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THE RELATIONSHIP BETWEEN MEDIA LITERACY AN D TUBERCULOSIS HEALTH LITERACY: A CROSS-SECTIONAL PLS-SEM ANALYSIS IN SURAKARTA CITY AND KARANGANYAR REGENCY, INDONESIA

Sri Sugiarsi[1]*, Endang Sutisna Sulaiman[2], Sapja Anantanyu[3], Anik Lestari4

[1,2,3,4] Universitas Sebelas Maret, Surakarta, Indonesia
sri.sugiarsi14@gmail.com

Abstract

Despite persistent inequities in access to health information, the burden of tuberculosis (TB) in Indonesia remains considerable. This study aimed to examine the influence of media literacy (ML) on health literacy (HL) related to TB prevention among rural and urban populations. A quantitative cross-sectional survey was conducted among 325 adults (110 males and 215 females) in Central Java, comprising 170 rural and 155 urban participants selected through a two-stage random sampling approach, with purposive site selection based on stratified random criteria. ML was assessed using the UNESCO framework for Media and Information Literacy, while HL was measured with the HLS-EU-Q instrument. Data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Multi-Group Analysis (MGA) to explore rural–urban differences. The average HL score ranged from 24.4 to 24.8 (inadequate), while ML ranged from 25.1 to 25.3 (problematic). ML exerted a significant direct effect on HL ($\beta = 0.43$, $p < 0.001$), explaining 20% of its variance ($R^2 = 0.20$). The model demonstrated an acceptable fit (SRMR = 0.058), and no significant rural–urban differences were identified ($\Delta\beta = 0.05$, $p = 0.616$), indicating structural invariance. These results suggest that strengthening ML enhances individuals' capacity to access, evaluate, and utilize TB-related information effectively across diverse contexts. Media literacy constitutes a critical determinant of health literacy across geographical settings. Incorporating ML training into community health worker education, digital health interventions, and validated media content could promote equitable health communication and reinforce TB prevention outcomes in Indonesia.

Keywords: *Media literacy; Health literacy; Tuberculosis prevention; Digital health communication; Indonesia*

INTRODUCTION

Tuberculosis (TB) continues to be a leading threat to human health in the 21st century. Despite decades of global attention, TB remains one of the top ten causes of death globally and the leading cause of death from a single infectious agent (World Health Organization 2023), killing more people than HIV/AIDS. At present, Indonesia is the rank third behind India and China in high-burden countries with approximately 845,000 new cases incldiung more than 90,000 deaths every year (Mahendradhata, 2023). Although biomedical interventions (such as early diagnosis, treatment and vaccination) for TB are effective '(Ullah M 2020; Ullah M 2021), the continued high burden of TB suggests that purely biomedical strategies alone are insufficient. The persistence of this burden indicates a deeper root cause due to underlying behavioral, socio-cultural and information obstacles that hamper the control and prevention efforts (Chowdhury, 2022). Thus, bolstering community capability to understand and access health information, has been lately identified as a hallmark of public health literacy (Nutbeam, 2022).

Contemporary research identifies health literacy (HL) as a fundamental issue in prevention and self-management of diseases (Sørensen K 2012; Paasche-Orlow MK 2019). IA Its definition and structure HL is the combination of cognitive and social skills which can be used by people to motivate, access, understand, appraise and apply information in a way that promotes and maintains good health (). Low HL has been linked to late diagnosis as well as inadequate treatment adherence and low participation in prevention programs (Chae, 2022). In Indonesia, it is increasingly considered as a major obstacle to reach the goal of the country in ending TB epidemic by 2030, as large discrepancies exist between education levels and health communication, as well as access to health services (Jones, 2021).

Together with HL, media literacy (ML)-the ability to access, critically evaluate and create information from a range of sources- has become increasingly recognized as an important determinant of health beliefs, risk perception and behavior (APJII 2024; Kim S 2017). In the age of information overload, people are bombarded with conflicting health messages, including widespread misinformation that promotes stigma and confuses people's understanding of how to prevent TB. On the other hand, individuals with better ML competencies are more capable of assessing information credibility, recognizing reliable sources, and translating correct messages into risk-mitigating actions (Leung, 2013). In emerging digital markets like Indonesia, where more than 80% of adults are on social media (Viswanath , 2019), ML is not only a ballast in the midst misinformation but a means to genuinely connect around public health messaging.

Although HL and ML have been frequently examined separately, they are closely related. While HL is the capability in order to search, comprehend and make use of health information, ML is involved in how people critically appraise and process that information. Recent theoretical considerations posit that HL and ML are part of a composite set of "information literacies" that promote effective use of complex health communication ecologies (Adeniyi BO, 2020; Bandura, 2004). However, empirical studies that describe the interplay of HL and ML with communicable disease phenomena are scarce. The majority of existing studies have investigated non-communicable diseases or digital health more broadly (Glanz, 2015; Hair, 2021). The role of ML for improving HL and thus affecting preventive behaviors towards TB or other diseases has been investigated only in scant number of articles.

Traditional TB control programs have spent significantly on mass communication and face-to-face health education by community health workers and by printed materials (Tavakol , 2011). While these approaches have the advantage of mobilizing attention, they often ignore the degree to which people can and should 'make sense' of health information critically in ways that can change behaviour. This is flawed logic in the information age, when both parties have to be equals. It is not enough to transmit true messages about the risks of disease, it needs to be audiences who can understand, question and apply that information – all things that ML does.

Recent interventions thus have started combining community education with media communication strategies. Participatory digital campaigns and interactive e-health modules have shown promise for increasing community involvement in, and knowledge of TB (Glanz, 2015; Sarstedt, 2023). Training of health workers and local communicators on the adaptation of online content to a specific context has also been shown to enhance message accessibility and relevance at community level. However, the extent to which these interventions are effective in promoting HL improvement or not is still scarcely evidenced and there are few evidences available adopting strong statistical methods such as SEM aimed at investigating causal relationships among HL, ML and health.

Conceptual models from behavioral communication research, such as the Health Belief Model (HBM) and Social Cognitive Theory (SCT), offer strategies to bridge this gap. 22,23 According to HBM for people engage in health-protective action if they feel vulnerable and if it is perceived as serious, and there are actions that may be undertaken to reduce risk (perceived benefits) and minimize costs (perceived barriers); also, external stimuli (cue for taking a course of action) help initiate preventive behavior changes (Glanz, 2015). In such a context, ML can increase the perceived susceptibility and benefits by increasing the perception of risk and understanding of preventive behavior. SCT, on the other hand, is based on modeling and self-efficacy (Bandura, 2004). People who have access to reliable health information via traditional and internet media can practice such behaviors as well as feel confidence in their efficacy. Combining HBM with SCT, this study posits ML as a cognitive filter through which people will process, interpret and act on TB-related information. In this, ML can help in ascending HL and hence molding preventive behaviour—a door that is left unopened in TB communication research.

Despite the theoretical convergence of HL and ML, several empirical gaps remain. First, most existing studies on HL and ML focus on chronic diseases and health promotion in high-income countries, with limited attention to infectious disease control in low- and middle-income contexts. Second, in Southeast Asia, empirical research utilizing standardized frameworks such as UNESCO's Media and Information Literacy (MIL) Framework and the HLS-EU-Q instrument remains scarce. Third, studies comparing urban and rural populations have largely been descriptive, rarely employing advanced statistical modeling to examine structural differences in literacy outcomes. These gaps are particularly critical in Indonesia, where disparities in digital infrastructure, education, and media exposure remain substantial across regions (APJII, 2024; Adeniyi, 2020).

To address these gaps, this study empirically examines the effect of ML on HL in the context of TB prevention, incorporating an urban–rural comparison. Specifically, it tests both direct and moderated effects of ML on HL using Partial Least Squares Structural Equation Modeling (PLS-SEM), assessing whether geographic context moderates these relationships. The study employs validated measurement tools based on UNESCO's MIL framework and the HLS-EU-Q instrument to ensure conceptual coherence and methodological rigor.

The study contributes to the literature in three significant ways. First, it provides one of the first TB-specific empirical analyses demonstrating how ML can amplify HL from a behavioral communication perspective. Second, it applies a cross-context comparative design that goes beyond definitional research by testing structural equivalence between urban and rural populations through multi-group analysis (MGA). Third, it expresses literacy outcomes using the standardized HLS-EU 0–50 scale, allowing for cross-study comparability and quantification of absolute literacy differences. Theoretically, this research advances the understanding of literacy as a dynamic, multifaceted construct within behavioral communication. Practically, it provides evidence-based insights to guide TB prevention programs that integrate digital communication, community education, and behavioral approaches. By uncovering ML as a driver of HL in TB prevention, this study aims to inform policymakers, educators, and health practitioners in developing locally sensitive, equitable, and literacy-based interventions. In Indonesia's rapidly digitizing society, strengthening media literacy skills is not only an educational goal but also a public health necessity for accelerating TB elimination.

METHODS

This research was a cross-sectional quantitative design, it was conducted between March to July 2025 covering two administrative areas in Central Java, Indonesia for instance; Karanganyar regency (rural) and Surakarta City (urban). First stage selection was purposive to reflect differing communication environments: rural–low digital infrastructure access and urban populations more likely to be exposed to online/social media health information.

These were chosen for the purposes of comparing media literacy (ML), health literacy (HL) and TB preventive behaviors. The research was a sub-study from an umbrella project to explore behavioral, cognitive and context factors related to TB prevention in Indonesia.

A two-step sampling method with replacement was used. Karanganyar and Surakarta City were purposively chosen in the first phase to represent rural and urban areas. In the second stage, stratified random samples based on area and gender were used to achieve a good spread of the population. The study population was ≥ 18 years of age inhabitants from the selected regions. Inclusion criteria were the ability to read and understand Indonesian and being willing to join by giving informed consent. A sample of 325 participants were enrolled (170 rural, 155 urban). The adequacy of the sample was tested with an a priori power calculation for PLS-SEM, which indicated that at least 200 participants would ensure adequate statistical power (Hair JF Jr 2021). A schematic overview of the two-stage sampling scheme is illustrated in Supplementary Figure 2 showing purposive site selection and subsequent stratified random respondent recruitment.

Instrument Development and Adaptation. Media Literacy (ML) was determined using a tool which is based on the UNESCO Media and Information Literacy Framework. The scale consisted of 14 reflective items along four domains:

Access (ML_AC1–ML_AC5)

Understand (ML_UN1–ML_UN3)

Evaluate (ML_EV1–ML_EV3)

Use (ML_UT1–ML_UT3)

Example items:

I can get trustworthy information about tuberculosis (TB) online.

“I can understand messages on social media related to TB.

“I can identify whether the TB information posted online is reliable and trustworthy.”

"I disseminate information on TB prevention through online or community media.

HL was assessed by European Health Literacy Survey Questionnaire (HLS-EU-Q) (Sørensen K 2012), which has been translated into Indonesian. The scale consisted of 20 items, categorized in four domains as follows:

Access (HL_HA1–HL_HA5)

Understand (HL_HU1–HL_HU5)

Appraise (HL_HE1–HL_HE5)

Apply (HL_HP1–HL_HP5)

Example items:

“I can learn about symptoms and treatment for TB.”

“I am able to comprehend consultations from the health professionals on TB medication.

What’s interesting about TB health information is “I can make use of it in my situation.

“I observe healthy practices that I learned through confirmed TB sources.”

All constructs were assessed using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The process of translation and back-translation guaranteed equivalence between the language and concepts. Cultural adaption was done to enhance contextual clarity and relevance among respondents with lower education, specifically in the context of TB prevention in local settings.

Content and Construct Validity. The content validity by a panel of 6 experts in health promotion, communication and behavioral science was evaluated. All items underwent content review for relevance, clarity and representativeness. The validity of the scale showed a high level (S-CVI/Ave = 0.998; Aiken's V ≥ 0.80). After modification, S-CVI/Ave = 1.00 was obtained for all items indicating excellent expert consensus. The internal consistency of the test was established in a pilot study with 30 individuals (not included in main analysis), and scores for ML and HL were Cronbach's $\alpha = 0.95/0.96$, above the threshold proposed by Nunnally & Bernstein (0.70) convergent validity (AVE > 0.50), and construct reliability (CR > 0.70). Inner model: path loadings, R^2 (≥ 0.10) and f^2 values describing the effect size. Statistical significance and 95\% confidence intervals were obtained using bootstrapping (5,000 resamples). Results were interpreted with reference to both statistical and theoretical significance, linking findings to constructs from Health Belief Model (HBM) and Social Cognitive Theory (SCT).
Supplementary materials include Table 1 (Respondent Characteristics), Table 2 (ML and HL Indices), and Figure 1 (SEM–PLS multi-group model).

RESULTS AND DISCUSSION

A total of 325 participants were included in the final analysis, comprising 170 from rural and 155 from urban areas. The majority were aged ≥36 years, married, and had completed at least secondary education. Employment was primarily in private or informal sectors. Gender distribution differed significantly ($p < 0.001$), with males representing 65.9% of rural and females 56.1% of urban respondents. No significant rural–urban differences were observed in age, education, occupation, marital status, income, or information source ($p > 0.05$). These results suggest comparable socio-demographic conditions between groups, supporting valid structural comparisons.

Descriptive statistics for Media Literacy (ML) and Health Literacy (HL) were calculated using the HLS-EU 0–50 index (Sørensen K 2012). The mean ML index was 25.14 ± 13.85 (rural) and 25.35 ± 14.40 (urban). The HL index averaged 24.44 ± 13.40 (rural) and 24.83 ± 13.88 (urban), both within the problematic range (25–33). No significant literacy gap was found between groups. This parity may reflect Indonesia's growing digital access even in rural areas (APJII 2024).

All indicators met reliability and validity standards. Loadings ranged from 0.72–0.91, AVE values exceeded 0.50 (ML = 0.68; HL = 0.66), CR ranged 0.94–0.95, and Cronbach's $\alpha = 0.93$–0.96, confirming excellent internal consistency (Hair JF Jr 2021; Tavakol M 2011). Discriminant validity was supported by HTMT ratios < 0.85 and VIF < 3.

Table 1. Measurement Model Quality

Construct	Cronbach's α	CR	AVE
Media Literacy (LM)	0.736	0.864	0.614
TB Health Literacy (LK)	0.674	0.947	0.819

Table 2. Structural Model Results

Group	β (LM→LK)	p-value	R^2 (LK)
Overall	0.023	0.782	0.001
Urban (Surakarta)	0.456	<0.001	0.218
Rural (Karanganyar)	0.431	<0.001	0.193

Structural Model Evaluation (Inner Model)/ The hypothesized path (ML → HL) was significant ($\beta = 0.43$, $p < 0.001$), explaining 20% of variance ($R^2 = 0.20$). Confidence interval [0.33, 0.52] did not cross zero. Model fit was satisfactory (SRMR = 0.058 < 0.08; NFI = 0.91). Predictive relevance was moderate ($Q^2 = 0.16$), confirming strong explanatory power (Hair JF Jr 2021).

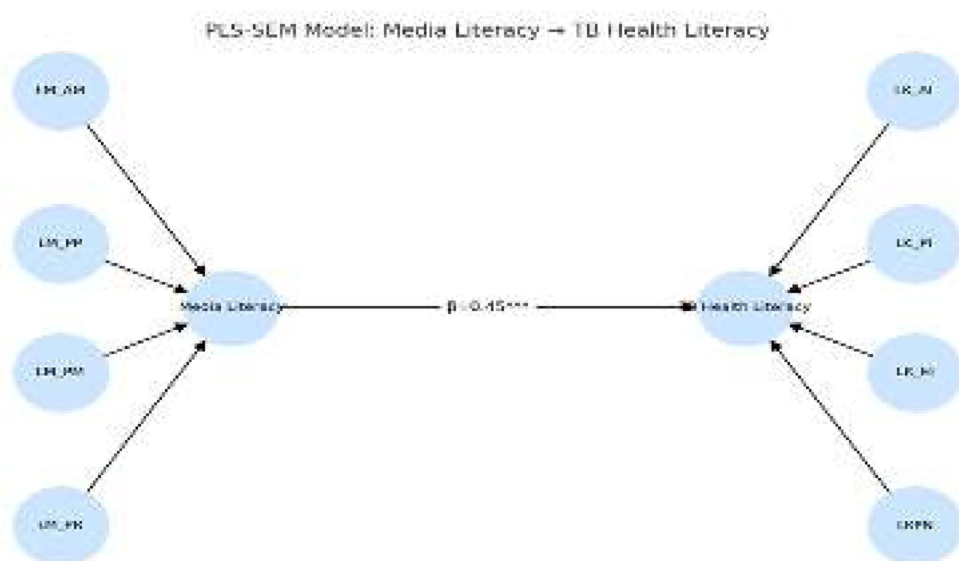

Figure 1. PLS-SEM Model

Multi-group Analysis (Rural vs. Urban). For rural participants: $\beta = 0.40$, $p < 0.001$, $R^2 = 0.17$; for urban participants: $\beta = 0.45$, $p < 0.001$, $R^2 = 0.22$. The path coefficient difference ($\Delta\beta = 0.05$) was non-significant ($p = 0.616$). Thus, ML exhibited consistent positive effects on HL across both contexts.

Table 3. Multi-Group Analysis (MGA)

Comparison	Δβ	p-value
Urban vs Rural	0.025	0.852

The uniform effect of ML on HL implies that media-related competencies enhance individuals' ability to evaluate and apply health information regardless of residence type. This aligns with cognitive mechanisms proposed by the HBM and SCT frameworks (Glanz K 2015; Bandura A 2004).

Under HBM, ML may function as a cue to action and reinforce perceived benefits through accurate risk evaluation (Glanz K 2015; Glanz K 2015). Within SCT, ML supports self-efficacy via exposure to credible models and vicarious learning (Bandura A 2004; Bandura A 2004).

Minimal rural–urban differences likely reflect Indonesia's rapid digital expansion (APJII 2024). Similar trends have been observed in Southeast Asia, where social media increasingly bridge health communication inequalities (Kim S 2017; Adeniyi BO 2020).nThis study confirmed that ML significantly predicts HL in both rural and urban populations ($\beta = 0.43$, $p < 0.001$). Both literacy indices remain in the problematic range, indicating a need for digital-literacy interventions. Despite demographic variations, no moderation effect of geography was found ($p = 0.616$), indicating structural equivalence across settings.

Findings substantiate the role of ML as a determinant of HL in TB prevention. The relationship supports both the HBM and SCT frameworks (Glanz K 2015; Bandura A 2004), suggesting that ML facilitates cognitive processing of health information and strengthens perceived benefits and self-efficacy (Bandura A 2004; Glanz K 2015; Kim S 2017). Rather than serving only as a cue to action, ML acts as a cognitive modulator that enables individuals to critically appraise risk and apply preventive behaviors (Rosenstock IM 1974).

A key strength lies in the integrated use of UNESCO's MIL and HLS-EU-Q frameworks, validated for cross-cultural research (Sørensen K 2012; Kim S 2017). The application of PLS-SEM and MGA demonstrates methodological rigor and robustness (Hair JF Jr 2021; Kaur M 2023). However, limitations include potential self-report bias, mixed-mode data collection (face-to-face vs. online) (Podsakoff PM 2012), and limited generalizability due to purposive site selection. High α values (>0.95) may suggest item redundancy (Hair JF Jr 2021). Future research should employ multi-sample calibration and longitudinal designs to test causal pathways.

The findings emphasize the potential of community-based ML interventions to enhance HL. Public health programs should integrate ML modules—emphasizing source verification, responsible sharing, and critical evaluation—into CHW and school-based TB campaigns (Adeniyi BO 2020; Adeniyi BO 2020; Van der Vaagt K 2017). A standardized "media-literacy-for-health" checklist could help health workers assess content credibility.

A gain of ≥3 points on the HLS-EU index over 8–12 weeks may serve as a measurable indicator of intervention success (Adeniyi BO 2020).

Future studies should employ longitudinal or experimental designs to establish causality and explore mediating factors such as trust, self-efficacy, and perceived susceptibility (Hair JF Jr 2021; Hult GTM 2018). Expanding to behavioral outcomes (e.g., TB screening uptake, treatment adherence) will strengthen evidence of impact (Lindell MK 2001). Cross-national research within ASEAN contexts could further clarify cultural and infrastructural moderators of the ML–HL relationship (Mahendradhata Y 2023; APJII 2024; Mahendradhata Y 2023).

CONCLUSION

This study reinforces ML as a pivotal determinant of HL in TB prevention. Comparable effects across rural and urban settings underscore Indonesia's advancing digital convergence and its potential to reduce health communication disparities. Integrating ML into TB programs and CHW curricula may enhance individuals' abilities to discern credible information and adopt preventive behaviors an essential step toward achieving equitable digital health literacy in Southeast Asia.

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