing public health challenges. This introduction offers a broad overview of mHealth technologies and JITAIIs, emphasizing their essential role in public health. The following subsections delve into JITAIIs as a tool to mitigate health disparities. We then discuss evaluation frameworks for JITAIIs, including effectiveness criteria and methodological complexities. Subsequently, we explore real-world applications of these scalable technologies in the context of addictive behaviors, mental health management, and physical activity promotion. We examine implementation approaches and scalability considerations, coupled with the role of technological innovations in enhancing JITAI capabilities. The conclusion summarizes key observations, outlines future directions for JITAIIs in public health, and addresses the critical need to bridge the gap between research and health care delivery practices, while factoring in social determinants of health (SDoH) in this rapidly evolving field.

1.1. Overview of Mobile Health Technologies

mHealth is defined as the use of mobile devices, such as computers, smartphones, tablets, and other wireless technologies, to support clinical and public health implementation goals. Interest in mHealth research has been proliferating (**Figure 1**). Digital health apps and wearable devices are increasingly popular mHealth tools for managing health behaviors and providing high-quality health care delivery (53, 55, 91). Intervention delivery via mHealth applications could be a promising pathway through which clinicians, community health workers, and health science researchers can improve access to health care in communities traditionally underserved by health care systems (85).

1.2. JITAIIs

Within the broad class of mHealth applications, a JITAI involves an intervention delivery strategy that adjusts the provision and type of support over time to deal with an individual's changing contexts and statuses, with the goal of delivering the most appropriate support on the right occasion (89, 117). Two key concepts distinguish JITAIIs from standard interventions: the just-in-time and adaptive aspects. Through the just-in-time aspect, JITAIIs aim to intervene only when needed to

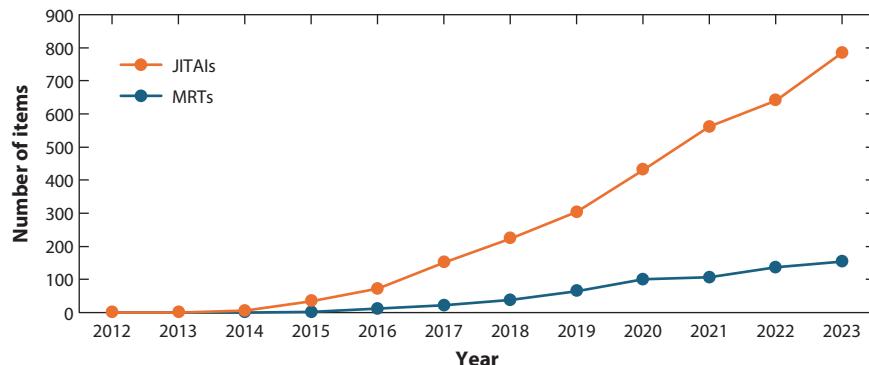


Figure 1

Literature search on Google Scholar, quantifying the interest in the literature (number of existing records) from 2012 to 2023 in the areas of microrandomized trials (MRTs) and just-in-time adaptive interventions (JITAIs).

alleviate problems linked to intervention fatigue and low engagement. The term adaptive refers to the strategy employed by the intervention design to determine which intervention to provide and when to intervene according to the user's ongoing information.

1.3. Importance of JITAI in Public Health

JITAIs signify a notable advancement in public health implementation strategies, offering context-aware, individualized support to persons at the most opportune moments. In real-world scenarios, JITAI are typically crafted to provide interventions just before, during, or after a state of opportunity or risk for an individual (52, 97). Low-cost ecological momentary assessment (EMA) self-reports are commonly used to measure these opportunity or risk states in JITAI and can be combined with data from costly passive sensors to capture real-time behavioral, physiological, or situational variables (91, 109). This dynamic strategy may dramatically enhance both medical and psychosocial interventions, including chronic noncommunicable disease management and mental health support.

The relevance of JITAI to public health centers on their capacity to bridge the gap between traditional static interventions and the complex, rapidly fluctuating realities of people's daily lives. By adapting intervention content, intensity, and timing on the basis of real-time EMA self-reports or wearables (e.g., monitoring heart rate variability or sleep), JITAI may circumvent numerous limitations related to one-size-fits-all strategies (87, 125). Moreover, the cost-effectiveness and scalability of digitally delivered JITAI may render them especially promising for addressing health disparities and enhancing access to high-quality health care among marginalized and underserved population segments.

2. CLOSER EXAMINATION OF JITAI IN PUBLIC HEALTH

Health disparities, deeply rooted in social and systemic inequities, persist as a major challenge worldwide. As we discuss in this section, mHealth has introduced potential avenues for addressing these disparities. Below, we explore how JITAI, through their adaptability and broad reach in leveraging tailored and timely mHealth applications, might offer a transformative solution to reduce health inequalities across various health domains and populations.

2.1. Definition of Health Disparity

Health disparity or health inequality has been defined as “potentially avoidable difference in health or in important influences on health that can be shaped by policies; it is a difference in which a disadvantaged social group or groups.. .systematically experience worse health or greater health risks than the most advantaged social groups” (16, pp. 180–81). Systemic disparities plague various strata of society worldwide: the socioeconomically disadvantaged, persons experiencing homelessness, those living in rural areas, ethnic and racial minorities, and sexual minorities, to name a few (110). Obviously, there is no panacea for the many SDoH-related disparities that affect these marginalized and underserved groups (17). Nonetheless, the JITAI design reviewed here is emerging as a promising intervention design to address health disparity at the individual level.

2.2. JITAI^s as a Vehicle to Reduce Health Disparities

JITAI^s offer the potential to advance health equity by targeting individual-level factors, such as stress management triggered by upstream SDoH (85), including exposure to environmental stressors such as drug retailers or neighborhood safety concerns (10, 39). The impressive reach of mHealth, facilitated by high rates of mobile phone ownership among marginalized and underserved groups (110), has made this approach particularly effective. For instance, in the United States, the rate of smartphone ownership among Hispanic Americans (85%) and African Americans (83%) is nearly equivalent to that of White Americans (85%), as reported by the Pew Research Center in 2021 (98).

Beyond their impact in high-income countries, the global surge in mobile phone access during the past two decades has amplified the potential of JITAI^s to address health disparities in low- and middle-income countries (LMICs) (137). This rapid increase is evident in the dramatic rise of mobile cellular subscriptions per 100 people in LMICs (**Figures 2 and 3**). For example, Sudan, a low-income country, saw its mobile cellular subscriptions per 100 people skyrocket from 0.69 in 2002 to 75.56 in 2021. This widespread access to mobile technology enables JITAI^s to reach individuals with inadequate access to conventional treatments, such as persons residing in regions lacking health care accessibility (29), thereby offering a powerful tool to bridge health equity gaps across diverse populations and geographic areas.

Furthermore, JITAI^s could help reduce opportunity costs by delivering timely, personalized health interventions directly to individuals’ daily environments, eliminating the need for time-consuming travel or sacrificing work shifts, especially for disadvantaged populations (132). Conventional “static” in-person health interventions held in clinics, community health centers, or hospital settings require participants to take time out of their daily lives to reap the potential benefits of these interventions (14). In essence, an opportunity cost is attached to the decision to attend an in-person health intervention. Socioeconomically disadvantaged people, for example, may have to choose between attending the in-person health intervention session or working an extra shift on a given day. In addition, those living in rural areas might have to weigh the benefits of the intervention against the hefty cost of physically traveling to and from the intervention location (129).

Moreover, JITAI^s might increase access to quality health interventions by tailoring to marginalized and underserved populations’ constraints, resources, and schedules. However beneficial these in-person health interventions might be, members of underprivileged communities may not perceive the benefits mentioned above as worth the opportunity cost. The JITAI design provides an elegant solution to this conundrum. Instead of having participants adapt their routines to in-person interventions, the JITAI design enables the interventions to adapt to participants and their ever-changing contexts by delivering intervention material exactly when it is needed, at the right

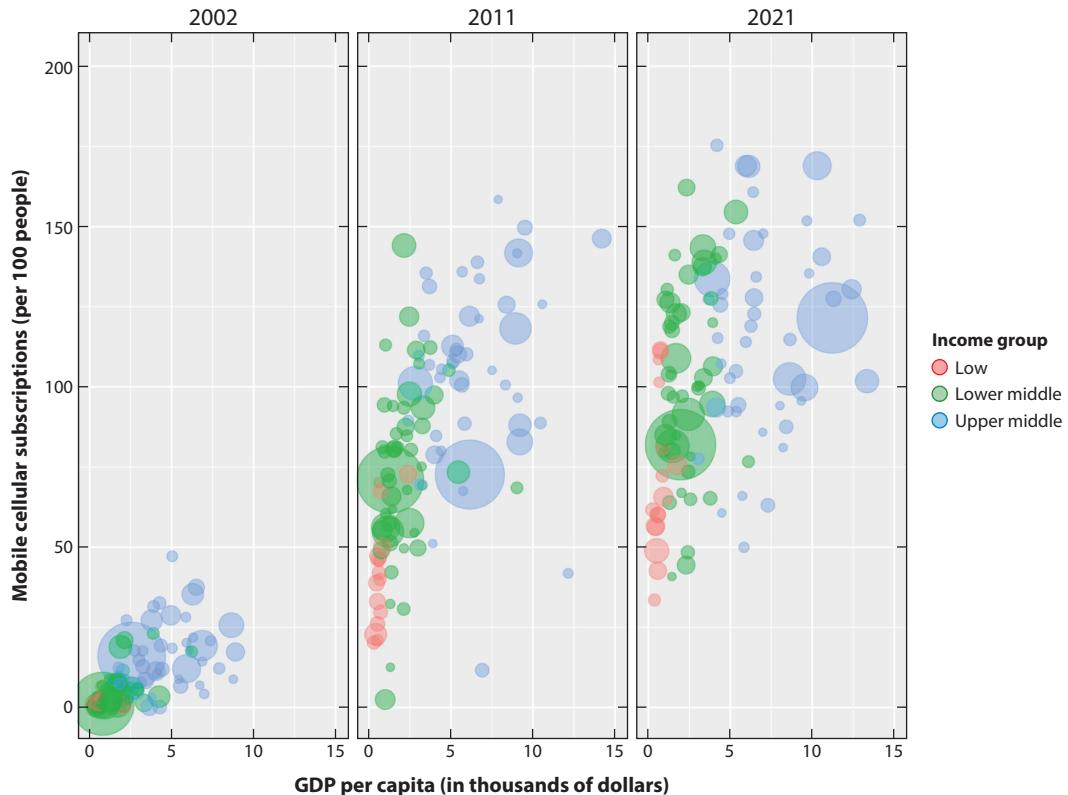


Figure 2

Mobile cellular subscriptions (per 100 people) in low- and middle-income countries in 2002, 2011, and 2021. Bubble size indicates population size. We strongly encourage the reader to also view **Supplemental Animation 1**, the animated version of this figure, to appreciate the rapid rise in mobile phone access over the years. Abbreviation: GDP, gross domestic product. Data from the World Bank's Open Data repository (137) (CC BY 4.0).

“dosage.” Thus, beyond leveraging the reach of mHealth applications, JITAI could also address health disparity by minimizing the opportunity cost incurred, affording all communities a fair opportunity to reap the benefits of various health interventions.

Supplemental Material >

2.3. Examples of JITAI in Various Health Domains

JITAI have shown their potential to alleviate health disparities among marginalized and underserved groups across diverse health domains. Collaborating with these communities during the JITAI design phase allows these interventions to be developed to improve lifestyle patterns and target local needs (105), potentially having a greater effect on individuals’ health care outcomes. For instance, JITAI could assist with chronic disease management by combining continual glucose monitoring with culturally adapted text messages to enhance self-management of diabetes or other chronic diseases with higher prevalence rates in marginalized populations (54). In addition, leveraging geolocation and wearable sensors might help provide individualized support for substance use management or prevention among homeless adults (131). In sexual health, JITAI that combine EMA self-report and geolocation data could decrease the risk of human immunodeficiency virus (HIV) and syphilis transmission as well as alleviate other health indicators

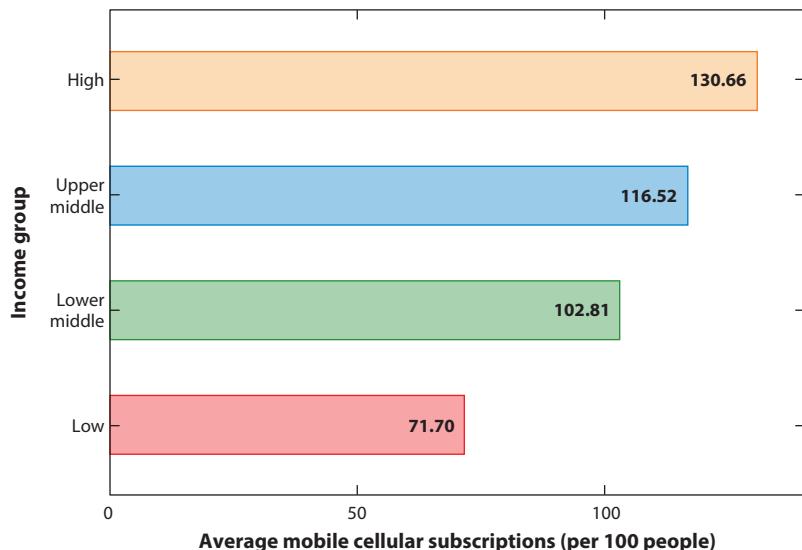


Figure 3

Average number of mobile cellular subscriptions (per 100 people) of each income group in 2021. Data from the World Bank's Open Data repository (137) (CC BY 4.0).

Decision points:

time points at which an intervention decision is made (e.g., each day or each minute)

Tailoring variables:

individual information and real-world external context (e.g., demographics, health status, location)

Intervention options:

various types or amounts of support (e.g., notifications or text messages)

Decision rules:

refer to the strategy that specifies which intervention option to provide at each decision point according to the tailoring information (e.g., a reinforcement learning algorithm)

(107, 112). Collectively, these examples highlight the promise of JITAIs to offer individualized, timely feedback and interventions to cater to the distinct circumstances and needs of marginalized population segments, possibly mitigating health disparities and enhancing overall health outcomes. In the next section, we describe the research methodologies used to evaluate the effectiveness of the components of JITAIs.

3. EVALUATION FRAMEWORKS FOR JITAIS

When evaluating the effectiveness of the components of JITAIs, one must keep in mind that these interventions comprise six key components: decision points, tailoring variables, intervention options, decision rules, proximal outcomes, and distal outcomes (91). An intervention option is selected at each decision point (e.g., after each prompt) based on the values of the tailoring variables via a predefined decision rule. The JITAIs is expected to indirectly improve the distal outcomes by directly cumulatively influencing the proximal outcomes. As discussed below, traditional randomized controlled trials (RCTs) and microrandomized trials (MRTs) are complementary evaluation frameworks that play crucial roles in developing, optimizing, and evaluating JITAIs overall and at the component level.

3.1. Criteria for Assessing the Efficacy and Cost-Effectiveness of JITAIs

Evaluating the efficacy and cost-effectiveness of JITAIs using traditional RCTs involves several main criteria. Efficacy is tested primarily by the intervention's capacity to attain desired health outcomes, such as behavioral changes, engagement, and improvements in other health metrics, through rigorous comparison between randomly assigned intervention and control arms, thereby ensuring robust causal inferences (139, 142). Cost-effectiveness is assessed by conducting economic evaluations, often using cost-utility analyses that measure outcomes in terms of quality-adjusted life years gained, to test how the health benefits justify the costs involved (92).

Altogether, RCTs help in understanding the value of investing money into developing and disseminating JITAIIs and guide resource allocation decisions in health care settings. Combining these criteria increases confidence that JITAIIs can be effective and economically viable, facilitating their broader implementation and scalability (36, 92, 118).

MRTs are a relatively novel experimental approach to evaluating the comparative effectiveness and cost-effectiveness of the components of JITAIIs, varying notably from traditional RCTs in two main ways. First, MRTs entail frequent randomization of intervention components at multiple decision points, such as whether or not to send a supportive text message (47, 66). This approach empowers researchers to model proximal causal effects and time-varying moderation effects of each intervention component within a JITAI, which is imperative for delivering adaptive interventions that necessitate real-time adaptations based on person-specific behaviors and contexts (66). In other words, MRTs can provide information on selecting beneficial intervention components and significant tailoring variables for future JITAIIs (15).

Second, departing from conventional RCTs, which usually test the global effect of JITAIIs, MRTs center on the temporally, spatially, and personalized dynamic nature of JITAIIs, offering insights into when and where specific intervention components are most effective. This novel method thus optimizes the precision of intervention component delivery. Moreover, reinforcement learning (RL) algorithms are often leveraged in JITAIIs tested within MRTs to continually learn from and adapt to each user's ongoing information (71). As a result, the MRT design enables a more nuanced understanding of cost-effectiveness by identifying the most impactful components and delivery periods, which might culminate in more efficient health care resource allocation (90, 120).

Proximal outcomes: short-term goals that the interventions intend to influence, which can be mediators or intermediate measures of the distal outcome (e.g., user engagement, physical activity)

Distal outcomes: ultimate goals of the JITAI, usually a primary clinical outcome (e.g., depression, chronic diseases)

3.2. Steps in Microrandomized Trials to Evaluate JITAIIs

Primary considerations for using MRTs to evaluate the components of JITAIIs to facilitate treatment personalization include the following steps: (a) optimizing design elements, (b) calculating adequate sample size, and (c) leveraging RL algorithms. These steps are critical for optimizing testing and dissemination, particularly for vulnerable populations that require tailored interventions that respond to their distinct and fluctuating needs. By attending to these steps carefully, clinical and public health researchers can ensure that the interventions are accessible and feasible. We describe these steps in detail in the following subsections (Figure 4 provides an example of a JITAI embedded within the MRT framework).

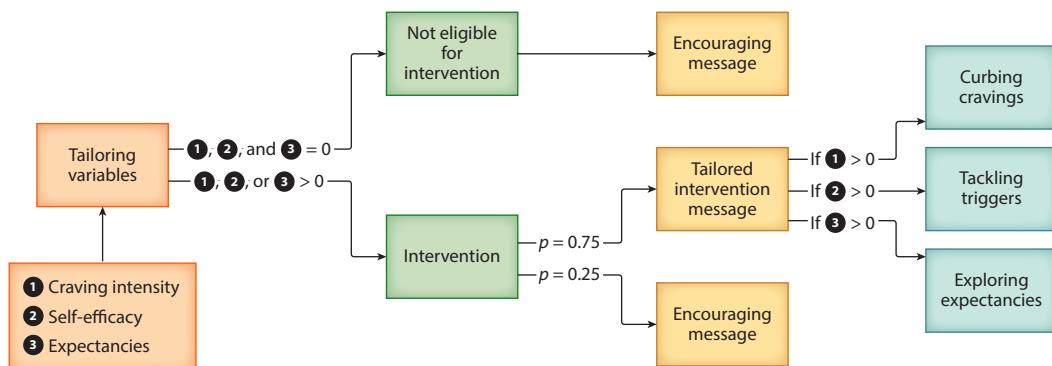


Figure 4

Design of the just-in-time adaptive intervention adapted from Reference 36. Tailoring variables were measured thrice daily. Abbreviation: p , the probability of being microrandomized to receive a tailored intervention message/encouraging message.

3.2.1. Optimizing design elements. Because an MRT is an experimental design for empirically informing the construction of JITAIIs, its design elements should be tightly connected with JITAI components. Interventions such as cognitive behavioral therapy and tailoring variables included in a JITAI are usually supported by empirical evidence obtained from an MRT. An intervention may consist of several components (e.g., behavioral activation, cognitive reframing), each of which may have multiple options. MRTs can be used to assess the proximal effects of one or more components simultaneously. Collection of potential tailoring variables, including individual-level information (e.g., mood, self-efficacy) and external contexts (e.g., alone versus with company, at home versus office/school, time of day), is essential during an MRT. By gathering this information, researchers can explore how these factors might influence the intervention's effectiveness for different individuals or situations (i.e., test moderation effects).

The decision points are determined by the frequency of meaningful changes in the tailoring variables (suggested by behavioral theories and empirical evidence) and the associated assessment burden. They might occur (*a*) at a prespecified time interval, (*b*) at specific times of day or days of the week, or (*c*) following random prompts (91). MRTs can also provide useful information regarding the selection of decision points. For example, time frames can be treated as an experimental factor to examine the differential intervention effects (2, 38), addressing the question of when to intervene each day and with what intervention component.

As mentioned above, decision points can be set up at fixed time intervals (e.g., every 2 h), at specific times of day or days of the week, or after random prompts. At each decision point, subjects are randomized to various options of an intervention component based on predetermined probabilities. These interventions are intended to influence an easy-to-measure proximal outcome. Proximal outcomes are often specified as mediators of the distal outcome. For example, ample evidence suggests that lack of physical activity is a risk factor for diabetes and depression. If the target distal outcome is comorbid diabetes and depression, physical activity would be a natural choice for the proximal outcome (2).

During an MRT, each participant may be randomized hundreds or even thousands of times. An important design element of an MRT is randomization probability, that is, the probability of assigning participants to each option of the intervention component. Depending on whether the randomization probabilities are updated to prioritize the intervention that appears to be optimal, MRTs can be further categorized as classical or outcome adaptive (76). In classical MRTs, randomization probabilities remain fixed throughout the study. In contrast, outcome-adaptive MRTs typically use RL algorithms to update the randomization probability in favor of the empirically apparent optimal intervention option on the basis of the data accrued so far, leading to a preliminary JITAI during the trial (discussed further in Section 3.2.3, below).

3.2.2. Sample size calculation and data analysis methods. Accurate sample size calculations ensure the ability to identify meaningful intervention effects. When calculating the sample size, it is necessary to specify a primary research question. In an MRT, the primary research question typically concerns the time-varying effects of an intervention component on the proximal outcome. In other words, researchers should first choose a main question to focus on, typically about whether an intervention component has an impact on the proximal outcome. Sample size calculations are performed to ensure adequate power to detect statistically significant effects. To facilitate MRT design, Liao et al. (73) proposed an approach to determine the sample size for continuous outcomes by modifying sample size formulas originally developed in the context of generalized estimating equations. Cohn et al. (27) developed a sample size formula for MRTs with binary outcomes that can also be extended to count outcomes. In addition, Dempsey et al. (34) developed a stratified MRT and provided a sample size formula, and Xu et al. (138) proposed

a flexible MRT design, allowing for the addition of intervention options during the study, and derived corresponding sample size formulas. Available software for sample size calculation includes an R Shiny app for MRTs with continuous outcomes, MRT-SS-Continuous (111); an R package for MRTs with binary outcomes, MRTSampleSizeBinary (136); and an R Shiny app for flexible MRTs, FlexiMRT-SS (138). Together, these tools can help researchers determine the appropriate number of participants needed for their specific MRT design, ensuring that the study is neither underpowered (too few participants to detect effects) nor wasteful of resources (too many participants).

Analysis of data from MRTs focuses on developing JITAIs through a concept called the causal excursion effect. This concept assists researchers in understanding how effective an intervention is, when it works best, and for whom it works best. The term excursion refers to temporarily changing the current treatment plan to test how well a different approach might work. The causal excursion effect contrasts two excursions from the current treatment plan. By comparing these temporary changes, researchers can determine the causal effects of alternative intervention assignments. Estimation methods for causal excursion effects have been studied for continuous (15), binary (102), and count outcomes (77). In addition, Shi & Dempsey (113) and Shi et al. (115) explored the use of covariate information or machine learning methods to improve the efficiency of causal effect estimation. Estimation methods for modified MRT designs, such as clustered MRTs and MRTs with networks (70, 114), have also been studied.

Furthermore, MRT data can be utilized to develop a preliminary warm-start policy, or strategy for future JITAIs (79), as well as to assess a specific policy (72). A warm-start policy is an initial intervention strategy based on early findings from an MRT. It serves as a starting point for developing more refined adaptive interventions in the future. The reader can think of it as a first draft of a treatment plan that can be improved over time. By using MRT data to create a warm-start policy, researchers can begin with an evidence-based strategy, save time developing future interventions, and potentially improve intervention effectiveness from the outset. Additional research is needed to more effectively link the insights gathered from MRTs to the practical application of JITAIs in real-world settings. An R package, MRTAnalysis, is available for MRTs with continuous (e.g., blood pressure readings) or binary outcomes (e.g., yes/no responses) (101).

3.2.3. Leveraging reinforcement learning algorithms. In outcome-adaptive MRTs and in real-world deployment of JITAIs, RL plays an important role in updating the randomization probabilities or deciding the optimal intervention components (78, 123). RL represents a framework of sequential decision-making problems where an agent continuously interacts with an environment or context and learns how to choose better interventions to maximize the cumulative proximal outcome over time. In the context of health interventions, RL can help determine which interventions work best in different situations.

Currently, most methods for constructing JITAIs fall into a subcategory of RL, namely contextual multiarmed bandits (MABs) (33, 123). These methods help balance the need to explore different intervention options with the goal of utilizing the most effective interventions as per current knowledge. Various algorithms have been proposed for contextual MABs, making different assumptions about the data-generating process. In particular, Thompson sampling has demonstrated valid theoretical performance guarantees and strong empirical performance (106). This approach is particularly useful because it naturally balances exploration (trying new options) with exploitation (using what is known to work). Due to these advantages and its randomized exploration nature, Thompson sampling has been adopted in several mHealth studies, such as DIAMANTE (1) and HeartSteps II (71, 117). Furthermore, many algorithms based on Thompson sampling or other RL algorithms have been developed specifically for mHealth studies (41, 42, 50,

77, 127). For comprehensive reviews of existing RL approaches for developing JITAIIs, see Deliu et al. (33) and Tewari & Murphy (123), and for guidelines regarding the design and implementation of RL algorithms in mHealth studies, refer to Trella et al. (128) and Figueroa et al. (37).

3.3. Challenges and Considerations in JITAI Evaluation

Evaluation of JITAIIs in traditional RCT and innovative MRT contexts poses several challenges and considerations. An essential consideration is that the MRT and RCT designs are not mutually exclusive. A key advantage of the MRT framework is its capacity to be integrated seamlessly into an intervention arm of an RCT. The upshot is that both the overall comparative average treatment effect or efficacy in the RCT and the effect of each unique JITAI microintervention component in the MRT can be assessed concurrently (69).

Simultaneously, the MRT design can be constructively set inside a sequential, multiple-assignment, randomized trial (SMART) (4, 133) to improve the creation and evaluation of JITAIIs. Embedding the MRT design within each stage of the SMART framework would empower researchers to concurrently optimize both the macro-level adaptive intervention approach (distal effect) and the microintervention components of JITAIIs (proximal effects) (88). This integrative method enables researchers to examine how microrandomized intervention components interact with broader treatment decision-making rules or sequences, offering a holistic comprehension of intervention dynamics over various timescales (100). This embedded strategy permits the optimization of decision rules at both the micro level (MRT) and the macro level (SMART), resulting in more effective and fine-tuned JITAIIs. The synergy capitalizes on the strengths of both novel designs, leading to a potent strategy for the design of personalized, sophisticated, behavioral digital health interventions that can adjust to individuals' evolving needs across contexts and time.

Furthermore, the way in which the MRT design overlaps and differs from another innovative intervention trial design—the multiphase optimization strategy (MOST) framework (28)—deserves mention. First, MRT and MOST designs vary in their application and scope. MOST is an umbrella framework encompassing multiple phases, in the order of preparation, optimization, and evaluation, to build and refine multicomponent health interventions systematically (19). MOST often harnesses full or fractional factorial designs to evaluate the effectiveness of unique intervention components (134). In contrast, MRTs are designed mainly to optimize JITAIIs by centering on the microtemporal dynamics of intervention delivery (88, 102). By iteratively randomizing participants to intervention versus control options at multiple decision points or prompts throughout the day, the MRT design empowers researchers to test the causal effects of unique JITAI components and their time-varying moderation effects (66). Although the MOST design aims to optimize the intervention package overall, MRTs are especially well suited for fine-tuning the unique intervention components embedded within a JITAI (88).

These variations notwithstanding, the MRT and MOST frameworks share the goal of building more effective and efficient behavioral health interventions through data-driven empirical optimization. Moreover, their core similarity is the creative approach to developing and optimizing behavioral health interventions, especially in digital health. These designs can complement one another when creating complex, multicomponent behavioral health interventions.

Finally, although MRTs are better suited to the testing of distinct JITAI components, they face challenges in managing the high-frequency randomization and intensive data collection required. All research designs inevitably contend with participant burden and fatigue considerations due to frequent EMA self-reports and interventions or passive sensors that can rapidly deplete battery power, which may result in high attrition or nonengagement rates (69). In addition, researchers must carefully weigh the ethical implications of withholding possible beneficial treatments in

control arms. Technical issues, such as ensuring reliable data collection from mHealth devices and preserving participant privacy, also present noteworthy challenges. Moreover, the intricacy of JITAI requires sophisticated statistical approaches to analyze the time-varying effects and higher-order interactions among JITAI components, contextual variables, and outcomes. Addressing these challenges necessitates careful and strategic planning, advanced quantitative analytic methods, and innovative trial designs such as the MRT approach to comprehensively capture and assess the efficacy and mechanisms of JITAI in real-world scenarios.

4. REAL-LIFE APPLICATIONS OF JITAI

As a plausible augmentation strategy or even a substitute for face-to-face interactions, JITAI in mHealth have been successfully employed in various public health domains, such as physical activity maintenance (52), mental health management (13), weight loss (40), smoking cessation (25, 132), and substance use discontinuation (23). The effectiveness of JITAI in various health outcomes has been demonstrated in empirical studies (132), showing enormous potential in public health research and practice. This section offers real-world case studies showing how JITAI can be effectively implemented in three specific health domains: (a) addictive behaviors, (b) mental health management, and (c) physical activity promotion.

4.1. Case Study 1: JITAI for Addictive Behaviors

To manage addictive behaviors, JITAI can identify high-risk places or situations, such as cravings, proximity to triggers, and urges, and promptly deliver coping skills, motivational texts, or other supportive messages to prevent lapses. Encouraging productive or recreational alternative activities during moments of high cravings or urges, such as physical activity or exercise, might reduce addictive behaviors over time (105, 131). The effectiveness of JITAI for addictive behaviors might be improved by their capacity to adjust to users' changing needs over time, taking into account current mood states, environmental situations, and treatment progress (30, 91). In this section, we discuss two recent examples targeting underserved groups.

First, Santa Maria et al. (107) evaluated the effectiveness of the Motivating Youth to Reduce Infection and Disconnection (MY-RID) intervention, a JITAI, to promote HIV risk reduction behaviors in homeless young adults enrolled in a two-arm RCT. MY-RID involved sending young adults messages to address the risk factors of HIV (such as drug use, stress, and drug/sexual urges) when periods of high risk were detected via daily EMAs. To ensure that appropriate messages were sent to the participants at the right time, the content of these messages was tailored (a) to an HIV prevention goal set by the participants before the start of the intervention and (b) by an algorithm that determined message content according to whether participants were at risk of using drugs or engaging in sexually risky behaviors. Compared with those in the control group, participants randomly assigned to the intervention reported reduced daily drug use, lowered urges for sexual activity, and decreased stress.

Second, Huh et al. (58) evaluated the effectiveness of MyQuit USC, a smartphone app-based intervention to address smoking relapses during attempts to quit smoking, in a sample of Asian American young adults. This intervention was centered around the notion that reminding participants about their implementation intentions regarding smoking (e.g., "When I drive, I will leave my cigarettes in my trunk") when they are most at risk of relapse will serve to reduce the occurrence of relapses. In order to tailor the intervention to meet each participant's daily schedule, each participant was tasked with providing their own or selecting from a list of prespecified high-risk smoking situations—context and time of day that they are most at risk of a relapse. In a just-in-time fashion, 10 min before a high-risk smoking situation, each participant received a push

notification containing their personalized implementation intention for that particular high-risk smoking situation (either self-generated or selected from the prespecified list). Utilizing within-person randomization (implementation intention reminders were sent only 75% of the time), Huh et al. found that this intervention was effective (i.e., relapses were less likely) when the participants carried out the personalized implementation intentions sent in the push notifications.

4.2. Case Study 2: JITAI for Mental Health Management

By detecting changes in actions, feelings, physiology, or thoughts, JITAI can deliver timely cognitive behavioral or other specific psychopharmacotherapy messages catered to an individual's present context and state. These prompts may relate to antidepressant medication management, behavioral activation, cognitive reframing, exposure therapy, or seeking social support. JITAI also show promise in promoting the use of emotion regulation skills during moments of impulse control difficulties (109, 122). In this section, we describe two recent examples in the context of a common mental disorder (CMD) and serious mental illness (SMI).

First, recognizing that repetitive negative thinking (RNT) is a cross-cutting feature driving CMDs such as anxiety and depression, Bell et al. (11) designed and tested a JITAI intended to interrupt RNT instantly for racially diverse youths in Australia with heightened CMD symptoms or RNT. Their two-arm RCT tested the efficacy of Mello, an entirely self-guided and individualized JITAI that repeatedly instructed transdiagnostic cognitive behavioral exercises at each prompt. Initial tests of the acceptability, engagement, retention, and uptake of Mello suggested that it was well received in this population. Compared with the control arm, Mello yielded larger reductions in anxiety and depression symptoms as well as RNT across 6 weeks after randomization. Furthermore, mediational analyses suggested that decreased RNT served as a potential mechanism through which the JITAI contributed to its comparative efficacy. Plausibly, a mechanisms-focused JITAI could provide effective and scalable mental health interventions for youths struggling with CMDs. The generalizability of this observed pattern of findings awaits further testing in adults and other populations, including marginalized communities.

Second, although we are unaware of any clinical trials that have examined the effectiveness of JITAI for patients with SMIs, especially psychosis (81), initial studies of mHealth applications in this population appear promising. For instance, Ben-Zeev et al. (12) and Cella et al. (24) tested multimodal mHealth tools to gather data continually and remotely for health care tracking purposes to detect clinical and objective digital markers of relapse among patients with schizophrenia-spectrum disorders. Patients enrolled in these studies were equipped with a tracking device coupled with limitless data or a Wi-Fi plan for an extended duration. The tracking system automatically logged multimodal behavioral data (app, call, and text activity) and passive sensor data (duration, geolocation, physical activity, and speech), while adverse events such as psychiatric hospitalizations were recorded continually. These studies indicated that each patient exhibited distinct digital markers of relapse, wherein EMA self-reports offered actionable portrayals of relapse prior to an adverse event, such as hospitalization. Moreover, other passive sensing data, such as geospatial shifts or changes in mHealth tool engagement (e.g., app usage cessation, higher prebedtime app usage), captured the changes patients underwent more precisely. As an example, during acute, distressing moments of self-reported delusions and hallucinations, patients displayed notably elevated skin conductance and reduced heart rate variability relative to periods when these symptoms did not trigger stress (24). These findings should be interpreted against the backdrop of high levels of SMIs affecting marginalized and underserved communities more so than the general population (108). Building on this research, advancing data management and modeling of JITAI in the context of RCTs or MRTs would be crucial to leverage mHealth broadly

and JITAIIs specifically to enhance intervention strategies for persons with or at risk for SMIs in ways that would benefit public health.

4.3. Case Study 3: JITAIIs in Physical Activity Promotion

By addressing distinct barriers and capitalizing on community strengths, JITAIIs can encourage healthier lifestyles, including increasing physical activity, among marginalized and underserved communities (48, 132). For example, JITAIIs can encourage healthier nonsedentary choices, such as walking rather than taking the bus during a commute (52, 91). These interventions could be adapted to account for myriad considerations such as cultural beliefs or preferences, limited access to safe physical exercise spaces, and socioeconomic realities that disproportionately affect marginalized communities. For instance, JITAIIs can emphasize free or low-cost community resources (e.g., safe basketball courts, parks), offer motivational or supportive texts, or provide culturally adapted exercise suggestions (8). By factoring in real-time data from sensor devices and other mHealth tools, JITAIIs can be tailored to evolving contexts, such as weather conditions or night-shift work schedules (52), which might especially affect underserved communities. Although research along this line of inquiry has been growing, more effort is needed to translate any observed benefits of JITAIIs for physical activity enhancement among underserved communities. Two pilot studies are discussed here as exemplars for future studies targeting marginalized communities.

First, Ismail & Al Thani (61) conducted a 66-day two-group experimental JITAI study among Qatari employees with sedentary lifestyles. Participants were randomly assigned to the intervention arm (MotiFit), which delivered personalized, context-specific prompts to encourage physical activity, or the control arm (MotiFit Lite), which provided static, nontailored messages after extended sitting periods. Participants self-reported high levels of satisfaction and subjective effectiveness of the JITAIIs. Moreover, the dynamic MotiFit message delivery JITAI was comparatively more efficacious than the static control in increasing engagement and physical activity. However, message type did not directly affect global everyday physical activity levels. Context-sensitive, individualized instructional prompts might thus encourage workplace adult employees to boost their physical activity during working periods.

Second, in a single-group feasibility trial, Mair et al. (82) similarly tested a JITAI to promote more physical activity among community-dwelling older adults in the United Kingdom. Their team created JitaBug, which is designed to help older adults boost or sustain healthy physical activity levels. JitaBug incorporated passive sensors (FitBit) and regularly provided EMA mood monitoring, goal setting, planning, reminders, and voice memo functionalities over 6 weeks. The JITAI was implemented as planned, with most participants (86%) completing it independently. Moreover, high levels of technical success were observed in sending and receiving instructional messages and tracking physical activity and weather conditions in ways that would enhance physical activity. Most of the accelerometer data could be used. Older adult participants were receptive to using the EMA mood tracking and voice memo features one-third to one-half of the time. Collectively, a smartphone-based JITAI is a well-received method for promoting physical activity among community-dwelling older adults.

5. IMPLEMENTATION AND SCALABILITY OF JITAIIs

Although mobile phone ownership rates are rising globally, significant disparities persist between low-income and wealthy countries. The lack of adequate fiscal and technical support for mHealth implementation in the health systems of LMICs (85), combined with the concentration of health care service delivery research in wealthy countries of the Global North (130), suggests that

most JITAIs will be developed, evaluated, and implemented in affluent nations. This imbalance raises concerns that JITAIs could potentially widen health disparities between countries unless researchers and organizations deliberately invest more effort, money, and time into developing purpose-built JITAIs specifically tailored for communities in LMICs.

5.1. Funding Models and Sustainability

Sustainable funding models for JITAIs targeting marginalized and underserved groups necessitate innovative strategies synergizing public and private funding resources. Government-level grants and public health initiatives could offer preliminary seed funding for JITAI design as well as feasibility and pilot evaluation (83). Pay-for-success models or social impact bonds could offer opportunities for attracting private investment by linking funding to measurable multimodal health care indicators in underserved communities (62). In addition, as elaborated in Section 5.3, below, community-focused participatory research methods could assist with securing buy-in and resources from community organizations and local institutions, raising the likelihood of greater and more sustainable funding streams. Global health organizations, philanthropic organizations, and technology firms should factor into the picture by offering targeted grant or seed funding programs or building sustainable infrastructures supporting mHealth dissemination, implementation, and preservation in LMICs and for other underprivileged groups (85, 94). Long-term viability is essential, underscoring the importance of a hybrid financial model that integrates diverse monetary sources and adjusts to evolving community needs and technological progress (35, 116). Importantly, any funding model should prioritize culturally appropriate interventions and equitable access to serve marginalized communities effectively.

These strategies should be understood within the context of the emergence of mHealth (functioning as an adjunctive or stand-alone treatment) as a cost-effective alternative to traditional in-person health interventions while enhancing health outcomes. Such funding models could decrease health care expenses by reducing the necessity for physical infrastructure, minimizing travel costs for both patients and clinicians, and encouraging more efficient use of finite and scarce health care resources (43, 104). The cost-effectiveness of mHealth interventions has been documented across diverse medical specializations, with studies indicating beneficial cost–utility ratios and promising cost savings (60, 104). For instance, mHealth tools, including JITAIs, can enhance medication adherence, facilitate remote health care outcome monitoring, and reduce hospital admission rates, resulting in improved health outcomes at lower net cost (104). Moreover, the scalability of mHealth interventions for underprivileged communities, in particular, implies that greater accessibility can be achieved without a proportional increase in cost (36). Although the initial investment in mHealth may be considerable, the long-term cost-effectiveness of mHealth interventions often supersedes that of traditional in-person health interventions, particularly when considering societal realities that factor in broader economic effects (20, 44, 99). As health care delivery systems globally experience greater financial pressure (46, 141), the adoption and integration of mHealth interventions represent a promising approach to providing high-quality clinical and health care services while optimizing resource allocation.

5.2. Strategies for Implementing JITAIs in Diverse Settings

This review summarizes seven strategies to implement JITAIs and related mHealth applications in diverse settings to benefit underserved communities in ways that harness a multifaceted plan that considers both sociocultural and technological factors. First, a bottom-up, community-based involvement strategy is critical, as detailed in the following subsection. Second, researchers should leverage existing digital technology infrastructure and relatively cheap passive sensors to reduce barriers to access (91). Third, adaptive algorithms (e.g., using the RL methods named

above) that account for contextual or situational factors specific to underserved populations, such as financial constraints or other SDoH variables, should be factored in when designing the JITAIIs (49). Fourth, behavioral models such as the Capability, Opportunity, Motivation, and Behavior framework should be integrated when tailoring interventions to the unique stressors experienced by marginalized populations (135). Fifth, forging partnerships with community-level organizations, local institutions, and health care administrators is essential to integrate JITAIIs into existing infrastructures and support systems (63). Sixth, JITAIIs incorporated into both universal and targeted programs could maximize impact, personalization efforts, and scalability across diverse populations (23). Seventh, attending to data privacy, security, and other ethical considerations is vital for trust building and long-term engagement among marginalized communities (49, 103). By synthesizing these approaches with continual community participation, and executing iterative improvements based on participant feedback, JITAIIs may be effectively implemented to enhance clinical and well-being outcomes and promote health equity in underserved groups.

5.3. Community Involvement and Participatory Design

In an exemplary case of JITAI studies involving community consultation, Robles et al. (105) conducted qualitative interviews with members of a predominantly low-income African American community to ensure the appropriateness of their JITAI to increase physical activity and reduce blood pressure. Through this participatory design approach, the authors identified several SDoH of physical activity that were somewhat unique to the target population. Also, they discovered that members of the target community felt it was necessary to expand the definition of physical activity to include activities such as performing household chores. With this knowledge in hand, the authors then proposed several changes to their planned JITAI (the original JITAI was designed and evaluated in a different population) to meet the needs of their target community. For example, because participants identified limited physical capability as a barrier to physical activity, the authors designed the JITAI to tailor the content of push notifications to each participant's functional capacity. Going forward, we believe that community consultations such as those conducted by Robles et al. (105) must become the norm in the field, given how most mHealth trials have overlooked SDoH that affect health disparities (119). Such endeavors are essential for ensuring that JITAIIs actually meet the needs of underserved communities.

6. TECHNOLOGICAL INNOVATIONS AND JITAIIS

Recent mHealth technological innovations might culminate in positive trickle-down effects for addressing health disparities in underserved populations. Sophisticated artificial intelligence and machine learning algorithms enable more advanced real-time data analysis and tailored interventions accounting for person-specific contexts and needs (65). The integration of Internet of Things devices and wearable passive sensors in diverse digital devices (e.g., actigraphy, smartphones, tablets) has expanded the array of health behaviors and psychophysiological states that can be assessed continually (124). Such technological advancements could thereby facilitate more targeted and timelier interventions. Innovative tools, such as augmented virtual reality interfaces, chatbots, and voice-triggered assistants, can refine and retain accessibility and engagement for users who represent members of underserved communities with limited literacy or technological experience (68). In addition, the design of energy-efficient and low-cost edge computing technologies can make mHealth tools and JITAIIs more feasible to implement and sustain in resource-limited settings (1, 68). These novelties, coupled with community consultation and culturally adapted content (18), may considerably enhance health care outcomes and remedy disparities in underserved populations.

6.1. Role of Mobile and Sensor Technologies in JITAI

The role of mobile and passive sensor technologies in JITAI is still nascent, especially when it comes to systematically evaluating their effects in underserved populations. First, an MRT study that randomly assigned a stress management intervention during moments when a person who recently quit smoking experienced stress or did not is underway (9). The optimal JITAI could promote health equity by determining the ideal timing (stressful versus nonstressful periods) for delivering the mHealth instruction to decrease the odds of relapse among underserved groups. Second, mHealth applications (including JITAI with passive sensing) appear to be a promising tool to support lay counselors in providing psychological interventions to adolescent mothers suffering from depression in rural settings, such as villages in Nepal (21). Clearly, more research is necessary to examine how JITAI promotes health equity, perhaps by encouraging the usage of individual-level, actionable interventions prompted by upstream SDoH (e.g., environmental or situational stressors) (10).

6.2. Addressing Fairness Concerns

Although mHealth represents a promising way to address health disparities in underserved communities, an interdisciplinary perspective is needed to ensure that new disparities are not inadvertently introduced (26, 96). In the machine learning community, the concept of fairness has been proposed to address various kinds of disparity. Yet, its application within mHealth remains inadequately explored.

Building upon research by Chien et al. (26), three primary sources of unfairness must be taken into account when designing an mHealth study and evaluating the specific mHealth application in question using the RCT or MRT design. First, disparities may occur in the process of participant selection due to the restrictive inclusion/exclusion criteria. For example, several studies excluded participants who do not speak a certain language, adults older than 60 years, or those who do not have digital devices to access mHealth applications (66, 67). In addition to such explicit exclusion, underrepresentation may result from a lack of information on those study recruitments, emphasizing the need to specifically recruit underserved participants.

Second, the strategy by which participants are allocated to intervention options may affect fairness. In standard MRTs, current participants cannot benefit from the findings gained in the study, as participants may be randomized to ineffective control arms (e.g., assessment-only prompts) very frequently. Outcome-adaptive MRTs are considered a more ethical alternative, given that the randomization probabilities are updated in favor of the currently optimal intervention versus the control option on the basis of accruing evidence. However, the randomization probabilities are often “clipped” to be not too close to zero or one so as to permit valid after-study analysis (71). Clipping might affect participants’ welfare to some extent, as they may still be randomized to suboptimal options. Further research on how to balance these competing goals is required. In addition, a significant aspect of potential unfairness lies in the RL algorithms that determine intervention options. Although many fairness metrics, such as individual fairness (45) and group fairness (56), have been proposed (26, 75), their application in mHealth settings broadly and to underserved communities specifically has not been systematically discussed and examined.

Lastly, unfairness may arise throughout the study implementation and after-study analyses. Specifically, participant heterogeneity could affect both the internal and external validity of a trial, as the findings may be limited to a well-defined population (121). Thoughtful participant selection, appropriate handling of missing data, and subgroup analyses may mitigate the effect of high levels of trial heterogeneity (64), and a clear interpretation of the degree of generalizability of the results is required (121).

6.3. Ethical Considerations of Mobile Health Research in Underserved Populations

When should the MRT design be leveraged to identify context-aware JITAI components for treatment optimization purposes in underserved communities? An MRT approach is not always required for all JITAI, mainly when there is sufficient evidence to identify key decision points, tailoring variables, and intervention options that effectively address the needs of underserved populations. For example, if prior research has established the optimal intervention strategies for improving mental health care access within these communities, conducting an MRT study may be unnecessary.

In addition, any mHealth researcher should keep in mind that systems of social oppression (e.g., racism, marginalization) have been linked to an increased risk of mental disorders among underserved populations (3). Therefore, if the need for clinical support arises infrequently, such as in moments of acute crisis (e.g., suicide attempts), an MRT approach may be neither desirable nor feasible. Among vulnerable populations such as individuals with low income facing financial difficulties (59) and those with psychiatric disorders (140), the frequency of such crises might be too low to yield sufficient data for optimizing interventions. Nonetheless, suicidal thoughts, which are more common than suicide attempts (7, 22), could offer an opportunity to leverage the MRT design to refine an intervention targeting those thoughts in underserved populations. Ultimately, researchers need to assess whether existing theory and evidence are sufficient to develop an effective mHealth intervention for the target community, whether the outcome is suited to an MRT framework, and whether more data are required to support optimization efforts.

Another noteworthy challenge in mHealth research targeting underserved communities involves ethical concerns, such as safeguarding individual confidentiality, privacy, and safety. Although mHealth offers the potential to reach diverse, often underrepresented populations and continuously collect real-time data on sensitive behaviors, it also raises serious data security and privacy issues (57, 89). For instance, privacy becomes especially important when mHealth tools gather data related to illegal substance use or other stigmatized behaviors prevalent in underserved groups (23, 74). With unintended adverse effects, mHealth systems can inadvertently capture detailed geolocation, user activity, and related personal data. Such information poses deidentification challenges due to the unique digital footprint each individual leaves behind (32, 95).

As a result, it is critical for JITAI and related mHealth trials focused on underserved communities to develop comprehensive data handling and aggregation strategies to ensure that privacy and confidentiality are maintained (5, 84). Additionally, ethical considerations must be prioritized when providing interventions in real-life situations. For example, support may need to be withheld in cases where it could cause harm, such as identifying a high-risk stress episode while someone is driving, or adapted to suit the situation, such as having a clinician respond to a user disclosing suicidal impulses or another clinical emergency. Given these broad ethical concerns, researchers must customize JITAI to address the unique confidentiality, privacy, and safety needs of vulnerable and marginalized populations.

7. CONCLUSION

This review has highlighted the transformative potential of JITAI specifically and mHealth applications broadly to mitigate health disparities among marginalized populations. By leveraging real-time data and adapting interventions accounting for complex SDoH factors, JITAI might provide cost-efficient, scalable strategies that could alleviate the complex and dynamic health challenges experienced by underserved communities. Future research should focus on refining the adaptive algorithms and ethical frameworks that guide and govern JITAI evaluation and

implementation. Such efforts could ensure that these interventions are universally accessible, culturally appropriate, and equitable. Bridging the lacuna between mHealth research and health care provision remains vital to achieving big-picture public health aims and fostering health care equity. We conclude with several key reflections for the reader.

7.1. Summary of Key Findings

The primary outcomes discussed in this review emphasize the large-scale positive impact that JITAIIs and related mHealth applications could have on health disparities. JITAIIs provide individualized real-time interventions catered to each person's distinct contexts and needs, rendering this subset of mHealth tools especially effective in targeting addictive behaviors, chronic diseases, and mental health problems in underserved groups. By capitalizing on adaptive algorithms and mHealth, JITAIIs may overcome traditional health care delivery barriers, providing cost-efficient, scalable solutions that reach marginalized populations. However, ethical considerations, especially regarding data privacy and participant safety, should be carefully factored in to ensure equitable health care access and benefits as well as the protection of vulnerable populations. JITAI and mHealth tools offer promising pathways to reduce health disparities. Nonetheless, further research is needed to refine and optimize their applications and to increase the likelihood of widespread implementation in diverse populations.

7.2. Future Directions for JITAIIs in Public Health

Future research in public health must prioritize harnessing the potential of JITAIIs and mHealth technologies to address long-standing health disparities, especially among underserved groups. As access to mobile digital devices continues to increase worldwide, public health efforts should aim to preserve sustainable funding models; integrate JITAIIs into health care delivery systems; and personalize interventions based on individual contexts, needs, and real-time data (31). In addition, data privacy measures and ethical guidelines must evolve to ensure the protection of vulnerable and marginalized populations. An emphasis on adaptive algorithms, multidisciplinary collaboration, and scalability will be essential to advance equitable health care delivery and enhance public health outcomes.

7.3. Bridging the Gap Between Research and Practice

Although research often generates cutting-edge technologies to address public health challenges, real-world application frequently lags due to complex systemic barriers. Bridging the research-practice gap is contingent on refining these scalable technologies via rigorous studies, harnessing innovative trial designs such as MRTs, and ensuring their accessibility and outreach in socially diverse real-world contexts. These efforts necessitate soliciting and integrating community input, making progress on data security and ethical frameworks, and securing sustainable funding models to ensure that innovations such as JITAIIs can deliver on their promise of mitigating health disparities and improving public health outcomes.

FUTURE DIRECTIONS

1. A multidisciplinary approach is essential for translating mobile health (mHealth) research into practical, real-world applications.

2. Fairness issues throughout the conduct of mHealth studies must be carefully addressed to avoid the emergence of new disparities.
3. The increasing use of reinforcement learning (RL) algorithms in mHealth studies necessitates the development of inference methods for adaptively collected mHealth data.
4. Development of sample sizes and data analysis techniques for specific outcome data types, such as count and ordinal data, is essential.
5. Habituation and disengagement significantly affect the effectiveness of mHealth interventions. Future research should explore diverse strategies, including innovative interventions or RL algorithms, designed to mitigate these issues.
6. Researchers should investigate the long-term effectiveness and sustainability of just-in-time adaptive interventions (JITAIs) in improving health outcomes and reducing disparities, particularly in underserved populations. Longitudinal studies are needed to assess the durability of behavior changes and health improvements initiated by mHealth interventions.
7. The integration of JITAIs with other emerging technologies, such as artificial intelligence and the Internet of Things, should be explored to enhance the precision and effectiveness of personalized interventions. This could involve developing more sophisticated algorithms for real-time data analysis and intervention delivery.
8. The potential of JITAIs in addressing multiple health behaviors simultaneously, such as combining interventions for diet, physical activity, and stress management, should be studied further. This approach could lead to more holistic and efficient health promotion strategies.
9. Investigations of the cost-effectiveness and scalability of JITAIs in low- and middle-income countries, focusing on overcoming infrastructure limitations and cultural barriers, could inform strategies for attaining global health equity and adapting mHealth technologies to diverse settings.
10. Sustainable funding models, such as public–private partnerships or social impact bonds, could support the long-term implementation and scalability of JITAIs in underserved communities. Such funding strategies are crucial for ensuring continuous access to these interventions, minimizing the risk of resource depletion, and facilitating the integration of JITAIs into routine health care practices.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

N.H.Z. acknowledges support from a National University of Singapore (NUS) Presidential Young Professorship start-up grant. X.L. is supported by a PhD student scholarship from Duke–NUS Medical School, Singapore. B.C. acknowledges support from the Ministry of Education, Singapore (grant MOE-T2EP20122-0013).

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