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Assessing digital health inequalities in Indonesia: an extended SEM–ANN model of socioeconomic status, mHealth usage, perceived access to healthcare services, and sustained physical activity

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Background: Enhanced access to health services and lowered health inequalities can possibly be associated with the usage of digital technologies. Unfortunately, differences in socioeconomic status (SES) and technological skill could be associated with disparities in their usage. Indonesia remains a nation with rural–urban disparity. Hence, to create strategies for equitable health service, it is crucial to comprehend the extent to which mobile health usage (MHL) and SES are associated with perceived sustained physical activity (PPA) and access to healthcare.
Purposes: This research extended the 2026 Sumarliah et al.'s framework by incorporating perceived access to healthcare services (PAHS) into the model and assessing its association with MHL, PPA, and SES among a broader sample of Indonesian rural–urban respondents. To deliver predictive and explanatory evaluations, it further integrated artificial neural network (ANN) and structural equation modeling (SEM) assessments.
Methods: This research adopted a stratified regional sampling to support representation of six major Indonesian regions: Papua-Maluku, Nusa Tenggara-Bali, Sumatra, Java, Sulawesi, and Kalimantan. A sum of 1,566 valid responses (78.3%) were retained, which comprised 871 urban (55.6%) and 695 rural (44.4%) respondents. To evaluate the gathered data, a three-stage quantitative approach was utilized, which involved SEM, multi-group SEM and ANN examinations.
Results: There was a positive association between PAHS and SES, as well as between MHL and SES. The PAHS was also positively linked to MHL. Conversely, PAHS was not significantly associated with PPA. As such, the indirect link between MHL and PPA via PAHS was insignificant. Multi-group SEM verified the much stronger positive correlations among PAHS, MHL, and SES within urban samples instead of rural samples. Supportive evidence to predict PPA was acquired through ANN exploration, where maximum normalized predictive importance was achieved by the MHL input construct.
Conclusion: From the present research it is evident that PAHS had statistically insignificant association with PPA, which is different from earlier works' findings. The

likely reason is that although PAHS can be associated with the usage of health services, it may be inadequate to account for differences in respondents' PPA.

KEYWORDS

artificial neural network, digital health inequalities, Indonesia, perceived access to health services, perceived sustained physical activity, socioeconomic status

1 Introduction

Given that there has been a speedy expansion of technology-enabled health solutions, the access and delivery of healthcare have greatly changed (1, 2). Mobile health (mHealth) apps can be identified as one of those digital health technologies used for delivering access to health information, communication between the patient and provider, scheduling appointments, monitoring and managing patients' health conditions (3–7). Focused on overcoming time and place-related obstacles, the mHealth usage (MHL) could facilitate the delivery of health services and stimulate healthy lifestyles (7, 8). Nevertheless, the beneficial impact of MHL is uneven throughout the whole population (5, 6, 9). Health disparities continue to exist because of the differences that arise from the socioeconomic status (SES), digital literacy, and availability of health care facilities (10–12). Particularly, digital-health inequities have been taking place throughout underdeveloped economies like Indonesia (5, 6). Indonesia stands fourth globally regarding population numbers; therefore, there are some disparities with regard to SES, geographic location, and healthcare access among rural and urban populations of the country, as well as among the main islands (13). While there are more and more opportunities for using the internet and smartphones, the problem of disparities in health access and health-promotion chances remains relevant (14). To build policies and programs for equitable healthcare services, therefore, it is important to find out the functions of SES and MHL in shaping health access and health behaviors (15).

Perceived access to health services (PAHS) is believed to be "the perception of the individual on how well health services are available, reachable, accessible, affordable, acceptable, properly structured and understood in order to fulfill their health demands (16). From the perspective of the assessment indicators established by Hoseini-Esfidarjani et al. (16), the PAHS is the perception of the patients about their access and utilization of health services with regard to its approachability, obtainability, tolerability, dexterity, adaptability, and sensitivity. It has been testified in earlier works that PAHS is related to SES as people with high SES are characterized by greater amounts of resources such as finances, education, and technologies necessary for using the digital technologies (5, 6) and healthcare services (17, 18). Similarly, PAHS is related to MHL as the MHL has been associated with improvement in delivery of healthcare services (19, 20), and patient engagement (21). Furthermore, PAHS has been linked to health behaviors (4, 7), especially sustained physical activity performance (22). In this work, perceived sustained physical activity (PPA) is defined as a self-assessment of the perceived degree or frequency of participation in physical exercise by adult individuals in their day to day life (5, 6). Here, the concept of PPA is viewed to be a reflection-based perception where self-reporting behaviors are taken into account to determine how much of an individual feel that he/she maintains physically active routine in the past year. It should be noted that the PPA does not assess the physical capability of individuals, fitness from a physiological perspective, or objective measurement of physical activity, rather it measures their perception of individuals regarding their own persistence, maintenance, and consistency in doing physical activity (5, 6). However, the ways in which SES and MHL may be linked to PAHS and PPA remain unclear.

The indicators of PPA were divided into six items. Indicators PPA1-PPA5 were established by Sumarliah et al. (5). These PPA indicators measure the respondents' perceptions of the regularity, consistency, time commitment, perseverance, and maintenance of physical activity behavior through a five-point Likert format with values from 1 (total disapproval) to 5 (totally approval). For instance, "I engage in physical activity regularly every week" (PPA1). Conversely, PPA6 was adopted from the Saltin-Grimby classification of intensity of physical activity (23), which measures the intensity of physical activity performed by individuals in leisure and commuting in the last year. Compared to PPA1-PPA5, the measurement of PPA6 was through a four-point ordinal format in which 1 designated 'almost inactive' and 4 indicated 'very active'. The specifications of all the PPA indicators are publicized in Table S1 in the supplementary materials.

Despite the presence of a significant number of scientific works dedicated to the topic of digital health and health disparity, there are certain gaps requiring further inspection. Firstly, the current scientific literature regarding mHealth emphasizes the usage of technological innovations in the field of medicine and behavioral interventions but does not consider the application of MHL for PAHS evaluation. Some examples are: MHL was used in Iran to improve the integration of central healthcare (3); to encourage positive health behavior in families with little children (4); to monitor the symptoms of coronavirus in Iran (24, 25); and in the management of diabetes within LMICs (26). Unfortunately, there are limited efforts to assess the degree to which PAHS relates to MHL as well as intercedes the association between MHL and wider outcomes linked to health. Secondly, even though the significance of PAHS in relation to the health outcomes is recognized for an extended period of time, the association between PAHS and health behaviors, such as PPA is not yet well explored. There have been journal articles revealing the link between health behaviors and healthcare service utilization (27, 28), advice from healthcare professionals (29), and healthcare system infrastructure (30). On the other hand, very little information has been given regarding the association between people's level of PAHS and their PPA. This is particularly true in LMICs like Indonesia, which suffer from inequalities in terms of health service and physical activities access (5, 6, 31, 32).

Thirdly, another gap lies in health disparity among the existing healthcare systems globally. Earlier works conducted on the topic of health disparity were related to issues such as health finance and allocation (10), socio-economic disparity for hypertensive screening and management (11) and health system performance and universal health coverage using structural determinants (12). But there have been very few instances in which researchers tried to solve the problem comprehensively by taking all the aspects of PAHS, PPA, MHL,

and SES into account together. In addition, there has not been sufficient evidence from different rural–urban parts of Indonesia (5, 6, 31).

This research intends to extend the theoretical framework stipulated by Sumarliah et al. (5) by considering perceived access to health services (PAHS) as another explanatory variable in the connection between MHL and PPA. While Sumarliah et al. (5) have concentrated on the examination of the association between SES, MHL, and PPA, this paper will address the following issues: whether MHL has a substantial link to PAHS and whether PAHS is associated with the connection between MHL and PPA. The status of SES as an independent socioeconomic variable is maintained, since there may be some likelihood that the SES has statistical relations with MHL and PAHS. Besides, SEM with multiple group assessments are utilized to identify whether all of the above-mentioned associations vary depending on the place where respondents come from, i.e., rural versus urban areas of Indonesia. PAHS is used in the present study as an outcome variable because earlier reports claim that the usage of mHealth apps affect health outcomes in an indirect manner in which they increase information access regarding health care, health services and providers (33, 34), thus assisting as a pathway for converting SES and MHL into health behavioral outcome (5, 6). Accordingly, the current paper endeavors to respond to the outlined research questions:

- RQ1: How is SES associated with MHL and PAHS among Indonesian adults?
- RQ2: Is MHL associated with PAHS?
- RQ3: Is PAHS associated with PPA, and does PAHS statistically relate to the association between MHL and PPA?
- RQ4: Do the associations among SES, MHL, PAHS, and PPA differ between rural and urban Indonesian adults?

There are three contributions of this paper to the existing literature. First, this paper enriches the extant scholarly publications on the issue of digital health inequalities by assessing the proposed associations in which SES and MHL are explanatory constructs, PAHS represents the outcome construct, and PPA is considered as a health behavioral outcome. Second, there are new insights for LMICs offered by this paper because of its empirical exploration of the hypothesized associations among SES, MHL, PAHS, and PPA through people from rural and urban areas of six major Indonesian regions among PAHS, PPA, MHL, and SES through people from rural and urban areas of six major Indonesian regions.

Third, this study gives methodological contribution because of the combination of ANN (artificial neural network), SEM (structural equation modeling), and multi-group SEM procedures. Earlier scientific works (35–38) have corroborated that the ANN-SEM procedure is successful in assessing nonlinear and linear associations jointly, which delivers a more far-reaching knowledge concerning the factors associated with outcome variables (like PAHS and PPA).

2 Literature review and hypotheses formulation

The paper relies on the concept of Social Determinants of Health (SDH), advising that economic level impacts the access to various resources, technologies, health services, and healthy way of life (39, 40). Therefore, this concept may provide some clues regarding the possible associations between the SES, MHL, PPA (5, 6), and PAHS. Those individuals who have a higher SES have better opportunities for applying MHL (5, 6) and PAHS (17, 18). The next theoretical concept that may be applied within this research is the Behavior Model of Andersen, which states that those enabling factors like health technologies and health services may help people to use health services and behavioral outcomes (41, 42). Therefore, the MHL is theoretically associated with the process of PAHS through the lessening of information barriers, and PAHS can be an explanatory construct in the association between MHL and health behavioral outcome like PPA. In general, the above frameworks form a holistic explanation of all the indirect and direct associations, as well as rural–urban disparities in the associations propositioned and empirically assessed within the paper.

The present research is built on the following two theories, which are interrelated: Social Determinants of Health (SDH) (11, 39, 40) and the Behavioral Model of Andersen (BMA) (41, 42). These two theories provide an understanding of the associations between SES, MHL, PAHS, and PPA. Despite the difference in the scope of the issue discussed by the two theories, both provide a basis for the understanding of the hypothesized associations in the framework. SDH has the advantage of having a more comprehensive structural model, since it considers the association between socioeconomic determinants (here: SES) and the perception of the individuals about their access and utilization of healthcare facilities (here: PAHS) (39, 40), whereas the BMA has the behavioral aspect of how individual and enabling factors are associated with healthcare access-behavioral outcome (here: PAHS) (41, 42).

2.1 SES → MHL

SDH negatively impacts equity in health care due to various reasons. As a consequence of low SES, people struggle with the problem known as "the digital divide," which entails difficulties in connection with Internet access, possession of devices and digital literacy and therefore inability to utilize mHealth apps (5, 6). Speaking about infrastructure, high speed Internet is not available in poor communities and rural regions; hence, mHealth communication is hampered (43). Regarding digital literacy, education is needed to acquire necessary skills in computer utilization and reading that would be required to communicate with complicated websites and mHealth apps (44). Lastly, concerning devices, despite the widespread availability of smartphones in contemporary society, poor people possess fewer gadgets such as tablets, laptops and wearable monitors than rich people (14, 45). It can thus be concluded that the MHL may not be societally impartial and can even be linked to SES, as has been substantiated in previous publications (5, 6, 46). Consequently:

In relation to SDH theory, the SES will definitely be a vital element of the socioeconomic and structural aspects that are associated with how individuals gain access to different resources such as materials, education, technology, and information (39). Individuals from greater SES cohort (i.e., those who are well-educated, who are financially better positioned, and who are employed in more stable occupations) will be most probable to possess wider access to smartphone, internet, and information, in order to utilize digital health technology (5, 6, 10–12). Consequently, SES inequities may not only be correlated with discrepancies in the people's perceived accessibility to health services but could even extend to inequities in utilization of digital health. This

becomes a theoretical foundation in support of the likelihood of positive association between SES and MHL. Thus:

> *H1:* SES is positively associated with MHL.

2.2 SES → PAHS

SDH states that high SES can help people with getting healthcare services including healthcare facility, transport, insurance, information, and navigation; thus, these individuals will have good perceptions about access to healthcare facilities (39). Various scientific studies indicate that SES is highly influential on the access to healthcare (47–50). Lack of money and resources creates various barriers like high costs of out-of-pocket payments, no insurance, isolated areas, and lack of health literacy. Consequently, these differences between wealth and health lead to delay in diagnosis and bad survival rates (49, 50). Even where universal access is present, a high cost of out-of-pocket expenses and medicine creates an obstruction in access to healthcare services by people of low SES (50). People of low SES usually live in residence type that suffers from poor medical facilities as well as remoteness to health centers and specialists (47, 48).

The concept of the SDH will be vital in the constructive linkage between SES and PAHS. There may be certain associations between the socioeconomic environment and the cost, availability, accessibility, and acceptability of the health care services (17, 18, 39). The people having high SES are less likely to have any financial constraints; they are more likely to possess adequate knowledge regarding health care and skills to navigate to health care services, and also more opportunities to access health care institutions. Thus, the SES is likely to relate to the degree to which people view their capabilities of reaching, obtaining and utilizing health services. Thus:

> *H2:* SES is positively associated with PAHS.

2.3 MHL → PAHS

The mHealth helps overcome the barriers caused by the emergence of SDH through helping the marginalized section of the population (5, 6). Using mobile phones makes it possible for individuals to have instant access to information, be in touch with health practitioners, and access health services (5–7). It has been revealed in earlier publications that there is an effect on access to health services caused by the adoption of mHealth (7, 9, 45). This is due to the use of mHealth technologies whereby consultations may be done virtually without encountering any logistical problems (7). This is exceptionally critical for individuals inhabiting in rural areas or those who do not receive adequate medical care (9, 45). Better MHL can be linked to better PAHS as mHealth apps make sure that individuals do not move physically to access medical facilities, communicate with medical specialists and get health information hence saving time and costs (5–7).

Behavioral model by Andersen (BMA) also supports the concept of SDH and provides an explanation for elements that are associated with healthcare services access and utilization which include predisposing factors, enabling factors, and need factors. As BMA theory suggests, the resources that enable patients to gain access to and utilize healthcare services are influential enabling conditions of PAHS. MHL should be seen as one of such enabling resources as digital health technologies can be linked to patients' interaction with healthcare professionals, provide information on health issues, make appointments, monitor their health state, and get healthcare services (3–9, 19–21). Consequently, patients who perform effective MHL are likely to feel that they have better access to healthcare services as they eliminate informational, communicational, and geographical barriers. Hence, the theory of BMA can be applied as a foundation to assume the link between MHL and PAHS. Accordingly:

> *H3:* MHL is positively associated with PAHS.

2.4 PAHS→ PPA

Good access to healthcare is likely to be linked to good access to health information, prevention services, and professional consultations that would motivate the patients to become physically active (28, 30). Within the SDH approach, "Health Care Access and Quality" can be considered as one of the key domains that would have impact on health behavior (like physical activity behavior) (39, 40). Good access to healthcare would provide an opportunity for the systematic support of long-lasting physical activity habit (22). Access to good healthcare and healthy lifestyle promoted by doctors has impact on the level of physical activity in many cases, according to earlier studies. For example, studies have substantiated that persons with good accessibility to health services are motivated to physical activity much more frequently than individuals without such access (28, 51).

BMA theory provides the theoretical foundation for assessment of the link between PAHS and PPA. The PAHS could be considered as an explanatory construct that allows people to utilize the preventive services and health information, receive counseling and behavioral services, which can assist in their engagement in PPA. From the earlier literature it is clear that there was an association between access to healthcare, counseling, and physical activity (27–30, 51, 52). Nonetheless, it does not mean that there is a causality or unidirection in PAHS→PPA association since PPA can be an explanatory construct for the PAHS as well. In light of the cross-sectional nature of this assessment, the association can thus be described as being a relational and not a causal one.

Different factors regarding PAHS and PPA that work in a cycle manner have been identified (51). For instance, first, general practice is very crucial as one way of assessing the level of physical activity among the clients and providing advice on exercise (7, 51). Access to health care facilities makes it possible to identify chronic illness which may prevent a person from undertaking physical exercises (28). Moreover, accessing allied health care providers like physiotherapists, registered dietician and exercise professional enables provision of safe exercise program (51, 52). However, physically active people do not require much health care; they use fewer inpatient services, lower incidences of chronic diseases and low cost of health care per year (22, 52).

The link between PAHS and PPA can be related to the function of accessible healthcare in giving individuals access to information, preventive counseling, professional advice, and behavioral counseling (27–30). Healthcare professionals may help in recognizing individual health risks and offer appropriate advice concerning physical exercises, encouraging individuals to stay physically active. There are some empirical evidence discovering the presence of a positive association between accessibility to health care services, the usage

of health facilities, professional advice, and physical activity or health-sponsoring behavior (28, 30, 51, 52). On the other hand, the link can also be bidirectional, because physically active individuals need specific health care demands/patterns of utilization which are likely to affect their perception of access (22, 52). In the current paper, PAHS serves as an explanatory variable, whereas PPA acts as an outcome variable, because it is believed that accessible healthcare can be associated with opportunities (e.g., support from professionals and resources) for staying physically active. Since the study is cross-sectional in nature, the single direction (of PAHS→PPA) would imply that the correlational or statistical association is expected rather than causative or time-related association (53).

The reason why this research has considered PPA as an outcome is that PPA represents a main preventive behavior and is not merely the result of utilizing healthcare services (54, 55). This makes it possible to test whether improved PAHS will actually be associated with a tangible outcome that matters for public health (here: PPA), as discussed in a prior report (56). Therefore:

> *H4:* PAHS is positively associated with PPA.

2.5 MHL → PAHS→ PPA

According to the SDH framework, digital determinants are theoretically associated with health outcomes via improving healthcare accessibility and access to essential reserves (39, 40). Accordingly, digital determinants can be viewed as "enabling infrastructure" that is associated with health outcomes mostly indirectly (5, 6). Community health organizations use the concept of digital inclusion as "super determinant" of health, since, besides having a direct association with health outcomes, it can help people get access to other health resources (39, 40). According to earlier publications, health care facility provision becomes an explanatory construct in the link between MHL and PPA due to the fact that provision allows for participation in regular physical activities (27, 51). Habitual interaction with health care providers makes it possible for people to cope with chronic illnesses, to be prescribed physical activity, and overcome health barriers (27, 51). Digital health literacy and health care facility provision can make it easier for people to see the link between health determinant (like MHL) and physical activity behaviors (like PPA) (57, 58).

Both SDH and BMA theories together give some form of base upon which to assess whether PAHS can actually be the possible enabler for the link between MHL and PPA. The MHL can likely be regarded as an enabler whereby individuals are motivated to perform PAHS. On the other hand, PAHS can offer the opportunities for getting information and professional advice concerning health and tips on how to maintain good health through PPA. Therefore, in the current research work, it is assumed that there could be a potential indirect role of PAHS in the MHL-PPA association. But in the current research that depends on cross-sectional data, the indirect role does not mean causal mediation; it merely implies an association derived from empirical assessment and theoretical hypothesis (59). Hence, it can be assumed that:

> *H5*: PAHS is indirectly related to the association between MHL and PPA.

2.6 Rural–urban inequalities

Using the SDH framework, the geographical location of a person, whether urban or rural, becomes the focal point of the analysis of systemic disparities (5, 6). It is apparent that the socio-economic opportunities, the medical facilities available, and internet connectivity differ among rural and urban areas, which can trigger inequalities in the whole constructs (5, 31). Earlier works have shown the distinction between people who live in urban versus rural in terms of health care availability (60, 61), SES, MHL, and behaviors related to health like PPA (5, 6). Residents of urban areas tend to have a higher SES, a better MHL, improved infrastructures, and better health care accessibility (and thus PAHS) compared to rural residents (60, 61). The most recent studies conducted in Indonesia reported how MHL, PPA, and SES were related differently in rural and urban zones (5, 6). Thus:

> *H6:* Rural–urban differences significantly exist in the associations among SES, MHL, PAHS, and PPA.

2.7 Hypothetical framework

This paper's model is specifically designed to be parsimonious in which SES is considered the exogenous variable whereas MHL is endogenous variable associated with PAHS. PAHS becomes a possible explanatory construct in the MHL-PPA association. There could be correlations between SES and MHL, as well as between SES and PAHS; however, in this work, SES → MHL → PAHS → PPA is not considered as a serial mediation path. The reason behind this is that the purpose of the assessment is to determine whether there is any statistically substantial association between PAHS and the MHL-PPA link, bearing in mind the differences of SES and the urban/rural setting. As viewed in Figure 1, the framework includes direct relations between (a) SES and MHL (H1), (b) SES and PAHS (H2), (c) MHL and PAHS (H3), (d) PAHS and PPA (H4), and indirect relation between MHL and PPA via PAHS (H5). The indirect relation between MHL to PPA via PAHS indicate that the path from MHL to PAHS to PPA (MHL → PAHS→PPA) was tested for statistical association (not causal mediation).

3 Methodology

3.1 Measurement items

3.1.1 PAHS

Perceived access to health services (PAHS) was gauged utilizing the Healthcare Access Scale, which has 30 item questions, established by an earlier work (16). The scale is made up of six dimensions of health care access, which includes accessibility (item code: PAHS1-PAHS4), availability (PAHS5-PAHS7), acceptability (PAHS8-PAHS16), affordability (PAHS17-PAHS19), accommodation (PAHS20-PAHS25), and awareness (PAHS26-PAHS30). The questions used to measure accessibility include: "The healthcare I seek are available within local primary care facility." Full 30 item wordings are displayed in Table S1 (Supplementary Materials). Each item's statement was rated between 1 and 5, with strong agreement for 5 and strong disagreement for 1.

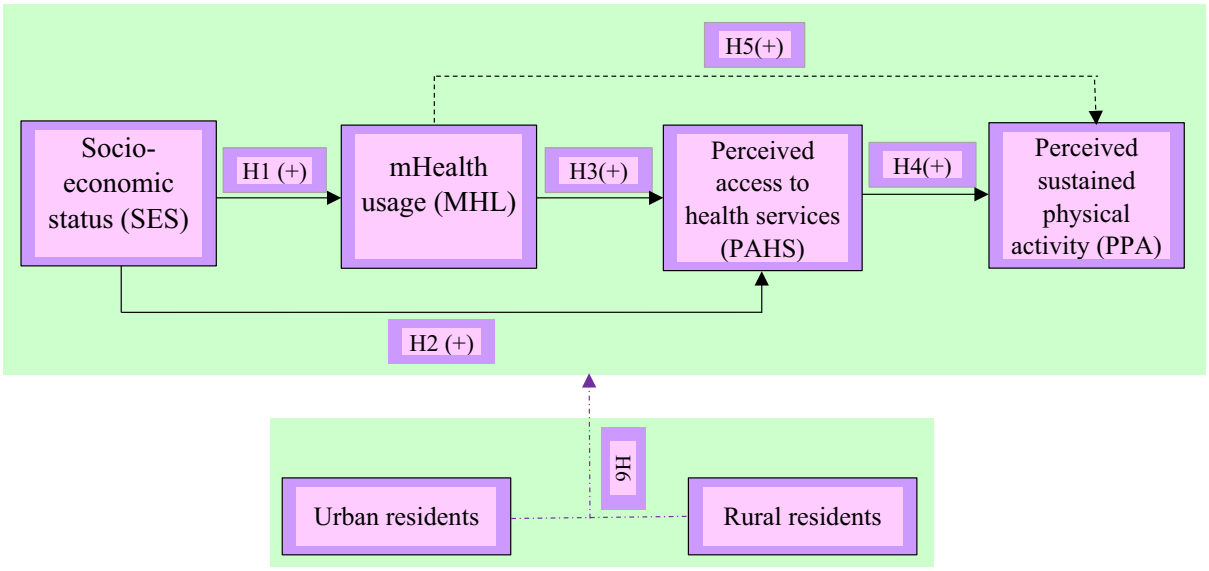


FIGURE 1
Hypothetical framework (Source: Authors' own work). Note: The black arrows designate the assumed direct relations, while the black dashed arrow signposts the assumed indirect relation (H5); the purple arrows specify the assumed difference in structural relations between rural and urban communities (H6). The black arrows with the "+" sign designate the hypothesized positive relations. The assumed structural relations designate the serial indirect relation between SES and PPA through MHL and PAHS as the empirically estimated indirect link.

3.1.2 SES, MHL, and PPA

The SES has been incorporated as the latent variable in the SEM with regard to three objective dimensions: education level, family income per month, and job stability, following scientifically validated measures in earlier works (5, 6). Next, the MHL has been measured with the help of six established item questions, which have been corroborated in previous literature (5–7). Those item questions were about benefits and experience of users due to the usage of mHealth applications and how much do they use such applications. An example item's statement is: "Usage of mHealth applications motivate me for being physically active". MHL value fluctuates to 5 (strongly agree) from 1 (strongly disagree), wherein elevated MHL score represents elevated mHealth usage among respondents.

The indicators of PPA were divided into six items. Indicators PPA1-PPA5 were established by Sumarliah et al. (5). These PPA indicators measure the respondents' perceptions of the regularity, consistency, time commitment, perseverance, and maintenance of physical activity behavior through a five-point Likert format with values from 1 (total disapproval) to 5 (totally approval). For instance, "I engage in physical activity regularly every week" (PPA1). Conversely, PPA6 was adopted from the Saltin-Grimby classification of intensity of physical activity (23), which measures the intensity of physical activity performed by individuals in leisure and commuting in the last year. Compared to PPA1-PPA5, the measurement of PPA6 was through a four-point ordinal format in which 1 designated 'almost inactive' and 4 indicated 'very active'. The specifications of all the PPA indicators are publicized in Supplementary Table S1.

Indicators PPA1 to PPA5 relate to questionnaires regarding regularity, persistence, and commitment in doing physical exercise, whereas PPA6 shows how frequently the individual participates in leisure and transport physical activities during the past year. Although there is a distinction between PPA6 (Saltin-Grimby item) and PPA1-PPA5 (Likert items) regarding content and period of time included, all six indicators have been retained since they measure one and the same tendency of individuals' reports of regularity and consistency in their physical activity behaviors. As far as reasoning behind the selection of two groups of indicators, the following can be mentioned. First, both groups include the same questions in measuring one and the same inclination of individuals to take part in body workouts and their intensity, frequency, and consistency. Second, the values of the external loadings of PPA items varied between 0.738 and 0.894 for the initial measurement framework. In addition, the composite reliability, Cronbach's alpha, and AVE of the PPA construct were quite satisfactory (CR = 0.927, Cronbach's $\alpha = 0.906$, and AVE = 0.681). One can state that this information is the corroboration of the convergent validity and inner consistency of the initial measurement framework; nevertheless, the statistics cannot be utilized to confirm the conceptual equivalence of the indicators using distinct response formats and periods of time. Consequently, for more robust discoveries, the sensitivity assessment of framework without PPA6 was executed (see section 4.4).

While PPA1-PPA5 were mostly focused on the perception of individuals regarding their consistency of the physical activities conducted, PPA6 was focused on the frequency and intensity of the physical activities done during leisure and travel times in the previous year. Therefore, PPA6 differed from PPA1-PPA5 in terms of type of responses and recall period. Nevertheless, the other measure, PPA6, was firstly included as a measure of the wider behavioral dimension of PPA. As PPA6 has different meanings from PPA1-PPA5, apart from assessing the complete framework that considered all the six items, this paper also assessed another framework that excludes PPA6 (see the sensitivity assessment in section 4.4). The questionnaire description of PPA1 to PPA6 can be viewed in the Supplementary material.

3.2 Collection of data

Collection of data was performed via the stratified regional sampling technique so that the collected data became representative of six major regions in Indonesia, that is, Maluku-Papua, Nusa Tenggara-Bali, Sumatra, Java, Sulawesi, and Kalimantan (Supplementary Table S2). Oversampling was applied to the smaller regions in order to obtain more representative samples for the urban–rural comparisons. Therefore, while there is geographic stratification of regions in relation to the sampling method utilized, each stratum's respondents were selected through volunteering in which they were told that their involvement was purely optional. The data was gathered during March–May 2026 using two modes of administering surveys. While the online survey mode involved distributing the survey questionnaires via the WhatsApp (Indonesia's most widely utilized messaging application), offline questionnaires were distributed at Posyandu (community health post) and Puskesmas (health center of a sub-district serving more than one village), which was according to the protocol applied in earlier works involving Indonesia (5, 6). The two recruitment methods have been applied so as to ensure greater representation of people with various degrees of Internet and technological access. Nevertheless, there might be differences in the techniques of selecting respondents in urban and rural regions in the sense that there might be extensive usage of online recruiting in the urban areas while face-to-face recruiting in the rural areas due to poor internet connection. Therefore, the present work must be considered as stratified regional sampling along with non-randomized voluntary sampling of the recruited respondents rather than individuals' probability sampling in each stratum.

Although there could be a risk of selection biases due to variations in recruitment methods, which could have led to urban–rural discrepancies, some efforts to minimalize these biases were performed. First, both the methods (online and offline) were used in all six regions of Indonesia in order to enlarge the size of sample and to ensure that the systematic exclusion of those people who lack internet access was minimalized. Second, the same set of questionnaire, eligibility criteria, consent form and screening criteria were utilized in the two methods of recruitment. Third, recruitment was done in rural and urban areas using both the online and offline methods whenever possible, thereby minimizing the reliance on one particular method of recruitment for one specific population group. Generally, the quantity of survey forms that were administered was 2000, and 1,566 of them (78.3%) were valid responses. Lastly, out of those selected respondents, 871 people were from urban areas making their percentage 55.6%, while 695 individuals were from rural areas with a percentage of 44.4%. This sample size of SEM and multi-group SEM was adequate as per advice from Kline (62).

A multigroup SEM was employed to evaluate if there are several disparities in the structural correlations of MHL, PAHS, PPA, and SES among the urban and rural respondents. The classification of respondents to the rural/urban group has been done using the respondents' own classification as to which category of place of residence they belong. Taking into account the above information that the survey participants were chosen through online and offline methods and those techniques were randomly allocated, it could mean that the observed dissimilarity is the result of the differences between rural and urban, and not just residential typology. For example, differences in internet access, knowledge of WhatsApp, and prior experience with healthcare institutions; these factors may vary among the participants recruited through the different methods of recruiting and this might have affected their willingness to respond.

3.3 Quantitative approach

The rationale for conjoining ANN and SEM is that there are many benefits of employing two approaches instead of just SEM (35–38): (1) SEM offers an opportunity to examine relations between variables on the theoretical level and statistically explore the nature of relations among PAHS, MHL, PPA and SES. (2) To enhance predictive ability, ANN can serve as a good addition to SEM since it allows taking into account non-linear and complicated relations between variables that cannot be observed in the traditional SEM. (3) ANN allows discovering the ranking of variables in accordance to their influence on the dependent variable. (4) Use of the two approaches will provide an opportunity to view the studied phenomenon from both explanatory and predictive perspectives and solve disadvantages of each approach. (5) ANN model used in this paper is expected to exhibit higher efficiency in the prediction of PPA than the SEM model, which exhibits the importance of machine learning techniques within health service and digital health spheres. As seen in Figure 2, this paper's methodology employs a three-stage analytical approach that combines SEM, multi-group SEM and ANN analyses.

From Figure 2, it is evident that initially, the SEM was used for analyzing the proposed associations among PAHS, PPA, MHL, and SES, and then for the analysis of mediation effect of PAHS in the theoretical model. For the purpose of comparative study of structural links among rural and urban societies, multi-group SEM approach was operated. To enhance the linear perspective of SEM, ANN technique was additionally used to identify any non-linear associations among the variables. Use of the amalgamated SEM and ANN increases the methodological strength since both have been used to explain and predict the phenomenon: SEM is useful to test hypotheses and associations among constructs included in the study's theoretical framework; whereas ANN is good to assess the complexity in nonlinear interactions and provide higher accurateness of prediction (35–38).

Inspired by earlier works (35–38), the ANN assessment is performed by using MLP (multilayer perceptron) neural network, which holds a solitary intermediate layer. In MLP, an input layer will contain the significant variables, which are obtained from SEM findings, while the output layer will have the endogenous construct., the weights assigned to the links between neurons in MLP are calculated as follows:

3.3.1 Hidden layer activation

Each neuron j within the intermediate layer will have a linear combination of the input and bias term, and this would be fed into the nonlinear transfer mechanism (either hyperbolic tangent or sigmoid), as calculated by Equation 1:

$$h_j = f\left(\sum_{i=1}^{n} w_{ji} x_i + b_j\right) \tag{1}$$

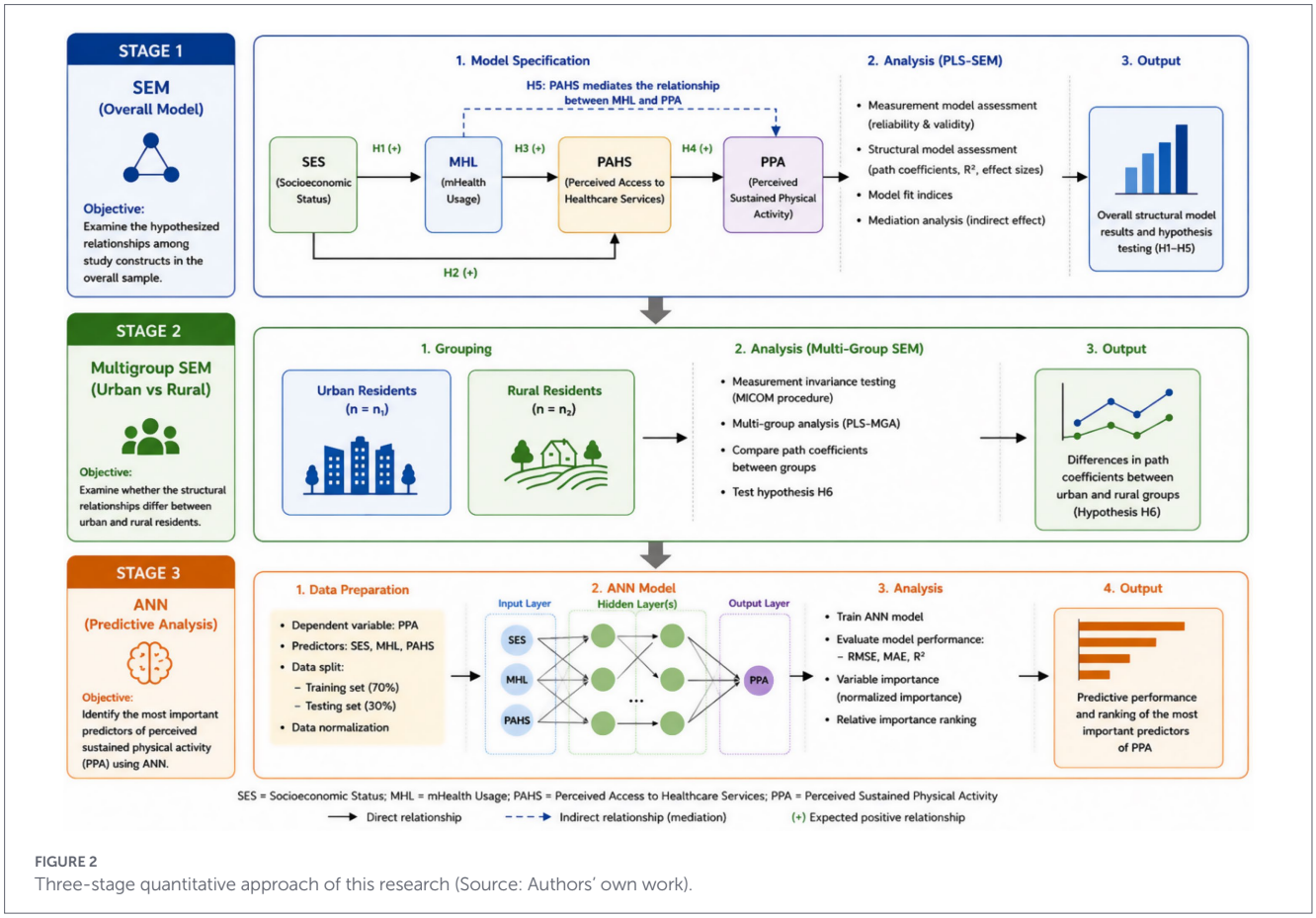


FIGURE 2
Three-stage quantitative approach of this research (Source: Authors' own work).

Here x_i designates the i-th input variable (such as the significant predictor variables obtained through the SEM technique such as SES, MHL, or PAHS), n symbolizes the sum of the input nodes, w_{ji} is the connection coefficient assigned to the input unit indexed by i to the intermediate node indexed by j, b_j symbolizes the offset corresponding to intermediate node j, and f implies an activation function of intermediate layer. In case of the hyperbolic tangent activation function, it will be defined mathematically by Equation 2:

$$f(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}} \tag{2}$$

3.3.2 Output layer activation

Endogenous target construct for the output layer (PPA, for instance) is determined by means of processing the outputs which have been activated by the hidden layer in Equation 3:

$$\overset{\vee}{y} = g\left(\sum_{j=1}^{m} v_j h_j + b_0\right) \tag{3}$$

In this case, $\overset{\vee}{y}$ denotes the estimated value of the endogenous variable under study, where m is the sum of nodes in the hidden layer, v_j denotes the synaptic load of the link from the intermediate-input neuron indexed by j to an output node, b_0 denotes the bias of the output node, and g means the transfer mechanism of the output layer.

3.3.3 Full integrated model equation

By substituting the equation of the intermediate layer into the equation of the output layer, the complete mathematical form showing the link between the SEM-generated predictors and the result can be expressed as per Equation 4.

$$\overset{\vee}{y} = g\left(\sum_{j=1}^{m} v_j . f\left(\sum_{i=1}^{n} w_{ji} x_i + b_j\right) + b_0\right) \tag{4}$$

Throughout the learning phase, the neural network adopts backpropagation technique to minimalize the RMSE (root mean squared error) through modifying all values of w_{ji}, v_j, b_j, and b_0.

3.3.4 Model training

The ANN training process was performed via backpropagation, whereby the connection weights and bias were tuned to minimalize the prediction error. The performance of the ANN model was based on the RMSE measure, defined by Equation 5:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \overset{\vee}{y}_i\right)^2} \tag{5}$$

TABLE 1 Sample profile of respondents (N = 1,566).

Characteristic	Category	*n*	%
Gender*	Male	781	49.9%
	Female	785	50.1%
Age cohort (years)*	18–24	326	20.8%
	25–34	471	30.1%
	35–44	365	23.3%
	45–54	246	15.7%
	≥55	158	10.1%
Residence*	Urban	871	55.6%
	Rural	695	44.4%
Region/island**	Papua-Maluku	119	7.6%
	Kalimantan	194	12.4%
	Sulawesi	159	10.2%
	Nusa Tenggara-Bali	198	12.6%
	Java	624	39.8%
	Sumatra	272	17.4%
Education*	Tertiary schooling	488	31.2%
	Senior secondary schooling	773	49.4%
	Junior secondary schooling	269	17.2%
	Primary schooling and under	36	2.3%
Household income (million IDR/ month)*	Below 2.8	364	23.2%
	2.8–5.0	479	30.6%
	5.0–8.0	341	21.8%
	8.0–12.0	233	14.9%
	More than 12.0	149	9.5%
Employment stability*	Unemployed / irregular work	186	11.9%
	Informal employment (unstable income)	394	25.2%
	Self-employed / small business	402	25.7%
	Formal employment (regular income)	584	37.3%
Total		1,566	100.0

*Categories based on Sumarliah et al. (5); **category based on Sensus BPS (70).

Here, y_i and $\overset{\vee}{y}_i$ designate observed and forecasted scores, correspondingly, and N denotes the aggregate of data points. A higher value of RMSE designates worse prediction accurateness and vice versa.

4 Results

4.1 Attributes of respondents

Table 1 gives 1,566 respondents' demographics and socioeconomic profile. The distribution of the respondents according to gender is relatively equal, with 781 males (49.9%) and 785 females (50.1%). Two-thirds of the respondents are within the age group 25–34 years (30.1%), subsequently 35–44 years (23.3%) and 18–24 years (20.8%). In addition, the urban respondents constituted 55.6% and the rural respondents constituted 44.4%. Geographically, the sample was chosen from all the six regions in Indonesia, with Java (39.8%) having the largest share, followed by Sumatra (17.4%), Bali and Nusa Tenggara (12.6%), Sulawesi (12.4%), Kalimantan (10.2%) and Maluku and Papua (7.6%). In relation to the education, 49.4% of the respondents have received upper secondary education while 31.2% have attended tertiary education. In terms of income, the highest percentage of the respondents earns IDR 2.8 to 5.0 million per month (30.6%), followed by those earning less than IDR 2.8 million (23.2%). With regards to employment status, 37.3% of the respondents are employed, 25.7% are self-employed/small business owners and 25.2% are informally employed.

4.2 SEM results

4.2.1 SEM measurement component

Findings concerning the reliability of the indicators of SEM measurement component are given by Table 2 below. Firstly, factor

TABLE 2 SEM measurement component.

Paradigms	Items*	Range of loadings	Cronbach's α scores	CR	AVEs
PAHS	30	0.703–0.887	0.967	0.970	0.519
PPA	6	0.738–0.894	0.906	0.927	0.681
MHL	6	0.742–0.881	0.902	0.924	0.672
SES	3	0.781–0.892	0.853	0.911	0.773

Criteria based on Hair et al. (65): Factor loadings > 0.700; Cronbach's α > 0.700; CR > 0.700; and AVE > 0.50. *The complete items are provided in Table S1 (supplementary materials). PAHS, perceived access to health service; PPA, perceived sustained physical activities; MHL, mHealth usage; SES, socioeconomic status.

TABLE 3 Discriminant validity assessment.

Construct	Fornell–Larcker criterion				HTMT			
	PAHS	PPA	MHL	SES	PAHS	PPA	MHL	SES
PAHS	0.720				—			
PPA	0.118	**0.825**			0.132	—		
MHL	0.512	0.205	**0.820**		0.563	0.236	—	
SES	0.437	0.183	0.444	**0.879**	0.472	0.211	0.486	—

Sloping scores (bold) exemplify $\sqrt{AVE}$. The entire HTMT scores are under conservative cutoff of 0.850 as well as liberal threshold of 0.900; indicating satisfactory discriminant validity. PAHS, perceived access to health service; PPA, perceived sustained physical activities; MHL, mHealth usage; SES, socioeconomic status.

TABLE 4 Fit statistics.

Index	Value	Cutoff point	Assessment
SRMR	0.058	< 0.080*	Acceptable
NFI	0.913	> 0.900*	Acceptable
d_ULS	1.247	HI95, 1.562**	Acceptable
d_G	0.782	HI95, 0.914**	Acceptable

The assessment criteria were based on: *Hair et al. (65); **Henseler et al. (67). PAHS, perceived access to health service; PPA, perceived sustained physical activities; MHL, mHealth usage; SES, socioeconomic status.

loadings were within the range of 0.703–0.892 which is higher than the advised value of 0.700. Secondly, coefficients of Cronbach's alpha reached 0.853 to 0.967 while composite reliability (CR) fluctuated between 0.911 to 0.970 which topped the minimum cutoff of 0.7. Besides, average variance extracted (AVE) reached 0.519 to 0.773 exceeding the least level of 0.50. In general, the construct of PAHS displayed the highest Cronbach's alpha (0.967) ad CR (0.970), whereas the construct of SES owned the highest AVE (0.773).

The calculation of the discriminant validity (DV) utilizing Fornell–Larcker and HTMT ratio are provided in Table 3. Specifically, the $\sqrt{AVE}$ of all constructs (PAHS = 0.720, PPA = 0.825, MHL = 0.820, and SES = 0.879) top the correlation amongst each construct and the other constructs. In addition, all HTMT ratios are between 0.132 and 0.563, much lower than the conservative limit of 0.850 and the liberal limit of 0.900. Cross-loading test results can be viewed in Supplementary Table S3.

Total fit of the framework has been inspected via d_G, d_ULS, normed fit index (NFI), and SRMR. As one can see from Table 4, SRMR (0.058) was less than the cut-off value of 0.080 and NFI (0.913) topped the end point of 0.900. Furthermore, one could observe that d_G (0.782) and d_ULS (1.247) went below their respective 95% bootstrapping-based confidence interval values (1.562 and 0.914).

4.2.2 SEM structural component

The three endogenous variables are MHL, PAHS, and PPA, while one of the exogenous variables utilized in the structural framework is the SES. H1 to H4 denote the associations of SES → MHL, SES → PAHS, MHL → PAHS, and PAHS→PPA, correspondingly, whereas H5 denotes the indirect relation between MHL and PPA via PAHS (MHL → PAHS→PPA). Given the cross-sectional design of the research, such relations were studied statistically but not causally. Besides the relations mentioned above, there is an indirect relation between SES and PPA via MHL and PAHS (SES → MHL → PAHS→PPA). Although this indirect relation is not assessed in the current paper, it becomes a part of the structural framework specified and should be presented accordingly.

From the estimates of the structural parameters of the SEM framework summarized in Table 5, it could be seen that the relation between SES and MHL was positive ($\beta = 0.444$, $p < 0.001$), and therefore, H1 received empirical support. Moreover, the relation between SES and PAHS was positive ($\beta = 0.181$, $p < 0.001$), and hence the support for H2 was confirmed. The relation between MHL and PAHS was also positive ($\beta = 0.413$, $p < 0.001$), and therefore, H3 was statistically supported. Contrary to the above mentioned hypotheses, the relation between PAHS and PPA was discovered to be statistically insignificant ($\beta = 0.072$, $p = 0.187$), and hence, H4 did not received empirical support. Also, the indirect linkage between MHL on PPA via PAHS was found to be statistically insignificant ($\beta = 0.031$, $p = 0.250$). It means that empirical support for H5 was not attained. Besides, the serial indirect link of SES and PPA via MHL and PAHS (SES → MHL → PAHS → PPA) was exposed to be insignificant ($\beta = 0.013$, SE = 0.009, $t = 1.444$, $p = 0.149$, 95% bootstrap CI [−0.004, 0.032]). Therefore, there was no empirical support for this serial indirect association.

The values for the endogenous factors concerning relevance of prediction (Q^2) and coefficient of determination (R^2) are reported by Table 6. One can observe that 19.7% of the variance in MHL was

TABLE 5 SEM structural component.

Hypotheses	Paths	β	SE	*t*-values	*p*-values	Assessments
H1	SES → MHL	0.444	0.043	11.001	< 0.001	Supported
H2	SES → PAHS	0.181	0.051	3.604	< 0.001	Supported
H3	MHL → PAHS	0.413	0.054	8.202	< 0.001	Supported
H4	PAHS → PPA	0.072	0.052	1.323	0.187	Not supported
H5	MHL → PAHS → PPA	0.031	0.021	1.153	0.250	Not supported

PAHS, perceived access to health service; PPA, perceived sustained physical activities; MHL, mHealth usage; SES, socioeconomic status.

accounted for by SES ($R^2 = 0.197$). The model accounted for 29.0% variance in PAHS ($R^2 = 0.290$). However, only 0.5% of the variance within PPA was vindicated by the model ($R^2 = 0.005$). In addition, all values of Q^2 were positive (MHL = 0.121, PAHS = 0.183, PPA = 0.002).

4.2.3 Measurement invariance assessment

Prior to conducting the comparison of structural parameters of the two cohorts (urban vs. rural), the measure of invariance was assessed utilizing a MICOM (measurement invariance of composite frameworks). There were three separate stages of the assessment done which were as follows: configurational invariance, compositional invariance and equality of composite means and variances. Configurational invariance attested to be valid since the same measurement framework, indicators, data processing and estimation procedures were utilized for the urban ($n = 871$) and rural ($n = 695$) cohorts. Table 7 displays the findings of the MICOM. The constructs were discovered to be compositionally invariant because their original correlations (c) were close to 1 while *p*-values from permutations overdid 0.05. In particular, correlations of the original and permuted composites ranged from 0.989 to 0.998, whereas the *p*-values of permutations ranged from 0.214 to 0.781. It means that throughout the urban and rural cohorts, these composites had equivalent formation.

Finally, the third step checked whether the equality of the composite means and variances existed. In this regard, it is possible to say that the differences of the composite means and variances did not have statistical significance because the entire *p*-values of permutation exceeded 0.05. The difference in means varied from −0.041 to 0.036, while the ratio of variances varied from 0.941 to 1.067. In this way, the empirical support has been received for equality of composite means and variances between urban and rural cohorts. Hence, measurement invariance was achieved for all three stages of the research using MICOM. This implies that the constructs can be compared across urban and rural cohorts and multigroup SEM can be utilized to compare the structural coefficients.

4.2.4 Multi-group SEM results

After confirming that complete measurement invariance holds true across the two samples (rural and urban), multigroup SEM were carried out to determine whether there are any differences in structural paths between the two cohorts. These results are presented in Table 8. Significant differences were noted in the structural path coefficients for three paths which include SES → MHL (Urban $\beta = 0.492$; Rural $\beta = 0.381$; $\Delta\beta = 0.111$, $p = 0.018$), SES → PAHS (Urban $\beta = 0.217$; Rural $\beta = 0.134$; $\Delta\beta = 0.083$, $p = 0.042$), and MHL → PAHS (Urban $\beta = 0.447$; Rural $\beta = 0.368$; $\Delta\beta = 0.079$, $p = 0.036$). In this case, the structural relations for SES and MHL/PAHS and MHL and PAHS was larger in the urban sample than the rural sample. However, the correlation between PAHS and PPA was not statistically distinct between urban ($\beta = 0.091$) and rural ($\beta = 0.048$), with a difference of 0.043 ($p = 0.287$). What needs to be noted is that although the beta value for urban population was high, the difference had no statistical significance.

TABLE 6 Predictive relevance and determination coefficient.

Endogenous factor	Q^2	R^2	Interpretation*
MHL	0.121	0.197	Weak–moderate
PAHS	0.183	0.290	Moderate
PPA	0.002	0.005	Very weak

*The interpretation of R^2 values follows Hair et al. (65) and Chin (71); while Q^2 values were assessed according to Hair et al. (65). PAHS, perceived access to health service; PPA, perceived sustained physical activities; MHL, mHealth usage; SES, socioeconomic status.

According to the R^2 coefficients, the variances in MHL for the urban and rural participants are 24.2 and 14.5%, correspondingly. The variances in PAHS accounted for by the two factors, SES and MHL, for the urban and rural participants are 33.8 and 23.1%, correspondingly. The explained variances in PPA for the urban and rural participants had extremely low explanatory power (R^2) of 0.008 and 0.003, correspondingly. The values of R^2 above indicated the strength of the ability of the framework to explain the phenomenon among different cohorts and did not represent causation. Therefore, it could be seen that there were some rural–urban differences concerning certain structural relations, especially those involving SES, MHL, and PAHS. Nevertheless, statistical significance was not discovered in rural–urban differences with regard to the relation between PAHS and PPA.

Results of multi-group SEM estimation for rural and urban respondents are exhibited in Table 7. The differences in the intensity of correlation between both samples are found in three structural equations: SES → MHL (urban $\beta = 0.492$; rural $\beta = 0.381$; $\Delta\beta = 0.111$, $p = 0.018$), SES → PAHS (urban $\beta = 0.217$; rural $\beta = 0.134$; $\Delta\beta = 0.083$, $p = 0.042$), and MHL → PAHS (urban $\beta = 0.447$; rural $\beta = 0.368$; $\Delta\beta = 0.079$, $p = 0.036$). However, there is no difference in the intensity of correlation between two populations regarding the path PAHS → PPA ($\Delta\beta = 0.043$, $p = 0.287$). The coefficient value was larger for those from urban zones ($\beta = 0.091$) compared to those from rural zones ($\beta = 0.048$), although this difference had no statistical significance ($\Delta\beta = 0.043$, $p = 0.287$). Finally, R^2 explains 24.2 and 14.5% of MHL variance and 33.8 and 23.1% of PAHS variance for urban and rural samples, correspondingly.

TABLE 7 Measurement invariance assessment using MICOM.

Construct	Compositional correlation (c)	5% quantile	Permutation *p*-value	Mean difference	*p*-value	Variance ratio	*p*-value	Invariance
SES	0.998	0.992	0.781	0.014	0.642	1.021	0.736	Full invariance
MHL	0.995	0.983	0.574	−0.028	0.418	0.968	0.681	Full invariance
PAHS	0.989	0.976	0.214	0.036	0.287	1.067	0.593	Full invariance
PPA	0.993	0.981	0.463	−0.041	0.352	0.941	0.624	Full invariance

SES, socioeconomic status; MHL, mHealth usage; PAHS, perceived access to health service; PPA, perceived sustained physical activities.

TABLE 8 Multi-group SEM results.

Path	Urban (n = 871) β	Rural (n = 695) β	Difference ($\Delta\beta$)	*p*-value (MGA)	Interpretation
SES → MHL	0.492	0.381	0.111	0.018	Significant
SES → PAHS	0.217	0.134	0.083	0.042	Significant
MHL → PAHS	0.447	0.368	0.079	0.036	Significant
PAHS → PPA	0.091	0.048	0.043	0.287	Not significant
R^2 (MHL)	0.242	0.145	—	—	Higher in urban group
R^2 (PAHS)	0.338	0.231	—	—	Higher in urban group
R^2 (PPA)	0.008	0.003	—	—	Very low in both groups

MGA, Multi-group assessment. Significant differences indicate that the corresponding path coefficient differs between urban and rural respondents at $p < 0.05$. PAHS, perceived access to health service; PPA, perceived sustained physical activities; MHL, mHealth usage; SES, socioeconomic status.

TABLE 9 ANN architecture and parameters.

Parameter	Specification
Outcome variable	PPA
Input neurons	3 (SES; MHL; PAHS)
Hidden layers	1
Hidden neurons	3
Output neurons	1 (PPA)
Activation function (hidden layer)	Sigmoid
Activation function (output layer)	Identity
Training sample	70%
Testing sample	30%
Number of networks	5

PAHS, perceived access to health service; MHL, mHealth usage; SES, socioeconomic status; PPA, perceived sustained physical activities.

4.3 ANN results

After the assessment with SEM, the predictive evaluation was conducted by employing the ANNs as another tool for SEM to identify whether there is any nonlinearity relation between the explanatory variables and PPA. The theoretical framework that is defined *a priori* in Figure 1 was utilized regardless of the statistical significance of individual relations detected during the process of SEM assessment. In other words, SES, MHL, and PAHS were taken as three explanatory variables while PPA was an outcome variable. The ANN framework consists of three input neurons corresponding to SES, MHL, and PAHS; one hidden layer containing three neurons, and one output neuron related to PPA. Sigmoid activation function was applied for the hidden layer while identity activation function was utilized for the output layer because PPA was a continuous variable. The sample data was randomly divided into two sub-samples where 30% of the total data were utilized for testing set and 70% were utilized for training set. Five different ANNs were built to assess the robustness and reliability of the attained outcomes. The quality of the framework was assessed using the following indicators: RMSE, MAE, r and R^2. Normalized importance values assisted in estimating the relative importance levels of each construct, that is, SES, MHL, and PAHS in terms of predicting PPA. Despite the fact that there was statistical insignificance between the PAHS construct and the dependent variable, PPA in the SEM assessment, PAHS was utilized as an independent variable in the ANN framework, considering that the ANN was applied in order to complement the SEM via the assessment of the ability to predict using the theoretical set of variables, even those that have no substantial relation in the linear regression framework (35–38).

The structure of ANN for predicting PPA value is summarized in Table 9 below. It is evident from the table that three neurons have been taken as the input neurons (SES, MHL and PAHS), while one neuron has been considered as the output neuron (PPA). Concerning the hidden layer, three neurons have been taken in the layer, whose neurons are activated utilizing sigmoid function for considering nonlinearity between the inputs and outputs. Since PPA is a continuous variable, identity activation function has been utilized in the output layer. The database is randomly divided into testing (0.3) and training (0.7) subsamples. Five frameworks of ANN were created to assess whether the prediction accuracy is stable.

The prediction by ANN was done to estimate PPA as the outcome construct with SES, MHL, and PAHS as explanatory constructs. This approach was followed according to the theoretical suggestion and irrespective of the significance of the structural associations in the SEM. In other words, even though there was insignificant linear association found between PAHS and PPA, PAHS was further incorporated in the ANN assessment. All five ANN frameworks maintained

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relatively consistent performance levels during the prediction process when working on both the training and test data sets. The training and testing errors of RMSE for all five frameworks were analyzed to gauge the predictive achievement of the ANN framework in addition to avoid the issue of over fitting (63). Slight variations between the two errors in testing and training designate that the ANN framework maintained consistency in predicting both data sets.

The ANN frameworks were evaluated through the RMSE for both testing and training data in order to determine their ability to predict and generalize. The performance of the five ANN frameworks in terms of prediction is fairly consistent in both testing and training data sets. The average RMSE of the testing data set was 0.51 while that of the training data set was 0.48 with only a difference of 0.03. This consistency in errors for both testing and training data sets implies that the performance of the frameworks in prediction is fairly consistent, meaning that there is no over fitting of these frameworks. Of the five ANN frameworks, the ANN 3 framework yielded the smallest testing RMSE value (0.50) and therefore has the lowest prediction error. Nonetheless, the differences between the five frameworks are small implying consistency in prediction performances. The outcomes are publicized in Table 10 below. When RMSE is lower, it means that there is less prediction error and thus better performance of prediction.

Accordingly, the relative importance of the three input factors, namely, SES, MHL, and PAHS, in relation to their predictive power in respect of PPA has been attained using the values of normalized importance. The input factor which is most important has been given normalized importance value of 100%, and then the normalized importance values of other inputs were measured against this benchmark value. In this regard, the present work has obtained the relative importance of three input factors theoretically proposed for predicting PPA through ANN despite the non-significant linear relation between these input factors and PPA in SEM. Outcomes for normalized importance have been presented in Table 11 below. The relative importance of input factor MHL has been exposed to be the highest at 0.61 and its normalized importance value was 100.0%, followed by input factor SES which had the relative importance of 0.50 and normalized importance value of 82.0%, and lastly by PAHS, which possessed an importance value of 0.39 and a normalized importance of 63.9%.

Predictive capability of ANN architecture in PPA is given in Table 12 below. RMSE mean value was 0.51 for the testing and 0.48 for the training data set. The ANN approach delivers the following outcomes: MAE = 0.39, correlation coefficient (r) = 0.56 and $R^2 = 0.31$. Those were the measures of the ANN's predictive capability while performance on testing designated the generalization capability of the framework (63, 64). The very small difference between the mean value of RMSE on testing and training data sets (0.03) implies that there was no acute problem of over fitting in the framework. It is clear from Table 12 that the constructs SES, MHL and PAHS could be taken together as the input factors for PPA within the ANN approach. Nevertheless, the empirical outcomes of the ANN must be taken as evidence of predictability and not causality.

Prediction efficiency of the ANN framework and SEM framework in predicting the PPA criterion is summarized in Table 13 below. The SEM framework explains the variance of the PPA by 0.5% ($R^2 = 0.005$) while the ANN framework explains the variance of the PPA by 31.0% ($R^2 = 0.310$). Besides, the correlation coefficient and RMSE value for predicted and observed PPA values in the ANN framework are 0.560 and 0.510, correspondingly. From the above statistical outcomes using current data sets, it is evident that the ANN framework performs better in predicting the PPA than the SEM framework. Nonetheless, the distinction is supposed to be made on the basis of the predictive power of those frameworks rather than their ability to identify relationship causality.

In general, the outcomes obtained from ANN framework give additional supportive information regarding the relative predictive

TABLE 10 Artificial neural network model performance.

Model	Training RMSE	Testing RMSE
ANN 1	0.48	0.51
ANN 2	0.47	0.52
ANN 3	0.49	0.50
ANN 4	0.48	0.51
ANN 5	0.47	0.52
Average	0.48	0.51

TABLE 11 Normalized importance of input factors for PPA.

Input factor	Relative importance	Normalized importance (%)	Rank
MHL	0.61	100.0	1
SES	0.50	82.0	2
PAHS	0.39	63.9	3

PAHS, perceived access to health service; PPA, perceived sustained physical activities; MHL, mHealth usage; SES, socioeconomic status. The normalized importance values designate the relative predictive importance of the three input constructs for PPA within the ANN framework.

TABLE 12 ANN predictive accuracy statistics.

Indicator	Value	Interpretation
Average RMSE (Testing)	0.51	Testing/generalization prediction error
Average RMSE (Training)	0.48	Training prediction error
Mean Absolute Error (MAE)	0.39	Mean absolute prediction error
Correlation Coefficient (r)	0.56	Moderate positive association between predicted and observed values
Coefficient of Determination (R^2)	0.31	31% of variance in PPA accounted for by the ANN predictions

TABLE 13 Predictive performance of ANN and SEM for PPA.

Method	Outcome variable	Predictive indicator	Value
SEM	PPA	R^2	0.005
ANN	PPA	R^2	0.310
ANN	PPA	r	0.560
ANN	PPA	Testing RMSE	0.510

PPA, perceived sustained physical activity; R^2, coefficient of determination; RMSE, root mean squared error; r, correlation coefficient.

TABLE 14 Comparison of structural estimates and PPA measurement quality before and after excluding PPA6.

Structural relation	Complete framework (including PPA6)				Framework after excluding PPA6			
	β	SE	t	p	β	SE	t	p
Direct associations								
SES → MHL	0.444	0.043	11.001	< 0.001	0.441	0.041	10.756	< 0.001
SES → PAHS	0.181	0.051	3.604	< 0.001	0.179	0.050	3.580	< 0.001
MHL → PAHS	0.413	0.054	8.202	< 0.001	0.411	0.051	8.059	< 0.001
PAHS → PPA	0.072	0.052	1.323	0.187	0.069	0.054	1.278	0.201
Indirect association								
MHL → PAHS → PPA	0.031	0.021	1.153	0.250	0.028	0.026	1.077	0.282

PPA measurement quality	Complete framework (including PPA6)	Framework after excluding PPA6
R^2	0.005	0.005
Composite reliability (CR)	0.91	0.90
AVE	0.67	0.69

importance of SES, MHL, and PAHS in relation to PPA using a non-linear modeling. Normalized importance of MHL is greater than those of SES and PAHS. This signifies the relative predictive performance of MHL, and this denotes neither causal relation between MHL and PPA nor superiority of ANN over SEM.

4.4 Sensitivity assessment

Based upon the outcomes of the sensitivity assessment (see Table 14), it was observed that the important findings obtained from measurement and structure have not been influenced by the omission of PPA6. This was evident from the observation that the composite reliability of PPA slightly lessened from 0.91 to 0.90, and AVE augmented from 0.67 to 0.69. Therefore, PPA's measurement excellence was still adequate following the exclusion of PPA6. With respect to structural framework, the correlation between SES and MHL was still positive and significant ($\beta = 0.441$, SE = 0.041, $t = 10.756$, $p < 0.001$), and the correlation in the full framework was: $\beta = 0.444$, SE = 0.043, $t = 11.001$, $p < 0.001$. Likewise, the correlation between SES and PAHS was positive and significant ($\beta = 0.179$, SE = 0.050, $t = 3.580$, $p < 0.001$), and for full framework, the correlation was: $\beta = 0.181$, SE = 0.051, $t = 3.604$, $p < 0.001$. In the same way, with respect to MHL-PAHS correlation, the positivity and significance in statistics were also achieved ($\beta = 0.411$, SE = 0.051, $t = 8.059$, $p < 0.001$), and for full framework, the correlation was: $\beta = 0.413$, SE = 0.054, $t = 8.202$, $p < 0.001$. Nevertheless, the relation between PAHS and PPA was insignificant even when PPA6 was dropped from the regression equation ($\beta = 0.069$, SE = 0.054, $t = 1.278$, $p = 0.201$) against the complete framework outcomes that yielded: $\beta = 0.072$, SE = 0.052, $t = 1.323$, $p = 0.187$. In addition, the indirect relation between MHL and PPA via PAHS was also insignificant ($\beta = 0.028$, SE = 0.026, $t = 1.077$, $p = 0.282$), while in the complete framework it was $\beta = 0.031$, SE = 0.021, $t = 1.153$, $p = 0.250$. Besides, PPA's R^2 value was still unaffected (at 0.005). From the outcomes described above, it can be concluded that the omission of PPA6 did not have any significant effect on the outcomes of the measurement and structural frameworks. This means that the sensitivity assessment has delivered further understanding of the effect of PPA6 inclusion on the research findings.

5 Discussion

5.1 Discussion of the results

Findings concerning the reliability of the indicators of SEM measurement component disclose that all constructs (PAHS, MHL, PPA, SES) showed acceptable psychometric properties built upon Hair et al. (65)'s principles: (1) factor loadings are higher than the advised value of 0.700, which means that indicators are the adequate representation of the latent variables, (2) Coefficients of Cronbach's alpha exceeds 0.7, which denotes the entire constructs' high inner constancy, (3) AVE exceeds the least level of 0.50, which means the presence of acceptable convergent validity of all constructs, and (4) The construct of PAHS turned out to be the most reliable one due to the high reliability of the 30-item measurement scale, whereas the construct of SES was characterized by the highest convergent validity. Moreover, it becomes clear that the DV has been achieved for all four constructs under investigation because (1) $\sqrt{AVE}$ of all constructs top the correlation amongst each construct and the other constructs; hence, the Fornell-Larcker criterion is satisfied (66), (2) all HTMT ratios are much lower than the conservative limit of 0.850 and the liberal limit of 0.900; therefore, the constructs are distinct (67), (3) the results obtained prove that the constructs measured by PAHS, PPA, MHL, and SES are different factors; hence, the measures have DV, and (4). DV is also proven by conducting cross-loading test results wherein all the indicators loaded significantly higher in their own constructs (bold numbers) than any other constructs in the rural and urban samples. Moreover, the SRMR and NFI scores indicate that the overall fit of the model was acceptable (65), and the d_G and d_ULS values insinuate the nonexistence of discrepancy between the observed and framework-implied matrices (67). Thus, it is possible to conclude that the proposed model is acceptable in terms of goodness of fit.

Furthermore, regarding structural assessment of SEM, it should be mentioned that, in general, the significant association between MHL and SES and PAHS was observed, although MHL had a more significant association with PAHS than SES. Unfortunately, the significant association between PAHS and PPA could not be observed; therefore, the significant association between MHL and PPA via PAHS could not be established. These results generated by the statistical assessments cannot confirm any indirect link between MHL and PPA via PAHS. Moreover, derived from the findings of R-square (R^2) in Table 6, the MHL displayed weak-to-moderate levels of explanatory power, PAHS exhibited moderate level of explanatory power, whereas PPA had very weak explanatory power ($R^2 = 0.005$). This designates that the inclusion of these constructs into the model accounted for an insignificant share of variance in PPA. Hence, the R^2 values reflect the various degrees of explanatory power of the three endogenous constructs (i.e., MHL, PAHS, and PPA). The statistical outcomes disclose that there was no statistical significance in the PAHS-PPA relation. Consequently, H4 did not received empirical support. However, it would be inappropriate to conclude from the outcomes that there is zero association between PAHS and PPA, because the statistically insignificant correlation cannot be utilized to prove that no relation exists. This just means that the statistical significance of the PAHS-PPA correlation cannot be detected in the current sample. The aspects that may determine PPA are motivation, self-efficacy, societal support of friends/ community, work barriers, family barriers, travel patterns, and physical activity environment access. Those are the likely factors that can be related to the PPA; unfortunately, they were not assessed in this paper. Furthermore, based on the BMA (behavioral model by Andersen), the absence of a significant relation between PAHS and PPA insinuates that the present set of data does not contain any statistical evidence to support the hypothesized PAHS-PPA relation. Despite PAHS having a certain degree of applicability in the wider aspects of the behavioral framework, the outcomes that have been derived from the current research cannot provide us with any clear relation between PAHS and PPA.

Further, looking at the outcomes of multi-group SEM assessment, the dissimilarities in the intensity of correlation between rural and urban samples are found in three structural equations: SES → MHL, SES → PAHS and MHL → PAHS. The $\Delta\beta$ values attained imply that MHL and SES variables can be associated with people's PAHS in a more efficient way in the urban population. R^2 values unveiled that the model fits urban sample better. Significant variation exists among both rural and urban environments when it comes to the relations between SES, MHL, and PAHS. Nonetheless, considering the voluntary recruitment through the mixed online-offline method used, some of the variance could be attributed not only to the residential type but also to the process of recruitment itself, to the Internet connection or to the availability of medical facilities. It is reasonable to see the rural–urban divide in the studied inter-construct relations, but it should be cautious to claim that the residential types (urban vs. rural areas) is fully responsible for being associated with it because other aspects like recruitment mode might also has non-zero association with it.

Compared to SEM, the prediction accuracy of the ANN framework was somewhat higher than SEM with respect to PPA. The explanation of the difference may lie in the capability of ANN to process non-linear and complex relations between variables. Nevertheless, SEM is still appropriate for verifying the presence of a theoretical associations between variables and its statistical significance, while ANN is better for prediction precision. Hence, a combination of SEM and ANN gives explanatory as well as predictive understandings into how independent constructs are associated with dependent variable (here: PPA), as also confirmed by earlier works (35–38).

It is necessary to note that both SEM and ANN approaches provide complementary findings and cannot be regarded as alternative methods of modeling. While the SEM technique was utilized to analyze linear relations between the variables under consideration, the ANN technique was used to estimate the predictive value of SES, MHL, and PAHS in regard to PPA and to identify whether there exist any types of nonlinear dependencies. It is necessary to mention that the non-significant PAHS→PPA path obtained by means of the SEM method should not be considered as an evidence of the absence of any kinds of associations in the process of prediction of PPA. This is due to the fact that the ANN approach considers the PAHS as the predictor variable. In this case, there is the possibility of having the existence of the fact that the association between PAHS and PPA is not linear or can only arise if being combined with other explanatory variables. Unlike the SEM approach, the ANN assessment offers a broader view of the structure that results in the formation of PPA; this reinforces earlier reports (35–38).

5.2 Comparisons with earlier studies' results

An interesting finding is the insignificant correlation between PAHS and PPA in this work, which signposted the inadequacy of statistical support for the assumed PAHS-PPA association in the current sample. It contradicts literature that implies the existence of such correlation between the usage of health facilities, prevention, counseling, obtainability of health services and physical activity or any health-supporting behavior (27–30, 51, 52). One of the possible explanations of such findings may be in the fact that it is more likely for PAHS to serve as an enabler of PPA than a direct determinant of it. Availability of health care services gives access to counseling and information, but its usage related to PPA requires something else like motivation, self-efficacy, societal support, safe recreational spaces, and environmental conditions. Specifically, the Indonesian environment can potentially decrease the intensity of correlation between PAHS and PPA. Physical activity depends on occupation, means of transport, domestic duties, and the social environment (31, 32). Physical activity that results from agricultural activity in rural environments gives significant PPA regardless of the accessibility of healthcare, while in comparison, urban residents have higher access to healthcare but are engaged in sedentary activities. Consequently, a variety of contextual factors may occur to affect PAHS and PPA, which would assist in explaining insignificant association between both. But then again, on the other hand, a reciprocal association could be established whereby being physically active can also affect pattern of utilization, the need for healthcare, and its associated risks. Regardless, given that the study design is cross-sectional, it cannot be concluded that physical activity is sustained through time and ascertain the time precedence of the association between PAHS and PPA. Hence, failure to show statistical significance of the results does not necessarily imply that PAHS does not relate to PPA; it is simply because a cross-sectional work fails to establish sufficiency regarding directionality, time sequence, and likely reciprocal nature when dealing with the association between the two constructs.

Besides, it is worth noting that there is greater emphasis on general physical activity or exercise involvement in those earlier works (27–30, 51, 52), while in the current paper, there is more focus on PPA, which is a measure of perceived persistence and consistency of

physical activity derived from respondents' personal self-reports. The measure of PPA in this paper does not represent an objective measure of physical activity or the actual persistence of physical activity derived from wearable-device activity data or pedometer-recorded step counts. It is possible that the difference in measures/indicators utilized could have caused the difference in findings. Further, the environment surrounding Indonesia can also be relevant in the absence of the strong linkage between PAHS and PPA. Work environment, travel habits, household responsibilities, and the surroundings of community can be associated with how people perceive themselves in regard to being able to engage in physical activities for an extended period of time (31, 32). For people living in rural settings, physical tasks at work can become a chance for engaging in PPA irrespective of the perception people have about their accessibility of healthcare. Meanwhile, the urban areas are accessible to health facilities and also where there are occupations involving prolonged sitting and vehicle-based mobility. For these reasons, the factors mentioned above could therefore weaken the PPA-PAHS association.

Contrary to expectations, the indirect link between MHL and PPA through PAHS was not significant ($\beta = 0.031$, $p = 0.250$). This finding suggests that although MHL relates to PAHS, there was no adequate statistical evidence from this work's findings that support the assumed positive correlation between PAHS and PPA. Additionally, the non-significant indirect linkage of MHL and PPA via PAHS further emphasizes the fact that PAHS was not a significant explanatory construct in the relation between MHL and PPA in this empirical effort. As stated earlier, even though there was a positive relation between MHL and PAHS, since the relation between PAHS and PPA was insignificant, it could not be used to understand the indirect linkage between MHL and PPA. The result partially contrasts with earlier publications that have linked healthcare utilization, preventive services, healthcare counseling, and access to care with positive health behaviors and physical activity outcomes (27, 51, 52). One possible explanation is that there are other elements that can be significantly linked to PPA, including motivation, self-efficacy, societal support, environmental conditions, and opportunities for exercise, which may operate independently of PAHS.

SES was supportively linked to MHL ($\beta = 0.444$, $p < 0.001$) and it underpins earlier works verifying that education, income, and other socioeconomic advantages are associated with access to digital technologies, internet connectivity, and digital skills, and is linked to engagement with mHealth applications and digital health resources (5, 6). Likewise, the finding of positive link between SES and PAHS ($\beta = 0.181$, $p < 0.001$) is consistent with earlier works on health inequalities demonstrating that socioeconomic advantages are associated with greater healthcare utilization, improved healthcare navigation, reduced financial barriers, and enhanced access to healthcare resources (47–50). The result further supports the SDH framework, which accentuates the function of socioeconomic conditions to form healthcare accessibility and well-being opportunities (39).

The findings offer critical knowledge regarding research factors that associate with *perceived* access to health service rather than objective access itself. This corresponds with earlier findings (68). According to Topbas et al. (68), in their survey that involved 1,491 adult participants in Türkiye, determinants that affected the perception of access were personal and situational determinants including health literacy, health behavior, SES, and travel time. This work complements the extant academic publications through the identification of MHL as one of the factors associated with the perception of access (here: PAHS). It advised that the access to information, communication of provider, and navigation of healthcare could be associated with digital-health resources. Moreover, the findings are comparable to those made by Mthembu and Mubangizi (69), which identified issues like infrastructural barriers, human resource issues, lack of education, referrals that do not work, and inadequacy of the healthcare system as barriers to access specialized care among rural communities in South Africa. Disparity in the level of SES, MHL, and PAHS between the urban and rural dwellers of Indonesia is one of the possible reasons for those structural constraints.

The disparities between rural and urban populations are evident from the analysis of the data from different population groups. Correlation between SES and MHL with PAHS, and MHL with PAHS is statistically significant in the urban population group. This is bound to be the case because of the difference in digital infrastructure, connectivity, access to health services, digital literacy, and utilization of digital services. These findings further confirm the significance of spatial and infrastructure variables in relation to the results found by Topbas et al. (68) and Mthembu and Mubangizi (69). Unlike other correlations considered, the correlation between PAHS and PPA is not significantly different between the rural and urban population groups. This suggests the existence of other variables apart from PAHS which associate with PPA, which could be behavioral, occupational, environmental, and social elements beyond PAHS.

Lastly, the finding that MHL significantly related to PAHS ($\beta = 0.413$, $p < 0.001$) is consistent with earlier mHealth works indicating that digital healthiness technologies might be associated with interaction with healthcare providers, improve access to health information, support appointment management, and enhance engagement with healthcare systems (7, 9, 45). The finding also extends prior research by demonstrating that mHealth usage is associated with not only healthcare utilization but also individuals' perceived access to health service.

6 Implications

6.1 Implications for theory

The work fosters the literature on socioeconomic inequalities, digital health, and physical activity by integrating PAHS, PPA, MHL, and SES within a unified framework. This work builds on the theoretical framework put forth by Sumarliah et al. (5) by adding one more healthcare-related construct, termed PAHS, which falls on the link between MHL and PPA. Although Sumarliah et al. (5) have examined the relation between SES, MHL and PPA, the goal of this paper is to uncover whether the linkage between MHL and PPA is related to the new variable, which is PAHS. It should be noted that this paper's findings reveal that there is insignificant correlation between PAHS and PPA. It means that the relation that was established between MHL and PPA in the earlier research (5) does not statistically operate via PAHS. There are likely other variables such as motivation, self-efficacy, behavioral reinforcement or even the existence of chances for physical activities in the surroundings that could be associated with MHL-PPA relation and need further assessment. Accordingly, the added value of this paper is situated not in developing another model of mediation but in verifying empirically that in Indonesia, even with good PAHS, PPA does not automatically follow. Besides, Sumarliah et al. (5) have verified that rural–urban

discrepancies are present within the correlations between SES, MHL and PPA in relation to Indonesian adults who are overweight or obese. At the same time, contrary to the earlier work (5), the current research focuses on PAHS as a separate access to health care variable and examines whether there is a correlation between PAHS and MHL-PPA linkage amongst broader Indonesian adult sample. Methodologically, the study advances public health research by integrating SEM and ANN, combining theory testing with predictive analytics to deliver a more far-reaching knowledge of the associations among SES, MHL, and PAHS factors.

Furthermore, it is clear that since MHL and SES have a positive link, there is an empirically substantial linkage between persons' engagement in digital healthcare technology (here: mHealth) and their socio-economic conditions. The same applies to the positive link between SES and PAHS, which displays that there is an association between socioeconomic status and individuals' perceived access to health services. It can be clearly seen from the above. Unlike earlier publications that reported positive associations between healthcare access and health-related behaviors (27–30), this paper disclosed that the direct and indirect associations of PAHS and PPA were non-significant. The paper also gives new insights into the significant association between MHL and PAHS, which further indicates that mHealth usage relates to individuals' ability to navigate healthcare systems and access health resources, underscoring the need for future models to incorporate behavioral, environmental, psychological, and contextual aspects linked to PPA.

6.2 Implications for policies

This work delivers important policy insinuations to address health inequalities through mHealth interventions. Globally, efforts to advance population health should extend beyond healthcare infrastructure development to include greater attention to mHealth usage. As healthcare systems increasingly adopt telehealth, mobile applications, and AI-based health services, individuals with lower SES may face greater risks of digital exclusion. Policymakers and international organizations should therefore support affordable internet access, digital devices, and user-friendly mHealth services, particularly for disadvantaged populations, to ensure consideration of whether technological revolutions are associated with lower rather than greater health inequalities. In Indonesia, the findings are especially relevant given persistent rural–urban inequalities in SES, healthcare access, and digital infrastructure. The positive associations among PAHS, MHL, and SES suggest that national digital health strategies should prioritize lower-income and rural populations. Integrating mHealth education into community health programs, primary healthcare services, schools, and public awareness campaigns could support digital health engagement. Community health centers (Puskesmas), village health posts (Posyandu), and local medical professionals can be relevant in this effort. Since healthcare's accessibility alone did not significantly relate to PPA, policies should also incorporate behavioral, societal, and environmental interventions to support strategies related to active lifestyles and health equity.

7 Conclusion

This study examined the relationships among PAHS, PPA, MHL, and SES in Indonesia using a combined SEM–ANN approach. The findings disclosed that SES was positively linked to MHL and PAHS, while MHL significantly related to PAHS, which highlighted the importance of socioeconomic resources and mHealth usage in their associations with perceived access to healthcare. The ANN results further signposted the predictive importance of MHL and SES. Nevertheless, a positive relation between PAHS and PPA could not be established statistically in this current research sample. The above-mentioned conclusion can only be interpreted as meaning that the predicted relation between PAHS and PPA could not be confirmed statistically and not the absence of any relation (or zero association) between the two constructs. Generally, this paper is consistent with the digital health and health equity academic works by delivering evidence that greater usage of mHealth technology is positively associated with perceived access to healthcare services, while the strength of several structural associations differs between rural and urban samples, specifically within rapidly digitalizing contexts like Indonesia.

The present research is an extension of the work carried out by Sumarliah et al. (5) where PAHS was introduced as a new factor assumed to have a linkage with their original framework comprising SES, MHL, and PPA. The analytical outcomes indicate that there is a strong positive association between SES and MHL, SES and PAHS, as well as MHL and PAHS. On the other hand, PAHS does not possess statistically significant association with PPA, and there is statistical insignificance in the indirect relation between MHL and PPA through PAHS. Rural/urban disparities existing in various pathways also show that the intensity levels of associations amongst SES, MHL, PAHS and PPA vary between those who live in urban and rural zones.

8 Limitations and future works

A number of caveats warrant consideration. To begin with, this paper's design restricts the capability of establishing causality, so in upcoming works, longitudinal reports are needed to verify the associations among SES, MHL, PAHS, and PPA. Second, the use of self-reported instruments can trigger systematic errors caused by inaccurate recollection and societal approval; upcoming research should encompass tangible indicators, e.g., wearable-device data, healthcare utilization records, and digital usage metrics. Third, because the study was conducted in Indonesia, the outcomes possibly cannot have generalizability to different culture and healthcare context. Additionally, important determinants of PAHS, including self-efficacy, societal support, environmental factors, and health status, were not examined and should be incorporated into future models. Although the SEM–ANN approach enhanced both explanatory and predictive insights, future studies may employ advanced machine learning and explainable AI techniques to explore more complex relationships. Next, further investigation of rural–urban dissimilarities and other population subgroups is indispensable for improved awareness on by what means MHL and PAHS contribute to reducing health inequalities and promoting active lifestyles.

Besides, the stratified method was applied in order to make sure that there was enough representation of the six major regions of Indonesia in the sample. However, respondents were selected voluntarily using both online and offline methods. There could be a possibility that the recruitment process varied in different urban and rural areas and the different recruitment processes could result in differences that appeared during the multi-group SEM

assessment. Any future study of this nature will require the use of probability sampling within both the rural and urban groups, and in case mixed methods of recruitment are inevitable, the method of recruitment has to be standardized and made as a controlled factor. Lastly, the lack of significance observed in the relation between PAHS and PPA should be viewed with caution due to the inability of a cross-sectional design to allow for any conclusions regarding the presence or absence of any actual relation between these variables. Future academic endeavors, operated with a longitudinal design and different variables, may help elucidate this PAHS-PPA relation.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary material.

Ethics statement

The studies involving humans were approved by Al-Ihya Islamic University of Kuningan's Institutional Review Board (Registration no.: IRB-UNISA/2026/III/061). The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

ES: Conceptualization, Writing – review & editing, Investigation, Methodology, Formal analysis, Project administration, Writing – original draft. KM: Methodology, Writing – review & editing, Conceptualization, Supervision, Writing – original draft. II: Conceptualization, Writing – review & editing, Writing – original draft, Visualization, Investigation. EA: Writing – review & editing, Writing – original draft, Methodology. AR: Validation, Writing – review & editing, Writing – original draft. DK: Writing – original draft, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2026.1946807/full#supplementary-material

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