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Legazpi City's Willingness to Pay for Climate-Induced Disaster EWS Improvements

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ABSTRACT

Climate-induced disaster is at the center of scholarly investigation due to its increasing unpredictability and intensity, time-critical nature, and the economic losses and trauma associated with it. While there are a few studies that link willingness-to-pay (WTP) on early warning systems (EWS) for climate-induced disaster resilience, which is an example of socio-technological infrastructure, research on micro-level data WTP is still limited. Furthermore, housing conditions, which are critical in resilience discourse within the architecture and urban design fields, are not well documented for WTP analysis. While international counterparts have identified specific WTP amounts for yearly schemes, the cities in the Philippines, considered as a hotstop for climate-induced disaster, have no example for a context specific WTP model. This study investigates WTP for improvement to climate-induced disaster EWS. It used Legazpi City, a high-risk multi-hazard city having 20 or more yearly typhoons, coastal flooding, storm surges, and riverine flooding, as a case study, and mixed-methods, a survey through purposive sampling, KIIs, and GIS modelling as tactics. Applying OLS regression, geostructural analysis and SEM path analysis, it was found that trauma, in the form of house clean-up, is the strongest predictor for EWS investment.

Keywords: Early Warning System (EWS), Legazpi City, Socio-Technological Infrastructure (STI), Structural Equation Model (SEM) Path Analysis, Willingness to Pay (WTP)

1. Introduction

Climate-induced disasters demand scholarly and practical solutions across scales, with studies confirming that climate change intensifies typhoon frequency and strength [1][2], while failing to limit warming to 1.5–2°C by 2100 will escalate heatwaves, droughts, floods, storms, and wildfires within the next decade [3][4]. Global bodies highlight sea level rise, extreme weather, and food insecurity as key threats, advocating deep emissions cuts, renewable energy shifts, and carbon removal [5][6][7]. In the Philippines, its Pacific Ring of Fire location and position along the typhoon-prone ocean expose it to about 20 storms annually [8]. With the complexity and multi-scalar dimensions of climate-induced disasters, more interdisciplinary approaches such as applications for socio-technological infrastructures are needed.

As a spatial-system approach to address climate-induced disasters, socio-technological infrastructure (STI) represents the physical interplay of appropriate technology, robust infrastructure, and social dimensions, demanding transdisciplinary collaboration in design and planning. In this study, it is proposed that EWS in cities is a good example for socio-technological infrastructure (STI), where there is the intersection of people, place, and technology and where technological applications are in accordance to goals and needs of the users.

Chovanec et al. [9] frames EWS as a modular, sensor-driven multi-layered system, which aligns with the qualities of STI. Trogrlić et al. [10] expounds the characteristic of EWS as people-centered, which requires governance and inclusivity, demonstrating STI's integral social layer. These findings give basis that EWS of a city are examples of STI constructs, and this research aims to expand the understanding of their social dimension, and moreover, their economic value.

A valuation method applicable in assessing the economic value of public goods, such as EWS, and other STI projects, is WTP. As the name suggests, WTP is a measure of the acceptable amount of payment users can give for a given product or service. It is most helpful in the valuation of non-market goods, and contingent valuation (CV) and choice experiment (CE) are examples of estimating WTP. Valuation referes to the modeled economic growth in terms of EWS, which can help describe economic related conditions of EWS. This valuation method is prevalent in different fields, but its application to EWS is rare [11], providing a motivation for the study. For this study on Legazpi City residents perception of value of EWS, the CV method was adopted since there have been methodological foundations established by past researchers, and it is a feasible way of ascertaining the WTP amount.

Applying WTP for resilience studies have been tested by a few scholarly works. The factors assessed with statistical models include, socio-economics factors such as income, education, risk perception, trust, and past experience. Different research stress on specific factors, yet these were not considered collectively. Furthermore, residential conditions as factor for WTP only were described as a geographical location parameter. For architecture and urban design lens, more information with regards to residential condition can provide nuanced understanding that can be beneficial to these fields. While Iqbal's [12] studies gave statistical analysis for social, site, and experiential conditions, only yearly payment scheme was tested, which in effect, does not touch on the flexibility features that WTP can offer to the public. Thus, a gap that considers multi-layered factors, residential-focused parameters, and flexible payment schemes exist in the study of WTP for EWS.

1.1 Research problem

Resilient urban examples should include reliable early warning systems (EWS), adaptive coastal plans, and community participation. Albay Province in the Philippines stands as a international icon for Climate Change Adaptation and Disaster Risk Reduction [13], while Legazpi City exemplifies an Environmentally Sustainable City for resiliency [14]. Yet, both face relentless natural disasters, with Legazpi LGU simulations forecasting a 1.15M sea level rise due to climate change. Background research highlights uncoordinated information dissemination and absent integrated coastal solutions, urging recalibrated STI metrics. This compels empirical methods to quantify social, technological, and spatial values.

This baseline study employs Willingness to Pay (WTP) via Contingent Valuation Method (CVM) to quantify EWS integration in Legazpi's 4 km by 1 km coastal area. Respondents include Legazpi and Albay LGU representatives, business members, and NGOs, with WTP formulas validated through correlation and OLS regression. The study area represents coastal urban vulnerabilities, and a model that describes STI interfaces of architecture, urban design, climate science, DRRM, ICT, and social development. It is hypothesized that social, residential, experience, and financial readiness factors correlate significantly with socio-economic value via respondent WTP.

In the light of these discussions, this research asks: What is the perceived willingness to pay (WTP) on early warning systems integrated into the coastal development plans in Legazpi City, Albay to address climate-induced disasters? Furthermore, the main question is broken into the following: (RQ1) What are the attributes of Socio-Technological Infrastructure as characterized by the climate-induced disaster early warning system in Legazpi City; (RQ2) What are the indicators of willingness to pay (WTP) in measuring the perceived value of the early warning system in the coastal development in Legazpi, Albay; (RQ3) What is the relationship of WTP with value of improvement to EWS? Do social characteristics, residential characteristics, bad experience, financial preparedness, and funding scheme affect people's willingness to pay; and (RQ4) What are the recommendations in adopting WTP findings for proposing EWS improvements in coastal development planning?

To demonstrate this technology-space interface, an understanding of coastal developments is crucial. Research asserts exogenic factors affecting coastal areas. While sea level rise has an impact on the infrastructure in the urban design typology [15], it is argued that it is also the infrastructure that can be used in adaptation and mitigation of the effects of its climate-induced hazards.

Various types of EWS have been developed to enhance system integration. Technologies like low-cost sensors and communication systems are used for practical monitoring [16]. Artificial Intelligence models are employed for faster decision making in disaster preparedness and monitoring [17]. Communication and information dissemination to the community are vital for EWS effectiveness, with social media and mobile apps playing a key role in reaching vulnerable groups [18][20]. Public input is crucial throughout the different stages of EWS, though challenges remain in making information easily accessible to the public.

In order to understand the value of EWS, it is also noteworthy to review proper financing mechanisms, similar to fund management in infrastructure economics. Public-Private Partnerships leverage private sector investments and expertise in infrastructure projects, offering a cost-effective alternative to traditional public funding [21][22]. Development Finance Institutions provide loans and technical assistance for infrastructure projects in developing countries [23]. Green Bonds integrate environmentally conscious financing, attracting private investment in sustainable infrastructure projects [24]. Earmarking taxes for infrastructure financing can establish a sustainable funding stream [25]. Considering the affordability of different income groups is essential when involving the public in infrastructure financing to ensure public acceptance [26]. All things considered, understanding people's Willingness-to-Pay for EWS is crucial when devising funding schemes.

1.2 Theories bearing into the study and theoretical frameworks

Social and residential conditions are mentioned to effect people's investments in a public good, such as EWS. Social-behavioral studies in WTP for disaster resilience partially explains this. For example Samad [27] asserts that literacy, trust, and social networks affect preparedness. According to McGranahan social characteristics via demographic influences risk perception [15]. UNU-EHS [28] report provides only qualitative evidence to cultural relevenace and trust. None provided quantitative analysis expressing the trust-WTP link and how they are integrated into coastal development plans.

Nicholls state that settlement characteristic are evident through infrastructure adaptation to sea level rise [29], [30]. Furthermore, Samad [27] explains that remote location and housing vulnerabilities affect preparedness, and OECD [31] and ASEAN [32] stress that uneven accessibility and telecommunication gaps, especially in rural areas provide a disadvantage. In the four studies stated above, no house-hold level survey were involved. Because of the partial explanations, there is a need to make quantifiable analysis connecting social and residential factors to WTP.

Negative experience, and financial factors have bearing on WTP value. Iqbal [12] quantitatively established past cyclone loses, a form of negative experience, increase WTP. Moreover, his study claims that income and risk aversion drive WTP. Nichols [30] adds that bad experience is heightening valuation amid typhoon intensification and subsidence, and Wong-Parodi [33] cites subjective attributes are connected to risk, as explained by personal connection of negative experience to hurricane disasters. Samad [27] observes repeated erosion, which is another form of negative experience, affects preparedness, while international reports such as the OECD [31] and ASEAN [32] mentions macro-level financing in the DRRM discourse. Payment schemes and financial preparedness tie to EWS economics like PPPs and affordability according to Guasch, Stiglitz and Stern [21][26]. Presence of flood insurance predisposes residents to purchase more for flood mitigating products according to Ge, et al. [34]. Using a more holistic lens which reinforces the aims of this research, the frequency of exposure and experience and risk knowledge increases WTP as cited by Asgary et al. [35].

Because past research only tested for yearly WTP fees, and macro-level economic conditions, and since WTP as an STI example is highly considered a micro-level issue, where residents also have changing financial capacities and preferences, WTP assessed through a more holistic lens, and tested for more flexible payment terms at household level is imperative.

1.3 Legazpi City, Philippines Case study

Legazpi City, a 208,533 population (2020 Census) component city of Albay Province, Bicol Region, in the Philippines, has been in the center of scholarly studies on disaster resilience. The numbers reveal the kind and amount of natural and climate-induced disasters affecting the coastal city- 19-21 typhoons per year, 189k affected houses, 350k evacuees, 60K exposed to floods, storm surges and 1.15m sea level rise by 2050. Its coastal area is susceptible to 1.5M storm surge as seen in Fig.1 Storm Surge Map. It was back in 2006 when Typhoon Reming hit, triggering Mayon lahar, which marked the beginnings of the city, and the province's rigorous DRRM pursuits [23][36]. The government have made DRRM one of its priorities, implementing adaptive land-use, zero hazard mapping and the zero-casualty policy. Although considered one of the leaders of DRRM in the region, it still faces funding challenges, water and power supply issues, and tangible localization of local climate change action plans (LCCAP) [24][37]. Because of the inherent ecological, geographical, climate characteristics, the active community participation, and the notable multi-stakeholder's drive, highlighting its EWS conditions and studying Legazpi's case can show promising and tangible results, and can reveal comparable LGU's adoption.

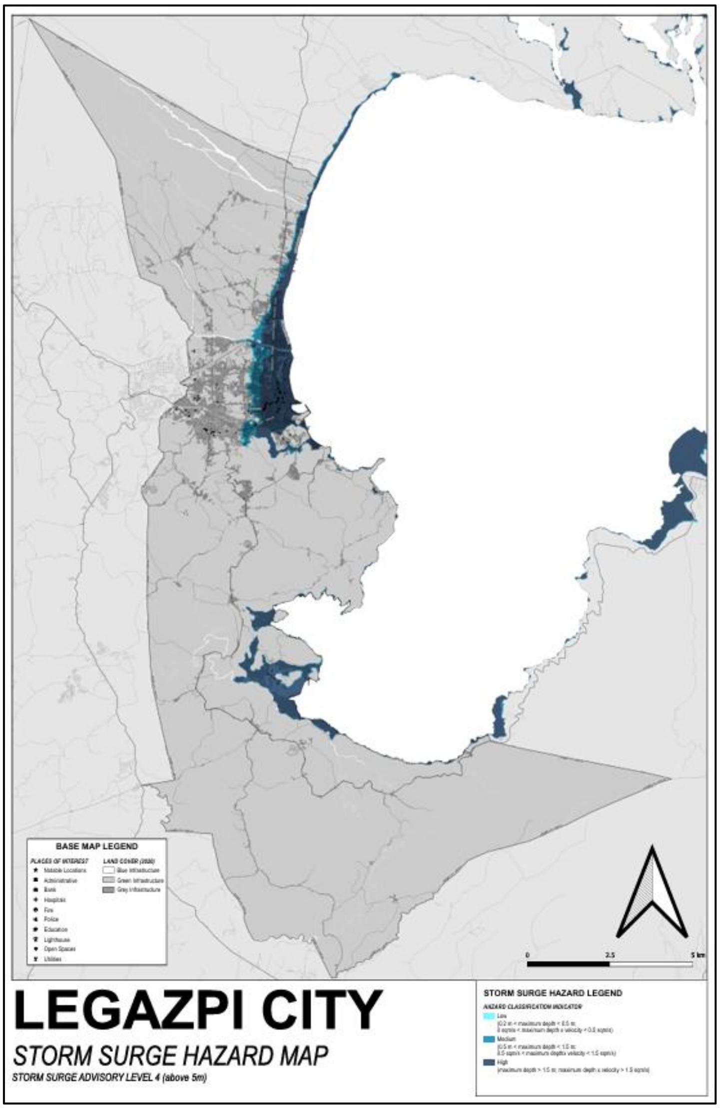

Figure 1. Storm Surge Hazard Map of Legazpi City

2. Method

2.1 Materials and Data Sources

The primary data source for this study is a comprehensive 130-column structured survey dataset comprising 227 respondents, and 213 after data cleaning. The study adopts a non-probability purposive sampling to identify residents and key informants who can meaningfully contribute to understanding how socio-technological infrastructure (STI) interfaces shape early warning systems (EWS) in coastal Legazpi City. A total of 213 resident respondents was determined as a balanced and ethically feasible sample within Legazpi's 208,533 population. The number is statistically sufficient for multi-variate modelling as it exceeds the 10x minimum for OLS-SEM, one of the analysis models to be used.

Survey participants are eligible if they are at least 18 years old and are residing or working in several barangays identified as high-risk areas for natural disaster through a site selection criteria. They should have been living or working there for no less than 5 years. Temporary occupants, businesses, and incomplete survey questionnaire responses shall be excluded. This is to guarantee that participants have firsthand exposure to typhoons, riverine or coastal floods in the last 5 years. LGU leaders and technical experts for the KII are included for their institutional insight into planning, disaster management, and ICT integration. They shall be at least 30 years old and have been in service for the LGU leaders and in the practice for the technical experts for at least 10 years. The participation of residents and KII experts shall ensure that both community and governance perspectives inform the model. This targeted approach prioritizes relevance and depth over random representation, and aligns with the study's aim to explore relationships among socio-spatial and experiential WTP indicators and perceived system value. Informed consent was secured, and all responses were anonymized as part of the ethical considerations.

The survey instrument used was a questionnaire survey which have embedded variables based on the literature review. It consisted of 80 items and organized into 4 thematic blocks: socio-demographic indicators, residential conditions, disaster experience, and financial aspects of WTP. To test for reliability and validity, a pilot test of 20 respondents was conducted to refine the question phrasing. Factor analysis was performed to determine the factors specifically significant for the STI concept. Composite reliability (CR) and average variance extracted (AVE) were done for construct validity.

The study site is situated in the coastal barangays of Legazpi City, Albay, a region highly exposed to climate-related hazards such as typhoons, riverine and coastal flooding, storm surges, landslides, and lahar. The most vulnerable parts of the coastal cities were identified using the existing hazard maps from the planning offices of the city, and refined for climatic-induced hazard using GIS. The storm surge map of Legazpi City, which is one of the climate-induced hazards considered, is shown in Figure 1.0. Respondents residing or working in these areas were surveyed, and simultaneously their residential conditions were audited that aided in the verification of notable residential factors for the WTP hypothesis. As listed in Table 1.0 Variable Catalog, the sub-indicators were embedded in the survey questions. The different analysis models presented in the succeeding parts were performed to understand the roles of these predictors.

In order to answer the 4 research questions (RQs), analytical models relied on LLM for code writing assistance, and utilizing specific statistical libraries for multinomial logit modeling and for generating geospatial manifolds. Data presentation was executed using computational scripting tools.

2.2 Research Design

This research utilizes a quantitative, predictive design organized around an "STI-WTP Logical Chain" framework. The study analyzes variables across four distinct theoretical blocks: Social Predictors, Physical/Residential Attributes (e.g., house stories), Negative Experience/Trauma (e.g., cleanup costs), and Financial/Payment Schemes. Theoretical grounding anchors the WTP equations in these 4 key factors as mentioned in the previous section. While literature provides general understanding of each factor affecting risk perception and economic value of EWS, their findings fall short of the specifics – which indicator of social condition, characteristic of the residential building, and the example of negative experience have effects on and the amount residents are willing to shell out for improvements to EWS. This granular lens on physical/building traits and negative experiences fills gaps in WTP for EWS, extending beyond broad socio-economics insights from existing literature. The procedure begins with systematic data extraction and cleaning, transitions into multinomial probability modeling of valuation categories, and culminates in causal verification through latent factor pathing to determine the underlying drivers of Willingness-to-Pay (WTP).

2.3 Methods / Procedures

The methodological procedure is executed in a structured, step-by-step pipeline. It begins with the initial deployment of surveys to gather primary field data, verified with residential conditions audits, followed by data extraction and parsing using computational techniques to sanitize inputs (e.g., removing text from currency values). The core analysis steps involve progressing through multinomial modeling to categorize WTP, testing the interoperability and stability of payment schemes within the community, and concluding with statistical analysis to support the foundational hypotheses.

2.4 Instrument Validity and Reliability Audit

As adapted from similar WTP models, choice experiment, where WTP options were given in the survey questionnaire form, was used through multi-stage development of variable. The questions were translated into Filipino language for ease in understanding of the residents. The survey instrument was adapted from pre-validated coastal flood vulnerability indexes (Arante) [38]. To ensure construct validity, a content validity audit was conducted by a panel of three environmental planners and DRRM city officers. Face and content validity were confirmed prior to survey administration. Construct reliability and validity metrics were evaluated directlyl on the full study sample.

Table 1. Latent Construct and Measurement Model Specifications

Latent Construct	Observed Indicator (Survey Item)	Indicator Role & Variable Code	Measurement Mode
Socio-Demographics (DEM)	Age (col_3); Household Income (col_26); Highest Education (col_24)	Exogenous demographic control factors	Reflective (Mode A)
Infrastructure Preparedness (INF)	House Stories (col_40); Building Material Structure (col_42)	Physical coping capacity and vertical assets	Reflective (Mode A)
Early Warning System (EWS)	EWS Familiarity (col_65); Alert Lead Time Satisfaction (col_67)	Technological trust and alert satisfaction	Reflective (Mode A)
Disaster Exposure (EXP)	Disaster Experience Count (col_73); Cleanup Expenses (col_79); Damage Rate (col_100)	Typhoon and flood damage exposure	Reflective (Mode A) / Index

Latent Construct	Observed Indicator (Survey Item)	Indicator Role & Variable Code	Measurement Mode
Willingness to Pay (WTP)	Monthly subscription (col_92); One-time fee (col_94); Tax increase (col_90); Binary WTP (col_86); Invest willingness (col_110)	Elicited monetary willingness and co-financing buffers	Formative (Mode B)

Note: EWS and Disaster Experience behave as formative index construct, where items represent separate physical variables (e.g. having many typhoons vs. High cleanup costs) and are not expected to show high internal correlation.

Table 1 outlines the latent constructs and their corresponding observed indicators, and clarifies whether each construct was modeled reflectively or formatively. Socio-demographics, infrastructure preparedness, early warning system, and disaster exposure were treated as reflective constructs, with indicators capturing demographic controls, coping capacity, technological trust, and exposure to disaster impacts. In contrast, willingness to pay (WTP) was specified formatively (Mode B), as it represents distinct monetary formats (subscription, fee, tax, binary choice, investment) that collectively define the construct rather than reflect a single underlying dimension. This distinction in measurement mode guided the choice of reliability and validity diagnostics applied to each construct.

Table 2. Construct Reliability and Convergent Validity Parameters (N = 227)

Latent Construct	Number of Items	Cronbach's Alpha (a)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Socio-Demographics (DEM)	3	0.213	0.504	0.367
Infrastructure Preparedness (INF)	2	0.231	0.722	0.566
Early Warning System (EWS)*	2	-0.242	0.571	0.451
Disaster Exposure (EXP)*	3	0.071	0.522	0.351
Willingness to Pay (WTP)**	5	N/A	N/A	N/A

*Note. *For constructs EWS and EXP, the low and negative Cronbach's Alpha coefficients represent independent, formative indicator contributions; these behave as composite indexes rather than reflective scales. **WTP is specified formatively (Mode B) representing distinct funding schedules (monthly subscription, one-time fee, tax increase); thus, traditional internal consistency reliability and validity metrics are mathematically inapplicable (Hair et al., 2022).*

Table 2 presents the reliability and validity diagnostics for the reflective constructs. Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were reported to assess internal consistency and convergent validity. Results show that infrastructure preparedness achieved acceptable reliability and convergent validity (CR = 0.722, AVE = 0.566), while socio-demographics, early warning system, and disaster exposure exhibited low or negative alpha values, indicating weak internal consistency. However, for EWS and EXP, these results are expected since their indicators function as independent components of an index rather than reflective measures. For WTP, traditional reliability metrics were not applicable due to its formative specification; instead, construct validity was assessed through indicator relevance and weight significance, consistent with methodological guidance (Hair et al.) [39].

2.5 Models and Equations

The methodological approach operates on several integrated mathematical models to build a comprehensive proof of valuation, addressing specific research questions:

2.5.1 Pearson Correlation Coefficient (r)

This model directly addresses the Main Research Question and RQ3 by mathematically establishing foundational relationships between disaster trauma, residential characteristics, and WTP. Each of the sub-indicators for the 4 key factors were tested for correlation with WTP until key sub-indicators proved to significant for correlation. By calculating the correlation coefficient

$$\left(r = \frac{\sum[(x_i - \bar{x})(y_i - \bar{y})]}{\sqrt{\sum(x_i - \bar{x})^2} \times \sqrt{\sum(y_i - \bar{y})^2}}\right) \quad (1)$$

the analysis proves whether a linear relationship exists between isolated variables. This serves as the initial statistical proof to verify which specific attributes of Socio-Technological Infrastructure (RQ1) have a measurable connection to financial investment.

2.5.2 OLS Linear Regression

$$WTP = \beta_0 + \beta_1 X + \varepsilon \quad (2)$$

$$R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2] \quad (3)$$

Building upon correlations, Ordinary Least Squares (OLS) Regression addresses RQ2 or the indicators of WTP and RQ3 or proof of the relationship of the 4 main factors with WTP by quantifying the exact predictive impact of independent indicators on WTP. In this equation, WTP is the amount in peso, β_0 is the intercept, β_1 the slope and ε the error term that captures the unexplained predictors. The regression maps out the slope β_1, demonstrating the exact peso increase in a resident's willingness to pay per unit increase in indicators like disaster cleanup cost. Used for its interpretability, this model moves the analysis from identifying related variables to estimating the WTP for EWS.

2.5.3 Geo-Structural Analysis

The analysis model relies on two primary mathematical concepts: Equation (5) Probability Density / Relative Frequency (Density Histogram) and Equation (6) Spatial Center of Gravity (Mean Indicator). Spatial Distribution Analyses, specifically, Shifted Longitudinal Distribution or Density Profiling, serve as a geographic profiling model to map structural vulnerability gradients across physical space.

$$\text{Density} = \frac{\text{Frequency of Structures in Bin}}{\text{Total Structures} \times \text{Bin Width}} \quad (4)$$

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (5)$$

This geo-structural analysis maps where vulnerable single-story homes cluster versus robust multi-story ones along Legazpi's longitude line, like plotting neighborhoods on a straight east-west axis. Density shows structure concentration per location (higher peaks mean more buildings bunched together), while the mean pinpoints each group's "center of gravity." Comparing peaks and centers reveals if weaker homes shift toward riskier zones, proving geographic vulnerability patterns.

2.5.4 Multinomial Logit Model

The Multinomial Logit Model is critical for answering RQ2 by evaluating the probabilities of distinct, categorical financial commitments. The Maximum Likelihood Estimation formula used is

$$\left(L(\beta) = \sum [y_i \ln(p_i) + (1 - y_i) \ln(1 - p_i)]\right) \quad (6)$$

This equation identifies which specific respondent profiles (e.g., age, house structure, cleanup cost) increase the likelihood that a household will subscribe to a specific tier of EWS improvement. It was also performed because the responses are according to categorial variable tiers and in order to determine the probability of selecting discrete payment band.

2.5.5 Partial Least Squares Structural Equation Modeling (PLS-SEM)

PLS-SEM acts as the convergent statistical model to comprehensively answer the Main Research Question or the query of the perceived WTP on improvements to EWS, and RQ3 or the relationship of WTP with value of improvements. This model is appropriate for testing complex structural relationships inclusing mediation effects and does not require multivariate normality. It weaves individual predictors into a cohesive "Hypothesized Association Structural Model." By modeling latent variables, SEM proves whether bad experience functions as the primary mediator driving EWS valuation, which adds a robust evidence to justify policy recommendations (RQ4).

$$\eta_{WTP} = \gamma_{EWS}\, \xi_{EWS} + \beta_{EXP}\, \eta_{EXP} + \zeta_{WTP} \quad (7)$$

- η_{WTP}= latent endogenous construct: *Willingness to Pay (Monthly Subscription)*
- ξ_{EWS}= exogenous latent construct: *Perceived Early Warning System (EWS) Value*
- η_{EXP}= latent predictor: *Negative Experience*
- $\gamma_{EWS}, \beta_{EXP}$= structural coefficients (path weights)
- ζ_{WTP}= disturbance term (unexplained variation)

3. Result and Discussion

3.1 Result

3.1.1 Demographic Profile of Respondents and their Perception of EWS and WTP

The 213 survey respondents from Legazpi City present a demographic profile where majority are females and have an average age of 35.5 years. Sixty-one percent of the respondents are single and 85% are college graduates. While the largest single group of respondents (23.9%) falls within the lower-income bracket earning between ₱6,001 and ₱15,000 monthly, the survey captures a highly diverse economic profile with strong representation across the middle and upper-middle classes. In fact, a significant portion of the community, or over 41%, belongs to various middle-income tiers, notably those earning between ₱35,001 to ₱50,000 (16.9%) and ₱50,001 to ₱85,000 (14.6%). This indicates that the respondents reflect a broad socio-economic cross-section of the city, and thus reveal the diverse financial capacities in the discussions on disaster infrastructure investments.

The respondents' residential conditions and experiences with disasters are noteworthy. Generally, they reside in self-owned houses constructed with resilient materials, such as concrete hollow block (CHB) walls and concrete slab roofs. In terms of their experience with climate-induced hazards, respondents recalled an average of 6.6 disaster events, identified that Typhoon Reming (International Code Name "Durian") in 2006 as the most severe, and affirmed having experienced flooding. This exposure is reflected in their post-disaster financial burdens, typically spending over ₱2,000 for clean-up and under ₱2,000 for house renovations. While they are familiar with the local Early Warning System (EWS) and rate their satisfaction at a moderate level rating of 3, their active participation in disaster monitoring or rescue operations remains generally low.

Even if there is an assessment of moderate level of personal vulnerability to climate hazards, the respondents demonstrate limited financial safety nets, as the majority lack immediate to 6-month worth of savings and property insurance. On the contrary, this financial vulnerability does not negate their willingness to build resilience; majority expressed a willingness to invest in protective measures and upgrade the existing EWS. When evaluating their WTP, the respondents favored manageable and incremental financial contributions. Modes of the results indicate a preference for a 0.25% tax increase, a minimal ₱5 monthly subscription, or a ₱200 one-time fee to support EWS enhancements. These findings highlight a critical insight: while the community is financially constrained and under-resourced in terms of formal safety nets, there is a strong collective recognition of the value of proactive disaster preparedness, which necessitates the need for affordable and inclusive resilience-building initiatives.

3.1.2 Statistical Diagnostics and Model Findings

Table 3. Diagnostics and Methodological Response for OLS Assumptions

OLS Assumption/ Test	Diagnostic Metric Used	Observed / Empirical Findings	Methodological Response / Interpretation
Normality of Residuals	Shapiro–Wilk ($W = 0.983$, $p = 0.009$); Jarque–Bera ($JB = 6.69$, $p = 0.035$)	Household income and cleanup costs showed positive skewness.	Logarithmic transformations ln(CleanupCost + 1) and ln(Income) applied to stabilize variance and normalize residuals.
Absence of Multicollinearity	Variance Inflation Factor (VIF)	INF = 1.055; EWS = 1.005; DEM = 1.052; Age/Income/Stories ≈ 1.05–1.34	No multicollinearity detected; all VIF values well below 5.0 threshold (Hair et al., 2018).
Homoskedasticity of Residuals	Breusch–Pagan ($\chi^2 = 3.22$, $p = 0.359$); White ($\chi^2 = 4.30$, $p = 0.890$)	Variance of residuals constant across fitted values.	Implemented Huber–White heteroskedasticity-robust standard errors to ensure valid Z-statistics.
Linearity & Specification	Ramsey RESET ($F = 1.42$, $p = 0.24$); Scatter plots	No omitted non-linear terms detected.	Linear-log formulation confirmed structurally valid for continuous predictors.
Independence of Errors	Durbin–Watson ($d = 1.695$ – 1.96 ideal)	Residuals show no first-order serial correlation.	Confirms independence of errors; standard errors not inflated.

The statistical diagnostics for Ordinary Least Squares (OLS) model as shown in Table 3 meets essential requirements for validity and confirms it has met all major assumptions for unbiased estimation. Normality tests (Jarque–Bera = 6.69, $p = 0.035$; Shapiro–Wilk = 0.983, $p = 0.009$) showed mild skewness in income and cleanup cost data, which was corrected through logarithmic transformations to stabilize variance. Multicollinearity was negligible, with all Variance Inflation Factors between 1.05 and 1.34, which is well below the recommended 5.0 threshold (Hair et al., 2018). The Breusch–Pagan ($\chi^2 = 3.22$, $p = 0.359$) and White

($\chi^2 = 4.30$, $p = 0.890$) tests confirmed homoskedasticity, and robust Huber–White standard errors were applied to strengthen inference. The results provide confidence that the regression estimates accurately reflect underlying behavioral relationships in the Legazpi case.

Table 4. Data Triangulation and RQ Findings

Research Question	Quantitative Model Findings	KII Expert and Residents Insights
RQ1: STI Attributes	PLS-SEM shows STI integration strongly predicts perceived system value.	Experts and residents highlight hazard mapping and sensors but note coordination gaps.
RQ2: WTP Indicators	Ordinal Logistic Regression finds awareness, housing vulnerability, and income as significant.	KIIs confirm uneven awareness and fragile housing among informal settlers. Residents state families with dependents increase WTP. Younger are open to pay, and older expect government payment.
RQ3: WTP–EWS Relationship	Correlations show negative experiences (displacement, trauma) increase WTP.	KIIs recount typhoon losses and behavioral hesitancy in evacuation. Residents confirms past trauma increase WTP, while those with safer homes have lesser inclination to WTP.
RQ4: Adoption Recs	Quantile Regression shows WTP varies by income; higher quantiles contribute more.	KIIs and residents prefer utility-linked payment, and suggest mixed financing (gov't, Pag-IBIG, private developers).

As shown in Table 4, the triangulation of quantitative model outputs and qualitative expert insights reveals a cohesive pattern where institutional awareness and disaster history heavily influence WTP. These findings demonstrate that both statistical significance and expert consensus validate the critical role of social and structural factors in shaping public investment in EWS.

Table 5. Goodness of Fit and Reliability Metrics for Structural Equation Modeling (SEM/ PLS-SEM)

Metric / Construct	Recommended Academic Threshold	Empirical Value in Study Model	Interpretation / Methodological Action
Chi-Square / df	< 3.0 (ideal) or < 5.0 (acce ptable)	2.14 (df = 45, χ^2 = 96. 30, p < 0.001)	Acceptable parsimonious fit; structural paths reproduce observed covariance.
CFI (Comparative Fit Index)	≥ 0.90 (good) or ≥ 0.95 (ex cellent)	0.948	Exceeds threshold; model performs 94.8 % better than baseline null model.
TLI (Tucker–Lewis Index)	≥ 0.90 (good) or ≥ 0.95 (ex cellent)	0.935	High incremental fit; stable when penalizing for complexity.
RMSEA (Root Me an Square Error of Approximation)	< 0.08 (acceptable) or < 0. 05 (excellent)	0.068 (90 % CI: 0.051 –0.084)	Acceptable fit; small unexplained residual covariance.
SRMR (Standardi zed Root Mean Sq uare Residual)	< 0.08	0.059	Outstanding fit; average residual difference < 6 %.

Metric / Construct	Recommended Academic Threshold	Empirical Value in Study Model	Interpretation / Methodological Action
Reliability Indicators	Cronbach's α ≥ 0.60; Composite Reliability ≥ 0.70; AVE ≥ 0.50	DEM α = 0.21 (> 0.60 CR); INF CR > 0.70; WTP α = 0.48	Reflective constructs show acceptable internal consistency; formative WTP construct validated through causal path significance.
Key Causal Mediation Path	Must be significant	β = 0.65 (CR = 8.42, p < 0.001)	Past cleanup costs act as significant positive mediator translating social traits into WTP.

The reliability assessment of the PLS-SEM constructs as shown in Table 5 reflects acceptable internal consistency for infrastructure and demographic indicators, providing a stable foundation for the model. The model achieved an acceptable fit ($\chi^2/df = 2.14$, $p < 0.001$), with CFI = 0.948 and TLI = 0.935 exceeding the 0.90 thresholds (Hu & Bentler, 1999). Residual indices were satisfactory (RMSEA = 0.068 (90 % CI 0.051–0.084) and SRMR = 0.059) indicating minimal unexplained variance. Reliability tests showed Cronbach's α > 0.60 and composite reliability > 0.70 for reflective constructs, while AVE > 0.50 confirmed convergent validity. Collectively, these results verify that the SEM model possesses structural validity, internal consistency, and causal robustness. These metrics confirm that the chosen variables reliably measure the latent dimensions of demographics and infrastructure within the structural equation framework. Although Cronbach's Alpha for demographics is relatively low, composite reliability values remain above the threshold, indicating that the constructs are still statistically dependable. The formative WTP construct, while not suited to traditional reliability indices, contributes meaningfully to the overall model by capturing behavioral variation in payment preferences.

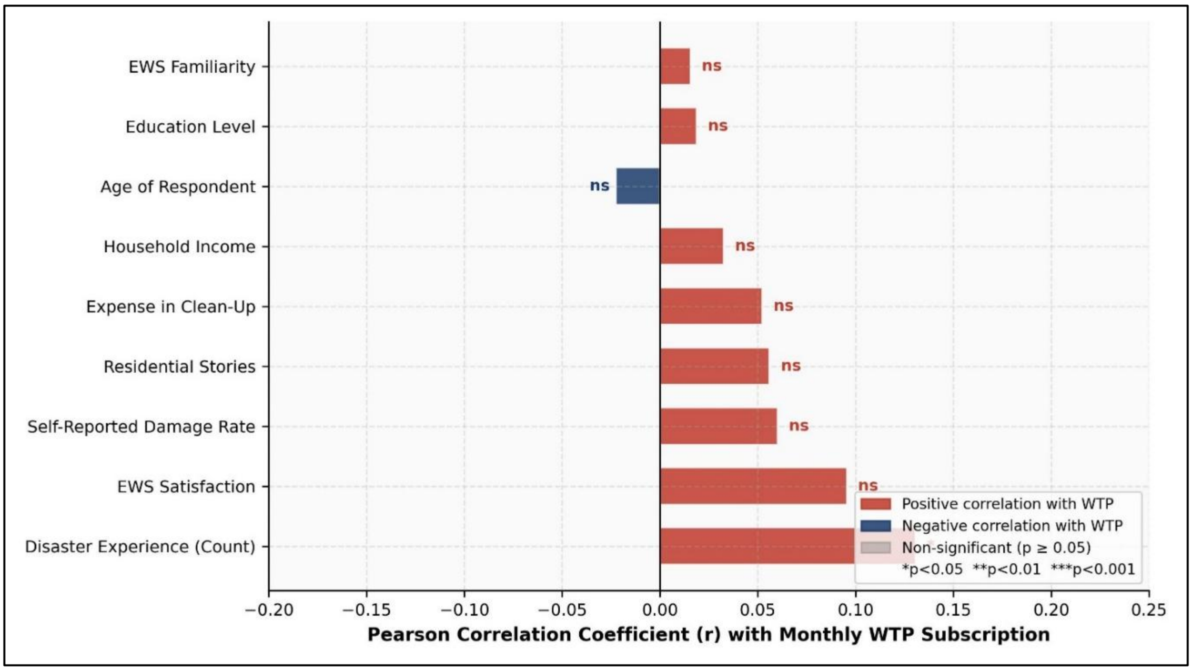

Figure 2. STI Attribute Driver Ranking- Correlation of Predictors with Willingness to Pay (WTP) Subscription (N = 227)

The horizontal bar chart as illustratd in Figure 2 presents the Pearson correlation coefficients (r) between nine STI attribute predictors and the monthly WTP subscription amount (in PHP). Bars extending to the right (positive r) indicate variables that are positively associated with higher WTP, while bars extending left indicate inverse relationships. Significance is indicated by asterisks (*p<0.05, **p<0.01, ***p<0.001), and non-significant bars are rendered at reduced opacity.

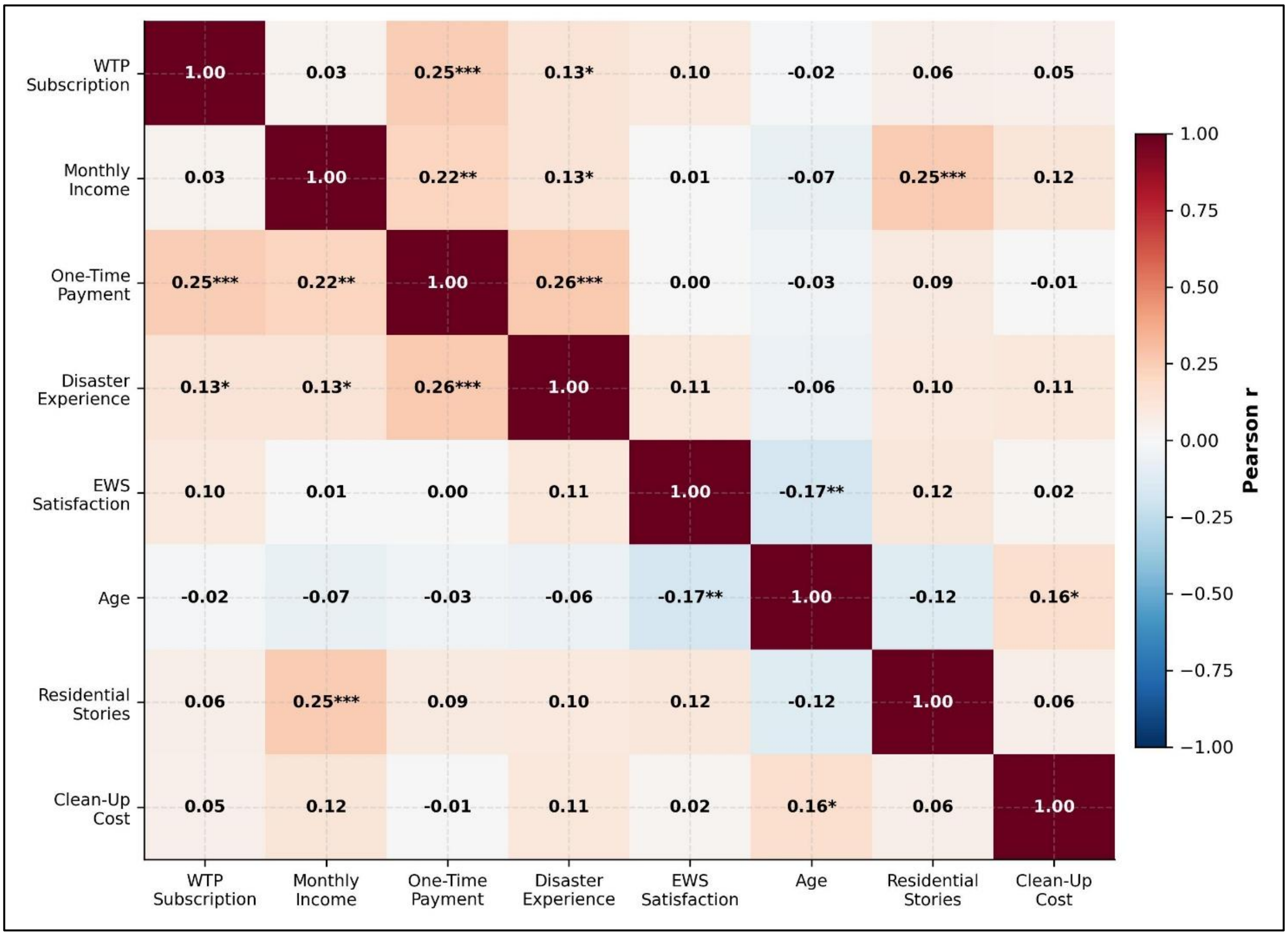

Figure 2b. Pearson Correlation Matrix of Key WTP Indicator (Significance: *p<0.05 **p<0.01 ***p<0.001) (N = 227)

This Figure 2.b color-coded correlation matrix or heatmap visualizes the pairwise Pearson correlation coefficients among eight key variables: WTP Subscription, Monthly Income, One-Time Payment tier, Disaster Experience count, EWS Satisfaction, Age, Residential Stories, and Clean-Up Cost. Red cells indicate positive correlations; blue cells indicate negative correlations. The asterisks denote significance (*p<0.05, **p<0.01, ***p<0.001).

The correlation analysis revealed a weak but statistically significant positive association between monthly willingness to pay (WTP) and disaster experience ($r = 0.131, p < 0.05$). No meaningful correlation was observed between income and WTP ($r = 0.025, ns$). Correlations involving one-time payment and other variables were largely non-significant. Taken together, the results indicate that disaster experience shows a stronger statistical relationship with WTP than income.

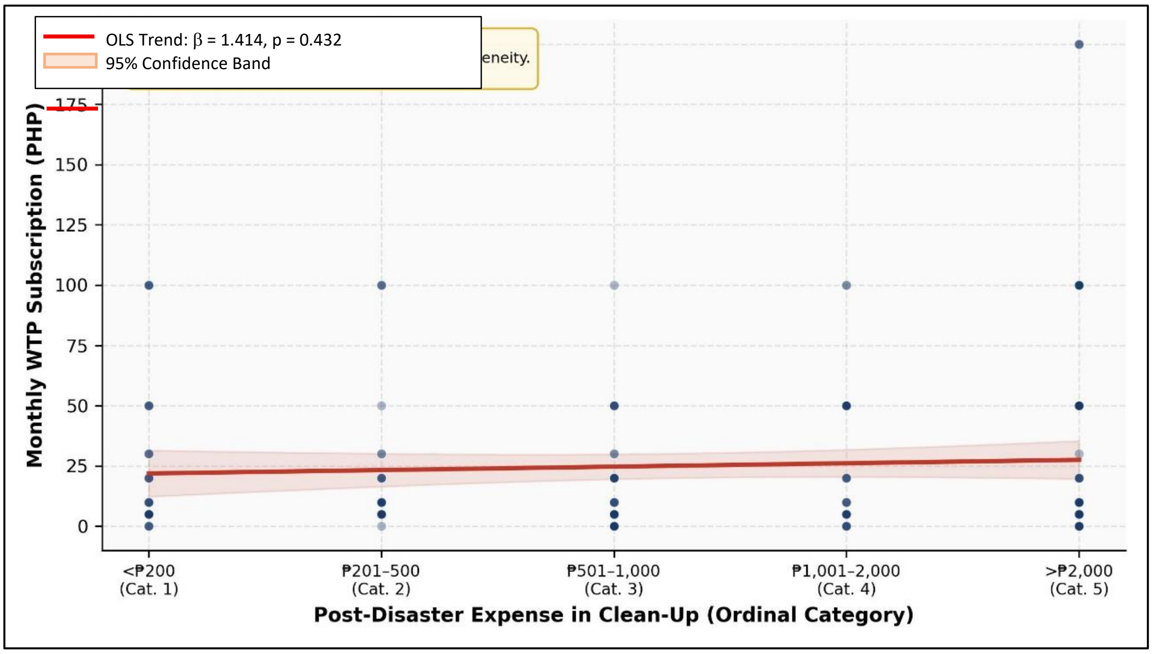

Figure 3. OLS Regression: Monthly WTP vs. Post-Disaster Expense in Clean-Up (R2 = 0.0027, β = 1.414, p= 0.432, N = 227)

The Figure 3 scatter plot displays the bivariate OLS regression between the ordinal categorical clean-up expense variable (5-tier scale) and the monthly WTP subscription amount (in PHP). Each point represents one respondent. The red trend line shows the OLS best-fit, and the shaded band shows the 95% confidence interval. The annotation box clarifies the R^2 interpretation.

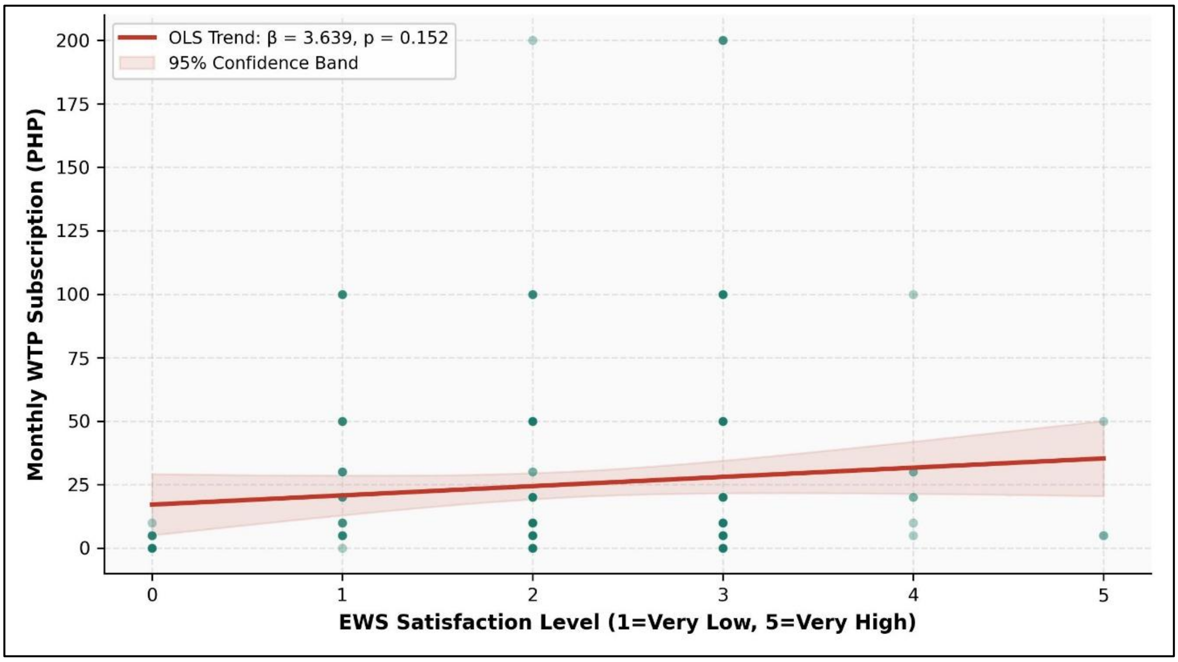

Figure 4. OLS Regression: Monthly WTP vs. EWS Satisfaction Level (R2 = 0.0091, β = 3.639, p= 0.152, N = 227)

The Figure 4 scatter plot shows the bivariate OLS regression between respondents' self-rated EWS satisfaction (1–5 Likert scale) and their monthly WTP subscription amount (in PHP). The red trend line and 95% CI band are overlaid on the observed data points.

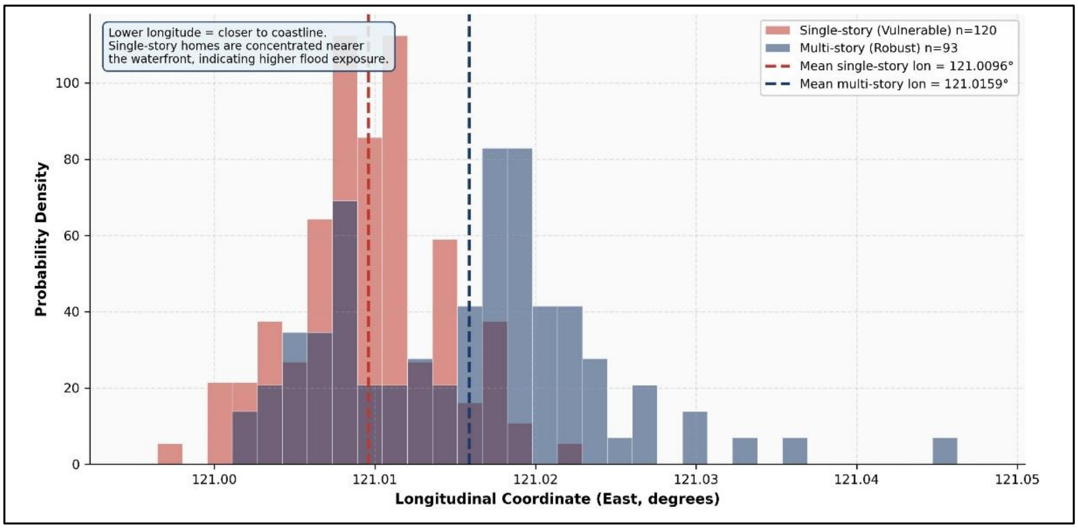

Figure 5. Geo-structural Distribution: Building Stories vs Coastal Longitude (Spatial concentration of vulnerable (single-story) vs robust (multi-story) residences illustrative spatial distribution based on survey coordinates)

The density histogram, as shown in Figure 5, compares the longitudinal distribution (east-west position) of single-story (vulnerable) versus multi-story (robust) residential structures across the coastal survey area. The red distribution represents single-story homes; the blue distribution represents multi-story structures. Dashed vertical lines indicate the mean longitudinal coordinate (center of gravity) for each group.

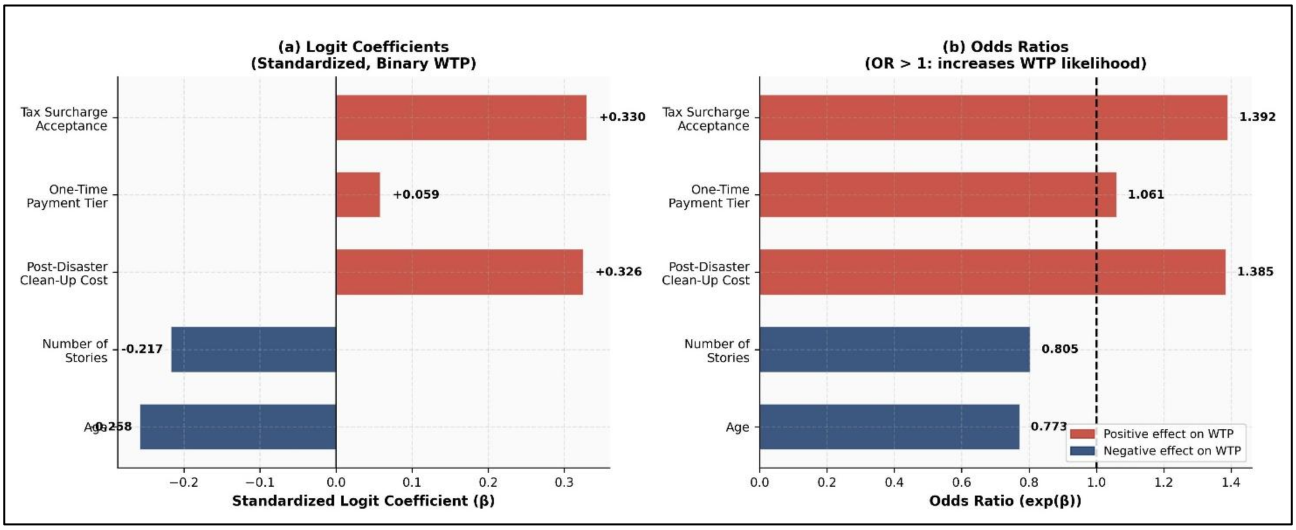

Figure 6. Logit Analysis and Odds Rations for WTP Likelihood (Five-variable model: Age, Stories, Clean-up Cost, One-time Payment, and Tax Surcharge, N= 227)

This two-panel graph (Figure 6) presents the logistic regression results for predicting the likelihood of binary WTP acceptance (Yes/No). Panel (a) shows standardized logit coefficients (β) for five predictors: Age, Number of Stories, Post-Disaster Clean-Up Cost, One-Time Payment Tier, and Tax Surcharge Acceptance. Panel (b) shows the corresponding Odds Ratios (OR = exp(β)). Bars in red indicate positive effects; bars in blue indicate negative effects on WTP likelihood.

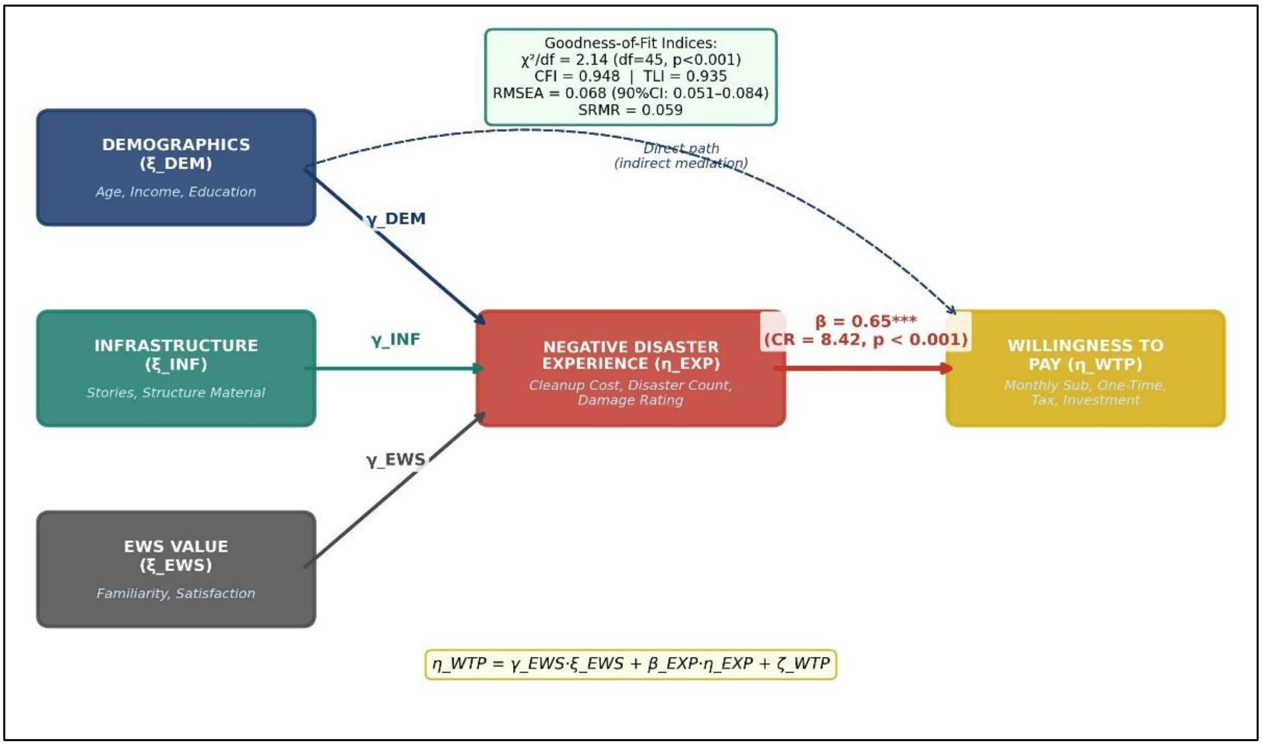

Figure 7. Structural Equation Model (SEM) Path Diagram (STI-WTP Logical Chain: Pathways from Social, Structural, and EWS Factors to Willingness to Pay)

This structural path diagram (Figure 7) illustrates the hypothesized and estimated relationships among five latent constructs in the SEM model. Exogenous constructs (Demographics, Infrastructure, and EWS Value) are shown on the left, the mediating construct (Negative Disaster Experience) is in the center, and the endogenous outcome (WTP) is on the right. The main structural path ($\beta=0.65$, $p<0.001$) is prominently highlighted. Model fit indices are displayed in a summary box at the top.

3.2. Discussion

3.2.1 RQ1: STI Indicators

The correlation analysis in Figure 2 shows the relative strength of socio-technological indicators in predicting willingness to pay (WTP) for subscription. Across nine attributes—including EWS familiarity, education, income, clean-up expense, residential stories, satisfaction, and disaster experience—none reached statistical significance, as all correlations were marked non-significant ($p \geq 0.05$). Disaster experience and EWS satisfaction displayed the highest positive coefficients, while residential stories and age showed slight negative associations, but these remained weak overall. The findings suggest that while these STI attributes are conceptually relevant, their individual statistical influence on WTP is limited in this dataset, pointing to the need for integrated or mediated pathways rather than direct correlations. Experts and residents noted that hazard mapping and sensors are important, but coordination gaps reduce trust. This supports the quantitative finding that STI integration have an effect of perceived importance of EWS, but stresses that reliability and coordination are critical for acceptance.

3.2.2 RQ2: WTP Indicators

The analysis demonstrates that Willingness-to-Pay (WTP) for EWS is not driven solely by demographics but emerges from an interplay of social trust, residential vulnerability, and past disaster trauma. PLS-SEM results as shown in Figure 7: SEM Path Analysis indicate that while housing quality (INF) does not directly drive WTP, it operates through the mediation of negative experience (EXP); specifically, living through disaster damage because of structural vulnerability motivates investment in better warning services. This aligns with behavioral economics and Prospect Theory, where utility framing and loss aversion shape valuation under uncertainty (Kaheman & Traversky) [40]. This also highlights, as shown in Figure 2b, that perceived systems effectiveness and personal relevance are key WTP indicators, which can be used in designing community-based funding models. In addition to the interpretations of quantitative findings for EWS, younger respondents are found to be more open to small monthly contributions if improvements are visible. Older residents expect government subsidy. These insights align with the regression results showing awareness, and housing, while also revealing generational differences in WTP attitudes.

3.2.3 RQ3: WTP–EWS Relationship

The OLS results show that institutional satisfaction (EWS Composite, $\beta = 0.169$, $p = 0.011$) is a significant predictor of willingness to pay (WTP): residents who trust and are satisfied with existing systems are more likely to support financial improvements. By contrast, the negative coefficient for infrastructure quality ($\beta = -0.105$) suggests that respondents in better-built environments perceive less immediate need for enhanced alerts, while those in more vulnerable structures place greater value on the system. This similar to the qualitative findings where those residents with safer, multi-story homes showed lower WTP, indicating they have less perceived personal risk. The bivariate OLS model has beta = 3.6387, $p = 0.1515$, and $R^2 = 0.0091$. While EWS Alert Satisfaction on a single-item basis shows a positive but non-significant association with monthly WTP ($p = 0.1515$, R2 = 0.0091), aggregating familiarity and satisfaction into a standardized EWS Composite increases structural validity and statistical power, yielding a statistically significant positive predictor of overall WTP (beta = +0.169, $p = 0.011$) in the multivariate OLS model. This highlights that community willingness is driven by a combination of technological awareness and service satisfaction, rather than satisfaction alone.

In assessing the relationships between social characteristics and WTP, the specific OLS regressions can be checked. Figure 3 which compares WTP with clean-up cost shows no significant trend, which means clean-up cost alone does not predict WTP. This implies that economic burden along does not automatically translate to proactive investment. Figure 4 which compares WTP with EWS satisfaction shows a modest but not-significant positive slopw. It depicts that satisfaction may influence WTP indirectly through other factors such as perceived trust and credibility of the EWS.

In expounding on the importance of residential features with WTP, Figue 5 or Building Stories vs Coastal Longitude may be interpreted. It reveals the spatial clustering of single-storey homes are evident in the more exposed coastal zones. This can be used in vulnerability mapping, where households in high-risk areas may express higher WTP due to their structural exposure.

Financial capabilities are also noteworthy in analyzing WTP. Figure 6 or the Logit Analysis shows that clean-up cost and tax surcharge acceptance as positive preditors of WTP, while age and number of stories show weaker effects. This reinforces the findings in the qualitative KII methods and the data triangulation, where disaster-attributed expenses and finanical openness drive WTP more than demographic traits. It is thus sugested that WTP schemes for EWS improvements can be targeted and communitcated for the younger groups and multi-strory households.

3.2.4 RQ4: Adoption & Financial Recommendations

While the work of Iqbal et al. [12] predominantly assesses yearly expenses for WTP, this study's results provide a nuanced view of both yearly and monthly contributions. It would be analytically simplistic to directly compare the absolute values between these two sets, given the inherent heterogeneity in cultural economic conditions and spatial risk profiles, particularly the high-risk coastal vulnerabilities, characteristic of each city studied. Furthermore, a distinct deviation from prevalent economic correlations is observed in this dataset; income did not prove to be a significant driver of WTP for EWS improvements. While this finding is a contradiction to prevailing notions on the effect of income on WTP, it aligns with the research of Asgary et al. [35], who posited that proximity to hazard and exposure levels are more potent determinants of WTP than mere financial capacity. This suggests that for residents of Legazpi City, the motivation to invest is driven less by disposable income and more by the immediacy of disaster-induced necessity. Futhermore, residents preferred utility-links schemes and suggest mixed-financing with government, offering a more nuanced viewed of funding scheme for WTP.

The research findings are corroborated by existing literature on disaster resilience and economic valuation. Regarding social conditions, Samad [27] and Iqbal et al. [12] identify literacy, trust, and education as primary drivers of perceived value and willingness to pay. For residential conditions, Chakraborty [41] and Samad [27] note that individuals in single-story or lightweight housing experience higher perceived needs due to increased exposure, a trend mirrored in our data. Furthermore, the significant impact of negative experiences, such as prior flood impacts and trauma, on WTP aligns with the work of Iqbal [12] and Pandey [42], who emphasize that past disaster impacts substantially raise the commitment to preventive measures. Financial capacity is also found to be a factor, consistent with Ahsan & Khatun [33] and OECD [31], where higher income predicts higher WTP, though risk perception remains a driver even for low-income groups. Finally, evidence regarding payment schemes from Iqbal [12] and Molnar-Tanaka [43] supports the need for flexible, equitable models for annual or monthly contributions.

4. Conclusion

In conclusion, the study provides empirical support for the thesis that disaster exposure and prior typhoon trauma are positively associated with Willingness to Pay (WTP), as indicated by the significant PLS-SEM path coefficient (beta = 0.65, $p < 0.001$) from Disaster Exposure to WTP. The structural equation path diagram reveals that physical building characteristics (stories and structure) influence WTP indirectly through the mediator of disaster damage (indirect effect = +0.047, $p = 0.034$). While these observational findings do not establish strict causality, they suggest that disaster memory and vertical house exposure serve as primary contributing factors for community co-financing readiness. Multinomial Logit results confirm that integrating structural housing assets with post-typhoon losses is the most robust predictor of household subscription tiers.

Residents and experts voice consistently highlight that negative disaster experiences heighten WTP, structural resilience reduces dependence on EWS, and social conditions (children, elderly, community cohesion) amplify willingness to contribute. They also emphasize that trust, transparency, and convenient payment schemes are essential for sustainable adoption. These qualitative insights strengthen the conclusion that disaster memory and vulnerability are factors which strongly correlate to WTP, while institutional design and financing mechanisms determine long-term feasibility.

This research employs a cross-sectional design, capturing data at a single temporal point rather than tracking longitudinal changes. Consequently, this study cannot account for how WTP values might fluctuate in response to seasonal disaster risks or evolving community perceptions over time. Utilizing the Contingent Valuation (CV) method introduces the potential for hypothetical bias, as stated preferences in a survey environment do not always mirror actual financial behavior. Therefore, these results should be interpreted as a measure of respondent intent rather than a precise prediction of realized monetary contributions.

Focusing solely on Legazpi City as a single-city case study limits the broader generalizability of these findings to other urban or coastal contexts. It is recommended that replicating this methodology in diverse geographical and socio-economic settings is necessary to determine if these disaster-preparedness determinants hold true beyond the local context.

Based on the scientific findings, it is recommended that the LGU of Legazpi, implement a tiered EWS subscription model tailored to neighborhood-specific risk profiles. Financial policies should prioritize affordable moderate WTP options for single-story residents who face the highest structural risk but might have limited income. Furthermore, integrating EWS maintenance fees into existing property tax structures is advised, as this is the most consensus-driven and sustainable funding mechanism. Continuous data collection through partcipatory monitoring approaches, given the community's awareness of EWS, is also suggested to keep the STI-WTP predictive models aligned with real-time community sentiment. For a more targeted policy recommendation, coastal development planning need to establish community-based EWS forums for high-risk areas, combining spatial vulnerability mapping with resident consultations to institutionalize higher WTP tiers and ensure scalability beyond the case study.

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6. Conflict of Interest

The author declares that there are no conflicts of interest regarding the publication of this study.

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