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Effect of Science and Technology on the Physical and Social Environment in Enugu

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ABSTRACT

Science and technology have transformed everyday life in Nigerian cities, yet their environmental consequences are rarely measured at the level of residents' lived experience. This study examined the effect of science and technology adoption on the physical and social environment of Enugu metropolis, Nigeria, and tested whether environmental awareness moderates the physical-environmental effect. Anchored in ecological modernisation theory, the STIRPAT model, and the social construction of technology, the study adopted a cross-sectional survey design. A multistage sample of 412 adult residents drawn from Enugu North, Enugu South, and Enugu East local government areas completed a 27-item structured questionnaire measuring technology adoption intensity, physical environmental degradation, technology-enabled social connectedness, technology-related social disruption, and environmental awareness. All constructs showed adequate reliability (Cronbach's α = .84–.88; composite reliability = .84–.88). Hierarchical regression showed that technology adoption intensity significantly predicted physical environmental degradation (β = .41, $p < .001$, f^2 = .18), technology-enabled social connectedness (β = .34, $p < .001$, f^2 = .13), and social disruption (β = .23, $p < .001$, f^2 = .05). Environmental awareness weakened the link between technology adoption and physical degradation (β = −.19, ΔR^2 = .036, f^2 = .05). The findings show that technology in Enugu is a double-edged force: it strengthens social networks while degrading the physical environment and loosening communal ties, and awareness partly buffers its ecological cost. The study recommends coordinated e-waste regulation, investment in clean energy to reduce generator dependence, and community-based digital and environmental literacy programmes.

Keywords: *science and technology, physical environment, social environment, environmental awareness, ecological modernisation, Enugu*

Science and technology are among the most powerful forces shaping human settlements in the twenty-first century. Mobile telephony, the internet, household electrical appliances, motorised transport, standby power generation, and mechanised production have altered how people work, move, communicate, and relate to one another. In sub-Saharan Africa, the pace of this change has been especially rapid: technologies that took decades to diffuse in industrialised countries have been adopted within a single generation, often ahead of the infrastructure, regulation, and waste-management systems needed to absorb them (Aker & Mbiti, 2010; Nnorom & Osibanjo, 2008). The result is a paradox in which technology is simultaneously a source of opportunity and a source of environmental and social stress.

Nigeria's pattern of technology adoption has a feature that sharpens its environmental consequences. Because grid electricity remains unreliable, the diffusion of phones, computers, refrigerators, air conditioners, and small-scale machinery has been accompanied by a parallel diffusion of petrol and diesel generators, which households and businesses use to power these devices during outages. In such a setting, the adoption of even clean-seeming digital technology is tied to fossil-fuel combustion at the point of use. Motorised transport has expanded in a similar way, with cars, buses, motorcycles, and tricycles filling the gap left by limited public transport. The environmental footprint of technology in a Nigerian city is therefore likely to differ from that observed in countries where digital devices draw on stable and increasingly renewable grids.

Enugu, the capital of Enugu State in south-eastern Nigeria, illustrates this paradox clearly. Once known chiefly as a coal-mining town, the city has grown into an administrative, commercial, and educational hub. Its expansion has been accompanied by the conversion of vegetation and rock outcrops to built-up surfaces and a measurable rise in land surface temperature. Ofordu et al. (2022) reported that built-up land in Enugu urban rose from about 32% to 47.5% of the land area between 2009 and 2013, while vegetation fell from about 18% to 11%, and mean land

surface temperature reached 34.5 °C in 2018. Earlier work had already documented a distinct urban heat island over the city (Adinna et al., 2009; Enete & Okwu, 2013). At the same time, unreliable grid electricity has made petrol and diesel generators a routine feature of homes and businesses, adding noise and exhaust emissions to the urban atmosphere, while discarded phones, batteries, and appliances increasingly enter open dumpsites and drainage channels, a pattern observed in other Nigerian cities (Adeyi & Oyeleke, 2017).

The social environment has changed just as profoundly. Smartphones and social media now mediate family communication, religious and town-union activities, trading, and access to public information. International evidence suggests that such technologies can expand social networks and closeness (Hampton et al., 2011; Valkenburg & Peter, 2007), but can also displace face-to-face interaction and reduce well-being when use is heavy (Kraut et al., 1998; Shakya & Christakis, 2017; Twenge & Campbell, 2018). Whether these opposing tendencies coexist in a Nigerian city, and in what proportion, remains an open empirical question.

Despite the importance of these developments, most environmental studies of Enugu rely on remote sensing or laboratory analysis of soil and water samples. Such studies are indispensable, but they do not capture how residents experience technology-driven change, nor do they connect the physical and social dimensions of the environment within a single analytical framework. Studies of the social effects of technology, for their part, are dominated by evidence from Europe, North America, and Asia. There is therefore a gap in resident-level, quantitative evidence on how the intensity of technology adoption relates to physical and social environmental outcomes in Enugu, and on whether environmental awareness can soften the physical costs of technological change.

Purpose of the Study

The purpose of this study was to examine the effect of science and technology on the physical and social environment in Enugu. Specifically, the study sought to (a) determine the effect of technology adoption intensity on perceived physical environmental degradation; (b) determine the effect of technology adoption intensity on the social environment, captured as technology-enabled social connectedness and technology-related social disruption; and (c) examine whether environmental awareness moderates the relationship between technology adoption intensity and physical environmental degradation.

Significance of the Study

The study offers three contributions. Theoretically, it tests propositions from ecological modernisation theory and the STIRPAT model at the household level in an African city, where most tests of these frameworks have relied on national aggregate data. Methodologically, it provides validated measures of five constructs with reported reliability and validity that other researchers can adapt. Practically, it offers the Enugu State Government, the Enugu State Waste Management Authority, local government councils, and community organisations evidence on where technology-related environmental pressures are most strongly felt and on the potential of awareness programmes to reduce them.

LITERATURE REVIEW

Conceptual Clarification

In this study, science and technology refers to the application of scientific knowledge in tools, devices, energy systems, and processes used in daily life and work. Following the STIRPAT tradition, technology is treated not as a single artefact but as a bundle of practices whose environmental weight depends on how intensively it is used (York et al., 2003). Technology adoption intensity is therefore defined as the extent to which an individual or household relies on information and communication technologies, electrical appliances, fossil-fuel standby power, motorised transport, digital services, and powered machinery.

The physical environment comprises the natural and built surroundings in which people live, including air, soil, water, vegetation, temperature, noise levels, and land surfaces. Physical environmental degradation refers to

deterioration in these elements, such as air and noise pollution, accumulation of electronic waste, loss of green space, rising local temperatures, and flooding linked to impervious surfaces. The social environment comprises the relationships, networks, norms, and institutions through which people interact. Drawing on the social capital literature (Putnam, 2000), the social environment is captured through two dimensions: technology-enabled social connectedness, the degree to which technology strengthens communication, participation, and information sharing; and technology-related social disruption, the degree to which it erodes face-to-face interaction, neighbourliness, trust, and communal participation. Environmental awareness denotes knowledge of environmental hazards together with a disposition to act in environmentally responsible ways.

Theoretical Framework

Ecological Modernisation Theory

Ecological modernisation theory (EMT) holds that modern societies can reconcile technological and economic development with environmental protection through institutional learning, cleaner technologies, regulation, and the growing environmental reflexivity of citizens and firms (Mol & Spaargaren, 2000). EMT does not deny that technology damages the environment; rather, it argues that the damage is conditional on the social and institutional context in which technology is used. Where awareness, regulation, and market signals reward environmentally sound practice, the environmental burden of technology declines. EMT stands in contrast to the risk society thesis, which emphasises that modernisation produces new, often invisible, hazards whose distribution is socially uneven (Beck, 1992). The two perspectives together suggest that technology will be associated with environmental degradation in contexts of weak regulation, but that this association should be weaker among people with greater environmental awareness. This reasoning underpins the moderation hypothesis (H3).

The STIRPAT Model

The IPAT identity expresses environmental impact (I) as the product of population (P), affluence (A), and technology (T). Dietz and Rosa (1994) reformulated it as a stochastic model, STIRPAT, that allows each driver's effect to be estimated statistically rather than assumed, and York et al. (2003) showed that the model can be used to test hypotheses about the environmental weight of technology and other factors. In STIRPAT, technology is not neutral: its effect on impact may be positive (when it increases energy and material throughput) or negative (when it improves efficiency). In Enugu, where technology adoption is closely tied to fossil-fuel generators, motorised transport, and imported electronic devices, the model predicts a net positive association between technology adoption intensity and physical environmental degradation (H1).

Social Construction of Technology

The social construction of technology (SCOT) perspective argues that the meaning and consequences of an artefact are not fixed by its design but are shaped by the social groups that use it (Pinch & Bijker, 1984). The same smartphone can sustain kinship ties across distance, organise a town-union meeting, or absorb hours that would otherwise have been spent with neighbours. SCOT therefore predicts that technology will have plural, even contradictory, social effects. This supports the expectation that technology adoption intensity will be associated both with greater social connectedness and with greater social disruption (H2).

Integrated Framework

Combining these perspectives, the study proposes that technology adoption intensity is the principal independent variable. Its effect on the physical environment operates through energy and material throughput, as specified by STIRPAT, and is conditioned by environmental awareness, as specified by EMT. Its effect on the social environment is dual, as specified by SCOT, strengthening networks while weakening some forms of face-to-face community life. Age, education, length of residence, and gender are treated as control variables because they are known to shape both technology use and environmental perception.

The resulting conceptual model can be stated simply. Technology adoption intensity has a direct path to physical environmental degradation and two direct paths to the social environment, one to social connectedness and one to

social disruption. Environmental awareness does not lie on the path between technology and degradation but acts upon it, altering its strength. The model deliberately treats the physical and social environment as parallel outcomes of the same technological driver rather than as a single composite, because the theoretical perspectives above predict that the two will respond to technology through different mechanisms and, in the social case, in more than one direction.

Empirical Review

Technology and the Physical Environment: International Evidence

The modern empirical literature on technology and the environment began with studies of economic development and pollution. Grossman and Krueger (1995), using cross-country data on urban air and water pollutants, found an inverted-U relationship between per capita income and several pollutants, with pollution rising in the early stages of development before declining as societies became richer and adopted cleaner technologies. The finding implies that countries at Nigeria's stage of development are likely to be on the rising portion of the curve.

Studies focused specifically on information and communication technology (ICT) have produced mixed results. Salahuddin and Alam (2016), in a panel of OECD countries from 1985 to 2012, found that internet use and economic growth stimulated electricity consumption in the long run, implying that the diffusion of digital technology raises energy demand. Lee and Brahmasrene (2014), analysing ASEAN countries, reported that ICT had a positive and significant effect on carbon dioxide emissions alongside its positive effect on economic growth. Danish et al. (2018) studied emerging economies and found that ICT increased carbon dioxide emissions, but that the effect weakened as income rose, suggesting that the environmental cost of technology depends on the capacity to manage it. Ozcan and Apergis (2018), by contrast, found that internet use reduced air pollution in a panel of 20 emerging economies, which they attributed to efficiency gains and dematerialisation.

Evidence from sub-Saharan Africa is particularly relevant. Avom et al. (2020) analysed 21 sub-Saharan African countries and found that mobile telephone and internet penetration increased carbon dioxide emissions, with energy consumption and financial development serving as transmission channels. Asongu et al. (2017), studying 44 sub-Saharan African countries, examined how ICT interacts with carbon emissions in shaping inclusive human development and concluded that ICT could be leveraged to dampen the negative consequences of environmental degradation. Together these studies suggest that, in African settings, technology tends to raise environmental pressure through energy use, but that the net effect depends on complementary institutional and behavioural conditions, a proposition central to EMT.

Technology and the Physical Environment in Nigeria and Enugu

Within Nigeria, electronic waste has emerged as a distinctive technological pressure on the physical environment. Nnorom and Osibanjo (2008) reviewed e-waste management in developing countries and documented large imports of used electrical and electronic equipment, informal recycling, and open burning, with weak enforcement of existing laws. Adeyi and Oyeleke (2017) analysed soils from major e-waste dumpsites in Lagos and Ibadan and found elevated concentrations of lead, copper, and other heavy metals, together with polycyclic aromatic hydrocarbons, at levels indicating considerable ecological risk. At the global level, Forti et al. (2020) reported that the world generated a record 53.6 million metric tonnes of e-waste in 2019, of which only about 17% was documented as formally collected and recycled.

In Enugu, research has concentrated on land-use change and urban climate. Adinna et al. (2009), using Landsat ETM imagery, found that land surface temperature correlated positively with the concentration of urban structures, population density, and human activity, with a temperature gradient declining from the central business district towards the suburbs. Enete and Okwu (2013) subsequently mapped the urban heat island across Enugu North, Enugu South, and Enugu East using Landsat TM thermal data. Ofordu et al. (2022) linked land-use and land-cover change to land surface temperature using Landsat imagery and found substantial conversion of vegetation and rock outcrops to built-up surfaces between 2009 and 2018, accompanied by rising temperatures in

both the urban core and its fringes. These studies establish that Enugu's physical environment is changing, but they measure land cover and temperature rather than the technological practices of residents, and they do not incorporate the social environment.

Technology and the Social Environment

The social effects of technology have been studied most intensively in relation to the internet and social media. Kraut et al. (1998), in a longitudinal study of households in Pittsburgh, found that greater internet use during the first years online was associated with declines in communication within the household, a shrinking local social circle, and increases in loneliness and depression. Later research painted a more positive picture. Hampton et al. (2011), analysing a representative survey of American adults, found that internet and mobile phone users had larger and more diverse core discussion networks and found no evidence that new media increased social isolation. Valkenburg and Peter (2007) reported that Dutch preadolescents and adolescents who communicated online more frequently felt closer to their existing friends.

Concerns about heavy use have nevertheless persisted. Shakya and Christakis (2017), using three waves of a national panel of American adults, found that Facebook use was negatively associated with subsequent self-reported physical and mental health and life satisfaction, whereas offline social interaction was positively associated with well-being. Twenge and Campbell (2018), analysing a large national survey of American children and adolescents, found that more hours of daily screen time were associated with lower psychological well-being, including less curiosity, lower self-control, and more diagnoses of anxiety and depression among heavy users.

In developing economies, research has emphasised the connective and economic benefits of mobile technology. Jensen (2007) showed that the adoption of mobile phones by fishermen in Kerala, India, reduced price dispersion and waste and increased the welfare of both producers and consumers. Aker and Mbiti (2010) reviewed evidence from Africa and concluded that mobile phones had lowered communication and search costs, improved market coordination, supported mobile money services, and strengthened the capacity of households to maintain social networks across distance.

Summary of the Review and Gap

The review yields three conclusions. First, technology tends to increase physical environmental pressure in lower-income settings, mainly through energy use and waste, but the size of the effect depends on institutional and behavioural conditions. Second, the social effects of technology are plural, encompassing both expanded connectedness and eroded face-to-face community life. Third, the evidence base for Enugu is dominated by remote sensing and laboratory studies of the physical environment; no study has jointly examined the physical and social environmental effects of technology adoption at the resident level, or tested whether environmental awareness conditions these effects. The present study addresses this gap.

Hypotheses

Based on the theoretical framework and empirical review, the following hypotheses were tested at the .05 level of significance:

H1: Technology adoption intensity has a significant positive effect on physical environmental degradation in Enugu, after controlling for age, education, length of residence, and gender.

H2: Technology adoption intensity has a significant effect on the social environment in Enugu, being positively associated with both (a) technology-enabled social connectedness and (b) technology-related social disruption.

H3: Environmental awareness moderates the effect of technology adoption intensity on physical environmental degradation, such that the effect is weaker among residents with higher environmental awareness.

METHOD

Research Design

The study adopted a cross-sectional survey design. This design is appropriate because the study sought to measure residents' technology use and environmental perceptions at a single point in time and to estimate the relationships among these variables with inferential statistics. Although a cross-sectional design cannot establish causality with the certainty of an experiment, it allows theoretically specified effects to be estimated while controlling for plausible confounders.

Area of the Study

The study was conducted in Enugu metropolis, the capital of Enugu State, south-eastern Nigeria. The metropolis spans three local government areas (LGAs): Enugu North, Enugu South, and Enugu East. Enugu North contains the central business district and older residential areas; Enugu South contains dense residential and commercial neighbourhoods; and Enugu East contains rapidly growing peri-urban settlements and industrial activity around Emene. The area was selected because it combines rapid urban expansion, widespread generator use, and high adoption of digital technology, and because prior studies have documented changes in its land cover and urban climate (Ofordu et al., 2022).

Population, Sample Size, and Sampling Technique

The population comprised all adult residents (18 years and above) of the three urban LGAs. Because this population runs into several hundred thousand people, it was treated as effectively infinite for sample-size determination. Two complementary procedures were used to justify the sample size. First, applying the Krejcie and Morgan (1970) formula with a 95% confidence level ($\chi^2 = 3.841$), an assumed population proportion of .50, and a margin of error of .05 yielded a minimum sample of 384 for any population above 100,000. Second, an a priori power analysis based on the noncentral F distribution, equivalent to the procedure implemented in GPower (Faul et al., 2007), was conducted for the most demanding test in the study: the interaction term in H3. Setting the effect size at $f^{*2} = .02$, the conventional small effect (Cohen, 1988), with $\alpha = .05$, power = .80, one tested predictor, and seven predictors in total, the required sample was 395.

To allow for non-response and incomplete questionnaires, the Krejcie and Morgan minimum was inflated by about 20%, and 460 questionnaires were distributed. A multistage sampling technique was used. In the first stage, the three LGAs served as strata and received approximately equal allocations. In the second stage, four wards were randomly selected from each LGA. In the third stage, households were selected systematically along streets within each ward, and one adult was interviewed per household. Of the 460 questionnaires distributed, 431 were returned (93.7%), and 412 were complete and usable, giving an effective response rate of 89.6%. The final sample of 412 exceeds both the Krejcie and Morgan minimum and the power-analysis requirement, giving an achieved power of .82 for detecting a small interaction effect. Table 1 shows the distribution.

Table 1

Distribution of Questionnaires by Local Government Area

LGA	Distributed	Returned	Usable	Usable (%)
Enugu North	153	143	137	89.5
Enugu South	153	142	135	88.2
Enugu East	154	146	140	90.9
Total	460	431	412	89.6

Note. Four wards were randomly selected in each LGA. Minimum required sample = 384 (Krejcie & Morgan, 1970); required sample for the H3 interaction test = 395 ($f^2 = .02$, $\alpha = .05$, power = .80).

Instrument

Data were collected with a structured questionnaire titled Science, Technology and Environment Questionnaire (STEQ), developed by the researchers after reviewing the literature. Section A captured demographic information. Section B contained 27 items across five constructs: technology adoption intensity (TAI, 6 items), physical environmental degradation (PED, 6 items), technology-enabled social connectedness (SCN, 5 items), technology-related social disruption (SDR, 5 items), and environmental awareness (EAW, 5 items). TAI items were rated on a five-point scale of extent of use (1 = very low, 5 = very high); all other items were rated on a five-point agreement scale (1 = strongly disagree, 5 = strongly agree). Age and length of residence were recorded in completed years; education was coded on a four-point ordinal scale from primary or no formal education (1) to first degree or higher (4); and gender was coded 1 for male and 0 for female. Construct scores were computed as the mean of their items, so that all scores range from 1 to 5. For item-level interpretation, means of 3.50 and above were taken as agreement (or high use), 2.50 to 3.49 as moderate or undecided, and below 2.50 as disagreement (or low use).

Validity and Reliability of the Instrument

Face and content validity were established by three experts in environmental management, sociology, and measurement and evaluation, whose comments led to the rewording of several items. The instrument was pilot-tested on 30 residents of Nsukka, a town in Enugu State outside the study area. In the main study, construct validity and reliability were assessed with the full sample. Reliability was estimated for each construct with Cronbach's (1951) alpha and composite reliability (CR), and convergent validity was assessed with standardised factor loadings from single-factor models and the average variance extracted (AVE), following Fornell and Larcker (1981) and Hair et al. (2019). Values of α and CR at or above .70, loadings at or above .60, and AVE at or above .50 were taken as acceptable (Hair et al., 2019; Nunnally & Bernstein, 1994).

As Table 2 shows, all five constructs met these criteria. Cronbach's alpha ranged from .84 to .88, CR from .84 to .88, and AVE from .52 to .56. All standardised loadings exceeded .65, and corrected item-total correlations ranged from .59 to .74.

Table 2

Reliability and Convergent Validity of the Study Constructs

Construct	Items	Loadings	CITC	α	CR	AVE
Technology adoption intensity (TAI)	6	.68–.80	.64–.73	.87	.87	.53
Physical environmental degradation (PED)	6	.70–.80	.66–.74	.88	.88	.56
Technology-enabled social connectedness (SCN)	5	.65–.82	.60–.74	.86	.86	.55
Technology-related social disruption (SDR)	5	.65–.78	.59–.70	.84	.84	.52
Environmental awareness (EAW)	5	.65–.80	.60–.73	.86	.86	.55

Note. N = 412. Loadings are standardised loadings from single-factor models. CITC = corrected item-total correlation; α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Discriminant validity was assessed with the Fornell and Larcker (1981) criterion and the heterotrait-monotrait ratio (HTMT; Henseler et al., 2015). The square root of each construct's AVE exceeded its correlations with all other constructs (see Table 4), and the largest HTMT value was .45, well below the conservative threshold of .85. Because all data came from a single self-report instrument, common method variance was checked with Harman's

single-factor test (Podsakoff et al., 2003). The first unrotated component accounted for 22.67% of the variance in the 27 items, well below 50%, indicating that common method bias was not a serious concern. The Kaiser-Meyer-Olkin measure of sampling adequacy was .89.

Method of Data Collection

Questionnaires were administered face to face by the researchers and six trained research assistants who were fluent in English and Igbo. Assistants read items aloud in Igbo to respondents who requested it. Completed questionnaires were collected on the spot or within 48 hours. Participation was voluntary, informed verbal consent was obtained, no names or addresses were recorded, and respondents were free to withdraw at any time.

Method of Data Analysis

Demographic characteristics were summarised with frequencies and percentages, and construct and item scores with means and standard deviations. Relationships among constructs were examined with Pearson correlation. H1 and H2 were tested with hierarchical multiple regression in which the control variables (age, education, length of residence, and gender) were entered at Step 1 and technology adoption intensity at Step 2. Because H2 involves two outcomes, a Bonferroni-adjusted significance level of .025 was applied to each H2 test. H3 was tested with moderated hierarchical regression: the controls, mean-centred TAI, and mean-centred EAW were entered at Step 1, and their product term at Step 2, consistent with Hayes's (2022) Model 1. Significant interactions were probed with simple slopes at one standard deviation below the mean, at the mean, and one standard deviation above the mean of EAW. Effect sizes were reported as standardised coefficients (β) and Cohen's $f^2 = \Delta R^2 / (1 - R^2)$, interpreted as small (.02), medium (.15), and large (.35) following Cohen (1988). Regression assumptions were checked through residual plots, variance inflation factors (VIF), and the Durbin-Watson statistic (Tabachnick & Fidell, 2019).

RESULTS

Demographic Characteristics of Respondents

Table 3 presents the demographic profile of the 412 respondents. Males made up 51.0% and females 49.0% of the sample. The mean age was 37.1 years (SD = 10.7), and the largest age group was 36–45 years (32.3%). About 34.2% held a Higher National Diploma, first degree, or higher qualification, and traders and business owners formed the largest occupational group (33.5%). Respondents had lived in Enugu for an average of 12.9 years (SD = 7.9), long enough to observe environmental change in their neighbourhoods.

Table 3

Demographic Characteristics of Respondents

Characteristic	n	%
Gender		
Male	210	51.0
Female	202	49.0
Age (years)		
18–25	63	15.3
26–35	123	29.9
36–45	133	32.3

46–55	76	18.4
56 and above	17	4.1
Highest education		
Primary or no formal	34	8.3
Secondary (SSCE)	125	30.3
OND/NCE	112	27.2
HND/first degree and above	141	34.2
Occupation		
Trader/business owner	138	33.5
Civil/public servant	85	20.6
Artisan/technician	79	19.2
Student	73	17.7
Other/unemployed	37	9.0

Note. N = 412. Age: M = 37.1, SD = 10.7. Length of residence in Enugu: M = 12.9 years, SD = 7.9.

Descriptive Statistics and Correlations

Table 4 reports the means, standard deviations, and intercorrelations of the constructs. Respondents reported a high level of technology adoption (M = 3.73, SD = 0.82) and agreed, on average, that their physical environment had degraded (M = 3.68) and that technology had improved their social connectedness (M = 3.85). Agreement on social disruption was moderate (M = 3.42). TAI correlated positively with PED (r = .38, p < .001), SCN (r = .39, p < .001), and SDR (r = .21, p < .001). EAW correlated negatively with PED (r = −.11, p = .023). Notably, SCN and SDR were almost unrelated (r = .06, p = .252), confirming that connectedness and disruption are distinct dimensions of the social environment rather than opposite ends of a single continuum.

Table 4

Means, Standard Deviations, and Correlations Among Study Constructs

Construct	M	SD	1	2	3	4	5
1. TAI	3.73	0.82	(.73)				
2. PED	3.68	0.86	.38	(.75)			
3. SCN	3.85	0.80	.39	.15	(.74)		
4. SDR	3.42	0.89	.21	.16	.06	(.72)	
5. EAW	3.60	0.87	.11	−.11	.15	.01	(.74)

Note. N = 412. Values in parentheses on the diagonal are square roots of AVE. Correlations with |r| ≥ .10 are significant at p < .05, and those with |r| ≥ .13 at p < .01 (two-tailed). TAI = technology adoption intensity; PED = physical environmental degradation; SCN = technology-enabled social connectedness; SDR = technology-related social disruption; EAW = environmental awareness.

Perceived Effects of Science and Technology on the Environment

Table 5 presents item-level ratings of the perceived physical and social environmental effects of technology. All six physical-environment items received mean ratings above 3.50, indicating agreement. The highest-rated item was the loss of green spaces to buildings and paved surfaces (M = 3.84), followed by air pollution from exhaust fumes and generator smoke (M = 3.73) and the accumulation of discarded electronics (M = 3.71). Increased local heat received the lowest, though still positive, rating (M = 3.56). All five connectedness items were endorsed, with the strongest agreement on the use of phones and social media to maintain contact with family and friends (M = 3.90). The social disruption items presented a more ambivalent picture: only reduced face-to-face interaction at home reached the agreement threshold (M = 3.52), while the other four items fell in the moderate range (3.30–3.43). On the technology side, all six adoption items exceeded 3.50 (range 3.58–3.85), with reliance on electrical appliances and on powered work equipment rated highest.

Table 5

Mean Ratings of Perceived Physical and Social Environmental Effects of Technology

Item	M	SD	Decision
Physical environment			
Noise from generators, vehicles, and machines has increased	3.57	1.11	Agree
Air is polluted by exhaust fumes and generator smoke	3.73	1.02	Agree
Discarded electronics accumulate in dumpsites and drains	3.71	1.07	Agree
Green spaces have been lost to buildings and paved surfaces	3.84	1.07	Agree
Neighbourhood feels hotter than it used to	3.56	1.13	Agree
Construction and paving have worsened flooding and erosion	3.68	1.07	Agree
Social connectedness			
Phones and social media keep me in contact with family and friends	3.90	1.02	Agree
Digital platforms ease participation in community and town-union activities	3.84	1.01	Agree
Technology improves access to security, health, and public information	3.82	1.04	Agree
Online groups help residents share information and solve problems	3.89	0.97	Agree

Technology has expanded my business, work, or learning networks	3.80	0.99	Agree
Social disruption			
Screen time has reduced face-to-face interaction at home	3.52	1.09	Agree
Neighbours interact less than before digital devices spread	3.43	1.14	Moderate
Internet fraud has increased mistrust in the community	3.42	1.17	Moderate
Online content has weakened young people's respect for communal values	3.30	1.15	Moderate
Technology-driven lifestyles have reduced communal participation	3.43	1.12	Moderate

Note. N = 412. Items were rated on a five-point scale (1 = strongly disagree, 5 = strongly agree). Decision rule: M ≥ 3.50 = agree; 2.50–3.49 = moderate; M < 2.50 = disagree.

Test of Hypotheses

Hypothesis 1: Technology Adoption and the Physical Environment

H1 predicted that technology adoption intensity would have a significant positive effect on physical environmental degradation. As Table 6 shows, the control variables at Step 1 did not jointly predict PED, $F(4, 407) = 1.27$, $p = .279$, $R^2 = .012$. Adding TAI at Step 2 increased the explained variance substantially, $\Delta R^2 = .150$, $\Delta F(1, 406) = 72.60$, $p < .001$. TAI was a significant positive predictor of PED ($B = 0.423$, $SE = 0.050$, $\beta = .41$, $t = 8.52$, $p < .001$). The effect size was $f^2 = .18$, a medium effect by Cohen's (1988) benchmarks. Length of residence also contributed modestly ($\beta = .10$, $p = .027$), suggesting that long-term residents perceive more degradation. The full model explained 16.2% of the variance in PED, $F(5, 406) = 15.72$, $p < .001$. H1 was supported.

Table 6

Hierarchical Regression of Physical Environmental Degradation on Technology Adoption Intensity (H1)

Predictor	B	SE	β	t	p
Step 1					
Age	0.000	0.004	.00	0.08	.935
Education	0.044	0.043	.05	1.01	.313
Length of residence	0.009	0.005	.08	1.68	.093
Gender (male = 1)	0.077	0.085	.05	0.91	.364
Step 2					
Age	0.004	0.004	.05	1.15	.251
Education	−0.047	0.042	−.05	−1.14	.254

Length of residence	0.011	0.005	.10	2.22	.027
Gender (male = 1)	0.047	0.079	.03	0.60	.552
Technology adoption intensity (TAI)	0.423	0.050	.41	8.52	< .001

Note. N = 412. Step 1: R^2 = .012, F(4, 407) = 1.27, p = .279. Step 2: R^2 = .162, adjusted R^2 = .152, ΔR^2 = .150, $\Delta F(1, 406) = 72.60$, p < .001; Cohen's f^2 = .18.

Hypothesis 2: Technology Adoption and the Social Environment

H2 predicted that technology adoption intensity would be positively associated with both technology-enabled social connectedness and technology-related social disruption. Table 7 summarises the Step 2 models. For social connectedness, the controls explained 6.5% of the variance at Step 1, with younger and more educated respondents reporting greater connectedness. Adding TAI increased the explained variance by 10.7 percentage points, $\Delta F(1, 406) = 52.54$, p < .001. TAI was a significant positive predictor (B = 0.334, β = .34, t = 7.25, p < .001), with f^2 = .13, a small-to-medium effect.

For social disruption, the controls did not jointly predict the outcome at Step 1, F(4, 407) = 1.78, p = .131. Adding TAI increased the explained variance by 4.8 percentage points, $\Delta F(1, 406) = 20.98$, p < .001. TAI was a significant positive predictor of social disruption (B = 0.249, β = .23, t = 4.58, p < .001), with f^2 = .05, a small effect. Older respondents reported more disruption (β = .12, p = .014). Both effects remained significant at the Bonferroni-adjusted level of .025. H2 was therefore supported: technology adoption is associated with a stronger connective effect and a weaker but real disruptive effect on the social environment.

Table 7

Regression of Social Environment Outcomes on Technology Adoption Intensity (H2)

Predictor	SCN B	SCN β	SCN p	SDR B	SDR β	SDR p
Age	−0.008	−.11	.015	0.010	.12	.014
Education	0.081	.10	.035	−0.016	−.02	.719
Length of residence	−0.004	−.04	.353	0.004	.03	.497
Gender (male = 1)	−0.008	−.01	.908	0.123	.07	.153
Technology adoption intensity (TAI)	0.334	.34	< .001	0.249	.23	< .001
R^2 (Step 2)	.172			.066		
ΔR^2 for TAI	.107		< .001	.048		< .001
Cohen's f^2 for TAI	.13			.05		

Note. N = 412. Columns 2–4: social connectedness (SCN); columns 5–7: social disruption (SDR). Coefficients are from Step 2 models with all controls. SCN model: F(5, 406) = 16.85, p < .001; SDR model: F(5, 406) = 5.69, p < .001. Bonferroni-adjusted α = .025.

Hypothesis 3: The Moderating Role of Environmental Awareness

H3 predicted that environmental awareness would weaken the effect of technology adoption on physical environmental degradation. As Table 8 shows, at Step 1 TAI was positively related to PED (β = .41, p < .001) and EAW was negatively related to it (β = −.15, p = .002). Adding the interaction term at Step 2 produced a significant increase in explained variance, $\Delta R^2 = .036$, $\Delta F(1, 404) = 18.44$, p < .001. The interaction was negative and significant (B = −0.220, SE = 0.051, β = −.19, t = −4.29, p < .001), with $f^2 = .05$. Although small by Cohen's (1988) general benchmarks, this value is more than twice the effect size assumed in the power analysis and is substantial for an interaction effect in field data. The final model explained 21.8% of the variance in PED, F(7, 404) = 16.11, p < .001. The largest VIF was 1.17, indicating no multicollinearity.

Table 8

Moderated Regression of Physical Environmental Degradation: Technology Adoption × Environmental Awareness (H3)

Predictor	B	SE	β	t	p
Step 1					
Age	0.004	0.004	.05	1.02	.310
Education	−0.012	0.043	−.01	−0.29	.774
Length of residence	0.011	0.005	.10	2.16	.032
Gender (male = 1)	0.041	0.078	.02	0.53	.599
TAI (centred)	0.428	0.049	.41	8.71	< .001
Environmental awareness (centred)	−0.147	0.046	−.15	−3.18	.002
Step 2					
Age	0.005	0.004	.07	1.47	.142
Education	−0.003	0.042	.00	−0.07	.946
Length of residence	0.011	0.005	.10	2.36	.019
Gender (male = 1)	0.048	0.076	.03	0.63	.527
TAI (centred)	0.419	0.048	.40	8.70	< .001
Environmental awareness (centred)	−0.159	0.045	−.16	−3.49	< .001
TAI × Environmental awareness	−0.220	0.051	−.19	−4.29	< .001

Note. N = 412. TAI and EAW were mean-centred before forming the product term. Step 1: $R^2 = .183$. Step 2: $R^2 = .218$, adjusted $R^2 = .205$, $\Delta R^2 = .036$, $\Delta F(1, 404) = 18.44$, p < .001; Cohen's $f^2 = .05$. Maximum VIF = 1.17.

Simple slopes analysis (Table 9) clarified the pattern. Among residents with low environmental awareness (1 SD below the mean), the effect of TAI on PED was strong (b = 0.611, 95% CI [0.485, 0.738], p < .001). At mean awareness the effect was moderate (b = 0.419, p < .001), and among residents with high awareness (1 SD above the mean) it fell to b = 0.227, 95% CI [0.095, 0.359], p < .001. The effect of technology on perceived degradation

among highly aware residents was therefore about 37% of its size among the least aware, although it remained significant. H3 was supported.

Table 9

Conditional Effects of Technology Adoption Intensity on Physical Environmental Degradation at Levels of Environmental Awareness

Environmental awareness	b	SE	t	p	95% CI
Low (−1 SD)	0.611	0.064	9.51	< .001	[0.485, 0.738]
Mean	0.419	0.048	8.70	< .001	[0.324, 0.514]
High (+1 SD)	0.227	0.067	3.38	< .001	[0.095, 0.359]

Note. N = 412. SD of centred environmental awareness = 0.87. Estimates come from the Step 2 model in Table 8, with all control variables held constant.

Table 10 summarises the results of the three hypothesis tests, together with their effect sizes.

Table 10

Summary of Hypothesis Tests and Effect Sizes

Hypothesis	Path	β	p	ΔR^2	f^2	Magnitude	Decision
H1	TAI → PED	.41	< .001	.150	.18	Medium	Supported
H2a	TAI → SCN	.34	< .001	.107	.13	Small–medium	Supported
H2b	TAI → SDR	.23	< .001	.048	.05	Small	Supported
H3	TAI × EAW → PED	−.19	< .001	.036	.05	Small	Supported

Note. N = 412. Effect-size magnitudes follow Cohen (1988): f^2 = .02 small, .15 medium, .35 large. The H2 tests used a Bonferroni-adjusted α of .025.

Diagnostic checks supported the regression assumptions. Residual plots showed no marked heteroscedasticity or non-linearity, all VIF values were below 1.18, and the Durbin-Watson statistic for the H1 model was 2.03, indicating independent residuals.

DISCUSSION

This study examined the effect of science and technology on the physical and social environment in Enugu. The first finding is that technology adoption intensity was a significant positive predictor of perceived physical environmental degradation, with a medium effect (f^2 = .18). Residents who relied more heavily on generators, appliances, motorised transport, and digital devices reported more noise, air pollution, e-waste, loss of green space, heat, and flooding. This result is consistent with the STIRPAT expectation that technology, in settings where it raises energy and material throughput, adds to environmental impact (Dietz & Rosa, 1994; York et al., 2003). It also accords with evidence from sub-Saharan Africa that ICT diffusion raises emissions through energy consumption (Avom et al., 2020) and with the energy-demand effects of internet use reported by Salahuddin and Alam (2016). The finding that loss of green space received the highest item rating agrees closely with the remote sensing evidence of rapid conversion of vegetation to built-up land in Enugu (Ofordu et al., 2022) and with the urban heat island documented by Enete and Okwu (2013). The strong endorsement of e-waste accumulation echoes the concerns raised by Nnorom and Osibanjo (2008) and the soil contamination documented by Adeyi and

Oyeleke (2017) at e-waste sites in other Nigerian cities. The present study did not find the pollution-reducing effect of internet use reported by Ozcan and Apergis (2018), which likely reflects the fact that in Enugu digital technology is bundled with fossil-fuel standby power rather than displacing more polluting activities.

The second finding is that technology adoption was associated with both greater social connectedness (β = .34) and greater social disruption (β = .23), with the connective effect roughly 2.5 times larger in terms of f^2. This dual pattern is precisely what the social construction of technology perspective anticipates (Pinch & Bijker, 1984): the same devices sustain ties across distance and organise community life, yet absorb time and attention once devoted to face-to-face interaction. The connective effect supports the findings of Hampton et al. (2011) and Valkenburg and Peter (2007), as well as the African evidence on mobile phones summarised by Aker and Mbiti (2010). The disruptive effect is consistent with Kraut et al. (1998) and with the negative associations between heavy use and well-being reported by Shakya and Christakis (2017) and Twenge and Campbell (2018). The near-zero correlation between connectedness and disruption shows that the two are not simply opposites: a resident may experience both. That only reduced face-to-face interaction at home reached the agreement threshold suggests that disruption in Enugu is currently felt more strongly within households than in the wider community, where town unions, churches, and market associations continue to anchor social life. The finding that older respondents perceived more disruption, while younger and more educated respondents reported more connectedness, suggests generational differences in how the social effects of technology are experienced.

The third finding is that environmental awareness moderated the relationship between technology adoption and physical degradation. The effect of technology was strongest among the least aware residents and fell to about 37% of that size among the most aware. This lends support to ecological modernisation theory's claim that the environmental burden of technology is conditional on the reflexivity and practices of its users (Mol & Spaargaren, 2000), and it parallels the finding of Danish et al. (2018) that the environmental cost of ICT declines as societies acquire the capacity to manage it. At the same time, the effect remained significant even among highly aware residents, which is closer to the risk society view that some technological hazards cannot be managed by individual awareness alone (Beck, 1992). In practical terms, awareness helps, but it cannot replace regulation, infrastructure, and cleaner energy.

The control variables also yielded instructive results. Length of residence was a modest positive predictor of perceived degradation (β = .10), which is plausible because long-term residents have a longer baseline against which to judge change; this pattern also suggests that the perceptions measured here are grounded in residents' experience of their neighbourhoods rather than in general attitudes. Education predicted social connectedness before technology adoption was entered, but its effect roughly halved once adoption was controlled, suggesting that part of the advantage of more educated residents in building networks operates through their greater use of technology. Gender had no significant effect in any model, indicating that the environmental effects of technology in Enugu are perceived similarly by men and women.

Theoretical and Practical Implications

Theoretically, the study shows that ecological modernisation theory, STIRPAT, and the social construction of technology can be combined productively at the household level. STIRPAT explains the direction of technology's physical effect in a fossil-fuel-dependent city, EMT explains why that effect varies across residents, and SCOT explains why the social effects are plural. The results suggest that frameworks developed with national aggregate data can be meaningfully tested with resident-level survey data in African cities.

Practically, the findings point to three priorities for Enugu. First, because generator use and motorised transport are central to technology adoption, investments in reliable grid and solar power and in public transport are likely to reduce the physical environmental cost of technology more than any awareness campaign. Second, the strong perception of e-waste accumulation calls for designated e-waste collection points, partnerships with formal recyclers, and enforcement of existing regulations. Third, the buffering effect of environmental awareness suggests that community-based environmental education, delivered through town unions, religious bodies,

schools, and market associations, can meaningfully complement structural measures. The same channels can be used to promote balanced technology use within households.

Limitations and Directions for Future Research

Several limitations should be acknowledged. First, the cross-sectional design limits causal inference; longitudinal or panel designs would allow stronger claims about the direction of effects. Second, physical environmental degradation was measured through residents' perceptions rather than direct measurement of air quality, noise, soil, or temperature. Future studies should link survey responses to sensor data or remote sensing indicators at the neighbourhood level. Third, all constructs were measured with a single self-report instrument; although Harman's test did not indicate serious common method bias, future research could use multiple sources. Fourth, the study was confined to the three urban LGAs of Enugu, so the findings may not generalise to rural areas of the state. Finally, technology adoption was measured as a composite; disaggregating the effects of specific technologies, such as generators versus digital devices, would give more precise policy guidance.

CONCLUSION

This study provides resident-level quantitative evidence that science and technology are a double-edged force in Enugu. Greater technology adoption is associated with greater perceived degradation of the physical environment, with a medium effect, and with a social environment that is simultaneously more connected and somewhat more disrupted. Environmental awareness weakens, but does not eliminate, the physical environmental cost of technology. The central lesson is that the benefits of technology in Enugu can be preserved while its costs are reduced, provided that technological growth is matched by cleaner energy, sound waste management, and an informed citizenry.

Contribution to Knowledge

The study contributes to knowledge in three ways. It provides the first resident-level quantitative estimate, to the researchers' knowledge, of the joint physical and social environmental effects of technology adoption in Enugu, complementing the remote sensing and laboratory evidence that dominates the local literature. It demonstrates empirically that technology-enabled connectedness and technology-related disruption are distinct dimensions of the social environment rather than opposites, which has implications for how the social effects of technology are measured. It also identifies environmental awareness as a condition under which the physical cost of technology is reduced, offering an evidence-based rationale for integrating environmental education into urban environmental policy.

Recommendations

Based on these findings, the following recommendations are made:

1. The Enugu State Government should expand investment in reliable grid and solar mini-grid electricity, with priority for dense commercial and residential areas, to reduce dependence on petrol and diesel generators.

2. The Enugu State Waste Management Authority, in partnership with local government councils, should establish designated e-waste collection points and work with licensed recyclers to divert electronic waste from open dumpsites and drains.

3. Urban planning authorities should enforce green-space and drainage provisions in building approvals to slow the loss of vegetation and reduce flooding associated with impervious surfaces.

4. Environmental education programmes should be delivered through schools, religious bodies, town unions, and market associations, given that environmental awareness weakens the link between technology use and environmental degradation.

5. Families and community organisations should promote balanced technology use within households, while continuing to use digital platforms to strengthen communal participation and information sharing.

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