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Eli Sumarilah

elisumarliah@unisa.ac.id

Al-Ihya Islamic University of Kuningan https://orcid.org/0000-0002-8680-8558

Evi Avicenna Agustin

Aisyiyah Health Polytechnic Banten

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Article

Obesity Management in Indonesia: Links Between mHealth Utilization, Digital Health Inequality, and Sustained Physical Activity

Eli Sumarliah [1,*], Evi Avicenna Agustin [2], Kawther Mousa [3], Dudi Komaludin [4] and Yogi Iskandar [5]

[1] Faculty of Engineering, Department of Informatics and Management, Al-Ihya Islamic University of Kuningan, Kabupaten Kuningan 45552, West Java, Indonesia
[2] Aisyiyah Health Polytechnic Banten, Department of Midwifery, Kabupaten Serang 42616, Banten, Indonesia; avicenna@polisa.ac.id
[3] Faculty of Health, Department of Public Health, Al-Ihya Islamic University of Kuningan, Kabupaten Kuningan 45552, West Java, Indonesia; kawther19842007@gmail.com
[4] Faculty of Teacher Training and Education, Department of Physical Education, Health, and Recreation, Al-Ihya Islamic University of Kuningan, Kabupaten Kuningan 45552, West Java, Indonesia; dudi.icka@gmail.com
[4] Institute for Research and Community Service-LPPM, Al-Ihya Islamic University of Kuningan, Kabupaten Kuningan 45552, West Java, Indonesia; yogiiskandar@unisa.ac.id
* Correspondence: elisumarliah@unisa.ac.id

Abstract

Background: Physical activity sustainability (PAS) is an essential aspect in the management of obesity. On the other hand, the disparity in accessing healthcare using digital technology such as mobile health (mHealth) may prevent an individual from maintaining healthy behavior. The mHealth has been viewed as an alternative by many to enable individuals to alter their behavior. Unfortunately, very little research has looked into the magnitude by which digital disparity forms the utilization of mHealth (UMH) and PAS, especially in emerging nations like Indonesia. This paper assesses PAS as the main endpoint, and looks at the mediating function of the UMH on the link between socioeconomic status (SES) and PAS, as well as any disparity in this link that might be seen within a rural compared to an urban setting. Methods: A cross-sectional survey was utilized, with a sample size of 1204 Indonesian responders who are either overweight or obese. Utilizing structural equation modeling (SEM), the linkages between SES, UMH, and PAS were evaluated. Subsequently, using multi-group SEM, a comparison of structural paths between rural and urban cohorts was conducted. Results: SES was discovered to possess significant correlation with UMH and PAS. In addition, UMH was significantly correlated with PAS and acted as a mediator between SES and PAS. The outcomes of multi-group SEM uncovered rural–urban disparities, in which more pronounced associations were detected in the urban cohort. Conclusions: As a result of these outcomes, encouraging non-discriminatory digital health access and digital inclusion policies to reinforce obesity control treatment programs is of critical importance.

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Keywords: obesity; physical activity; mHealth; digital health inequality; socioeconomic status; structural equation modeling; Indonesia

1. Introduction and Theoretical Framework

1.1. Obesity, Digital Inequality, and Research Gap

Obesity is a significant public health concern that has been growing around the world and specifically in Southeast Asia, including in Indonesia [1,2]. Rapid urbanization, alterations in eating patterns, and a more inactive way of life are some of the reasons behind the increased occurrence of obesity [3–5]. Nevertheless, the risks of obesity do not affect everyone equally since there are inequalities in socioeconomic status (SES) and geographic distribution that affect access to healthcare facilities, health-related information, and supportive circumstances that enable sustained health-promoting behaviors [6,7]. Despite the traditional emphasis placed on individual behavioral interventions for addressing obesity [1,5,6], such interventions may not take into account wider structural constraints that limit individuals' ability to practice sustained healthy behavior, especially among low-SES and rural populations [7].

The adoption of digital health technologies, particularly mHealth, has gained significant attention in recent times owing to its potential as an economical technology-driven approach for addressing issues associated with obesity, health monitoring, and physical activity [1,8]. Unfortunately, the adoption of digital health technologies has not reached all people evenly because of rural–urban disparities in digital literacy, the availability of the Internet, mobile phones, and infrastructure [9–12]. Hence, although mHealth can contribute to better access to health information, the digital divide has led to further health disparities in society [8,13].

Notably, research gaps have not disappeared. Although various research projects have been conducted in examining the influence of social factors associated with obesity [1,14-16], there is still inadequate research that sheds light on the structure of digital inequalities and their impact on obesity prevention strategies, especially in emerging nations [7, 17]. The available scientific works conducted in developing countries mainly accentuate the feasibility, acceptance, and efficacy of mHealth within a brief period of time [1,8,18–21], especially to enhance obesity-linked results like individuals' weight and height [22]. Nevertheless, few efforts have been made to explore whether the utilization of mHealth (UMH) acts as a mediating factor between SES inequities and physical activity sustainability (PAS) amongst people with obesity or who are overweight living in rural and urban areas in less-industrialized nations [23]. It has been recently discovered that people who have a high SES and live in urban areas gain the most benefits from digital health because they have access to the Internet, know how to operate a computer well, possess smartphones, and generally know how to use technology [8,7,23]. Hence, while digital health could be beneficial for increasing access to healthcare services, it might also contribute to social disparity.

This paper aims at filling the aforementioned void by looking at the linkage between SES, UMH, and PAS. As opposed to viewing digital health tools as naturally equalizing instruments, the goal of this current paper is to find out if there are any discrepancies in the UMH associated with broader structural disparities in terms of SES, territory infrastructure, and digital access. Specifically, to resolve the pinpointed scientific gap, an integrative research question (RQ) is formulated: Does UMH mediate the link between SES

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and PAS among samples who are overweight and obese, and do these structural associations differ between rural and urban cohorts? To answer this RQ, this work employs multi-group SEM for hypotheses assessment.

1.2. Theoretical Framework and Research Objective

In this paper, SES is considered as a structural determinant because it indicates wider societal and economic settings, whose importance cannot be overstated in determining the level at which an individual can access resources and opportunities that promote their good health [13]. The reason why public health organizations such as the World Health Organization consider SES to be a structural determinant is that it propagates proximal residential, occupational, and social settings [13]. As an illustration, low SES has made it difficult for people to embrace digital health technology in overcoming obesity by engaging in physical exercise [6]. In this paper, SES is specified as the relative individual's economic and societal advantage, which is measured by educational attainment, household income, and job stability [24, 25].

On the other hand, UMH has been identified as a behavioral determinant whereby a person may undertake self-regulatory health practices and engage in physical activity sustainability (PAS) [1,9,19,21]. Universally, UMH signifies the use of mobile digital technology such as smartphones, wearable technologies, mobile apps, and wireless technologies for providing healthcare, health surveillance, health education, and behavioral health interventions [1,19,21]. The above definition is not based on any single research; it is derived from numerous original publications and global health organizations [15]. Further, the principal outcome variable in this paper was PAS because it stands for sustained involvement in physical activity that is one of the important behaviors helping to deal with obesity in the long term [26]. In this paper, the meaning of PAS is the lifelong practice in the daily lives of individuals which includes physical activities for recreational, transport, and home purposes [16]. Accordingly, the suggested framework presumes that SES difference may be strongly linked to inequalities concerning UMH, which, in turn, may alter people's capability of performing PAS. The integrative hypothesis guiding this work is that UMH operates as a structural mediating mechanism whereby SES inequalities inspire PAS among Indonesians who are overweight and obese.

Though digital health solutions can be regarded as an intervention strategy at the personal level [1,20,21], this work attempts to investigate how social determinants such as SES and rural–urban difference may relate to the effectiveness of UMH in Indonesia through the lens of social determinants of health (SDH), which has emphasized the influence of numerous structural elements on health behaviors and health outcomes [13,27]. Furthermore, digital health interventions are marketed as cost-saving approaches to obesity, presented as neutral technologies for individual behavior change [1,5]. This work challenges this premise and suggests that the UMH may be related to PAS for obesity management and broader health outcomes, with potential implications for health inequalities. Digital health inequalities can include disparities in the accessibility of technology and health information [7,8]. The digital divide (DD) theory emphasized the contribution of digital technologies like mHealth to the continuation of existing disparities between societal groups [8,7,28]. Earlier works also unveiled that UMH was dependent on various SES and geographical conditions [17,23,29], although it has the possibility to lessen health inequalities [7]. This work represents an initial attempt to conduct a multi-group examination of the association between UMH and health inequalities in relation to PAS for managing obesity in Indonesia, and the difference in structural relations between urban and rural cohorts. The context is fitting not only with respect to the theory of SDH, which highlights the importance of broader societal, economic and environmental conditions in shaping health opportunities [15,27], but also with regard to the DD theory that focuses

on the role of asymmetrical access to technology and digital divides in reproducing current societal stratification [7,28, 30]. In this regard, the concept of UMH can be theoretically interpreted as the socio-technical phenomenon where inequalities associated with SES and geographic locations could affect individuals' engagement in PAS to deal with obesity problems [17,23].

1.3. Hypotheses Development

1.3.1. SES and UMH

SES (socioeconomic status) is among the most reliable forecasters of health-linked activities and care services [23,29]. The digital divide theory states that "discrepancies in accessibility and skills with technology mirror existing social inequalities" [7, 28]. People belonging to a higher SES have better prerequisites in terms of financial, digital, and technological competence for using mHealth technologies [23,29]. Individuals belonging to a higher educational status are more health-literate and aware of the required precautions that are needed for a healthy lifestyle [31]. People belonging to a higher financial status are in a better position to afford the cost of a smartphone and internet services [31]. It can thus be concluded that the utilization of mHealth (UMH) will not be socially neutral and may even show a relation with SES, as reported in existing publications [7,23,29].

H1. *Socioeconomic status is positively associated with mHealth utilization for obesity control.*

1.3.2. UMH and PAS

The UMH offers individuals the chance to build self-monitoring skills, goal setting, development of feedback mechanisms, and behavioral reinforcement [1,18,20]. Those qualities are in proportion to the social cognitive theory that underlines the significance of personal regulation skills and the development of feedback mechanisms in the maintenance of health-related behaviors [5,32]. Time tracking usage and visualization can also be vital in progressing individuals' self-confidence for upholding regular exercise performance [5]. Furthermore, empirical works have shown that personal monitoring with digital kits has positive effects on health outcomes by increasing individuals' engagement in health-related behaviors [18,33]. Regarding handling obesity, physical activity sustainability (PAS) is substantial for the management and maintenance of weight [1,5]. Therefore:

H2. *mHealth utilization is substantially linked to physical activity sustainability.*

1.3.3. SES and PAS

Apart from digital engagement, SES has independent effects on health behaviors [17,34]. The SDH theory asserts that engaging in physical activity for obesity control is determined by various factors at the environmental and structural levels [27]). Individuals belonging to higher SESs have the advantage of living in a safe environment, having access to recreational facilities, flexible work schedules, and the support of their social network, which may encourage them to be physically active [35, 36]. These environmental and structural factors may encourage them to adopt and maintain their physical activity behavior, irrespective of their engagement in digital health [35]. Individuals belonging to lower SESs may have to face environmental barriers such as living in an unsafe environment, having to labor hard at their workplaces, and having less leisure and fewer recreational facilities [36]. Those structural factors may discourage them from engaging in physical activities, which has been attested in earlier empirical works [35-37]. Hence, SES is expected to exert a direct influence on physical activity sustainability (PAS).

H3. *Socioeconomic status is substantially linked to physical activity sustainability.*

1.3.4. Mediation of UMH

Considering the fact that SES affects digital engagement and exercise behavior [35-37], the UMH could be an intermediary between SES and exercise behavior [23,38]. The digital divide model states that persons with higher SES have more chances of using digital tools to manage their health [7, 28]. These factors can potentially enable individuals to use their SES resources to improve their health behaviors through digital engagement. Meanwhile, the SDH theory indicates that health-related activities could be influenced by structural factors through numerous pathways [27]. Considering the fact that SES also influences the physical environment for exercise behavior, as suggested by empirical reports [23,39], fractional mediation is expected. Hence, the UMH can act as a vital behavioral mediator through which obesity-related outcomes are influenced by SES inequality.

H4. *mHealth utilization mediates the relation between socioeconomic status and physical activity sustainability.*

1.3.5. Urban–Rural Differences

Spatial inequalities have an important impact on physical activity opportunities and digital health usage [7,40,41]. Socioecological theory highlights the environmental component in the adoption of health behavior through the availability of infrastructure and resource apportionment [66]. Urban areas usually have better telecommunications infrastructure, fitness centers, and exposure to digital health promotion campaigns [40, 42]. Those factors may affect the adoption of mHealth services and physical activity involvement [7, 9].

On the contrary, there might be limitations in connectivity, recreational facilities, and health promotion programs in rural areas [7,40]. Based upon the digital divide theory, spatial inequities could cause the development of differences in the efficiency of technological access and digital health adoption, which has been documented in earlier work [7,28,30]. The spatial differences in the aforementioned contexts indicate the potential variability in the structural relations amongst SES, mHealth utilization, and physical activity. Hence:

H5. *Structural relations amongst SES, mHealth utilization, and physical activity sustainability differ between urban and rural populations.*

1.4. Conceptual Framework

This paper builds five hypotheses (H1–H5) to quantitatively assess distinctive structural pathways that inspire the integrative hypothesis, which involves unmediated, mediated, and rural–urban comparative linkages among SES, UMH, and PAS. Figure 1 exemplifies the hypothesized structural inter-construct relations among SES, UMH, and PAS, which encompass the mediation of the UMH and the moderation of the urban–rural comparative framework. Derived from the integrative RQ, SES is positioned as a structural determinant or independent/exogenous variable, UMH as a mediating mechanism, and PAS as the principal outcome within a rural–urban comparative scope.

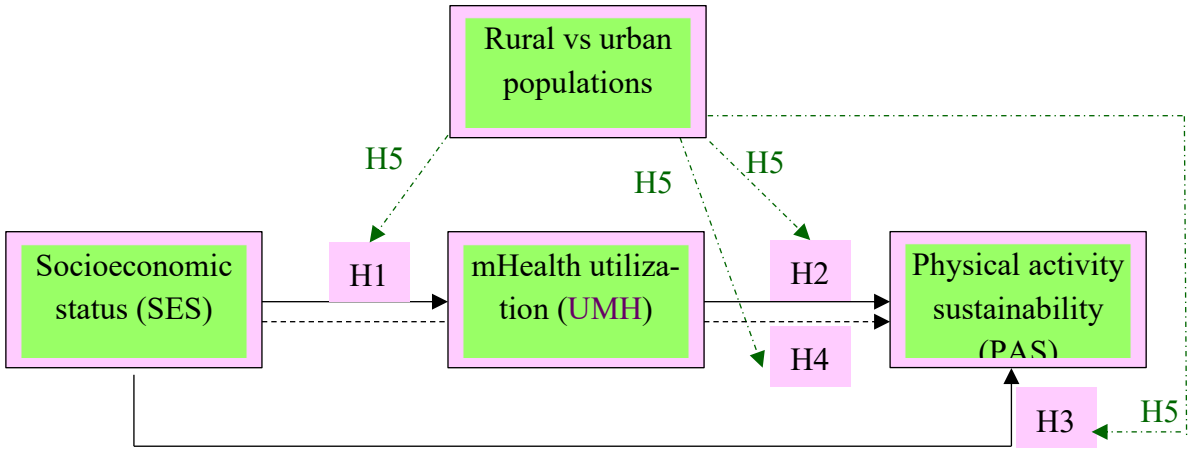


Figure 1. Conceptual framework. Note: Solid arrows = direct hypotheses (H1, H2, H3); dashed arrow = mediation (H4); dashed connections from H1–H4 to the rural-vs-urban box = moderation of urban/rural status on those associations (H5).

2. Methodology

2.1. Sample and Data Gathering

The work was carried out following the cross-section scheme advised by Oetoro et al. [1] to assess socioeconomic and spatial variations in utilization of mHealth for obesity management in Indonesia. The survey focused on universal mHealth applications that are used to monitor the health of individuals and their physical activities. Some mHealth applications widely used by Indonesian people include Halodoc, Alodokter, Mobile JKN, and SATUSEHAT Mobile, which help people manage their health via consultation services, reminders, and basic monitoring functions like goal setting and habit tracking. Examples of other fitness tracking applications include Strava, Mi fitness, and Huawei Health, which act as activity trackers, step counters, and energy expenditure counters of the users. The survey responders also utilized applications for healthy living management and exercise such as FITA and Yes. Fit, which also help monitor food intake as well as body weight goals. The survey did not restrict responders to any particular brand or app; thus, their reactions reflect general engagement with mHealth technologies instead of their personal experience with a particular brand.

Data collection for the research was carried out from 7 to 27 February 2026, wherein a set of questions was administered to adults who were obese or overweight according to their personal reports concerning weight and height measures. BMI (body mass index) was computed according to standard criteria, wherein a BMI of 25 or higher was considered for inclusion in the study [1]. Responders were at least 18 years of age and were capable of independently completing the set of questions, as those who were not capable of providing reliable self-reported data were excluded from the study. A proportionate stratified sampling design was applied in this research, as suggested by earlier works [40, 42], taking into account the urban–rural proportion of the population in Indonesia, encompassing multiple provinces and various digital infrastructures and socioeconomic progression. The strata considered in this work are as follows: (a) urban inhabitants, which designates individuals dwelling in kota (municipalities), and (b) rural inhabitants, which specifies people residing in desa (villages). The concepts of urban and rural are based on the classifications of Badan Pusat Statistik, i.e., Indonesia's Central Bureau of Statistics [10]. A 'rural' area (desa) is an area where more than 50 percent of its residents are occupied in agriculture and other informal sectors, which has a low density and lack

of facilities. An 'urban' area (kota) is a region/city where more than 50 percent of its residents are engaged in non-agricultural occupations, which has a high density and greater infrastructure and facilities. Indonesia consists of different peri-urban and small town areas; nonetheless, in this paper, special consideration was paid to respondents from only rural and urban zones. The motive was to make the study more internally valid and distinctive regarding infrastructure, digital access, and lifestyle. In addition, the binary categorization delivers the biggest possible differentiation in structures and socio-environment applicable to the UMH and PAS among the two distinct cohorts**.** For multi-group SEM purposes, it is imperative to classify the area into two categories to ensure an adequate number of respondents in each group. Based on data from 2025, 40.5 percent of the Indonesian population reside in rural areas while 59.5 percent of them reside in urban areas [12]. The allocation of samples in this research is geared toward ensuring that there is a proportionate representation of sample units in accordance with the abovementioned ratio of urban to rural areas among the entire population of the country. This is to ensure adequate power for multi-group SEM comparisons**.** Since the proportional representation issue was addressed during the process of sampling, the strata created would be proportional to those found in the population [41]. In other words, using the post-stratification weighting method will not make any statistical difference since this would only increase the standard error [41].

The questionnaire was composed in the Indonesian language, which was dispersed through physical distribution through Puskesmas (community health centers), Posyandu and Kader (health volunteers), and via a digital approach through WhatsApp, the most popular messaging app in Indonesia [43]. The research was carried out voluntarily, and responders were asked for their consent prior to collecting information. No personal identifiable data was included in the dataset to safeguard confidentiality. The work obtained authorization from the Research Ethics Committee within the Al-Ihya Islamic University of Kuningan (Reference number: AIU-REC/2026/II/024). The research included 1204 valid data from the 1356 initial data points. The final data encompassed 706 (58.6%) members of urban populations and 498 (41.4%) members of rural populations, which is close to the demographics of Indonesia [12]. This sample was satisfactory for multi-group SEM assessment [42,44].

Because in-person anthropometric assessment was impractical for the large-scale community-based research, body height and weight measurements were detailed as per the self-reports. Despite the likely inaccuracies of classification regarding BMI due to possible biases associated with self-report, this procedure is still widely utilized in epidemiological and public health research [22]. Physical activity sustainability (PAS) was measured using self-reports that captured data on multi-dimensional physical activities, which included recreational exercises, commute, and occupational physical activities [41]. This operationalization was done to avoid any underreporting related to physical activities other than exercises [26]. Despite the possible bias in self-reports for estimating PAS levels, several studies have indicated that self-reports are reliable tools for the evaluation of physical activities among large community samples [45].

To avoid the occurrence of CMB, certain procedural steps have been taken, such as securing the anonymity of respondents, maintaining confidentiality, preserving clear language in the survey form, and the organization of constructs into distinct questionnaire sections [46]. Using Harman's one-factor solution technique, the first unrotated factor elucidates 37% of the variation in the entire data, and this percentage is less than the advocated point of 50%. This means that CMB did not influence the outcomes of the empirical assessment. Furthermore, according to SEM's latent common method factor exploration, there has been a negligible impact of method factors on observed associations.

2.2. Measures

2.2.1. SES

SES (socioeconomic status) has been reflected as an underlying construct based on three indicators of the responders: educational level (SES1), household income (SES2), and job stability (SES3) (see Supplementary Materials, Table S1, column 2 and Questionnaire Part 3 for the complete measurement items). These indicators were selected based on the validated measures from an earlier study [17] except for social class identity, which, in this paper, is replaced by job stability. Such substitution is justified as job stability delivers a more objective, structurally relevant, and context-sensitive indicator of SES, whereas social class identity is subjective and potentially less reliable in measuring actual socioeconomic conditions. The SES' three measures (SES1–SES3) utilize standard multivariable indicators of SES in connection with public health and social epidemiology [24, 25]. Employment stability can have different operations in urban and rural areas. To solve this problem, (a) multi-group SEM is used to compute the factor loadings for both cohorts while ensuring that the latent variable SES incorporates common variability of the items, while at the same time allowing for context-specific variability, and (b) the factor loadings of employment stability were revealed to be significant for both cohorts (λ = 0.71 rural, λ = 0.74 urban), which suggests its meaningful contribution to the total SES construct regardless of market dissimilarities. In the SEM approach, if the studied variable is a latent variable on account of its method of construction, then in the construction of this variable, all the three variables contribute equally according to their factor loading, whereas in any other framework where there is an assumption of equal weighting, all the three contribute equally in construction of this variable. In this research sample involving urban residents, factor loadings of variables such as education, income, and occupation stability were 0.78, 0.82, and 0.74, respectively. It means that education was highly significant, although it did not dominate the construction of the variable. This was corroborated by sensitivity examination with a new framework wherein education was the sole indicator. It can be noted that both SEM paths related to mHealth utilization and sustained physical activities had statistical significance; thus, it is clear that the detected inter-variable links were not merely triggered by education but by the amalgamation of several SES elements.

The level of education was computed with four categories based on national classification by the Central Bureau of Statistics, Indonesia [10]. The categories included higher education, upper secondary schooling, lower secondary, and primary education and below. Additionally, monthly income of the individual households was determined by the sorted income ranges based on the national poverty statistics of the Central Bureau of Statistics, Indonesia [47]. As per March 2024, the line of poverty for each household was IDR 2,786,415 monthly. Hence, the responders were classified into five groups based on monthly income: less than IDR 2.8 million (poor), IDR 2.8–5 million (lower income), IDR 5 million to 8 million (lower-middle), IDR 8 million to 12 million (middle), and more than IDR 12 million (upper). Further, the measurement of employment stability is based on the main employment status and income regularity of the responders, and is divided into four types: (a) unemployed or having an irregular work pattern, (b) having an informal job with an unstable income, (c) being self-employed or having a small business with moderately stable income, and (d) having formal employment with regular income. The higher the SES scores, the greater the socioeconomic advantage.

Despite being modeled as a formative construct in some publications, e.g., Ref. [17,48], SES was seen as a reflective construct in this paper since its elements (i.e., educational achievement, income levels, and job stability) were manifestations of socioeconomic benefits that led to behavioral outcomes [49], namely mHealth utilization and PAS for obesity control. Operationalizing SES reflectively is suiTable Ss its measurement items had good

factor loadings, reliability, and convergent validity in both urban and rural samples in the SEM paradigm [50].

2.2.2. UMH

To measure UMH (utilization of mHealth), we used six items (UMH1–UMH6) where responders signposted their agreement using a five-point Likert-type response format: 1 = fully disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = fully agree. Responses were averaged across items to compute an overall mHealth utilization score for every responder, such that bigger values denoted greater mHealth utilization for sustained physical activity and obesity management**.** The five items (UMH2–UMH6) were validated items adapted from earlier works [1,51]. Meanwhile, the first item (UMH1) stating that "Using mHealth applications motivates me to maintain regular physical activity" was newly created by the authors and later validated through assessment from 10 experts before gathering data (see Supplementary Materials, Table S1, column 2 and Questionnaire Part 1 for the complete measurement items). The Cronbach's alpha (α) estimates were 0.85 for the rural subsample and 0.88 for the urban subsample, signifying tolerable internal consistency for the two cohorts. For the UMH construct, it employs a reflective method for the measurement of usage, usefulness, and motivation, which gauges the person's tendency towards using the mobile application for mHealth purposes. Even though there have been some behavioral and attitude indicators employed within the instrument, technology adoption and UMH have been closely related to both behavioral and perceptual measures [52, 53]. For all six UMH measures, loadings were very high in both urban ($\lambda \geq 0.77$) and rural ($\lambda \geq 0.74$) areas, which reinforces the latent construct's one-dimensionality. The UMH scale demonstrated acceptable psychometric properties in both samples. This is evidenced by the fact that Cronbach's alpha and composite reliability scores exceeded the necessary cutoff level, which is enough to certify the instrument's validity and reliability.

2.2.3. PAS

Physical activity sustainability (PAS) was computed by a reflective multi-item scale that measured the respondents' habitual and consistent involvement in physical activity behaviors that are necessary for obesity control. Five items (PAS1, PAS2, PAS3, PAS4, and PAS5) were constructed by the researcher based on pilot interview findings with experts in public health and physical activities, as well as a bibliometric examination of physical activity publications for content validity and context-specificity for obesity control. An example of a scale item is: "I engage in physical activity regularly every week" (see Supplementary Materials, Table S1, column 2 and Questionnaire Part 2 for the complete measurement items). The responders' agreement with the scale items was gauged via a five-category Likert measure, from 5 (fully agree) to 1 (fully disagree), with a higher score designating more consistent physical activity. Physical activity levels were quantified by adjusted Saltin–Grimby scales [54], which calculated the responders' physical activity levels for the past year in their leisure time and other activities (including transportation-linked activities). The item (PAS) was appraised on a scale from 1 (almost inactive) to 4 (highly active). In short, the PAS measurement comprised five items based on a Likert scale and one item based on the four-category Saltin–Grimby scale. Explanation as to why this measurement is used is as follows: (a) each group uses the same sets of items in measuring the same tendency to engage in physical exercise, which consist of frequency, consistency, and intensity; (b) the factor loadings of $0.75 \leq \lambda$ for all the items used in PAS have been found to be good in the CFA, showing that the question taken from the Saltin–Grimby scale was congruent with self-reported daily activities; and (c) the AVE and CR of both rural and urban cohorts were good and thus reinforce construct validity.

2.2.4. Control Variables

Some demographic aspects were added as control variables, which were able to control the impact of possible confounding outcomes. They were age, gender, and residential area. Gender was inscribed as a twofold component (1 = female, 0 = male), and residential area was also enciphered as dualistic (0 = rural, 1 = urban). These controllers were added because some earlier publications showed that they might affect digital health adoption as well as physical activity [1,55].

Continuous numerical variables like age, monthly household income, UMH, and PAS were reported as mean ± SD (standard deviation), as advised by experts [30]. Rural–urban comparison for these variables utilized an unpaired *t*-test after meeting the assumptions of homogeneity and normality [56]. Frequency and percentage assessments of categorical variables such as gender, tertiary education, and BMI were conducted with a chi-square test [57]. Level of significance was set at p <.05 for two-tailed tests, as advised by statistical experts [58, 59].

2.3. Analytical Approach

Measurement invariance was specified to ensure that digital literacy, mHealth use, and physical activity were considered equally across subgroups in both contexts. Multi-group SEM is also beneficial for gauging the comparison of coefficients in paths across contexts, investigating possible moderating roles of geographical location [42]. For example, the association between digital access and mHealth use may be greater in cities with developed connectivity infrastructure than in rural areas with infrastructural issues. By specifying mHealth as a mediator and moderator of the association between SES and obesity, this study will contribute to the understanding of whether digital health technologies can mitigate social inequalities or, on the contrary, widen the breach between the poor and the rich. This will improve evidence-based knowledge about the complex associations between structural determinants and individual behavior [27], which offer actionable insights for public health initiatives and policy strategy.

Mathematical equations to assess hypotheses are as follows.

For direct associations in hypotheses 1, 2, and 3 (H1–H3), let Age, Gender, Residence (Urban = 1, Rural = 0) be control variables.

The first hypothesis (H1: SES → UMH) is tested by Equation (1):

$$\mathrm{UMH} = \beta_1 \mathrm{SES} + \Upsilon_1 \mathrm{Age} + \Upsilon_2 \mathrm{Gender} + \zeta_1 . \quad (1)$$

For the second and third hypotheses (H2 and H3: UMH→ PAS and SES→ PAS), use:

$$\mathrm{PAS} = \beta_2 \mathrm{MHU} + \beta_3 \mathrm{SES} + \Upsilon_3 \mathrm{Age} + \Upsilon_4 \mathrm{Gender} + \Upsilon_5 \mathrm{Residence} + \zeta_1. \quad (2)$$

Here, H1, H2, and H3 are supported when $\beta_1, \beta_2, \beta_3 > 0$, separately.

For the mediating function (H4), use Equation (3), and for the total effect of SES on PAS, use Equation (4):

$$\text{Indirect effect} = \beta_1 \times \beta_2; \quad (3)$$

$$\text{Total effect} = \beta_3 + (\beta_1 \times \beta_2). \quad (4)$$

Mediation is supported if $\beta_1 \times \beta_2 > 0$, and significance was tested via bootstrapping. Partial mediation is attained when $\beta_3 \neq 0$, and full mediation when $\beta_3 = 0$.

For multi-group SEM for urban–rural differences (H5), estimate structural paths separately for group 1 (urban) using Equations (5) and (6), and group 2 (rural) using Equations (7) and (8):

$$MHU_U = \beta_{1U} SES + \zeta_{1U}, \quad (5)$$

$$SPA_U = \beta_{2U} MHU + \beta_{3U} SES + \zeta_{2U}, \quad (6)$$

$$MHU_R = \beta_{1R} SES + \zeta_{1R}, \quad (7)$$

$$SPA_R = \beta_{2R} MHU + \beta_{3R} SES + \zeta_{2R}. \quad (8)$$

H5 is supported if $\beta_{1U} \neq \beta_{1R}$ or $\beta_{2U} \neq \beta_{2R}$ or $\beta_{3U} \neq \beta_{3R}$.

Further, test the chi-square difference using Equation (9) where significant $\Delta\chi^2$ indicates structural path differences.

$$\Delta\chi^2 = \chi^2_{constrained} - \chi^2_{unconstrained}. \quad (9)$$

The full structural system is computed by Equation (10):

$$\begin{matrix} MHU & = \beta_1 SES + \Gamma_1 Controls + \zeta_1 \\ SPA & = \beta_2 MHU + \beta_3 SES + \Gamma_2 Controls + \zeta_2 \end{matrix}. \quad (10)$$

Here, $Controls = (Age, gender, residence)$.

Following expert scholars [56], the indices used in measuring the goodness of fit in the SEM technique are chi-square to degree of freedom ratio (χ^2/df), comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Supplementary Materials, Table S2 exhibits universally advocated SEM cutoff points for framework fit, convergent validity (AVE, factor loadings), and composite reliability (CR) to indicate satisfactory internal consistency.

The test for measurement invariance between two cohorts from an urban–rural sample was conducted in sequence (see Supplementary Materials Table S3). First, the baseline framework exhibited excellent fitness (CFI = 0.952; RMSEA = 0.041) which indicates that the same factor structure was found to exist in the two samples. Second, while conducting measurement invariance tests regarding factor loading, some discrepancies were observed in the value of CFI (0.003), indicating that metric invariance existed. Full scalar invariance was not present but partial scalar invariance was confirmed because only a few item intercepts were free (ΔCFI = 0.002). It therefore means that the constructs under consideration have been measured equally in the two samples, which justifies the assessment of path estimates in the multi-group SEM.

All activities associated with data cleaning, descriptive statistics, and preliminary assessments were conducted by means of IBM SPSS Statistics version 29.0. SEM, CFA, mediation, and multi-group SEM assessments were conducted using AMOS version 29.0. Bootstrapping was conducted using 5000 bootstrap samples and bias-corrected 95% confidence intervals in order to test the existence of indirect effects.

3. Results

3.1. Sample Characteristics

Table 1 highlights the demographic characteristics of the rural–urban cohorts. Overall, from the 1204 individuals who took part in the present work, 498 (41.4%) were residing in rural areas, while 706 (58.6%) lived in urban areas. The average age of all responders was 38.7 ± 11.4 years. The average age for those residing in rural areas was 39.4 ± 11.8 years, and in urban areas it was 38.2 ± 11.1 years, though no quantitative significance existed concerning such findings (t = 1.76, p = 0.079). In terms of percentage, 653 responders were females (54.2%), of whom 273 (54.8%) resided in rural areas and 380 (53.8%) in urbanized regions. No evidence of significance existed between gender and residence ($\chi^2(1)$ = 0.12, p = 0.729). As far as education level is concerned, 613 responders possessed a ter-

tiary education (50.9%). A smaller number of individuals who obtained a tertiary education was found in rural areas (173 subjects; 34.7%) compared to urban areas (440 subjects; 62.3%), and inferentially significant differences existed ($\chi^2(1) = 89.64$, $p < 0.001$).

The average monthly household income for the total sample is 5.12 ± 2.41 million IDR. Mean monthly income for the urban cohort proves to be significantly higher than that for the rural cohort: 5.89 ± 2.36 million IDR for the former and 4.03 ± 2.08 million IDR for the latter. Inferential significance of rural–urban differences in this regard was determined (t = 14.01, $p < 0.001$). The mean score of mHealth utilization for all responders is 3.41 ± 0.87. The mean score for the urban cohort is higher than that for the rural one: 3.63 ± 0.79 and 3.09 ± 0.88, respectively; inferential significance occurred in rural–urban differences (t = 9.42, $p < 0.001$). Likewise, the average score regarding PAS was revealed to be 3.38 ± 0.84, with urban residents observed to have a relatively better score than those of rural areas (3.52 ± 0.81 vs. 3.18 ± 0.84), (t = 7.21, $p < 0.001$).

In the case of BMI classification, 740 responders (61.5%) were overweight (BMI = 25.0–29.9), whereas 464 responders (38.5%) had a BMI ≥ 30.0 and were considered as obese. In relation to the urban sample, 254 responders (36.0%) were overweight and 452 responders (64.0%) were obese. Meanwhile, for rural residents, 288 responders (58.0%) were overweight and 210 participants (42.0%) were obese. Inferential significance was discovered within the association between BMI classification and rural–urban responders ($\chi^2(1) = 4.58$, $p = 0.032$).

Table 1. Sample characteristics by urban–rural residence (N = 1204).

Variable	Total Sample (N = 1204)	Urban (n = 706)	Rural (n = 498)	Test Statistic	p-Value
Residence, n (%)	1,204 (100.0)	706 (58.6)	498 (41.4)	—	—
Age (years), Mean ± SD	38.7 ± 11.4	38.2 ± 11.1	39.4 ± 11.8	t = 1.76	0.079
Female, n (%)	653 (54.2)	380 (53.8)	273 (54.8)	$\chi^2(1) = 0.12$	0.729
Tertiary education, n (%)	613 (50.9)	440 (62.3)	173 (34.7)	$\chi^2(1) = 89.64$	<0.001
Monthly household income (IDR million), Mean ± SD	5.12 ± 2.41	5.89 ± 2.36	4.03 ± 2.08	t = 14.01	<0.001
UMH, Mean ± SD	3.41 ± 0.87	3.63 ± 0.79	3.09 ± 0.88	t = 9.42	<0.001
PAS, Mean ± SD	3.38 ± 0.84	3.52 ± 0.81	3.18 ± 0.84	t = 7.21	<0.001
BMI classification, n (%)				$\chi^2(1) = 4.58$	0.032
Overweight (BMI 25.0–29.9)	740 (61.5)	452 (64.0)	288 (58.0)		
Obese (BMI ≥ 30.0)	464 (38.5)	254 (36.0)	210 (42.0)		

Notes: SD = standard deviation, UMH = utilization of mHealth, PAS = physical activity sustainability, BMI = body mass index. Procedure: unpaired/two-sample t-test was performed on the continuous data and chi-square (χ^2) test was carried out for categorical data. Percentages may not total exactly 100% due to rounding.

Informative statistics (Table 2) specified moderate total engagement in the use of mHealth applications for tracking physical activity and exercise management. The results indicated higher scores for mHealth application use among urban residents than rural residents. The difference was statistically significant (M = 3.63, STD = 0.79 vs. M = 3.09, STD = 0.88; t = 9.42, $p < 0.001$). The same trend was observed for physical activity sustainability, which was higher among urban residents (M = 3.52, STD = 0.81) than rural residents (M = 3.18, STD = 0.84; $p < 0.001$). Bivariate correlation assessment provided strong support for the proposed paradigm by denoting significant and positive relations between SES and mHealth application usage ($p < 0.001$, r = 0.42,), sustained physical activities and mHealth application use ($p < 0.001$, r = 0.48), and sustained physical activities and SES ($p < 0.001$, r = 0.36).

Table 2. Correlation patterns and informative data.

Variables	Mean	STD	1	2	3
1. Socioeconomic status (SES)	—	—	—		
2. Utilization of mHealth (UMH)	3.41	0.87	0.42 ***	—	
3. Physical activity sustainability (PAS)	3.38	0.84	0.36 ***	0.48 ***	—

Notes: N = 1204. Pearson correlation coefficients reported. *** $p < 0.001$.

3.2. Measurement Framework Assessment

Discriminant validity was confirmed via the Fornell–Larcker principle (Table 3). It was found that the matrices for rural and urban groups were psychometrically sound for structural assessment as the crosswise numerical representatives outstrip inter-construct links.

Table 3. Fornell–Larcker matrix by residence types.

	Urban (n = 706)			Rural (n = 498)		
Construct	**SES**	**UMH**	**PAS**	**SES**	**UMH**	**PAS**
Socioeconomic Status (SES)	**0.783**	0.521	0.427	**0.771**	0.513	0.420
mHealth utilization (UMH)	0.490	**0.847**	0.562	0.482	**0.834**	0.553

Physical activity sustainability (PAS)	0.431	0.564	**0.825**	0.424	0.555	**0.812**

Notes: Crosswise values (bold) are square root of AVEs. Off-crosswise values are inter-construct links.

Table 4 exhibits the measurement framework outcomes attained for urban (n = 706) and rural (n = 498) groups. The entire item loadings for both clusters have robustness and statistical significance, with numerical representatives between 0.71 and 0.88 ($p < 0.001$), designating satisfactory indicator consistencies. Similarly, composite reliabilities for urban and rural vary between 0.83 and 0.90; greater than the counseled 0.70, and thus establishing good composite reliability. Finally, the AVE (average variance extracted) value is between 0.60 and 0.69, greater again than the minimum required 0.50, thus establishing good convergent validity. It is clear that the constructs of SES, mHealth utilization, and continued physical activity have good reliability and validity for both groups.

Table 4. Measurement framework outcomes.

Construct	Indicator	Urban (n = 706) λ	AVE	CR	Rural (n = 498) λ	AVE	CR
Socioeconomic status (SES)	Education level	0.78 ***	0.60	0.86	0.76 ***	0.60	0.83
	Household income	0.82 ***			0.79 ***		
	Work stability	0.74 ***			0.71 ***		
Utilization of mHealth (UMH)	UMH1	0.88 ***	0.69	0.90	0.86 ***	0.66	0.87
	UMH2	0.85 ***			0.82 ***		
	UMH3	0.81 ***			0.79 ***		
	UMH4	0.79 ***			0.81 ***		
	UMH5	0.77 ***			0.74 ***		
	UMH6	0.86 ***			0.83 ***		
Physical activity sustainability (PAS)	PAS1	0.83 ***	0.64	0.88	0.81 ***	0.63	0.85
	PAS2	0.80 ***			0.76 ***		
	PAS3	0.79 ***			0.74 ***		
	PAS4	0.81 ***			0.81 ***		
	PAS5	0.77 ***			0.77 ***		
	PAS6	0.75 ***			0.75 ***		

Notes: *** $p < 0.001$, λ = item loading.

3.3. Structural Framework Assessment

Given the values that have been formed by the indices (χ^2/df = 2.41, CFI = 0.95, TLI = 0.94, RMSEA = 0.048, and SRMR = 0.041), it can be concluded that the structural framework had excellent fitness with the data. Table 5 displays that SES had positive significant links with UMH ($p < 0.001$, $\beta = 0.44$) and PAS ($p < 0.001$, $\beta = 0.21$). It was discovered that UMH had a significant linkage with PAS ($p < 0.001$, $\beta = 0.46$). Five thousand samples in bootstrapping divulged that SES had a substantial indirect linkage to PAS, controlling for mHealth usage ($\beta = 0.20$, 95% CI [0.16, 0.24]). As depicted in Table 5, the effect coefficients are moderate-to-strong for the link between SES and utilization of mHealth (SES→UMH, $\beta = 0.44$), while for the link between the utilization of mHealth and physical activity sustainability, (UMH→PAS) $\beta = 0.46$. The effect coefficient for the link between SES and physical activity sustainability (SES→ PAS) was $\beta = 0.21$, which is relatively small compared to the other two relations. On the other hand, the indirect effect was $\beta = 0.20$, which is moderate and comparable in magnitude to the direct link. This suggests that UMH exemplifies a consequential pathway connecting SES with PAS.

Table 5. Structural framework outcomes.

Hypothesized Path	β	SE	95% CIs	*p*-Value	Outcome
Direct associations					
H1. SES → UMH	0.44	0.04	[0.36, 0.52]	<0.001	Supported
H2. UMH → PAS	0.46	0.04	[0.38, 0.54]	<0.001	Supported
H3. SES → PAS	0.21	0.05	[0.12, 0.30]	<0.001	Supported
Indirect association					
H4. SES → UMH → PAS	0.20	0.02	[0.16, 0.24]	<0.001	Supported

Notes: N = 1204. Standardized coefficients (β) reported. Confidence intervals (CIs) derived from 5000 bootstrap samples. SES = socioeconomic status, UMH = utilization of mHealth, PAS = physical activity sustainability.

3.4. Multi-Group SEM for Urban–Rural Disparities

To test spatial moderation effects, a multi-group SEM assessment was used to compare subsamples of urban and rural residents. Configural invariance tests disclosed excellent fit for the overall framework (SRMR = 0.048; RMSEA = 0.052; CFI = 0.955). Metrical and scalar invariance tests reinforced the framework (ΔCFI = 0.004 and ΔCFI = 0.006, respectively); thus, structural contrasts could proceed. Table 6 displays that the link between SES and mHealth utilization was stronger in the urban than the rural group ($p < 0.001$, β = 0.49 vs. β = 0.34); group differences had statistical significance ($\Delta\chi^2 = 9.87$, $p = 0.002$). mHealth utilization had a significant positive relation with physical activity sustainability for both clusters, but was stronger for the urban than the rural group (β = 0.52 vs. 0.37, $\Delta\chi^2 = 11.24$, $p = 0.001$). The SES → PAS path was significant for the urban group ($p < 0.001$, β = 0.24) and weaker within the rural group ($p = 0.041$, β = 0.12); marginal group differences emerged ($\Delta\chi^2 = 3.84$, $p = 0.050$).

The direct/unmediated association of SES with PAS through UMH had evidence of significance (β = 0.20, $p < 0.001$), which means that the partial mediation of UMH did take place. The extent of partial mediation was moderate and equivalent to the unmediated link of SES–PAS (β = 0.21), which implies that UMH possessed an important role in the linkage between socioeconomic advantage and physical activity sustainability. It can be inferred that the mediation was not complete because of the significance of the unmediated SES–PAS association.

The strong link between UMH and PAS does not mean that using this technology is good for all population cohorts in equal measure. On the contrary, the quantitative outcomes indicate that individuals with a higher SES and urban advantage have more chances to use mHealth tools in maintaining physical activity to cope with obesity. Furthermore, the emergence of high structural correlations within the urban cohort might be explained by a range of other rural–urban inequalities, including those related to internet access, availability of smartphones, digital ecosystem, and e-health services.

Table 6. Multi-group SEM comparison of structural paths: urban vs. rural.

Structural Path	Rural (n = 498) β	Urban (n = 706) β	$\Delta\chi^2$ (1 df)	*p*-value (Difference Test)	Interpretation
H1. SES → UMH	0.34 *	0.49 *	9.87	0.002	Stronger in urban
H2. UMH → PAS	0.37 *	0.52 *	11.24	0.001	Stronger in urban
H3. SES → PAS	0.12 *	0.24 ***	3.84	0.05	Marginally stronger in urban
Indirect path	Urban β (95% CI)		Rural β (95% CI)		Interpretation
H4. SES → UMH → PAS	0.25 [0.20, 0.30] ***		0.13 [0.09, 0.17] ***		Stronger mediation in urban

Notes: Harmonized coefficient (β). * $p < 0.001$; *** $p < 0.05$. $\Delta\chi^2$ reflects chi-square difference test comparing constrained and unconstrained frameworks. PAS = physical activity sustainability; SES = socioeconomic status; UMH = utilization of mHealth.

Further, as displayed in Table 7, the RQs are answered: (1) SES has a positive link with the usage of mHealth, (2) SES and UMH positively relate to the maintenance of physical activities, (3) UMH has a partial mediation in the link between SES and PAS, and (4) the outcomes of multi-group SEM designate that the structural relation is significantly different between the urban and rural samples, and the relations are stronger in urban cohorts.

Table 7. Alignment between the integrative RQ, hypotheses, and empirical outcomes.

Integrative RQ	Hypothesis	Path	Empirical Answer
Does UMH mediate the link between SES and PAS among samples who are overweight and obese, and do these structural associations differ between rural and urban cohorts?	H1	SES → UMH	Supported
	H2, H3	UMH → PAS SES → PAS	Supported
	H4	SES → UMH → PAS	Supported
	H5	Multi-group SEM contrast	Supported (consistently stronger relations in urban)

Notes: SES = socioeconomic status; UMH = utilization of mHealth; PAS = physical activity sustainability. The integrative RQ was assessed using SEM and multi-group SEM.

4. Discussion and Implications

4.1. Discussion of Results

The empirical outcomes suggesting the strong SES–UMH linkage is in line with Koivusilta et al. [29], reinforcing that the accessibility of smartphones, internet connection, affordability of data services, and health application literacy require people to be financially and cognitively endowed. Nevertheless, the finding is against that of Chang et al. [24], possibly due to the different forms of digital health examined which do not require individuals to continuously perform UMH. The next finding exhibiting the direct SES–PAS linkage contrasts with Miranda-Vicente et al. [25]. Contextual differences may explain this discrepancy: (a) in their cohort, higher wealth was linked to inactivity, possibly due to motorized transport and sedentary lifestyles, and (b) they examined children and adolescents, not adults, whereas SES disparities in leisure time exercise are typically more pronounced in adulthood, while children's activity often depends on daily routines such as active transport [17,35].

Further, the evidence of the strong UMH–PAS linkage, which was more significant in the urban sample, is supported by Zhang et al. [7]. Notably, while the current paper's finding has established a robust association between UMH and PAS to solve issues concerning obesity, this result is not in agreement with some earlier publications [60-62]. The possible reason for this is that UMH is significantly influenced by various socioeconomic, infrastructural, and demographic characteristics. For instance, within the emerging economy of Uganda, Kansiime et al. [60] discovered that high costs of training, poor infrastructural conditions, low digital literacy, poor understanding amongst community members, and low motivation amongst users are barriers to the UMH. Likewise, Yang et al. [61], through their meta-analysis, unveiled that older age had a negative link with UMH, which implies that demographic inequalities could be among the variables linked to UMH. Additionally, Deniz-Garcia et al. [62] noted that the UMH in everyday care practices faces hurdles such as privacy of personal data, cyber security, reproducibility of outputs provided by artificial intelligence algorithms, inadequate measures for clinical usability of the apps, and difficulties in changing behaviors and engaging in sustained health activities. Golbus et al. [52] showed no significant improvement for patients who performed UMH over six months. This could be due to the fact that in their research, the clinical context might be limited to the benefits of digital health.

Furthermore, the finding that UMH partially mediates the link between SES and PAS reinforces Rick et al. [53]'s research; however, this study has further added value by analyzing general citizen who are obesity/overweight, as opposed to just employees, and revealed a stronger mediating urban–rural linkage. Overall, although UMH may be positively correlated with PAS, the increasing divide between tech-savvy and tech-naive populations could aggravate disparities in access to obesity treatment, which reinforces the DD theory. It can be explained by the fact that individuals who belong to upper SESs and live in urbanized regions have more opportunities to gain from mHealth due to proficiency in digital literacy, technological infrastructure, and Internet access, which confirms the SDH theory. Hence, this work's outcomes contrast with the view that UMH should be evaluated merely in terms of its influence on individual behavior, as the association between UMH and PAS to overcome obesity may greatly depend on SES and geographic factors.

4.2. Implications

4.2.1. Implications for Theory

This paper's findings have some theoretical implications. It contributes to digital health inequality, structural modeling in public health, and obesity management research. It reconceptualizes mHealth utilization as both an independent and mediating variable rather than solely a dependent outcome. Earlier publications primarily assessed mHealth adoption as shaped by socioeconomic and demographic factors (e.g., [9,20,53]), improving understanding of access and acceptance but offering limited insight into how digital tools translate structural resources into health behaviors. By modeling mHealth as predictor and mediator, this paper advances a socio-technical perspective in which digital technologies link SES to physical activity sustainability. The findings display that mHealth is shaped by SES while also influencing behavioral outcomes and partially mediating inequality, extending prior work that focused mainly on determinants of adoption [7,23]. Moreover, the mediating nature of mHealth usage differs among urban and rural groups, as reflected in the multi-group SEM assessment outcomes. As earlier works on the mHealth-obesity linkage is predominantly conceptual, e.g., [19,63], the current paper makes a contribution to extant publications via empirical provision concerning mHealth's function as a management tool for obesity.

4.2.2. Implications for Policy

In the context of Indonesia, there are a number of policy implications that emerge from the outcomes of this work. Firstly, policymakers may consider creating programs that promote digital health, where they should emphasize using different digital devices by improving infrastructure, providing affordable mobile phones for people, and designing mobile health apps that are easily understandable by people living in rural and low-SES areas. So far, apps like Alodokter and Mobile JKN are widely used across Indonesia to chat with doctors for appointment booking and to read healthcare articles in Indonesian which use local context to help with low literacy; however, most apps in Indonesia are urban-first designs. Indonesia does also have fitness apps for supporting sustained physical activities (like Fita and Fumai), but most are not truly designed for low-SES rural users as barriers may still include internet access, digital literacy, and complex interfaces. Secondly, integrated public health programs could incorporate financial incentives for people with low-SES and mobile apps aimed at performing physical exercises. Thirdly, challenges arise with the digitization of the Posyandu (a community-based health service in Indonesia that operates at village level and is a main part of primary healthcare), possibly due to the absence of necessary technical skills among healthcare workers operating at the grassroots level. Hence, the digital illiteracy of people who live in rural and low-SES areas

should be addressed because this could be an effective way of resolving digital inequality problems. It may be equally important to adopt an evaluation framework that quantifies the utilization of mHealth technology and physical activity levels across different socioeconomic strata.

5. Conclusion, Limitations, and Future Work

The aim of this work is to assess the mediating role of UMH in the SES–PAS link among responders who are obese or overweight in Indonesia, as well as the difference in this structural link in rural and urban areas. It has been observed in the present work that SES and rural–urban disparities have strong correlations with inequitable UMH and PAS. High SES and living in urban areas are viewed as the essential structural features associated with UMH by participants who are overweight and obese. In other words, there are socioeconomic and geo-spatial factors which place UMH within a broader context than merely as a behavioral support tool. The implication is that any existing disparity in internet connectivity and digital literacy can lead to a further widening of inequalities in managing obesity. The importance of public- and digital-health policies that promote equiTable Sccessibility to digital facilities in underserved areas and enhance digital literacy among disadvantaged populations is highlighted by these findings. It indicates that intervention programs aimed at providing assistance to behavioral change in respondents with obesity are not sufficient; there is a need to look into the social setting from which the opportunities for accessing digital health resources emerge.

Notably, several weaknesses exist. Firstly, the data employed in the current paper are cross-sectional data, which only offer information over a particular span of time. Hence, it should be noted that the cause-and-effect relation proposed by SEM needs to be considered as a statistical association. Although SES and UMH are considered reliable predictors of sustained physical activities, there exists the possibility of reverse causality between the two. Longitudinal research should be performed in the future to determine the influence of UMH and SES on sustained physical activities. In addition, the connection between SES and UMH could be prone to the problem of endogeneity because those who have a higher SES tend to have more access to IT platforms as well as better skills to use digital tools, which subsequently shape health awareness, community support, and chances for healthy behavior. These possibly reciprocal relations could not be entirely unraveled because a cross-sectional design was utilized.

Secondly, recall and social desirability biases were possible due to self-reports utilized in the study's anthropometric and behavioral instruments. Misclassification of anthropometrics could occur due to the nature of self-report measures in classifying responders' BMI. However, despite statistical efforts minimizing CMB, errors of measurements could be incompletely minimized. Objective measures like GPS-assisted movement tracking, wearable health monitoring, clinical anthropometric evaluations, and behavioral data collected through mobile applications should be included in future research. Furthermore, there are certain aspects associated with the conceptual framework that could have played a significant role in this particular case, but were not taken into account during the analysis; these include digital literacy, neighborhood setting, and access to the Internet. Such aspects can have a substantial influence on UMH and PAS and thus should be included in future investigations. Cross-country findings must be attained to assess the bearing of national differences in digital infrastructure on inequality. Lastly, mixed-method approaches should be considered to enrich understanding of lived experiences underlying statistical relations.

Both online recruitment from the WhatsApp distribution method and offline recruitment from community health centers (Puskesmas) were used for this study. This combination of approaches was effective for improving territorial coverage and responder reach,

but still could create some form of digital bias where individuals who are more familiar with virtual communication, and who have greater internet accessibility and possess smartphones, would be more likely to engage in the survey, thus causing overrepresentation of mHealth users [64]. The possibility that the outcomes overrepresent responders who are more at ease using mHealth can cause an overestimation of UMH in the broader population [65]. For future work, offline recruitment should be increased for disadvantaged digitally based populations living in rural communities to avoid the problem of digital divide bias. Also, adopting more objective measures such as using data obtained from wearables or apps is advised. In addition, as this paper utilized reflective SES, future research can compare reflective and formative measures of SES to improve operationalization of the concept in studies of digital health disparities.

Lastly, there could be other contextual and behavioral factors that influence the assessed inter-construct relations but which were not taken into account in this paper, like health motivations, chronic illness condition, societal support system, availability of health care services, and knowledge about technology, which possibly relate to UMH and PAS. In addition, some structural factors were not looked at in this paper regarding their correlations with the primary outcome/dependent variable; for instance, recreational facilities, digital literacy, Internet connectivity, walkable communities, and environments that support physical activity, which may be substantially linked with UMH and PAS. When inferring the hypothesized structural relations, confounder functions should be looked into as they were not well quantified in this paper's dataset. The lack of strong quantification of such potential confounding variables is likely to constrain the degree to which the structural correlations can be illuminated through the SEM approach. Future works that assess digital health inequality and obesity management should address this issue.

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Supplementary Materials

Questionnaire and Tables S1–S3 (previously Tables A1-A3) can be accessed at https://doi.org/10.5281/zenodo.20387918.

References

1. Oetoro, S.; Permadhi, I.; Sumarliah, E. The impacts of mHealth technology and healthcare e-consultation on workout levels among obese and overweight people post-COVID-19. *Kybernetes* **2023**, *52*, 2288–2304.
2. Tee, E.S.; Voon, S.H. Combating obesity in Southeast Asia countries: Current status and the way forward. *Glob. Health J.* **2024**, *8*, 147–151.
3. Nguyen, T.T.L.; Do, H.D.; Pham, Q.T.; Le, X.T.T.; Le, H.T.; Giang, L.M. Sociodemographic, dietary, and lifestyle factors associated with overweight and obesity among young industrial workers in Vietnam. *Obesities* **2026**, *6*, 17. https://doi.org/10.3390/obesities6020017.
4. Poulain, J.P. Sociology of obesity: How to justify fighting against the development of the obesity epidemic. *Obesities* **2024**, *4*, 389–398. https://doi.org/10.3390/obesities4040031.
5. Xu, S.; Guo, Z.; Hu, L. Effectiveness of a Social Cognitive Theory-Guided, Multi-Component mHealth Intervention on Physical Activity Among Young Adults with Overweight or Obesity. *Res. Q. Exerc. Sport* **2025**, *Epub ahead of printing*. https://doi.org/10.1080/02701367.2025.2599886.
6. Myers-Ingram, R.; Sampford, J.; Milton-Cole, R.; Jones, G.D. Effectiveness of eHealth weight management interventions in overweight and obese adults from low socioeconomic groups: A systematic review. *Syst. Rev.* **2023**, *12*, 59. https://doi.org/10.1186/s13643-023-02207-3.
7. Zhang, K.; Cheng, X.; Li, D.; Meng, X. The digital divide of older people in communities: Urban-rural, gender, and health disparities and inequities. *Health Soc. Care Community* **2025**, *2025*, 1361214.
8. Price-Haywood, E.G.; Arnold, C.; Harden-Barrios, J.; Davis, T. Stop the divide: Facilitators and barriers to uptake of digital health interventions among socially disadvantaged populations. *Ochsner J.* **2023**, *23*, 34–42.
9. Kumala Putri, D.S.; Sari, K.; Utami, N.H.; Nazarina, N.; Amelia, T.; Salwa, N.Y.; Sulistiyowati, N.; Ega, A.V.; Azzumar, M.; Rachmawati, R.; et al. Usability evaluation of the "Teen 'n Fit" mobile health application: A formative study among Indonesian adolescent girls. *PLoS ONE* **2025**, *20*, e0337013.
10. BPS. Percentage of Population Aged 15 Years and over by Urban-Rural Classification, Sex, and Highest Education Level, 2009–2025. Jakarta: BPS. 2025. Available online: https://www.bps.go.id/en/statistics-table/1/MTYxMCMx/percentage-of-population-aged-15-years-and-over-by-urban-rural-classification--sex--and-highest-education-level--2009-2024.html (accessed on 16 March 2026).
11. Sumarliah, E.; Al-Hakeem, B. The effects of digital innovations and sustainable supply chain management on business competitive performance post-COVID-19. *Kybernetes* **2023**, *52*, 2568–2596.
12. Kemp, S. Digital 2025: Indonesia. DataReportal. 2025. Available online: https://datareportal.com/reports/digital-2025-indonesia (accessed on 16 March 2026).
13. Amri, M.; Enright, T.; O'Campo, P.; Di Ruggiero, E.; Siddiqi, A.; Bump, J.B. Health promotion, the social determinants of health, and urban health: What does a critical discourse analysis of World Health Organization texts reveal about health equity? *BMC Glob. Public Health* **2023**, *1*, 25. https://doi.org/10.1186/s44263-023-00023-4.
14. Toorang, F.; Amiri, P.; Djazayery, A.; Pouraram, H.; Takian, A. Worse becomes the worst: Obesity inequality, its determinants and policy options in Iran. Front. Public Health 2024, 12, 1225260. https://doi.org/10.3389/fpubh.2024.1225260.
15. Istepanian, R.S.H. Mobile health (m-Health) in retrospect: The known unknowns. *Int. J. Environ. Res. Public Health* **2022**, *19*, 3747. https://doi.org/10.3390/ijerph19073747.
16. Evans, J.T.; Phan, H.; Buscot, M.J.; Gall, S.; Cleland, V. Correlates and determinants of transport-related physical activity among adults: An interdisciplinary systematic review. *BMC Public Health* **2022**, *22*, 1519. https://doi.org/10.1186/s12889-022-13937-9.
17. Yang, X.; Gao, X.; Shu, Y.; Li, L.; Xiong, Y.; Zhou, X.; Jiang, W.; Sun, Q.; Zhou, C.; Yang, L. Impact of socioeconomic status on obesity in older adults: The suppressive effect of social support and sleep quality. *BMC Geriatr.* **2025**, *25*, 440.
18. Crane, N.; Hagerman, C.; Horgan, O.; Butryn, M. Patterns and predictors of engagement with digital self-monitoring during the maintenance phase of a behavioral weight loss program: Quantitative study. *JMIR mHealth uHealth* **2023**, *11*, e45057.
19. Yoshiuchi, K.; Brytek-Matera, A. Mobile Health (mHealth) Technology for Eating-Related Behaviour and Health Problems Related to Obesity in Japan: A Systematic Review. *BioPsychoSoc. Med.* **2025**, *19*, 8.
20. Abdellatief, M.; Aloatibi, R. From Intelligence to Trust: Evaluating AI-Powered Service Quality for User Satisfaction and Continuance in mHealth. *Stat. Optim. Inf. Comput.* **2026**, *15*, 295–310.

21. Asadollahi, F.; Zagami, S.E.; Roudsari, R.L. Designing, validation and evaluation of an mHealth app for prenatal health promotion based on the unified theory of acceptance and use of technology: A mixed methods study protocol. *Sci. Rep.* **2025**, *15*, 27603.
22. Fayyaz, K.; Bataineh, M.F.; Ali, H.I.; Al-Nawaiseh, A.M.; Al-Rifai', R.H.; Shahbaz, H.M. Validity of measured vs. self-reported weight and height and practical considerations for enhancing reliability in clinical and epidemiological studies: A systematic review. *Nutrients* **2024**, *16*, 1704. https://doi.org/10.3390/nu16111704.
23. Brennan, C.; O'Donoghue, G.; Keogh, A.; Rhodes, R.E.; Matthews, J. Developing an evidence-and theory-informed mother-daughter mhealth intervention prototype targeting physical activity in preteen girls of low socioeconomic position: Multiphase co-design study. *JMIR Pediatr. Parent.* **2025**, *8*, e62795.
24. Chang, E.; Penfold, R.B.; Berkman, N.D. Patient Characteristics and Telemedicine Use in the US, 2022. *JAMA Netw. Open* **2024**, 7, e243354.
25. Miranda-Vicente, A.K.; Zevallos-Villanueva, N.K.; Fernández-Ahumada, A.C.; Bernabe-Ortiz, A. Socioeconomic Status and Physical Activity Levels: Analysis of the Young Lives Cohort Study in Peru. *Public Health Rep*. **2026**, 141, 448–457. https://doi.org/10.1177/00333549251403890
26. Lee, Y.S.; Nishita, Y.; Tange, C.; Zhang, S.; Shimokata, H.; Lin, S.Y.; Chu, W.-M.; Otsuka, R. Association between objective physical activity and frailty transition in community-dwelling prefrail Japanese older adults. *J. Nutr. Health Aging* **2025**, *29*, 100519. https://doi.org/10.1016/j.jnha.2025.100519.
27. Williams, M.S.; McKinney, S.J.; Cheskin, L.J. Social and Structural Determinants of Health and Social Injustices Contributing to Obesity Disparities. *Curr. Obes. Rep.* **2024**, *13*, 617–625.
28. Yue, Y.; Langjie, H.; Yuen, L.C.; Wang, F.H. Bridging the Older Adult Digital Divide Through the Digital Habitus. *J. Aging Res.* **2026**, *2026*, 6656355.
29. Koivusilta, L.K.; Acacio-Claro, P.J.; Mattila, V.M.; Rimpelä, A.H. Health and health behaviours in adolescence as predictors of education and socioeconomic status in adulthood—A longitudinal study. *BMC Public Health* **2024**, *24*, 1178.
30. Koirala, B.; Baptiste, D.L. Just stats: T tests, analysis of variance tests, and nonparametric equivalents. *J. Nurse Pract.* **2026**, *22*, 105692. https://doi.org/10.1016/j.nurpra.2026.105692.
31. van Kessel, R.; Wong, B.L.H.; Clemens, T.; Brand, H. Digital health literacy as a super determinant of health: More than simply the sum of its parts. Internet Interv. 2022, 27, 100500. https://doi.org/10.1016/j.invent.2022.100500.
32. Sze, W.T.; Waki, K.; Enomoto, S.; Nagata, Y.; Nangaku, M.; Yamauchi, T.; Ohe, K. StepAdd: A personalized mHealth intervention based on social cognitive theory to increase physical activity among type 2 diabetes patients. *J. Biomed. Inform.* **2023**, *145*, 104481.
33. Lin, H.; Yang, M.; Zhou, Z.; Zhang, Y.; Deng, N. Exploring the dynamics of dietary self-monitoring adherence among participants in a digital behavioral weight loss program: Model development study. *J. Med. Internet Res.* **2025**, *27*, e65431.
34. Ge, J.; Chen, M.; Xiong, X.; Zhai, Y. Bidirectional associations between socioeconomic status, physical activity, and depressive symptoms in middle-aged and older adults: A cross-lagged prospective cohort study. *J. Affect. Disord.* **2026**, *403*, 121334.
35. Fountain, S.M.; Cooper, S.B.; Williams, R.A.; Sunderland, C.; Bowes, A.; Dring, K.J. Barriers, facilitators, and factors influencing the perceived feasibility of family-based physical activity: The role of socioeconomic status. *Adv. Exerc. Health Sci.* **2025**, *2*, 205–214.
36. Salmi, L.; Hasanen, E.; Simula, M.; Virmasalo, I.; Muukkonen, P. Perceived barriers to physical activity in the social spaces of low socioeconomic status suburbs. *Wellbeing Space Soc.* **2023**, *5*, 100164.
37. Mulderij, L.S.; Verkooijen, K.T.; Groenewoud, S.; Koelen, M.A.; Wagemakers, A. The positive impact of a care–physical activity initiative for people with a low socioeconomic status on health, quality of life and societal participation: A mixed-methods study. *BMC Public Health* **2022**, *22*, 1522.
38. Sousa Basto, P.; Ferreira, P. Mobile applications, physical activity, and health promotion. *BMC Health Serv. Res.* **2025**, *25*, 12489.
39. Rajabi-Gilan, N.; Zardoshtian, S.; Sarabi, N.; Khezeli, M. The effect of the work-family conflict, subjective socio-economic status, and physical activity on the perceived quality of life of working women in Iran: The mediating role of quality of work life. *BMC Womens Health* **2025**, *25*, 45.
40. Tsekpetse, P.; Salu, S.; Otoo, D.M.; Dushime, J.F.; Shiuma, J.; Oloo, B.; Ahinkorah, B.O. Rural-urban disparities in cervical cancer screening uptake and its predictors among women aged 30–49 years in Ghana: A multivariate decomposition analysis. *BMC Womens Health* **2025**, *25*, 396.
41. Gary, S.; Lenhard, W.; Lenhard, A.; Herzberg, D. A tutorial on automatic post-stratification and weighting in conventional and regression-based norming of psychometric tests. *Behav. Res. Methods* **2024**, *56*, 4632–4642. https://doi.org/10.3758/s13428-023-02207-0. Feter, N.; Duncan, B.B.; de Paula, D.; Reis, R.C.P.D.; Harter Griep, R.; Feter, J.; Alexander, G.E.; Raichlen, D.; Schmidt,

M.I. Association between physical activity during active commuting and leisure time with cognitive decline: Findings of the ELSA-Brasil study. *J. Phys. Act. Health* **2026**, *23*, 370–377. https://doi.org/10.1123/jpah.2025-0481.

42. Dany, F.; Dewi, R.M.; Tjandrarini, D.H.; Pradono, J.; Delima Sariadji, K.; Handayani, S.; Kusumawardani, N. Urban-rural distinction of potential determinants for prediabetes in Indonesian population aged ≥15 years: A cross-sectional analysis of Indonesian Basic Health Research 2018 among normoglycemic and prediabetic individuals. *BMC Public Health* **2020**, *20*, 1509. https://doi.org/10.1186/s12889-020-09592-7
43. Sumarliah, E.; Usmanova, K.; Mousa, K.; Indriya, I. E-commerce in the fashion business: The roles of the COVID-19 situational factors, hedonic and utilitarian motives on consumers' intention to purchase online. *Int. J. Fashion Des. Technol. Educ.* **2022**, *15*, 167–177.
44. Miah, M.S.; Kabir, M.B. Decision-making autonomy and depressive symptoms among women in Lesotho: Rural–urban differences. *J. Affect. Disord. Rep.* **2026**, *25*, 101080. https://doi.org/10.1016/j.jadr.2026.101080.
45. Husu, P.; Vähä-Ypyä, H.; Tokola, K.; Sievänen, H.; Rocha, P.; Vasankari, T. Reliability and validity of self-reported questionnaires assessing physical activity and sedentary behavior in Finland. *Int. J. Environ. Res. Public Health* **2024**, *21*, 686. https://doi.org/10.3390/ijerph21060686.
46. Sumarliah, E.; Amrullah, N.I.H.; Al-Hakeem, B. The roles of green entrepreneurial concerns and sustainable management of supply chains post COVID-19. *J. Ind. Integr. Manag.* **2023**, *11*, 45–67. https://doi.org/10.1142/S2424862223500203.
47. BPS. In March 2024, the Poor Population Percentage Decreased into 9.03 Percent. Jakarta: BPS. 2024. Available online: https://www.bps.go.id/en/pressrelease/2024/07/01/2370/in-march-2024--the-poor-population-percentage-decreased-into-9-03-percent-.html (accessed on 16 March 2026).
48. Ranjan, S.; Thakur, R. The effect of socioeconomic status, depression, and diabetes symptoms severity on diabetes patient's life satisfaction in India. *Sci. Rep.* **2024**, *14*, 12210. https://doi.org/10.1038/s41598-024-62814-5.
49. Fleuren, B.P.I.; van Amelsvoort, L.G.P.M.; Zijlstra, F.R.H.; de Grip, A.; Kant, I.J. Handling the reflective-formative measurement conundrum: A practical illustration based on sustainable employability. *J. Clin. Epidemiol.* **2018**, *103*, 71–81. https://doi.org/10.1016/j.jclinepi.2018.07.007.
50. Sharma, N.; Singh, N.P. Formative & reflective measurement models. *Southeast Asian Bus. Rev.* **2025**, *3*, 87–102. https://doi.org/10.20473/sabr.v3i2.71007.
51. Azam, M.; Bin Naeem, S.; Kamel Boulos, M.N.; Faiola, A. Modelling the Predictors of Mobile Health (mHealth) Adoption among Healthcare Professionals in Low-Resource Environments. *Int. J. Environ. Res. Public Health* **2023**, *20*, 7112. https://doi.org/10.3390/ijerph20237112.
52. Golbus, J.R.; Gupta, K.; Stevens, R.; Jeganathan, V.S.E.; Luff, E.; Shi, J.; Dempsey, W.; Boyden, T.; Mukherjee, B.; Kohnstamm, S.; et al. A randomized trial of a mobile health intervention to augment cardiac rehabilitation. *NPJ Digit. Med.* **2023**, *6*, 154.
53. Rick, V.B.; Rasche, P.; Mertens, A.; Nitsch, V. Workplace Health Promotion: mHealth as a Preventive Mediator Between Psychosocial Workplace Characteristics and Well-Being at Work. In *Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management. Health, Operations Management, and Design*; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland; 2022; pp. 249–265.
54. Lennartsson, A.K.; Jonsdottir, I.H.; Jansson, P.A.; Sjörs Dahlman, A. Insulin sensitivity in individuals with burnout is associated with physical activity level—A study using oral glucose tolerance test. *Front. Psychiatry.* **2026**, *17*, 1664680.
55. Lee, M.; Ash, G.; Nam, S. Wearable devices and physical activity disparities: Insights from the 2022 Health Information National Trends Survey. *Health Policy Technol.* **2025**, *14*, 101017.
56. Sathyanarayana, S.; Mohanasundaram, T. Fit indices in structural equation modeling and confirmatory factor analysis: Reporting guidelines. *Asian J. Econ. Bus. Account.* **2024**, *24*, 561–577. https://doi.org/10.9734/AJEBA/2024/v24i71430. Pereira, S.M.C.; Leslie, G. Testing differences between two samples of continuous data. *Aust. Crit. Care* **2010**, *23*, 160–166. https://doi.org/10.1016/j.aucc.2010.06.002.
57. Hu, L.Y.R.; He, Y.; Irimata, K.E.; Beresovsky, V. Much ado about survey tables: A comparison of chi-square tests and software to analyze categorical survey data. *Am. Stat.* **2025**, *79*, 480–491. https://doi.org/10.1080/00031305.2025.2501800
58. Costello, M.S.; Bagley, R.F.I.I.; Fernández Bustamante, L.; Deochand, N. Quantification of behavioral data with effect sizes and statistical significance tests. *J. Appl. Behav. Anal.* **2022**, *55*, 1068–1082. https://doi.org/10.1002/jaba.938.
59. Boscardin, C.K.; Sewell, J.L.; Tolsgaard, M.G.; Pusic, M.V. How to use and report on p-values. *Perspect. Med. Educ.* **2024**, *13*, 250–254. https://doi.org/10.5334/pme.1324.

60. Kansiime, W.K.; Atusingwize, E.; Ndejjo, R.; Balinda, E.; Ntanda, M.; Mugambe, R.K.; Musoke, D. Barriers and benefits of mHealth for community health workers in integrated community case management of childhood diseases in Banda Parish, Kampala, Uganda: A cross-sectional study. *BMC Prim. Care* **2024**, *25*, 173. https://doi.org/10.1186/s12875-024-02430-4..
61. Yang, S.; Cha, M.J.; van Kessel, R.; Warrier, G.; Thrul, J.; Lee, M.; Yoon, J.; Kang, D.; Cho, J. Understanding inequalities in mobile health utilization across phases: Systematic review and meta-analysis. *J. Med. Internet Res.* **2025**, *27*, e71349. https://doi.org/10.2196/71349.
62. Deniz-Garcia, A.; Fabelo, H.; Rodriguez-Almeida, A.J.; Zamora-Zamorano, G.; Castro-Fernandez, M.; Alberiche Ruano Mdel, P.; Solvoll, T.; Granja, C.; Schopf, T.R.; Callico, G.M.; et al. Quality, usability, and effectiveness of mHealth apps and the role of artificial intelligence: Current scenario and challenges. *J. Med. Internet Res.* **2023**, *25*, e44030. https://doi.org/10.2196/44030.
63. Riccalton, V.; Milne-Ives, M.; Brownson-Smith, R.; Ananthakrishnan, A.; Cong, C.; Oliver, E.; Meinert, E. Effectiveness and Theoretical Foundations of mHealth Apps for Physical Activity, Healthy Eating, and Weight Loss: Protocol for a Systematic Review and Meta-Analysis. *JMIR Res. Protoc.* **2026**, *15*, e72664.
64. Lee, E.; Agustines, D.; Woo, B.K.P. Selection bias in digital conversations on depression before and during COVID-19. *JMIR Form. Res.* **2023**, *7*, e42545. https://doi.org/10.2196/42545.
65. Benedict, C.; Hahn, A.L.; Diefenbach, M.A.; Ford, J.S. Recruitment via social media: Advantages and potential biases. *Digit. Health* **2019**, *5*, 1–11. https://doi.org/10.1177/2055207619867223.

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