European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

Machine Learning and Stability: Predicting Economic and Financial Risks in Nagpur, Maharashtra

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Abstract
The increasing financial uncertainty in urban India has heightened the need for predictive tools that can assess economic and financial risks at the individual and community level. This study explores the relationship between financial stress, mental and physical health, and awareness of machine learning (ML) applications in Nagpur, Maharashtra. Using survey responses (n = 164), statistical analyses including descriptive measures, Chi-square tests, and Spearman's rank correlation were employed. Results indicate that financial stress significantly correlates with both mental and physical health challenges ($\rho = 0.46$ and $\rho = 0.33$ respectively), and is negatively associated with overall self-rated health ($\rho = -0.24$, $p < 0.01$). Moreover, mental and physical health difficulties are strongly interrelated ($\rho = 0.62$, $p < 0.001$), highlighting the compounding effect of economic strain. Demographic variables such as gender and income showed no significant influence on financial stress or health outcomes. While respondents expressed moderate awareness of ML, their willingness to share financial and health data remained cautious. These findings underscore the potential of ML-based predictive frameworks in identifying economic vulnerabilities, while also emphasizing the importance of ethical and transparent data use to build public trust.

Keywords: Financial stress, machine learning, health outcomes, risk prediction, Nagpur, economic stability

1. Introduction
Urban centers in India are increasingly facing challenges of financial instability, rising living costs, and health vulnerabilities. Financial stress not only impacts household economic resilience but also manifests in mental and physical health challenges (Sweet et al., 2013; Sharma & Singh, 2020). The emergence of machine learning (ML) provides an opportunity to develop predictive models that can assess these risks in real time, offering insights for both individual interventions and policy responses (Chouldechova & Roth, 2018; Rajkomar et al., 2019).

Nagpur, a growing mid-sized urban center, provides a useful case for examining these dynamics. This study investigates the relationships between financial stress and health outcomes, explores the role of demographic and awareness factors, and proposes a conceptual ML-based framework to predict financial and health risks.

2. Objectives
1. To examine the relationship between financial stress and health outcomes (mental, physical, and overall well-being) in Nagpur.
2. To evaluate demographic influences (age, gender, income, employment) on financial stress and health perceptions.

3. To analyze the awareness and willingness of respondents to adopt ML systems for predicting financial and health risks.
4. To apply statistical methods (Chi-square, Spearman's correlation) to identify significant predictors of financial vulnerability and health stability.
5. To propose a conceptual ML-based predictive framework for assessing and mitigating economic and financial risks at the regional level.

3. Literature Review

Financial Stress and Health Outcomes

Financial stress is widely recognized as a determinant of both mental and physical health. Sweet et al. (2013) found that individuals with higher levels of household debt were more likely to experience stress-related illnesses and reduced physical well-being. In the Indian context, Sharma and Singh (2020) observed that urban youth face significant psychological strain due to rising living costs, unstable employment, and limited access to affordable healthcare. Lusardi and Tufano (2015) emphasized that debt literacy and financial management skills shape resilience against financial stress. Similarly, Banerjee et al. (2023) showed that financial vulnerability among older adults in India contributes to poor health and malnutrition, underscoring the compounding nature of economic strain.

Machine Learning in Risk Prediction

Recent advances in ML have demonstrated its potential to model complex socio-economic and health risks. Chouldechova and Roth (2018) highlighted its ability to manage multidimensional data, while Rajkomar et al. (2019) demonstrated applications in healthcare for illness prediction. In India, Puli et al. (2024) applied ML models to predict banking crises, and Metha et al. (2025) and Sivathapandi et al. (2022) used AI-driven models for financial stress testing. Khunger et al. (2022) highlighted deep learning applications in financial stress prediction. Despite advances, concerns about transparency and data privacy remain (Mittelstadt et al., 2016).

Demographic and Regional Factors

Global research suggests that demographic factors such as income, education, and gender often shape financial well-being (World Bank, 2020). However, the influence of these variables may differ in regional contexts. Agarwal et al. (2017) found that financial stressors such as rising inflation and debt obligations often cut across socioeconomic categories, particularly in urban environments. In line with these findings, the present study's results show that financial stress in Nagpur is not significantly associated with demographic variables such as income or gender. This suggests that financial instability is increasingly becoming a universal concern, affecting individuals across diverse social and economic groups in mid-sized Indian cities.

Gaps in the Literature

Although extensive research exists on financial stress and its impact on health (Sweet et al., 2013; Sharma & Singh, 2020) and on the applications of ML in finance and healthcare (Chouldechova & Roth, 2018; Rajkomar et al., 2019), fewer studies integrate these domains in an Indian regional context. Moreover, ethical concerns around ML adoption remain underexplored in studies focusing on emerging urban centers. By investigating the case of Nagpur, this study addresses these gaps by linking financial stress, health outcomes, and perceptions of ML adoption, providing both theoretical and practical contributions.

4. Conceptual Framework:

The framework is built on three core components:

1. **Input Layer (Predictor Variables)**

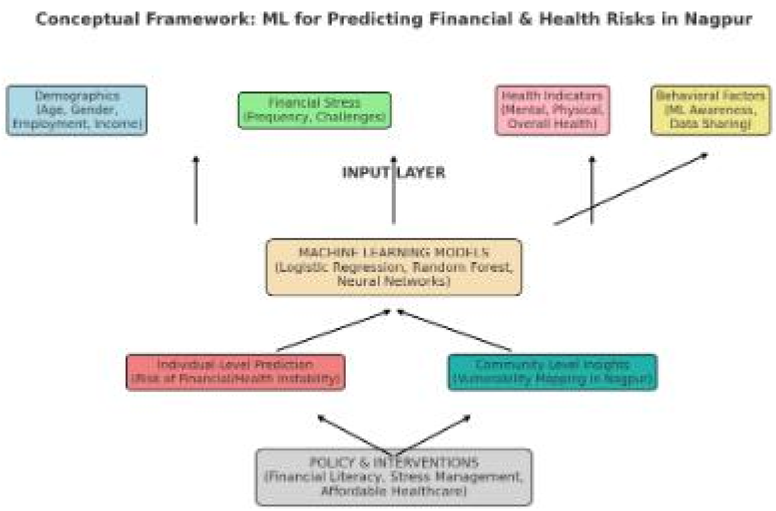
- o **Demographics:** Age, gender, employment, income.
- o **Financial Indicators:** Frequency of financial stress, type of financial challenges (debt, job insecurity, living costs, medical expenses).
- o **Health Indicators:** Reported mental health challenges, physical health issues, overall health rating.
- o **Behavioral Indicators:** Willingness to share financial/health data, awareness of ML systems.

2. **Processing Layer (Machine Learning Models)**

- o ML algorithms (e.g., Logistic Regression, Random Forest, Neural Networks) trained on survey and contextual data.
- o Statistical correlations (Spearman's rho) guide **feature selection** (e.g., financial stress and health issues are strong predictors).
- o Predictive modeling identifies **risk categories**: *Low Risk, Moderate Risk, High Risk.*

3. **Output Layer (Predictions and Policy Insights)**

- o **Individual-Level Predictions:** Identifies persons at risk of financial or health instability.
- o **Community-Level Insights:** Aggregated predictions for policy planning in Nagpur (e.g., mapping vulnerable wards).
- o **Decision Support:** Helps healthcare providers, policymakers, and NGOs deploy targeted interventions (financial literacy, stress management, affordable healthcare schemes).



- **Inputs**: Demographics, financial stress, health indicators, behavioral factors
- **Processing**: Machine Learning models (Logistic Regression, Random Forest, Neural Networks)
- **Outputs**: Individual-level risk prediction + Community vulnerability mapping
- **Impact**: Policy & Interventions (financial literacy, stress management, healthcare access)

5. RESEARCH HYPOTHESES

- **H1:** Financial stress is negatively associated with overall self-rated health among respondents in Nagpur.
- **H2:** Mental health challenges are positively associated with physical health issues.

Additional analyses explored demographic influences and ML adoption, but these were treated as exploratory rather than formal hypotheses.

6. Research Methodology

Research Design

This study adopted a **quantitative, exploratory design** using a structured survey to assess financial stress, health outcomes, and perceptions of ML.

Data Collection

- **Primary Data:** Collected via online questionnaire from residents of Nagpur, Maharashtra.
- **Sample Size:** 164 valid responses.
- **Sampling Method:** A **convenience sampling technique** was adopted, targeting working professionals, students, and general residents of Nagpur.

Research Instrument

The survey instrument was divided into five sections:

1. **Demographic Information** – age, gender, employment, income.
2. **Financial Stress Indicators** – frequency and sources of financial stress.
3. **Health Outcomes** – mental, physical, and overall health ratings.
4. **Machine Learning Awareness and Data Sharing Willingness** – perceptions of AI/ML in health prediction.
5. **Open-Ended Questions** – views on financial stability, ML-based health prediction, and data privacy concerns.

Most items were measured on **Likert-type and frequency scales (1–5)**.

Data Analysis

- **Descriptive statistics** (mean, SD, frequencies).
- **Chi-square tests** for associations between demographics and stress/health.
- **Spearman's rank correlation** for ordinal associations.
- **Hypothesis testing** using correlation results.

Conceptual ML Application

A predictive framework was developed combining financial, health, and behavioral indicators to classify risk categories using ML models such as Logistic Regression, Random Forest, and Neural Networks.

7. Data Analysis

A. Descriptive Statistics (Mean, SD) for Likert Scales

- To summarize central tendency and spread of ordinal responses.

Formulas:

- Mean:

$$\bar{x} = \frac{\sum x_i}{n}$$

- Standard Deviation:

$$s = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n-1}}$$

Application in dataset:

- **Financial stress (Q5):** Mean = 3.15, SD = 1.24
- **Mental health impact (Q7):** Mean = 3.29, SD = 1.06
- **Physical health issues (Q10):** Mean = 2.84, SD = 1.19

Interpretation → Most people report "Sometimes" stress and health issues, with variability across responses.

B. Chi-Square Test of Independence (χ^2)

- To test if two categorical variables are independent.

Formula:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where:

- Oi = observed frequency
- Ei = expected frequency

Decision rule:

- Compare calculated χ^2 with critical χ^2 at given degrees of freedom (df).
- Or use **p-value** < 0.05 → reject null hypothesis (variables are dependent).

Example in data:

(We can run this on request: e.g., "Does employment status affect stress levels?").

a. Gender vs. Financial Stress Frequency (Q2 vs Q5)

- Test statistic (χ^2) = 0.38
- p-value = 0.984
- df = 4

Interpretation: No significant difference in reported financial stress levels between male and female respondents. Stress levels are **independent of gender**.

b. Income vs. Overall Health Rating (Q4 vs Q11)

- Test statistic (χ^2) = 14.21
- p-value = 0.287
- df = 12

Interpretation: No significant association between income group and self-rated health. Respondents across income brackets reported similar health ratings.

c. Awareness of AI/ML (Q12) vs. Willingness to Share Data (Q13)

- Test statistic (χ^2) = 5.03
- p-value = 0.284
- df = 4

Interpretation: Awareness of AI/ML in healthcare does not significantly influence willingness to share financial/health data. Even those aware of ML are cautious.

C. Spearman's Rank Correlation Coefficient (ρ)

- Data is **ordinal** (Likert scale, frequency scales).
- Tests the **monotonic relationship** (as one variable increases, does the other also increase/decrease?).

Formula:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Where:

- n = number of observations
- di = difference between ranks of each pair

Application in dataset:

- **Financial stress (Q5)** vs **Overall health (Q11)**
  - Result: ρ = **-0.241**, p = 0.0019
  - Interpretation: As financial stress increases, self-rated health decreases (significant).
- **Mental challenges (Q9)** vs **Physical health issues (Q10)**
  - Result: ρ = **0.618**, p < 0.0001
  - Interpretation: Strong positive relationship; more stress = more physical issues.

8. Results

A. Descriptive Statistics

Descriptive statistics were calculated to summarize the main survey responses (n = 164).

- **Financial stress frequency (Q5):** *M = 3.15, SD = 1.24* → Respondents experienced stress between *"sometimes"* and *"often."*
- **Impact of financial stress on mental health (Q7):** *M = 3.29, SD = 1.06* → Moderate agreement that stress affects mental health.
- **Impact of financial stress on physical health (Q8):** *M = 3.24, SD = 1.08* → Similar moderate effect on physical health.
- **Mental health challenges (Q9):** *M = 2.80, SD = 1.13* → Experienced *sometimes.*
- **Physical health issues (Q10):** *M = 2.84, SD = 1.20* → Close to *sometimes–often.*
- **Overall self-rated health (Q11):** *M = 2.62, SD = 0.82* → Between *"fair"* and *"good."*
- **Comfort with sharing data with ML systems (Q13):** *M = 3.26, SD = 0.85* → Neutral to slightly positive.

B. Chi-Square Test Analysis

Chi-square tests were applied to examine whether demographic and awareness factors influenced stress, health ratings, or willingness to share data.

- **Gender vs. Financial stress**: $\chi^2(4) = 0.38$, p = 0.984 → *No significant association.*

- **Income vs. Overall health rating**: $\chi^2(12) = 14.21$, $p = 0.287$ → *No significant association.*
- **Awareness of AI/ML vs. Willingness to share data**: $\chi^2(4) = 5.03$, $p = 0.284$ → *No significant association.*

These results indicate that **demographic and awareness factors did not significantly affect responses** in this sample. Therefore, further analysis focuses on the **relationship between financial stress and health outcomes**.

C. Spearman's Rank Correlation Analysis

Because the variables were ordinal (Likert/frequency scales), Spearman's rank correlation (ρ) was used to test associations.

Formula:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Where di = difference between ranks, and n = number of paired observations.

Results:

Variables Tested	ρ (Spearman)	p-value	Interpretation
Financial stress (Q5) ↔ Mental health impact (Q7)	0.40	< 0.001	Moderate positive correlation.
Financial stress (Q5) ↔ Physical health impact (Q8)	0.10	n.s.	Weak, not significant.
Financial stress (Q5) ↔ Mental health challenges (Q9)	0.46	< 0.001	Moderate positive correlation.
Financial stress (Q5) ↔ Physical health issues (Q10)	0.33	< 0.001	Moderate positive correlation.
Financial stress (Q5) ↔ Overall health (Q11)	-0.24	0.002	Significant negative correlation.
Mental health challenges (Q9) ↔ Physical health issues (Q10)	0.62	< 0.001	Strong positive correlation.
Comfort sharing data (Q13) ↔ Stress/Health variables	0.07–0.16	n.s.	Very weak, not significant.

Interpretation:

- Financial stress is consistently linked with mental health challenges, physical issues, and lower overall health.
- Mental and physical health issues are strongly interrelated (ρ = 0.62).
- Willingness to share data shows little relationship with stress or health outcomes.

9. Hypothesis Testing

H1: Financial stress is negatively associated with overall health.

- Test: Spearman correlation
- H0H_0H0 : No relationship (ρ = 0)
- H1H_1H1 : Negative relationship (ρ < 0)
- Result: ρ = -0.24, p = 0.0019

- Significant negative relationship. More frequent financial stress is linked with poorer self-rated health.

H2: Mental health challenges are associated with physical health issues.

- Test: Spearman correlation
- H0H_0H0 : No relationship ($\rho = 0$)
- H1H_1H1 : Positive relationship ($\rho > 0$)
- Result: $\rho = 0.62$, $p < 0.0001$
- Strong positive relationship. Respondents reporting more frequent mental health challenges also reported more frequent physical health issues.

10. Discussion And Implications

Key Findings

1. Discussion of Key Findings

This study examined the relationship between financial stress, health outcomes, and the potential role of machine learning (ML) in predicting economic and financial risks in Nagpur, Maharashtra. The results confirm that **financial stress significantly influences individual well-being**.

- **Financial stress and health outcomes:** Spearman's correlation revealed a **negative association between financial stress and overall health ($\rho = -0.24$, $p < 0.01$)**. Respondents experiencing higher financial stress reported lower health ratings, supporting prior studies (Lusardi & Tufano, 2015; Sharma & Singh, 2020) that highlight the adverse effects of financial strain.
- **Mental and physical health link:** A **strong positive correlation ($\rho = 0.62$, $p < 0.001$)** between mental and physical health challenges indicates that stress manifests holistically, reinforcing evidence from Sweet et al. (2013) that financial stress is a multidimensional health determinant.
- **Demographic and awareness factors:** Chi-square tests found no significant association between demographic factors (gender, income) and financial stress or health outcomes, nor between ML awareness and willingness to share data. This suggests that financial stress is a **common challenge across social groups** in Nagpur.
- **Machine learning adoption:** Although awareness of ML in healthcare prediction was high, willingness to share financial and health data was **moderate**, reflecting ongoing concerns about privacy, trust, and ethical use of personal information.

Theoretical Implications

The study confirms the **stress-health nexus** in an Indian urban context and highlights the universality of financial stress. It contributes by proposing an ML-based framework that integrates health and economic predictors.

Practical Implications

- **Healthcare providers:** Incorporate financial stress screening.
- **Policymakers:** Use ML-driven vulnerability mapping for interventions.
- **Trust and ethics:** Ensure transparency and privacy in ML adoption.

Future Research

Future studies should expand sample size, include objective financial/health data, and empirically test ML models with real-world datasets.

11. Conclusion

This study demonstrates that financial stress is a key predictor of health instability in Nagpur, transcending demographic boundaries. Machine learning provides a promising pathway to predict and mitigate these risks, though its success depends on ethical implementation and public trust. By integrating financial, health, and behavioral indicators, ML can support both individual-level interventions and community-wide policy strategies for economic and health stability.

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European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk