Evaluating Similarity Variables for Peer Matching in Digital Health Storytelling

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Peer matching can enhance the impact of social health technologies. By matching similar peers, online health communities can optimally facilitate social modeling that supports positive health attitudes and moods. However, little work has examined how to operationalize similarities in digital health tools, thus limiting our ability to perform optimal peer matching. To address this gap, we conducted a factorial experiment to examine how three categories of similarity variables (i.e., Demographic, Ability, Experiential) can be used to perform peer matching that supports the social modeling of physical activity. We focus this study on physical activity because it is a health behavior that reduces the risk of chronic diseases. We also prioritized this study for single-caregiver mothers who often face substantial barriers to being active because of immense employment and household responsibilities, especially Black single-caregiver mothers. We recruited 309 single-caregiver mothers (49% Black, 51% white), then we asked them to listen to peer audio storytelling about family physical activity. We randomly matched/mismatched the storyteller's profile using the three categories of similarity variables. Our analyses demonstrated that matching by Demographic variables led to a significantly higher Physical Activity Intention. Furthermore, our subgroup analyses indicated that Black single-caregiver mothers experienced a significant and immediate effect of peer matching in Physical Activity Intention, Self-efficacy, and mood. In contrast, white single-caregiver mothers did not report any significant immediate effect. Collectively, our data suggest that peer matching in health storytelling is potentially beneficial for racially minoritized groups; and that having diverse representations in health technology is required for promoting health equity.

CCS Concepts: • **Human-centered computing → Collaborative and social computing**

Additional Key Words and Phrases: peer matching, storytelling, social modeling, personal informatics, health, physical activity, social cognitive theory, similarity

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1 INTRODUCTION

Physical activity is a health behavior that lowers the risk of chronic diseases (e.g., diabetes and cardiovascular diseases) among adults and children [58]. However, for mothers of single-caregiver households, being active can be challenging. They face many barriers beyond their control, such as

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limited time to be active due to arduous employment and household responsibilities [25]. As a result, they often had limited time to use and reflect on their fitness sensor data with their children [65]. At the same time, single-caregiver mothers are disproportionately burdened by poverty, especially single-caregiver Black mothers [23]. Poverty is particularly a concerning factor because it is associated with physical inactivity as well as adult and childhood obesity [51] — children of single-caregiver households have fewer opportunities to exercise [26]. As the COVID-19 pandemic unfolds, exercise barriers worsened. Schools switched to remote learning and single-caregiver mothers had to take over some of the teachers' roles [64]. This causes them to de-prioritize using fitness apps. Given that regular exercise could prevent chronic diseases, equitable interventions should be prioritized for single-caregiver mothers to be physically active with their children [32].

Health research showed that health behavior interventions are more effective if they incorporate social support [17, 38, 51, 57, 77]. In the space of Human-Computer Interaction (HCI), researchers have examined how health technologies can facilitate social support through social modeling. Technology-mediated social modeling helped people choose adequate fitness goals [59] and learn that their active behavior is valued by their peers [50].

Furthermore, Chung et al., Grimes et al., and Saksono et al. show that technology-mediated social modeling supports health behavior by using peers' health behavior stories [18, 31, 64]. Peer stories are advantageous for health promotion, as opposed to relying solely on didactic methods for health promotion [36]. For example, a mother sharing a story about giving birth could calm a newly pregnant person by helping them learn strategies on how to communicate with medical professionals during labor [46]. Moreover, Lipsey et al.'s review of conventional health storytelling shows that peer stories can positively affect health outcomes, especially among minoritized racial and ethnic groups [46].

Indeed, social modeling has an advantage in promoting healthy behavior because it allows people to go beyond their personal experiences to acquire complex behavior [5]. Thus, given the growing proliferation of digital health tools, it is critical that we go beyond examining health goal-setting and health data presentation. These design elements are important, but we also need to investigate how users of health technologies can leverage their social environment, for example by using technology-mediated social modeling.

According to Social Cognitive Theory, social modeling is more effective if the observer perceives the models as similar [4, 6, 7]. The importance of model's similarity is further supported by empirical studies in health and learning [9, 11, 24, 29, 34, 49, 63, 64, 76]. Therefore, understanding how technologies can match people with similar models will advance HCI research on supporting learning and positive health behavior. For example, an online health community may have a vast number of users [34]. A subset of these users might be more effective models if they share certain similarities with the observing user. Thus, helping users to find similar peers can help the user learn from their peers and increase the effectiveness of the health technologies.

Motivated by the potential of social modeling, we sought to examine similarity variables that are effective for peer matching and health social modeling. We reviewed prior studies and identified three categories of similarity variables: Demographic, Ability, and Experiential variables. However, there is a gap in our understanding of the effectiveness of these categories for supporting peer matching, social modeling, and health behavior.

We, therefore, conducted a factorial between-subjects experimental study to answer our overarching questions: How can peer matching facilitate health storytelling that supports health behavior? We recruited single-caregiver mothers to participate in our study (n = 309). Given the potential advantage of health storytelling for racially minoritized groups [46], we specifically recruited racially balanced samples of Black and white mothers.

Our first contribution is demonstrating that the sense of similarity with a peer can be conveyed using a digital tool. Second, we show that peer matching using Demographic variables led to a more positive change in Physical Activity Intention than not matching. Finally, we demonstrated an interaction between Demographic matching and users' racial identities. Among Black single-caregiver mothers, Demographic matching led to more positive changes in Physical Activity Intention, Self-efficacy, and mood. We did not detect such changes among white single-caregiver mothers. These findings suggest that peer matching in health storytelling can be a promising approach to promoting health equity.

2 RELATED WORK

2.1 Physical Activity Among Single-Caregiver Families

Parents' physical activity also influences their children's physical activity. A review by Gustafson et al. shows that the number of active parents in a household influences the children's physical activity level, with children who had no active parents being the least active [32]. Although having an active parent is critical, single-caregiver mothers are often time-constrained to be active because of employment and household duties [25]. Single-caregiver mothers are also at a greater risk of poverty (especially single-caregiver Black mothers) [23], and poverty is linked to physical inactivity [51].

The relationship between single-caregiving and lowered health also occurs in other health domains. For example, in the domain of childhood obesity, studies show that children of single-caregiver mothers are disproportionately burdened with the risk of obesity [3, 15, 28]. Similarly, children of single-caregiver mothers often had lower physical and mental health, compared to children of single-caregiver fathers [78]. Single-caregiver mothers also tend to have lower income and to be unemployed compared to single-caregiver fathers [52]. In a fitness tracking study with low-income families, single-caregiver mothers often had limited time to reflect on their fitness data with their kids [65].

Therefore, health interventions (specifically for physical activity) should be prioritized for single-caregiver mothers because they face lowered family health outcomes and are marginalized through poverty and unemployment.

2.2 Social Modeling and Digitally-Mediated Social Support

Health attitudes and behavior are often shaped by observing other people around us. This is a process known as social modeling. According to Social Cognitive Theory (SCT) [4, 6, 7], social modeling can support self-efficacy and outcome expectations, two attitudinal constructs that facilitate a behavior [5]. Self-efficacy is our belief in our ability in completing a task appropriately and outcome expectations are our beliefs about what happens after we perform the task. In turn, both self-efficacy and outcome expectations affect our intention (or proximal goals). Behavioral intention regulates and guides our effort to do the action [5]. Put more concretely, by observing other people performing a task successfully, we learn that carrying out the task is doable (self-efficacy) and can lead to desirable outcomes (outcome expectations).

Prior work in HCI had begun to show that digital health technologies can facilitate social modeling and facilitate a healthy diet [18, 31] as well as physical activity [50, 59]. For example, Puussaar et al. found that fitness tracking users observed their peers' fitness data and used these observations to inform their own fitness goals [59]. Saksono et al. found that peer audio stories can inform parents about community-tested strategies to be active as a family [64]. Similarly, Miller et al. showed that fitness data sharing can help teens develop social norms that being active is valued [50]. Collectively, being informed with more reasonable goals and strategies to carry out the goals could enhance self-efficacy; while knowing that the behavior is aligned with the social norms enhances outcome expectations.

Furthermore, interacting with our peers can also provide emotional support which could enhance the outcome expectations of being physically active. For example, Saksono et al. found that peer stories can vicariously convey the positive emotional outcomes of family physical activity [64]. This finding echoes Grimes et al.'s work that showed peer health stories convey the joys of having a healthy diet [31]. In a similar vein, Chung et al. also showed that peers' stories on Instagram can provide emotional support for attaining a healthy diet [18]. These HCI findings echo Lipsey et al.'s systematic review that shows the effectiveness of health storytelling, especially among minority groups [46].

Together, these studies suggest that social modeling through peers' data and stories is a form of social support in the form of informational, belongingness, and emotional support [74]. Informational support by learning the steps to do the healthy behavior, belongingness support by noticing that many other people are dealing with similar challenges; and emotional support by observing the joys that other people experienced when performing the healthy behavior. In turn, informational support could enhance self-efficacy, whereas belongingness and emotional support could enhance emotional states — which also improves self-efficacy. With this approach, physical activity intervention technologies would rely more on peer collaborations rather than competition (which could induce negative effects [78]).

2.3 Peer Matching and Model Similarity

Social Cognitive Theory posits that social modeling is more effective if the observer perceives the model to be similar [4:302, 403, 5]. A person's actions are readily facilitated and constrained by their physical and social environment, thus observing similar models helps the person to feel assured that they can closely replicate the models' behavior.

Indeed, prior work in health technologies emphasized the importance of peer matching because of its health and practical benefits [2, 34, 35, 54, 56]. In terms of the health benefits, Pendse et al. suggest that peer matching in online health communities can better promote wellbeing [56] and Smith et al. suggested that peers who share similar backgrounds can provide more relatable support in chat-based mental health technologies [70]. In terms of practicality, Hartzler et al. suggested that peer matching could help patients to find the most appropriate peers [35], especially in large online health communities where finding the appropriate mentor can be arduous [34].

However, despite the value of having similar models, only a few studies have begun to examine how health technologies can match similar users. For instance, Hartzler et al. examined how to match patients with mentors in an online health community using mentors' profile elements (i.e., health interest, language style, demographic, and sample posts) [34]. Among these profile elements, sample posts appeared to be the preferred piece of information to choose a mentor. Saksono et al.'s studies with families showed that the peer family's number of children and neighborhood was the most useful information because those pieces of information were indicative of similarities in health barriers [64]. This finding resonates with the work by Daskalova et al. on a digital sleep intervention [24] and Puussaar et al.'s on a fitness data visualization [59]. Both studies found that people preferred peer models who faced the same restrictions and experiences. However, Feustel et al.

found that people prefer to use demographic information and health data when selecting cohorts [27]. In short, the work examining model similarity is still inconclusive — needing a larger study to examine peer matching further.

To further examine model similarity in peer matching, we begin by identifying model similarity variables using prior work from psychology, learning, and HCI. In this paper, we define *model similarity* as the perceptions of an observing person that they share similar characteristics with the observed model. Then, we group these variables into more general categories and examine their efficacy for peer matching. These are the three categories of similarity variables:

Demographic variables are similarities that are often readily observable, such as gender and race. For example, Oyibo et al. found that women tend to be more efficacious than men after watching videos of a woman exercise model [55]. This finding was echoed by Meaney et al. [49] and Weeks et al.'s [76] studies, as well as Cruwys et al.'s review [21]. Oyibo et al. also examined SCT in health tools and used models with dark skin tones [55]. Thus, in our study, we specifically examined the effect of racial identities on social modeling. Furthermore, Lipsey et al.'s systematic review shows that health storytelling is more effective among racially marginalized groups [46].

Ability variables are similarities in the model's ability to perform the task relative to the observer's ability. For example, in a study with female students who had limited athletic experience, George et al. found that observing models with limited athletic experience led to better athletic performance than observing an athletic model [29]. Similarly, Braaksma et al. found that low-aptitude students performed better in a writing task after observing a weak model, whereas high-aptitude students performed better after observing a strong model [9]. Similarly, Brown and Inouye found that observing failing models who were perceived to have similar abilities tended to make the observer less persistent, compared to observers who perceived the model to have a lower ability [11]. In contrast, however, Andalibi et al. suggest that peer matching by similar mental health diagnoses could perpetuate unhealthy coping behaviors [2].

Experiential variables are similarities that the observer sees from the model's life experiences. In Hartzler et al.'s study, patients preferred to choose mentors based on the mentor's stories rather than the mentor's demography [34]. In a family fitness app study, Saksono et al. found that parents preferred peers with a similar number of children and who lived in similar neighborhoods because they were perceived to experience similar barriers [64]. Daskalova et al.'s study on a cohort-based sleep recommendations tool also showed that users preferred peers who faced similar barriers [24].

Indeed, this body of work highlighted that some form of similarity matching works. However, we have yet to identify which of these categories are effective in facilitating social modeling for health. This gap represents a missed opportunity to identify how to maximize the effectiveness of digital health tools.

3 METHOD

Informed by SCT and prior work in HCI and health, we propose these research questions (RQs):

- **RQ1**: Which of the similarity categories are effective in increasing perceived similarity?
- **RQ2**: Which of the similarity categories are effective in improving health attitudes and mood?
- **RQ3**: Do the similarity categories have similar effects in increasing perceived similarity as well as improving health attitudes and mood among people who are racially dominant race (e.g., white) and racially minoritized (e.g., Black)?

Specifically in RQ3, we examined whether peer matching could have different effects between racially dominant and minoritized groups. This question was informed by Lipsey et al.'s review that shows story-based interventions were more efficacious among racially minoritized groups [46]. (Throughout this study, when we say "race" we are referring to the participants' self-reported race, which reflects a person's perception of their racialized identity [44].)

To answer these questions, we conducted a 2×2×2 factorial between-subjects pre-post experiment to answer the research questions above, especially among mothers of single-caregiver households. The factors were similarity variables (Demographic, Ability, and Experiential) and each had two matching levels (Matched, Not matched). The dependent variables were Perceived Similarity, Health attitudes (i.e., Physical Activity Intention and Self-efficacy), as well as Mood Valence and Arousal. We used Physical Activity Intention as the proximal outcome and Physical Activity Self-efficacy as the distal outcome which may require repeated exposures to the peer stories interventions.

3.1 Study Task and Conditions

We asked the participants to listen to a 2-minute audio story with transcripts. The stories were adapted from a prior study about exercise storytelling with families of low-socioeconomic status backgrounds [64]. We hired voice actors to tell the stories. Fig. 1. shows the web-based study interface for this experiment.

On the top of the interface is a video player that plays the audio-recorded story and the transcript. The audio-recorded story tells two elements: (1) the profile of the storyteller, and (2) the story content. The profile of the storyteller included their demographic, ability, and experiential information. The story content consisted of personal accounts that indirectly told information on how to be active as a family (to support self-efficacy) and information on the positive results (to support outcome expectations). We discuss the story content in more detail in Section 3.2.

On the bottom of the interface is a text version of the storyteller's profile. The goal of having a text version was to reinforce the participants' sense of similarity with the storyteller. Once a participant finished listening to the story, she could proceed with the remainder of the study. Table 1 shows the variables we used in the profile of the storyteller.

We used audio stories because of the growing use of multimedia-based social media (e.g., TikTok) for online and community-based health promotion [19], especially for knowledge sharing among minoritized groups [47].

Participants were randomly assigned to one of the eight factorial study conditions (Table 2). We kept the story content the same across all participants, but we manipulated the profile of the storyteller based on each participant's condition. More specifically, we matched or mismatched the profile of the storyteller's Demographic, Ability, and Experiential variables depending on each participant's randomly assigned condition.

Fig. 1. The study interface for this experiment. The participants were asked to listen to the story and storyteller's profile using this dynamic web page. The transcript, synchronized to the story recording, was shown in the upper part of the interface, while the basic information about the storyteller was shown below. In this example, the participant was a Black mother of three children with a low PA level and facing high PA barriers. She was matched to the storyteller by demography, ability, and experiential variables.

Table 1. Similarity categories we used in our experiment and their respective variables.

Category	Variable	Matched Example	Not Matched Example
Demography	Gender	"I'm a mother..."	"I'm a father..."
	Race	"I identify as Black"	"I identify as white"
Ability	7-day PA recall	"I'm not active."	"I've been active ..."
Experiential	Single-caregiver status	"I'm a single mother..."	"I'm a mother. My husband and I..."
	Number of children	"I have three children."	"I have one daughter."
	Environmental barrier	"I don't have any nice park near my house"	"I have a nice park near my house"

The example columns show how the profile of the storyteller is communicated in the Matching/Not Matched profile. Here, the participant is a single-caregiver mother who self-identifies as a Black woman with three children, with a 7-day PA recall of less than 3, and a high environmental barrier.

Table 2. The eight factorial study conditions and the number of participants in each condition.

Condition	Demography	Ability	Experiential	Total participants	Black participants	White participants
1	Not matched	Not matched	Not matched	37	17	20
2	Matched	Not matched	Not matched	38	19	19
3	Not matched	Matched	Not matched	41	20	21
4	Matched	Matched	Not matched	39	19	20
5	Not matched	Not matched	Matched	39	20	19
6	Matched	Not matched	Matched	38	18	20
7	Not matched	Matched	Matched	38	19	19
8	Matched	Matched	Matched	39	20	19

As an example for the analysis, when comparing Demographic Matching and Not matching, we compared participants in conditions 1, 3, 5, and 7 (Demography Not matched, n = 155) versus participants in conditions 2, 4, 6, and 8 (Demography Matched, n = 154).

For instance, suppose participant A self-reported as a Black mother of three children with low physical activity level and high barriers. If participant A is in condition #4, the storyteller will be matched by A's demography and ability features but will be mismatched by A's experiential features. Conversely, in condition #8, the participant will be matched by demography, ability, and experiences. Put more concretely, If she is in condition #4, she will get a story told by a Black mother of a child, with a low physical activity level, and low barriers. If the same participant is in condition #8, she will get a story told by a Black mother of three children with a low physical activity level and high barriers.

3.2 Study Material

As we have described, the study material is an audio-recorded story that tells (1) the profile of the storyteller and (2) the story content. We hired four voice actors to tell the audio-recorded story, each representing two genders (men, women) and two racial groups (white, Black). We directed the voice actors to tell the story with a slow-paced and relaxed delivery, mimicking a person who is telling a story for the first time.

The profile of the storyteller contains information about their demography (i.e., gender, racial identity), ability (7-day physical activity recall), and experiential (i.e., environmental barrier to physical activity, number of children, and single-caregiving status). Below is an example of the part of the story that communicates the storyteller's profile.

> "*I'm a single mother in my early 30s and I have three young children. We identify as Black.*"
> "*I'm not active. I've been trying to exercise with my family for the past few weeks. And I'm still working on it. I think being active together with my family is hard. I don't have any nice park near my house. So, I can't exercise with my family safely.*"

The story content contains information that supports self-efficacy and outcome expectations, two key constructs from SCT. We developed the content by adapting story elements from a fitness app study with parents of low-socioeconomic status backgrounds [64], specifically story elements that were mentioned by other participants who used the fitness app. Self-efficacy elements include practical exercise ideas, such as walking together to a beach and using YouTube to learn Zumba. Outcome expectations elements include the happiness of being active as a family, having the children go to bed early because of exercise, and the joy of doing Zumba. Finally, in the conclusion, we adapted a story element about a parent's long-term aspiration to live healthy. We chose this ending because prior work on family fitness tracking shows that parents' short-term health behavior is influenced by their long-term aspirations [66]. Below is an excerpt of the story content. An example of a complete script is in the Supplementary Material.

"*I remember the time that my children and I walked from my house down to a small beach, about a 60-minute walk from our house. We walked to the beach and all the way home. It was fun. We were running. We were laughing. We had the chance for one another to keep up. The kids were super exhausted when they came home then they took showers and went straight to bed. We had a lot of fun and we got to spend a great time together as a family. I really enjoyed being together as a family doing something.*"

While the story was based on stories that came from community members, we took an additional step to ensure the appropriateness of the story. We conducted a one-hour focus group to review the stories with three parents of low-income neighborhoods. Before the focus group, we asked a colleague to record the story. During the focus group, we played the story and solicited feedback from the parents on the relatability of the story. We compensated each participant with US$30 gift cards. This amount was based on US$15/hour living wages and for compensating the reviewing work that requires the participants' expertise as community members. The focus group participants expressed that the story resonates with their experience in trying to be active as a family, especially for single-caregiver mothers. Informed by this focus group, we decided that the story is suitable for the experiment.

3.3 Study Procedure

We conducted the study online using Qualtrics XM and recruited the participants using online panels, namely Prolific, Amazon Mechanical Turk (MTurk), and Qualtrics Panel. The study procedure was as follows. First, participants were screened for eligibility. To be included, each participant had to be a single caregiver, self-identify as a woman and as either Black or white, be 26-39 years old, have at least one child aged 3-8 years old, and live in the United States. Second, eligible participants were asked to fill out a demographic survey (e.g., gender, race, marital status, children's ages), environmental barriers to physical activity survey, and physical activity pre-surveys (i.e., Intention, Self-efficacy). Then we asked them to fill out mood pre-surveys. Third, we randomly assigned the participants to one of the eight conditions and asked them to do the task as described in section 3.1. The randomization was separated by the participants' self-reported race to ensure uniform racial distribution across conditions. Then, we asked the participant to fill out mood post surveys. Fourth, we asked the participants to answer three comprehension check questions, to verify they understood the story. Fifth, we asked the participants to fill out physical activity post surveys (i.e., Intention, Self-efficacy) and perceived similarity to the storyteller. We also added two simple attention check questions before and after the intervention (e.g., "Please answer 0 for this question"). Finally, we thanked the participant for completing the study.

We chose relatively narrow inclusion criteria to reduce the variability in the participants' backgrounds. Stories, and health stories specifically, are value-laden [33]. As a consequence, broad inclusion criteria will introduce more variations in the participants' backgrounds which necessitate more variations in the storytellers' racial and ethnic backgrounds. In turn, more variations could increase variability in the results. As the aim of our study was to begin identifying the optimal similarity variables and motivate future work in peer matching, we opted to narrow the inclusion criteria.

Initially, we recruited participants only using Prolific and MTurk, but we were unable to recruit a racially-balanced sample (83% white) even when we took explicit steps to recruit Black participants. Therefore, we expanded our recruitment using Qualtrics Panel as our vendor. This approach allowed us to balance the participant numbers by their racial identity (combined: 49% Black, 51% white).

Participants recruited through Prolific and MTurk received US$ 3.75 compensation for participating in a 15 to 20-minute study. On the other hand, Qualtrics Panel participants received compensation valued between US$4.5 to US$6.5. Qualtrics determined these ranges of compensation rates based on compensation type (e.g., cash, merchant/loyalty points). We did not have the control to change them. The compensation was based on a US$15 hourly living wage for a 15-minute activity. The study received ethical approval from Harvard University Area Institutional Review Board (protocol: #IRB21-0859).

3.4 Factors

Our study used a factorial design with three between-subjects factors: Demographic Matching, Ability Matching, and Experiential Matching, each with two levels: Matched or Not Matched. These factors corresponded to the three categories of similarity variables: demographic, ability, and experiential.

Demographic Matching. In this matching, a participant was matched to a peer of the same self-identified gender and race. For example, a mother self-identifying as Black was demographically-matched with a Black mother storyteller. Conversely, she would be demographically not matched with a white father storyteller.

Ability Matching. In this matching, a participant was matched to a peer with low or high physical activity ability. For example, a participant with low ability who was matched by Ability will be exposed to a storyteller with low physical activity. We used a 7-day physical activity recall measure [20] to determine whether the participant was at a low or high ability. Physical activity less than 3 times in the last seven days was marked as low. Otherwise, it will be marked as high. This is based on the physical activity guidelines by the U.S. Department of Health and Human Services [57, 73].

Experiential Matching. In this matching, a participant was matched using their single/dual caregiving status, the number of children, and access to physical activity facilities. More specifically, access to physical activity facilities was captured using the environmental barriers survey ("*There is somewhere at home where my child and I can go out and exercise (such as a garden)*", "*There are play areas, parks, or gyms close to our home where my child and I can exercise comfortably and safely*") using 4-point Likert scale (1 = Strongly disagree, 4 = Strongly agree) [48]. Access to physical activity facilities less than 3 is marked as a high environmental barrier. Otherwise, it will be marked as low.

3.5 Dependent Measures

The dependent variables are Perceived Similarity as well as Physical Activity Intention change (proximal variable) and Physical Activity Self-efficacy change (distal variable). We also included Mood Valence and Arousal changes to evaluate whether peer matching could provide emotional support. The measures are as follows.

Perceived Similarity to the storyteller was measured using Stok et al.'s identification survey [72]. This measure consists of two questions ("*I identify with the person who told the story" and "I feel a connection with the person who told the story*") using a 7-point Likert scale (1 = Not at all, 7 = Very strongly).

Physical Activity Intention change was measured using a pre-post intention survey [20]. This proximal measure detects near-term plans to be active. In turn, behavioral intention regulates the person's actions [5]. This measure has one question ("*I intend to engage in physical activity with my family next week the following number of times*") using a 7-point Likert scale (0 = 0, 6 = 6+ times).

Physical Activity Self-efficacy change was measured using a pre-post self-efficacy survey [62]. There are nine questions in this survey, each using a 7-point Likert scale (0 = Not at all confident, 6 = Completely confident).

Mood Valence and Arousal changes were calculated as the difference in the mood just after hearing the story compared to the mood just before hearing the story. Both of them were measured using the Self-Assessment Manikin (SAM) [10]. Each of these measures consists of a question using a 9-point scale with pictograms (1 = Completely Unhappy, Completely Calm; 9 = Completely Happy, Completely Excited).

3.6 Covariates and Demographic Variables

We used past physical activity (measured using Physical Activity Recall) and race as covariates. The reason being prior work shows that past physical activity influenced exercise behavior among single-caregiver mothers [25] and story-based interventions were more effective for minoritized racial groups [46].

Physical Activity Recall was measured using Courneya and Mcauley's 7-day recall [20]. This measure has one question ("*I engaged in physical activity with my family last week the following number of times*:") using a 7-point Likert scale (0 = 0 times, 6 = 6+ times).

Race was assessed using US Census' six racial categories. This question captures each participant's self-reported race, which is a person's perception of their racialized identity [44].

Gender was assessed using Spiel et al.'s recommendation to ask about gender using five choices [71]. Additionally, we also collected the participants' background information, including dual/single caregiving status, the number of children and adults, employment status, educational level, income ranges, and state of residence.

3.7 Statistical Analysis

We used R version 4 to analyze the data. To address RQ1 and RQ2 on the main effects of matchings using the three similarity categories, we conducted linear regressions for between-subject analyses. Besides the three independent variables, we also included past Physical Activity Recall and race as covariates. We also calculated Cohen's *d* to show the standardized effect sizes. Additionally, to answer RQ1, we calculated Pearson's correlation coefficients to assess the linear relationship between Perceived Similarity with changes in health attitudes and moods.

To address RQ3, we also evaluated the interactions between matching on demographic variables and race. To further explore the differences in experiences between Black and white participants, we conducted additional linear regression analyses separately for the two groups. These analyses included the three independent variables and physical activity recall as a covariate. Similarly, we also calculated Cohen's *d* to show the standardized effect sizes.

3.8 Participants Overview

We recruited a total of 345 single-caregiver mother participants. Then, we removed 36 responses (10%) because of their incorrect response to at least one of the two attention checks in the survey. We used 309 samples in our final analyses.

All eligible single-caregiver participants self-identified as women with a mean age of 33 (*SD* = 2.97). About 49% self-identified as Black and 51% self-identified as white. The median number of children was two (*IQR* = 2) and the median number of adults was one (*IQR* = 1). In terms of physical activity, the mean was 2 family exercise bouts in the past 7-days before the study (*SD* = 1.83). The mothers also reported high access to physical activity facilities (*Mean* = 3.57 *SD* = 0.76). On average, the mothers spent 16 minutes completing the study (*SD* = 16.02). The median educational level was some college or vocational training (41%). A majority of the mothers had full-time (53%) or part-time employment (16%). The median household income range was US$32,227 to US$40,626.

In terms of the women participants' intersectional disadvantages and privileges by their socioeconomic status, we found that Black participants (72%) are less likely to be employed (full-time or part-time) or self-employed than white participants (82%), X^2 (1, n = 309) = 4.85, p < .05. However, both Black (56%) and white (63%) participants had similar percentages of college and graduate degree education, X^2 (1, n = 309) = 1.62, p = *n.s.* Similarly, both Black and white participants had similar income distributions, X^2 (1, n = 309) = 12.95, p = *n.s.*

Table 3. Descriptive statistics of the study participants' numeric data (*n* = 309). *PA* = physical activity.

		All		Black		White	
Age	Mean age (*SD*)	33.46	(2.97)	33.70	(2.95)	33.23	(3.02)
Household size	Median number of children (*IQR*)	2	(2)	2	(2)	2	(1)
	Median number of adults (*IQR*)	1	(1)	1	(1)	1	(1)
Physical Activity	Mean Seven-day PA recall on a 0-6 scale (*SD*)	2.37	(1.83)	2.47	(1.86)	2.27	(1.80)
	Mean Access to PA facilities on a 1-4 scale (*SD*)	3.57	(0.76)	3.53	(0.79)	3.60	(0.73)

Table 4. Descriptive statistics of the study participants' categorical data (n = 309).

		All		Black		White	
		n	**%**	***n***	**%**	***n***	**%**
Gender	Woman	309	100.00%	152	100.00%	157	100.00%
Employment	Full time	161	53.49%	77	51.33%	84	55.63%
	Part-time	50	16.61%	16	10.67%	34	22.52%
	Self-employed	29	9.63%	17	11.33%	12	7.95%
	Unemployed	26	8.64%	19	12.67%	7	4.64%
	Homemaker	28	9.30%	15	10.00%	13	8.61%
	Unable to work	7	2.33%	6	4.00%	1	0.66%
Education	Some high school	6	1.94%	2	1.32%	4	2.55%
	High school	51	16.50%	29	19.08%	22	14.01%
	Some college or vocational training	127	41.10%	65	42.76%	62	39.49%
	College (undergraduate)	101	32.69%	45	29.61%	56	35.67%
	Graduate	24	7.77%	11	7.24%	13	8.28%
Income	< \$23,828	91	29.93%	48	32.00%	43	27.92%
	\$23,828 - \$32,227	55	18.09%	27	18.00%	28	18.18%
	\$32,227 - \$40,626	35	11.51%	16	10.67%	19	12.34%
	\$40,626 - \$49,025	30	9.87%	12	8.00%	18	11.69%
	\$49,025 - \$57,424	28	9.21%	15	10.00%	13	8.44%
	\$57,424 - \$65,823	13	4.28%	10	6.67%	3	1.95%
	\$65,823 - \$74,222	12	3.95%	7	4.67%	5	3.25%
	\$74,222 - \$82,621	16	5.26%	7	4.67%	9	5.84%
	\$82,621 - \$91,020	8	2.63%	5	3.33%	3	1.95%
	> \$91,020	16	5.26%	3	2.00%	13	8.44%

4 RESULTS

4.1 Main Analyses

Answering RQ1, we suggest that the peer matching using the three similarity variables (Demographic, Ability, and Experiential) had similar effects on the participants' Perceived Similarity with the storyteller. Our analysis showed that, on average, the three matchings led to significant differences in Perceived Similarity, compared to not matching (Table 5). The effect sizes are small (d = 0.212 − 0.348, Table 6). It should be noted that in subsection 4.3, we also found that the correlations between Perceived Similarity with health attitudes and mood changes were small to negligible. We will discuss the implications in the Discussion.

Answering RQ2, we suggest that Demographic matching is the preferred way to enhance health attitude. Our analyses showed that, on average, Demographic matching led to a significant increase in Physical Activity (PA) Intention, than not matching (Table 5). The effect size is small (d = 0.253, Table 6). However, we did not detect significant differences in Ability and Experiential matching. We also did not detect significant effects on PA Self-Efficacy and mood.

Table 5. Linear Regression models on the outcome variables [estimate (std. error)].

	Perceived Similarity	PA Intention	PA Self-Efficacy	Mood Valence	Mood Arousal
(Intercept)	4.16 (0.20) *	0.48 (0.12) ***	0.36 (0.08) ***	0.22 (0.19)	0.12 (0.22)
Demographic matching	0.36 (0.17) *	0.23 (0.11) *	0.06 (0.07)	0.05 (0.16)	0.01 (0.18)
Ability matching	0.42 (0.17) *	-0.09 (0.11)	-0.12 (0.07)	-0.17 (0.16)	-0.07 (0.19)
Experiential matching	0.51 (0.17) **	0.02 (0.11)	-0.05 (0.07)	0.20 (0.16)	-0.25 (0.19)
Demographic matching × Participant's race	0.40 (0.24)	0.36 (0.15) *	0.28 (0.10) **	0.69 (0.23) **	-0.05 (0.26)
PA Recall	0.15 (0.05) **	-0.14 (0.03) ***	-0.04 (0.02) *	0.01 (0.04)	0.01 (0.05)
Participant's Race (white=0, Black=1)	-0.42 (0.17) *	-0.38 (0.11) ***	-0.18 (0.07) *	-0.30 (0.16)	0.23 (0.18)
R^2	0.11	0.12	0.06	0.04	0.01
Adj. R^2	0.09	0.11	0.04	0.02	-0.01

$n = 309$; *** $p < .001$; ** $p < .01$; * $p < .05$

Table 6. Effect sizes of matchings on the outcome variables.

	Perceived Similarity	PA Intention	PA Self-Efficacy	Mood Valence	Mood Arousal
Demographic matching	0.212 *	0.253 *	0.097	0.033	0.004
Ability matching	0.297 *	-0.139	-0.218	-0.119	-0.036
Experiential matching	0.348 **	-0.025	-0.097	0.141	-0.148

$n = 309$; *** $p < .001$; ** $p < .01$; * $p < .05$

In terms of the covariates, PA Recall and the participants' race were significantly associated with Perceived Similarity, PA Intention, and Self-Efficacy. No significant association between PA Recall and the participants' race on Mood Valence or Mood Arousal.

4.2 Subgroup Analyses

Answering RQ3, we suggest that only among Black study participants, Demographic matching is effective for enhancing Perceived Similarity, health attitudes, and mood. To reach this conclusion, we first examine the interaction effects between Demographic matching and the participants' race on PA Intention, PA Self-Efficacy, and Mood Valence changes (Table 5). Given the significant interactions, we explored this further by disaggregating the participants by their self-reported race and then conducting subgroup analyses by race.

Among Black mother participants, we suggest that Demographic and Ability matchings are effective for enhancing Perceived Similarity, but only Demographic matching had positive effects on health attitudes and mood. Our analyses detected that Demographic and Ability matchings had significant effects on Perceived Similarity (Table 7). The effect sizes are medium ($d = 0.389 - 0.422$, Table 8).

Furthermore, Demographic matching had significant effects on PA Intention, PA Self-Efficacy, and Mood Valence changes (Table 7) — among Black mothers. The effect sizes are medium (d = 0.353 – 0.467, Table 8). There was no significant effect on Mood Arousal.

Table 7. Linear Regression models on the outcome variables [estimate (std. error)], among Black mothers

	Perceived Similarity	PA Intention	PA Self-Efficacy	Mood Valence	Mood Arousal
(Intercept)	3.85 (0.29) ***	0.20 (0.19)	0.25 (0.12) *	-0.19 (0.29)	0.36(0.35)
Demographic matching	0.64 (0.25) *	0.48 (0.17) **	0.26 (0.11) *	0.54 (0.25) *	-0.03 (0.30)
Ability matching	0.64 (0.25) *	-0.07 (0.17)	-0.12 (0.11)	0.00 (0.25)	0.04 (0.30)
Experiential matching	0.22 (0.26)	-0.19 (0.17)	-0.06 (0.11)	0.07 (0.25)	-0.51 (0.31)
PA Recall	0.17 (0.07) *	-0.10 (0.05) *	-0.04 (0.03)	0.08 (0.07)	0.01 (0.08)
R^2	0.12	0.10	0.07	0.04	0.02
Adj. R^2	0.10	0.07	0.04	0.01	-0.01

n = 152; *** p < .001; ** p < .01; * p < .05

Table 8. Effect sizes of matchings on the outcome variables among Black mothers.

	Perceived Similarity	PA Intention	PA Self-Efficacy	Mood Valence	Mood Arousal
Demographic Matching	0.389 *	0.467 **	0.391 *	0.353 *	-0.014
Ability Matching	0.422 *	-0.090	-0.190	0.015	0.025
Experiential Matching	0.183	-0.237	-0.135	0.071	-0.273

n = 152; *** p < .001; ** p < .01; * p < .05

The PA Recall covariate among Black mothers was only significantly associated with Perceived Similarity and PA Intention.

Among white mother participants, we suggest that Experiential matching is effective in enhancing Perceived Similarity. Our analyses show that only Experiential matching had a significant effect on Perceived Similarity (Table 9) with a medium effect size (d = 0.543, Table 10) However, none of the matchings enhanced health attitudes or mood.

Table 9. Linear Regression models on the outcome variables [estimate (std. error)], among white mothers.

	Perceived Similarity	PA Intention	PA Self-Efficacy	Mood Valence	Mood Arousal
(Intercept)	4.44 (0.27) ***	0.75 (0.15) ***	0.47 (0.10) ***	0.63 (0.25) *	-0.13 (0.26)
Demographic matching	0.08 (0.23)	-0.04 (0.13)	-0.14 (0.09)	-0.46 (0.21) *	0.04 (0.22)
Ability matching	0.22 (0.23)	-0.11 (0.13)	-0.13 (0.09)	-0.34 (0.21)	0.17 (0.22)
Experiential matching	0.78 (0.23) ***	0.20 (0.13)	-0.03 (0.09)	0.29 (0.21)	0.00 (0.22)
PA Recall	0.14 (0.06) *	-0.17 (0.04) ***	-0.04 (0.02)	-0.06 (0.06)	0.02 (0.06)
R^2	0.11	0.14	0.04	0.06	0.00
Adj. R^2	0.08	0.12	0.02	0.04	-0.02

n = 157; *** $p < .001$; ** $p < .01$; * $p < .05$

Table 10. Effect sizes of matchings on the outcome variables among white mothers.

	Perceived Similarity	PA Intention	PA Self-Efficacy	Mood Valence	Mood Arousal
Demographic Matching	0.028	0.020	-0.239	-0.325 *	0.027
Ability Matching	0.170	-0.195	-0.250	-0.271	-0.122
Experiential Matching	0.543 ***	0.236	-0.050	0.217	0.005

n = 157; *** $p < .001$; ** $p < .01$; * $p < .05$

Furthermore, Demographic matching had a significant negative effect on Mood Valence — among white mothers. The effect size is small (d = 0.325, Table 10) There were no significant effects of Demographic matching on other dependent variables. Additionally, there were no significant effects of Ability and Experiential matchings on the dependent variables either.

The Physical Activity Recall covariate was only significantly associated with Perceived Similarity and PA Intention.

4.3 Correlations with Perceived Similarity

To complement RQ1, we also calculated Pearson's correlations between Perceived Similarity and the other outcome variables. Table 11 shows that the correlations were small to negligible. More specifically, among all mothers in the study, Perceived Similarity had positive but small correlations with Mood Valence and Arousal. Among the Black mother participants, Perceived Similarity also had positive but small correlations with Mood Valence and Arousal. Conversely, among white mothers, Perceived Similarity was not correlated to any of the outcome variables.

Table 11. Correlations between Perceived Similarity with other outcome variables.

	Perc. Similarity	PA Intention	PA Self-Efficacy	Mood Valence	Mood Arousal
All	1.00	-0.01	0.05	0.15	0.13
Black mothers	1.00	-0.02	0.02	0.21	0.21
White mothers	1.00	-0.05	0.09	0.09	0.02

5 DISCUSSION

In this 2×2×2 factorial experiment, we examined which categories of similarity variables are effective for peer matching and social modeling in digital health technologies. These categories are Demographic, Ability, and Experiential variables. We recruited single-caregiver mothers (n = 309) to listen to a brief audio story (~2 minutes) aimed at promoting family physical activity (PA). The storytellers' profiles were matched or not matched using three categories of similarity variables. These are the three key takeaways.

First, we found that participants had higher Perceived Similarity across three categories of matching. However, we also found that Perceived Similarity did not correlate with health attitudes or mood. Thus, we caution against using Perceived Similarity as a proxy for peer matching — especially if the interactions with the peers were relatively brief. As exemplified by our finding, asking people whether they feel a sense of similarity or a connection with a peer, did not seem to guarantee the peer will enhance the observer's health attitudes. Therefore, future work in peer matching should identify matching strategies that directly influence positive health attitudes and behavior.

Second, we found that Demographic peer matching (using gender and race variables) led to a significant and positive increase in PA Intention. Given that Choi et al.'s systematic review of reviews shows that Intention is correlated with PA [17], this finding highlights the promise of Demographic peer matching to support PA. This positive effect on proximal health attitude (i.e., Intention) also suggest that long-term applications of peer matching could affect distal health attitudes such as Self-efficacy. Self-efficacy is a complex set of beliefs that are shaped by mastery and vicarious experiences. Thus, a more elaborate intervention is required. As a comparison, Lipsey et al.'s review showed that storytelling-based interventions usually last about 12 minutes and are often a part of larger interventions [46].

Finally, we found significant interaction effects between Demographic peer matching and race, suggesting that Black and white mother participants were impacted differently by peer matching. Our analyses on disaggregated data by race indicated that Black mother participants experienced significant increases in PA Intention, PA Self-Efficacy, and Mood Valence after listening to the story matched by Demographic variables. Given that Choi et al.'s systematic review of reviews also shows that Self-efficacy is strongly correlated with PA [17], this finding shows that Demographic peer matching can support PA and indirectly facilitate emotional social support [18, 31, 64, 74]. Based on these findings, we will first discuss the design implications followed by our interpretation of the racial differences in our experiment.

5.1 Design Implications: Using Demographic variables for peer matching

Our results suggest that using Demographic variables for peer matching and social modeling can enhance PA Intention. Furthermore, Demographic peer matching is particularly effective among Black participants in enhancing PA Intention, Self-efficacy, and mood. With these findings in mind, we propose four design directions for peer matching and social modeling in health technologies. We also highlighted potential tensions when employing peer matching.

5.1.1 Explore how to support the sharing of identities in a way that is comfortable for the identity sharer — and also investigate whether and how members of marginalized groups want to share identity information. Our study shows that Black mother participants gained significant benefits when observing the Black mother storyteller. Our finding suggests that there should be an opportunity for users to disclose their racial and gender information (e.g., using text labels [35]) as a way to motivate their community to live healthier lives.

However, allowing users of marginalized groups to disclose their identities could lead to the paradox of exposure [22], where making identities visible is beneficial for marginalized groups, but at the same time, such visibility also increases the risk of discrimination. On the other hand, people already informally share identities online (e.g., when they posted photos, the language they use). Thus, a nuanced investigation is needed on identity disclosures in the context of amplifying social modeling and peer matching for health equity.

A potential design direction is to allow people to disclose their identities at the group or community level, rather than universally. With this approach, moderators could prevent discrimination and abuse by managing the membership and content in a way that is sensitive to the community's needs [68].

To explain the underlying process of why identity disclosure is beneficial for health technologies that use social modeling and peer matching, we bring the research in social categorization. Social categorization is when humans categorize a person into a category using the person's identities, then the category is used to infer something about the person [42, 60]. People also project their selves into a group of people who share similar features, especially if social categorization is encouraged [43]. In our study, we made the storyteller's gender and racial identities visible in their profile. This might have caused identities to become a salient social categorization and encouraged participants to try to project themselves into the storyteller. In turn, this projection enhanced social modeling and influenced PA Intention as well as PA Self-efficacy and Mood among the Black participants.

Furthermore, social categorization is intersectional and dynamic [60]. Intersectional because a person will not be viewed by one identity but rather from multiple compounding identities [45] and dynamic because certain identities become more focal when a person's behavior highlights the category [8]. Thus, more work is needed to study how to present intersectional identities, and also how the peers' behavior (as told in their stories) would affect peer matching. More importantly, this future work should be done with a goal to enhance health equity.

5.1.2 Continue to provide behavioral support tools along with peer matching. Although we detect significant and positive changes in PA intention (which is linked to PA [17]), we also note that people who intend to be active do not always carry out the exercise behavior [61]. This is known as the intention-behavior gap. This gap can be mitigated by providing support for behavioral self-regulation and for developing the habit to perform the behavior [61]. Therefore, when implementing peer matching, digital health tools should also still incorporate well-established design elements in health behavior promotion, such as goal-setting, behavioral monitoring, feedback, and rewards that enhance self-efficacy.

5.1.3 Mitigate the risk of over-matching by facilitating outgroup matching. The goal is to ensure equitable exchanges of health information. The desire to connect with similar peers could limit access to new sources of health information [14]. Thus, over-matching would work against minoritized groups because they will be constrained to learn about the knowledge held by the privileged groups. Additionally, over-matching would limit the privileged groups to learn about the unjust discrimination experienced by minoritized groups. Perhaps, when peer matching is being used, it can be complemented with cross-matching to ensure exposures to diverse experiences.

5.1.4 Diversify online health communities. Although Demographic matching appeared to be effective among Black mother participants, such matching would not be possible if there is not enough people of similar identities to be matched with. Therefore, concrete inclusion efforts need to be taken to make sure there is a sufficient number of diverse peers, especially in health equity interventions. Put more broadly, our results highlight the importance of having members of marginalized communities play an active role in health promotion in their community.

5.2 Positive effects on health attitdues in peer matching among Black mother participants

We suggest that incorporating storytelling and peer matching in digital health tools could be beneficial for promoting healthy behavior among marginalized social groups. Although our story- and audio-based intervention was relatively brief and participants were only exposed to the intervention once, we found significant, positive, and immediate effects of peer matching on health attitudes and mood among Black single-caregiver mothers participants. Since Black Americans are less likely to have the opportunity to meet the recommended PA levels [51], Demographic peer matching has the potential to lessen exercise disparities among Black Americans [51] and reduce health disparities associated with lowered PA (e.g., diabetes and cardiovascular diseases).

Indeed, larger and longer studies would be needed to generalize our findings. However, we have a reason to believe in the efficacy of our approach given the evidence in support of storytelling and peer matching among minoritized social groups. First, our finding is consistent with Lipsey et al.'s systematic review that shows story-based interventions have a greater effect among minoritized racial and ethnic groups [46]. Second, prior work in academic life, advertising, and medicine shows that there is a preference among Black individuals to connect with other Black individuals. This preference is most likely the effect of experiencing racism [75]. As Vyas et al. have argued, such racial differences often reflect "*the experience of being black in America rather than being black itself*" [75].

This preference can be explained using structural and agentic stances [30]. From the structural stance, we suggest that the effectiveness of Demographic matching among Black participants might be because of the way American society is structured. More specifically, in the U.S., the dominance of white individuals in American life led to Black individuals being underrepresented in many aspects of society. For the Black mothers, the Black mother storyteller was (1) congruent to their racial identity and (2) stood out more than the white mother storyteller. Conversely, among white mother participants, the white mother storyteller was indeed (1) congruent to their racial identity (2) *but* stood out less than the Black mother storyteller. These congruence and distinctness (the way the storyteller stood out) might play a role in enhancing health attitudes and moods among Black participants.

There is numerous evidence of Black underrepresentation in the U.S. In the medical field, although Black individuals represent 12% of the general population [13], data from the U.S. Census Bureau from 2019 shows that only 5% of physicians in the U.S. were Black [67]. Similarly, Black models were underrepresented in social media advertisements with Black women models only appearing in 3% and 4% of Instagram and Facebook ads, respectively [1]. On television, white actors were dominating the leading roles at 81% [39]. Collectively, as a result of this underrepresentation, having Black individuals are more distinct in many areas, including in medicine and media.

Second, from the agentic stance [30], we suggest that Black individuals wielded their agency by actively and effortfully controlling who they want to make social connections with. In this stance, Demographic matching was more effective among Black mother participants (than white mothers) because Black individuals saw a greater benefit in same-race relationships, potentially due to their experiences of systemic racism.

This stance is informed by Gilkes Borr's framework about the experiences of Black students in a predominantly white university [30]. Although Black students needed more effort in making connections with same-race students, they still exerted efforts to make such connections. They persisted to connect with Black students because they thought Black peers would be more supportive and understanding of their backgrounds as a racially minoritized group.

Similar phenomena have been identified in the field of medicine and advertising. In medicine, Black patients disproportionately preferred same-race physicians compared to white patients [16]. This preference was due to Black patients' high perception of racially discriminatory practices in medicine, such as unfair treatment, access to services, quality of care, and cost [16]. For instance, medical students who held false beliefs about Black patients tended to underestimate the pain reported by Black patients and thus prescribed inaccurate treatments, in comparison to white patients [37]. In advertising, Black individuals rated ads with Black models more positively; compared to white individuals who rated ads with white models [40]. However, such racial preferences are moderated by the intensity of ingroup identification [69]. We suggest future work to examine the effects of ingroup identification in peer matching.

Informed by these studies, we suggest that both structural (i.e., racial underrepresentation of Black individuals) and agentic (i.e., Black individuals trusted other Black individuals) factors played a role. Furthermore, both factors are linked to systemic racial discrimination against Black Americans. We recommend future work use the Experience of Discrimination scale to disentangle racial differences in the effectiveness of digital health technologies [41].

Speaking more broadly, our results support findings from prior non-technological health interventions about the importance of actively including members of marginalized communities in health promotion efforts. A review found that having community health workers can positively support people in managing their hypertension in seven out of the eight randomized controlled trials [12]. These interventions were prioritized for racially and ethnically minoritized populations in the U.S. (e.g., Black, Latino); and the community health workers were recruited from the community and resembled the participants' race and ethnicity. Another review on the role of community health workers in promoting diabetes care also found similarly promising results [53]. Our work contributes to these existing studies by demonstrating a potential design of community participation that could be effectively implemented in digital health interventions for promoting health equity. More importantly, our work further underscores the importance of the active involvement of members of marginalized communities in health interventions.

5.3 Limitations

An important limitation of our work is that we had one voice actor to represent each gender and racial combination (i.e., Black mother, Black father, white mother, and white father). Thus, there is a possibility that the results on the interaction between participant race and match on Demographic variables were confounded by small differences in story delivery across actors. However, we carefully instructed all actors to tell the story with similar pacing and style of delivery. In some cases, we replaced the actors or asked them to re-record the stories to ensure that the stories delivered by the four actors had a similar pace and tone. Thus, we are reasonably confident that the confounding effects, if any, were small compared to the effects of the experimental manipulations and differences in participants' gender and race.

Our study is only focused on single caregivers who self-identified as women. We did not examine single-caregiver men. The reason is, poverty is linked to physical inactivity and childhood obesity [51], and single-caregiver women are at a higher risk of poverty than single-caregiver men [52]. Additionally, we only examineed cisgender identities because, in our preliminary examination of peer matching, we need to narrow the variability of the participants' backgrounds. It is critical to examine the experiences of peer matching among trans and non-binary people. Therefore, we recommend future work to replicate the study with a larger number of participants and for a longer duration with members of marginalized social groups (e.g., non-binary, trans, Black/African Americans, Hispanic/Latino, Asian, American Indians, Native Hawaiian, Alaska Native, and Native Hawaiian populations).

6 CONCLUSION

We conducted an experimental study with single-caregiver mothers (n = 309) to identify peer matching variables that are effective for promoting health attitudes, specifically family physical activity. We asked the participants to listen to a family physical activity story in which the storyteller was matched or not matched using Demographic, Ability, and Experiential variables. We found that overall, peer matching using Demographic variables led to an increase in Physical Activity Intention. Furthermore, our subgroup analysis revealed that Demographic matching led to a greater increase in Physical Activity Intention, Self-efficacy, and mood among Black single-caregiver mother participants. In contrast, among white single-caregiver mother participants, there was no effect of peer matching on health attitudes. Collectively, these results suggest that peer matching and digital storytelling could be a promising means for enhancing health equity.

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