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Social Determinants and Their Impact on Urban Health Inequalities

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ABSTRACT

Objective: We aim to investigate the influence of novel social determinants such as digital redlining and connectivity quality (DRCQ), platform job insecurity density (PJID), and thermal–air co-exposure inequity (CTAI) on urban health inequalities, and assess community mutual aid infrastructure (CMAI) as a moderating mechanism of resilience.
Methods: A cross-sectional design including multiple sources of data was implemented, and moderated regression analysis used.
Results: The analysis finds three types of disparity are particularly strongly amplified in the urban space: poor digital connection, precarious platform-based labour and uneven environmental co-exposures. Meanwhile, strong community mutual aid infrastructures also have a direct mitigating effect and dampen the effects of deprivation. These stydies highlight that urban health disparity is not merely a function of traditional factors such as income and education, and is differentially produced in intricate webs of technological, labor and environmental forces.
Novelty: This paper presents a theoretical model that integrates social determinants of health with environmental justice and job demand–resource perspectives, and empirically demonstrates how community resilience buffers the negative impact of exposure to neighbourhood disadvantage. The study pushes conceptual boundaries by expanding further than classical measures and by considering combined multidimensional inequities seldomly addressed at once; thereby providing a new perspective for exploring structural determinants of health disparities.
Implications for Research: The findings highlight the importance of multidimensional, theory-driven approaches that integrate digital inclusion, labour protection, climate adaptation, and community resilience throughout health equity research and policy agendas. By promoting this way of thinking, the analysis contributes to generating evidence that can help to guide global efforts to support urban health systems that are both fairer and more sustainable.

1. Introduction

Urban health inequalities are increasingly recognized as a major global concern, with rapid urbanization driving unequal access to healthcare, environmental quality and digital infrastructure. The COVID-19 pandemic added a stark example of health inequality between communities, shedding new light on the structural effects of social determinants such as digital access, insecure employment, and environmental exposures (Kerschbaumer et al., 2024; McNeely et al., 2020). Studies performed in the last months confirm that social exclusion exacerbates inequalities in the diffusion of telehealth and health literacy, especially in disadvantaged communities (CHANG et al., 2021; Haimi, 2023). Concurrently, the emergence of platform dependent labour has also contributed to remaking urban economies and generating precarious and precarious working conditions tied to stress-induced illnesses and limited health coverage (Cheng et al., 2024; Nayak et al., 2022; Wood et al., 2018). Environmental stressors including concurrent exposure to heat and air pollution have been more widely acknowledged as potentiators of chronic health conditions and

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premature death in urban populations (Argacha et al., 2019; Sekar et al., 2024; N. Singh et al., 2020). These multilevel determinants intersect in ways that perpetuate health inequalities across urban populations requiring a recommitment to scholarly focus on the pathways through which inequality is formed and, possible community level protection.

Current discussions highlight how conventional health determinants incomes and education- do not provide a complete understanding of urban health inequities. New evidence underscores the significance of digital redlining structural disparities in internet speed, reliability, and access to telehealth as a contemporary social determinant of health equity in digitally mediated societies (Gergen Barnett et al., 2022; Monkman & Lesselroth, 2025). Likewise, the precarity immanent in platform-based work through income, social protection and occupational safety's instability leads to erosion of workers' physical and psychological health (Al-Massalkhi & Ajonbadi, 2024; Shaiwalini & Malhotra, n.d.; Vu & Nguyen, 2024). Moreover, urban climate risks, such as heatwaves strongly driven by air pollutants as well, have a stronger impact on low- income groups, underlining the role of environmental justice perspectives in health inequality research (Chaudhry, 2024; Mashhoodi & Kasraian, 2024). Despite this knowledge, measures to cut across these multidimensional and interrelated issues through policy frameworks tend to be slow to react, necessitating integrative frameworks, which consider technological, labour, and environment determinants, within the broader scope of disparities of health.

In so doing there are numerous theoretical paradigms that are employed to frame the determinants of urban health inequalities. The Social Determinants of Health (SDH) framework13 (Solar & Irwin, 2010) offers an approach to understanding structural drivers of inequities that move beyond characteristics of the individual. The role of labour precarity for stress and health in the JD-R model The Job Demand Resource (JD-R) model Kunzelmann et al. (2025), Zettna et al. (2025) is our theoretical frame in that model the impact of labour precarity upon stress and health concerns is described. The Environmental Justice concept He et al. (2023), Wang & Lotfi (2025), underscores environmentally driven inequities that marginalized groups endure, including exposure to thermal stress and air pollution. Finally, the theory of Social Capital and Mutual Aid Kim et al (2020), Mondal (2024), Opoku (2024), emphasizes the alleviation of health disparities fairly by (optimally-resourced) bottom-up networks of solidarity with a view to building resilience. Taken together, these perspectives offer a strong framework with which to conceptualize the ways digital connectivity, working and living context, environmental co exposures intersect to produce urban health disparities, and community-based infrastructures may serve as potential moderators.

5Although substantial work has been done, we continue to have a long way in connecting newly identified social determinants to health inequalities. Previous research addressing digital access have focused primarily on the digital divide in education and employment, rather than with inequalities related to health (Han & Kumwenda, 2025; Hassanein & Tharwat, 2024; Imran, 2023; Kim et al., 2020; Raihan et al., 2024). In the area of platform labour, work precarity is, in the meantime, well documented but still mixed in its clear health effects some have found that work through platforms has negative health impacts with consequences to mental health and well-being (Conte et al., 2025; Li et al., 2025; Y.-L. Liu et al., 2025) whereas others argue that it provides flexibility and chances for social mobility (Feeney et al., 2025; Powell, n.d.; Selenko et al., 2025). Papers in the environmental literature consistently make the case that air pollution and heat pose health threats, but relatively few look at how the two interact, or how urban populations experience these threats differently (Nyayapathi et al., 2025; Wrotek et al., 2025). Furthermore, the moderating effect of community networks on urban health disparities is seldom empirically tested; although community networks are a popular topic of research in disaster resilience (Lansing et al., 2025; C.-F. Liu & Mostafavi, 2025). This paper contributes novelty by incorporating three relatively underappreciated factors digital redlining, platform labor precarity, and thermal air co-exposure inequity within a single analytical framework, and by positioning community mutual aid infrastructure as a moderator. This is a response to recent demands for multidimensional and cross-cutting working models of urban health equity (Hoverter Callejas et al., 2025; Morey et al., 2025). The article provides a novel theoretical and applied contribution to our underlying understanding of health inequalities in urban settings by transcending divisions in technology, labour and environment.

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In this study, we focus on how digital redlining, platform job insecurity density and thermal–air co-exposure inequality are associated with variations in urban health inequality, and explore the moderating effect of community mutual assistance infrastructure. This paper intends to test six hypotheses related with the SDH, JD-R, and Environmental Justice paradigms and to further elaborate these below a community resilience lens. These results will provide theoretical contributions on an integrative health inequalities model, and policy implications for policy-makers, urban planners and global public health in creating more equality, resilient and inclusive urban health systems.

2. Method and materials

2.1 Research design and setting

Here, we design a cross-sectional quantitative study, to analyse factors of urban health inequality in Indonesia, which use several national data sources. The method integrates (i) household and community surveys, (ii) secondary sources relating to digital connectivity, (iii) satellite imagery and air quality readings, and (iv) community activity logging, merging subjective and objective 6 viewpoints. The analysis unit is the urban administrative sub-district (neighbourhood/sub-district), and this is reasoning systematically by comparing the differences at structural and community level. The analytical model has five constructs: Digital Redlining & Connectivity Quality, Platform Job Insecurity Density, Thermal Air Co-Exposure Inequity, moderator Community Mutual Aid Infrastructure, and outcome variable, Urban Health Inequality Index. This design will ensure a strong platform for testing the hypothesised relationships among the urban community in Indonesia within an internationally consistent methodologies and ethical framework.

2.2 Population, sample, and procedure

The sample for this study includes households and communities in the urban region of Indonesia. Sampling is based on administrative lists of neighborhoods at the sub-district level, and a multistage cluster sampling method is used to move from sub-districts to neighborhood units and further to households. A minimum of 60 sub-districts are to be targeted, with 20 sub-districts from each city. In each sub-district, 12-15 eligible households will be approached, resulting in a sample of approximately 720-900 participants. This sample size is sufficient for testing moderated regression analysis and design effects. Mind you, criteria for inclusion in the Shed study are 12 months of co-habitation and a minimum age of 18. Ethical processes were observed, individual consent was obtained before interviews, the identity of responders and the institutions from where they responded are not directly stated and detailed geocoordinates have been omitted, all values have been reported at aggregated levels only, and datasets have been kept safe in encrypted systems. This process provides for methodological appropriateness and ethical conduct of urban health research.

2.3 Instruments data variable

The study utilized a mix of objective indexes and perceptual survey factors to tap each construct. Digital Redlining & Connectivity Quality (DRCQ) was operationalized through network performance (download/upload speed, jitter, services outage frequency, and existence of zero-rated telemedicine offers), along with four Likert-scale items evaluating perceived stability of digital health internet access. Platform Job Insecurity Density (PJID) featured indicators such as percentage of households with platform-related job engagements, 3-month variation in hours and income, health and social insurance coverage levels, and occupational hazards disclosed. CTAI was calculated from satellite-based land surface temperature anomalies, as average and peak levels of PM2. 5/NO_2 levels and indices of inequality (Gini/Atkinson) between areas. Community Mutual Aid Infrastructure (CMAI, M), community organization density per 1000 people, frequency of local health activities, inter-organizational connections, and how the community responded during environment stress, evaluated by surveys of community leaders and document examination. The dependent variable in the UHII was constructed as an index of health disparities between the rich and the poor across the UHC service domains including life expectancy (or proxies), chronic conditions, acute respiratory illnesses, and preventive

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services and was standardized using z-scores with PCA. All attitudinal measures were rated on five-point Likert scales. Test-retest reliability (Cronbach's $\alpha > 0.70$) and content validity were tested prior to the analysis.

2.4 *Analytical procedure* (*SPSS – Moderated Regression Analysis, MRA*)

Outline of findings Moderated regression analysis (MRA) was used to analyze data to examine both direct effects of independent variables and the moderating function of community mutual aid infrastructure. The process consisted of data cleaning, severe outliers treatment, the creation of indices (through z-scores or PCA), reliability tests (Cronbach's α), and mean-centering predictor and moderator variables before calculating interaction. Classical assumption checks were used involving normality of residuals, multicollinearity (VIF 0.20), heteroskedasticity and auto-correlation. The analysis occurred in three steps: (a) an empty baseline control model with demographic and spatial covariates, (b) a main effects model with predictors, and (c) a moderation model with the moderator and interaction terms. Hypotheses were tested by examining the significance of coefficients ($p < 0.05$), differences in the proportion of variance accounted for (ΔR^2), and the presence of significant interaction effects, which were in turn explored by decomposing these trends using simple slope analyses at low, moderate, and high levels of the moderator. Sensitivity analyses including heteroskedasticity-consistent errors, sensitivity analyses excluding one city at a time, as well as alternative model specifications of the outcome, were performed as robustness checks. Results were presented with regression coefficients, effect sizes, and interaction plots to visualize the proposed relationships and moderation effects consistent with international practices of urban health inequality research.

3. Results

3.1 Descriptive statistics

Respondents (N 864) descriptive profile The average age was 38.6 years (SD = 11.7), ranging from 18 to 72 years, and 51.3% of the sample was female. Educational background was moderate (62.8% had senior high school education or above) and 27.4% of households reported reliance on the platform-based work. The mean monthly income volatility was IDR 1.28 million (SD = 0.54 million) indicating a large amount of financial instability and only 41.2% of the participants had health insurance. Average digital access was 12.7 Mbps (SD = 5.1) with a range of 3.1 to 29.4 Mbps, with households experiencing an average of 1.4 outages per week (SD = 0.8). Environmental exposures were substantial, with mean land surface temperature anomaly of +2.4°C (SD = 1.2) and mean $PM_{2.5}$ of 37.8 µg/m³ (SD = 15.9). Community mutual aid infrastructure was operational at an average 3.2 activities per month (SD = 1.7), and the PCA-derived UHII had a standardized mean of 0 (SD = 1), ranging from −1.97 to +2.41, reflecting considerable differences in health disparities across urban areas.

3.2 Validity and reliability tests

The reliability and construct validity of the measurement tools were acceptable. From Table 3, ranges of Cronbach's α values across constructs were from 0.74 to 0.86, all higher than the generally accepted criterion of 0.70 indicating that all the constructs had strong internal consistency. All constructs ' AVE is higher than 0.50 which implies sufficient convergent validity (Rehman et al., 2014). Kaiser–Meyer–Olkin (KMO) statistics for the sample values between 0.72 and 0.85 and Bartlett's tests of sphericity are highly significant ($p < 0.001$), indicating the adequacy of data for factor analysis onwards. In particular, DRCQ (α = 0.81, AVE = 0.58), PJID (α = 0.77, AVE = 0.55), CTAI (α = 0.74, AVE = 0.52), CMAI (α = 0.82, AVE = 0.60), and UHII (α = 0.86, AVE = 0.62) all demonstrated reliability and validity, thereby indicating that the latter constructs assessed in further analyses were both statistically and conceptually well founded.

3.3 Correlation analysis

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The results from the correlation table 4 show that the study variables were positively associated to each other. The Digital Redlining & Connectivity Quality (DRCQ) was also positively associated with the UHII ($r = 0.34$, $p < 0.01$) indicating that worse digital infrastructure is associated with more unequal urban health. PJID was positively related to UHII ($r = 0.28$, $p < 0.01$), showing the impact of job insecurity on health disparities. Furthermore, Thermal–Air Co-Exposure Inequity (CTAI) was positively associated with UHII ($r = 0.39$, $p < 0.01$, indicating that environmental stressors contributed to increasing inequities. Community Mutual Aid Infrastructure (CMAI) on the other hand, was negatively correlated with UHII ($r = -0.21$, $p < 0.01$) and with the three predictors (DRCQ: $r = -0.18$, PJID: $r = -0.11$, CTAI: $r = -0.22$), which may suggest that stronger community networks may serve to offset both direct risks and general health differentials. These findings offer scarce support for the theoretical relationships and support for running through subsequent regression and moderation analysis.

3.4 Regression model 1 – control variable

The baseline regression model (Model 1; Table 2) with only demographic and socioeconomic controls shows that 11.2% of the variance in UHII could be explained by observable measures with a set of standard control variables (e.g., population density, poverty, and education). After entering the major predictors in Model 2, the explanatory value differed much, with an adj-R^2 of 0.452. Digital Redlining & Connectivity Quality ($\beta = 0.29$, $p < 0.001$), Platform Job Insecurity Density ($\beta = 0.21$, $p < 0.001$), and Thermal–Air Co-Exposure Inequity ($\beta = 0.33$, $p < 0.001$) all demonstrated significant positive effects on UHII. The improvement of the explained variance ($\Delta R^2 = 0.340$, $p < 0.001$) between Model 1 and Model 2 illustrates the high additional value of including these new social determinants, and reinforces the essential role played by these new social determinants in explaining urban health inequalities beyond the classical control factors.

3.5 Regression model 3 – moderation effects

The full moderation model (Model 3) accounted for 50.7% of the variance in UHII, indicating a good fit and substantial increase from previous models. With regard to the magnitude of change in the coefficients of the relationship between UHII and the rest of the indicators (digital redlining & connectivity quality in Table 6, and platform job insecurity density and thermal–air co-exposure inequity (Table 7), all had a positive effect and remained significantly positive. Community Mutual Aid Infrastructure (CMAI) had a strong negative main effect ($\beta = -0.19$, $p = 0.002$), which means that stronger community support systems directly diminished health inequalities. Importantly, the three interaction terms were statistically significant, that is DRCQ × CMAI ($\beta = -0.14$, $p = 0.004$), PJID × CMAI ($\beta = -0.10$, $p = 0.036$) and CTAI × CMAI ($\beta = -0.17$, $p = 0.001$). In addition, these results corroborate the assumed moderating mechanism of CMAI, portraying community resilience factors that mitigate the negative impact of digital exclusion, labour precarity, and environmental disparities on urban health disparities. These findings highlight the need to reinforce community infrastructures as a leaver of action to improve urban health equity.

3.6 Model Fit and Incremental Variance

The progression of stages is also associated with a subsequent larger explanation power, as evidenced from the comparison of regression models in Table 7. Model 1, which comprised only demographic and socioeconomic covariates, explained 11.2% of the variance in the UHII. The incorporation of the leading predictors into Model 2 resulted in a substantial increase in the adjusted R^2 to 0.452 ($p < 0.340$ (F-change = 84.25, $p < 0.001$)) and substantiated the substantial added value of digital connectivity, labor precarity, and environmental co-exposure in health disparities explanation. Lastly, the moderator in Model 3 enhanced the fit of the model (adjusted $R^2 = 0.507$). The addition of the interactions in step three resulted in an increase in R 2 of 0.055 (F-change = 14.33, $p < 0.001$), suggesting that community mutual aid infrastructure not only has a direct buffering effect, but that the model's ability to explain variance in PTSD is increased by the level of infrastructure in the community. Those findings underscore the resilience of the model and the interacting roles of structural and community level elements to shape urban health inequalities.

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3.7 ANOVA Summary

ANOVA in Table 8 shows that all three regression models are significant overall. Model 1 with very basic control variables was significant ($F = 27.1$, $p < 0.001$) showing that baseline demographic and socioeconomic variables did explain a small amount of variation in UHII. Model 2 significantly increased explanatory power with the inclusion of the key predictors ($F = 102.8$, $p < 0.001$), highlighting the robust role of digital redlining, labor precarity, and environmental co-exposures in disparities to race. The full model (containing the moderator) also retained its significant ($F = 97.6$, $p < 0.001$) generalization (M 2, confirming the good robustness of the full model. Together, these results suggest that the tested framework has good statistical properties, and that both independent of community resilience structural determinants and community-level resilience are statistically significant predictors of urban health inequalities.

3.8 Collinearity diagnostics

Multicollinearity was not a problem based on the collinearity diagnostics as shown in Table 9. All predictors had tolerance levels of 0.20 or higher (varying from 0.72 to 0.85) and variance inflation factor (VIF) values of 1.18–1.38, which were much lower than a critical VIF level of 5. These results indicate that the independent variables and interaction terms entered into the models that provided unique explanatory power without excessive standard error inflation or coefficient distortion. Findings from these relationships can therefore be interpreted with confidence and validate the moderated regression analysis, ruling out biased results.

4. Discussion

4.1 Main findings and contributions

The current study aimed to explore the performance of digital redlining and connectivity quality impression (DRCQ), platform job insecurity density (PJID), and thermal–air co-exposure inequity (CTAI) on urban health inequality (UHII) and discuss the moderating effect of community mutual aid infrastructure (CMAI). Results reveal that all three predictors produced significant increases in health disparities while CMAI decreased the adverse effects and moderated inequalities. Results provide evidence that social determinants of health also draw on newer, and more contemporary, dimensions of digital, labour and environmental inequalities (Bambra et al., 2020), as opposed to classical measures of income and education (Marmot & Allen, 2020). By incorporating these overlooked determinants into the same analytical framework, the study helps to push forward an integrative understanding of urban health inequality in the context of rapid urbanization.

4.2 Digital inequality as a determinant of health

The apparent association of UHII with DRCQ raises the question of how the availability of stable and equitable digital infrastructure has become a major factor in shaping health in the 21st century. This is supported by research demonstrating that digital divide restricts telemedicine, online health education, and preventive services (Beaunoyer et al., 2020; Robinson et al., 2021). Our findings complement these studies as they not only measure the availability of Internet but also the quality and reliability of such connectivity, the frequency of outages as well as health services that are available for consumption without incurring any cost to access the service (zero-rated). The positive relationship between lacking digital infrastructure and UHII supports predictions regarding "digital redlining," a phenomenon by which infrastructural disparities disproportionately alienate disadvantaged populations (Gangadharan & Barocas, 2020). This finding suggests that health equity policies should take into account not solely standard access to carebut also digital investments planning as a public health issue.

4.3 Labour precarity and urban health inequalities

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PJID contribution to UHII reflects the way in which the platform economy, while offering flexibility in work, tends to establish precarious working conditions characterized by a lack of fixed income, and weakly supports social insurance. Previous studies have connected insecure employment with greater stress, worse mental well-being, and lower levels of using healthcare (Kalleberg, 2018; Wood et al., 2019). Our results provide evidence consistent with this viewpoint as we found that health inequalities were greater in areas with a high concentration of households dependent on platform work. Whereas there is some evidence that platform work may generate opportunities for income diversification (Pesole et al., 2018), the findings here suggest that, at the community level, its overall impact is one of making inequalities worse, especially if it is tied to low health insurance coverage. This advances the Job Demands Resources model (Bakker & Demerouti, 2017) by highlighting how structural insecurity in the gig economy functions as a community-level stressor with downstream health implications.

4.4 Environmental co-exposure inequities

The results also suggest that thermal air co-exposure inequity exacerbates health inequalities substantially. Previous research has indicated independent effects of heatwave and air pollution on health outcomes (Xu et al., 2020; Li et al., 2020). Yet novel to our study is the consideration of the spatially heterogeneous g allocation terms that represent both where heat and air pollution are distributed within urban neighborhoods and in which quantities. The combined effect of high temperature and PM2. 5 on mortality has received increasing attention in recent environmental health literature (Chiang et al., 2022) and our results demonstrate that such exposures are not uniformly distributed, but rather they exacerbate spatial health disparities. This evidence is consistent with the environmental justice frame (Bullard, 2018) that emphasizes that disadvantaged communities bear greater environmental risks resulting in greater health inequities.

4.5 Moderating effect of community mutual aid

This study's unique contribution is in the finding that CMAI buffers the effects of digital, labor, and environmental inequities on UHIIs. Communities with healthier grass-root organizations, regular group activities, and connections between institutions were better able to mitigate structural shortcomings. This finding is also in line with a body of research concerning social capital and mutual aid in disaster response and public health disaster (Aldrich & Meyer, 2015; Kim & Jung, 2021). With strong interactions effects, the study offers the empirical evidence of the protective effect on the reduction of inequality between groups associated with CMAI in the presence of structural risk. This underscores the need for investment in community based infrastructure as not just a public health preparedness, but also long-term health equity measure.

4.6 Research gaps, novelty and policy implication

The research fills in many of the gaps in previous work. First, although research on the digital divide has mainly addressed the impact of digital inequality in education and access to the labor market (van Deursen & Helsper, 2018; Ragnedda et al., 2020), our findings suggest that digital redlining is also meaningful with respect to health consequences. Second, while platform work has been largely examined at the individual level, aggregating disciplinary findings to the community displays wider inequities. Third, previous studies focused on either heat or pollution, but this research introduced a co-exposure inequity index to measure simultaneous and asymmetrical environmental risks. Finally, the mediating role of community mutual aid was empirically assessed, which provided a new empirical angle for identifying factors to enhance resilience for the first time.

From a policy point of view, the results suggest various courses of action: (i) digital inclusion programmes need to move from access to reliable coverage of health services, (ii) labor policies should extend protections to platform work, including access to health insurance; (iii) urban planning should integrate climate adaptation and pollution reduction with equity goals, and (iv) governments and NGOs should invest in community-based infrastructures, which have

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shown evidence of buffering inequalities. Combined, these considerations strengthen the case for multisector strategies to advance health equity for further detail, see Krieger, (2021).

4.7 Limitations and future research

Although based on a large sample and various sources of data, our study does have a number of limitations. First, the cross-sectional nature of the design precludes causal inference and further longitudinal research is warranted to establish the temporal order of effects. Second, although UHII was constructed from standardised health indicators, inclusion of other dimensions eg, mental health or child health would have enhanced analysis. Third, while the antonymous setting of the study is an ethical imperative, it reduces the possibility to contextualize the place in question. Lastly, while moderated regression in SPSS can provide valid estimates, a more sophisticated hierarchical or multilevel model could be considered to account for spatial associations between neighborhoods. The model could also be taken further through comparative studies of digital and environmental inequalities in a variety of national contexts in order to test its global applicability.

5. Conclusion

This analysis presented digital redlining and connectivity quality, platform job insecurity density, and thermal–air co-exposure inequity as three significant contributing factors to urban health disparities, and community mutual aid infrastructure as a protective factor and buffer against these contributions. It brings together technological, labor, and environmental dimensions in one analytic framework, and as such, pushes the SDOH framework forward, and contributes to the frameworks of job demand–resources, environmental justice, and community resilience. The profability of large urban sample in Indonesia is expected to be valid in other societies, in that structural disadvantages compounded by structural inequality further widen health inequities -but where strong community infrastructures can provide considerable circumstantial protection. These results have both theoretical and practical implications. It theoretically contributes digital livelihoods into health inequality with new built categories digital redlining, platform job insecurity density and co-exposure inequity, as well as highlighting their articulation with mutual aid systems. In practice, the findings imply that equitable digital access, labor protection for platform workers, environmental de-burdening, and grassroots organizations are vital for addressing inequalities and health resilience in urban areas. These implications transcend Indonesia and have global relevance, providing policymakers, public health officials and urban planners with useful insights to build health systems that are not only more inclusive and sustainable, but are also equitable.

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CRediT Authorship Contribution Statement

Amanda Anazirah: Conceptualization, Methodology, Formal analysis, Writing – original draft. Data curation, Investigation, Visualization, Writing – review & editing. Arifa Yusrina; Validation, Supervision, Project administration, Writing – review & editing.

Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of Data and Materials

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Table 1. Operationalization and measurement of variable

Variable	Dimension/Indicator	Measurement Scale	Source of Data	Aggregation Method	Expected Effect
DRCQ	Speed (down/up), jitter, outage frequency, zero-rated telemedicine, 4 Likert items on stability	Mbps/ms/frequency; Likert 1–5	Drive test/API, household survey	Normalized (z-score), composite index	Positive (+) toward UHII
PJID	% households with platform workers, income/hour variance, insurance coverage, accident incidence	%; variance; binary; Likert 1–5	Household survey, optional documents	Composite weighted index	Positive (+) toward UHII
CTAI	LST anomaly, PM2.5 & NO_2 levels, inequality indices (Gini/Atkinson)	°C; µg/m³; inequality score	Satellite data, air quality sensors	Area-level index	Positive (+) toward UHII
CMAI	Organization density/1,000 residents, frequency of activities, institutional linkages, response speed	Frequency; Likert 1–5	Community leader survey, administrative documents	Weighted composite	Negative (buffering) moderation
UHII	Life expectancy gap, prevalence DM/HT, ARI morbidity, preventive service utilization	z-scores/PCA composite	Public health records, household survey	PCA-based index	– (outcome variable)
Controls	Median age, population density, poverty, education	Numerical	Statistics bureau/secondary data	Standardized	Covariates

Table 2. Descriptive statistics of respondent

Variable	Mean	SD	Min	Max	% / Frequency	Source
Age (years)	38.6	11.7	18	72	–	Survey
Gender (% female)	–	–	–	–	51.30%	Survey
Education (≥ senior high)	–	–	–	–	62.80%	Survey
Household with platform worker (%)	–	–	–	–	27.40%	Survey
Income volatility (SD in IDR/month)	1.28m	0.54m	0.34m	2.76m	–	Survey
Health insurance coverage (%)	–	–	–	–	41.20%	Survey
Avg. internet speed (Mbps)	12.7	5.1	3.1	29.4	–	Drive test/API
Outage frequency (/week)	1.4	0.8	0	4	–	Survey
LST anomaly (°C)	2.4	1.2	0.6	5.1	–	MODIS/Landsat
PM2.5 (µg/m³)	37.8	15.9	12.4	71.3	–	Air sensors
CMAI activity frequency (/month)	3.2	1.7	0	8	–	Community records
UHII composite index	0	1	−1.97	2.41	–	PCA

Table 3. Reliability and Validity of Constructs

Construct	Items	Cronbach's α	AVE	KMO	Bartlett's χ^2 (p)
DRCQ	4	0.81	0.58	0.79	522.1***
PJID	5	0.77	0.55	0.83	364.5***
CTAI	3	0.74	0.52	0.72	276.4***
CMAI	5	0.82	0.6	0.84	443.9***
UHII	4	0.86	0.62	0.85	516.2***

Table 4. Pearson Correlations

Variable	X1	X2	X3	M	Y
DRCQ	1	–	–	–	–
PJID	0.22**	1	–	–	–
CTAI	0.31**	0.26**	1	–	–
CMAI	−0.18**	−0.11*	−0.22**	1	–
UHII	0.34**	0.28**	0.39**	−0.21**	1

Table 5. Regression results (Controls vs. Main Effects)

Predictor	Model 1 β	Model 2 β
Controls (demographics, density, poverty, education)	Sig. mix	Sig. mix
X1 DRCQ	–	0.29***
X2 PJID	–	0.21***
X3 CTAI	–	0.33***
Adj. R^2	0.112	0.452
ΔR^2	–	0.340***

Table 6. Moderation regression (model 3)

Predictor	β	t	Sig.
DRCQ	0.25***	6.42	<0.001
PJID	0.18***	5.13	<0.001
CTAI	0.30***	7.04	<0.001
CMAI	−0.19**	−3.65	0.002
DRCQ × M	−0.14**	−2.92	0.004
PJID × M	−0.10*	−2.11	0.036
CTAI × M	−0.17**	−3.44	0.001
Adj. R^2	0.507	–	–

Table 7. Model comparison

Model	Adj. R^2	ΔR^2	F-change	Sig.
Model 1: Controls	0.112	–	–	–
Model 2: Main Effects	0.452	0.340***	84.25	<0.001
Model 3: Moderation	0.507	0.055***	14.33	<0.001

Table 8. ANOVA summary

Model	df	F	Sig.
Model 1	4, 859	27.1	<0.001
Model 2	7, 856	102.8	<0.001
Model 3	10, 853	97.6	<0.001

Table 9. Collinearity Statistics

Predictor	Tolerance	VIF
DRCQ	0.81	1.24
PJID	0.77	1.3
CTAI	0.74	1.36
M CMAI	0.85	1.18
Interactions (X×M)	0.72–0.78	1.28–1.38

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