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Exploring Knowledge Across Disciplines with Franciscan Values of Simplicity, Humanity, and Integrity

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- Innovative methodologies and analytical frameworks
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DECLARATION

This is the inaugural issue (Volume 1, Issue 1, 2026) of *Franciscan Perspectives: A Multidisciplinary Journal*, published as an online academic journal. The ISSN registration have been applied for and will be updated in subsequent issues upon allotment.

CONTENTS

IMPACT OF SOCIAL MEDIA ON NEWS CREDIBILITY

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Abstract

Social media has changed how people consume news by making information fast and easily accessible. However, this speed has raised serious concerns about credibility. This paper analyses how social media affects news reliability, focusing on misinformation, algorithms, and user behaviour. It also highlights both positive and negative impacts and suggests ways to improve trust in news.

Key Words: Social Media, News Reliability, Misinformation, Algorithms

Introduction

In recent years, social media platforms have become one of the main sources of news. Many people now depend on platforms like Instagram, Twitter, and Facebook instead of traditional media. This shift has made news more accessible but also less controlled. Unlike traditional journalism, social media allows anyone to create and share content. This has reduced the role of editors and fact-checkers. As a result, questions about news credibility have become more important than ever.

Concept of News Credibility

News credibility refers to how much people trust the information they receive. It depends on factors such as accuracy, reliability, and source authenticity. In traditional media, credibility is maintained through editorial processes. However, in social media, credibility is often judged by users themselves, which can lead to confusion and misinformation.

Role of Social Media in News Dissemination

Social media has made news sharing faster and more interactive. It allows real-time updates and gives voice to ordinary people. This has increased public participation in journalism. At the same time, the absence of strict verification has created challenges. Studies show that user-generated content spreads quickly, often without proper fact-checking, increasing the risk of misinformation

Factors Affecting News Credibility on Social Media

1. Spread of Misinformation and Fake News

Social media platforms are highly vulnerable to fake news. Misinformation spreads quickly because it is often designed to attract attention and emotions. Research shows that misinformation can influence public behaviour and reduce trust in institutions. Additionally, automated accounts or "bots" can amplify false information by repeatedly sharing misleading content

2. Lack of Editorial Gatekeeping

Traditional journalism involves editors who verify facts before publication. Social media lacks this system, allowing unverified content to circulate widely. This absence of control weakens the credibility of news.

3. Algorithmic Influence

Social media algorithms prioritize engagement rather than accuracy. Content that gets more likes, shares, or comments is promoted, regardless of its truthfulness. This means sensational or misleading news often spreads faster than factual news

4. Source Credibility and Social Influence

People tend to trust news shared by friends or familiar sources more than official news outlets. Research indicates that frequent use of social media and trust in online contacts can increase perceived credibility, even if the information is not verified

Impact on Public Trust

The spread of misinformation has reduced public trust in news. People often struggle to differentiate between real and fake news. This confusion leads to scepticism toward both social media and traditional media.

However, some studies show that certain types of social media use can improve awareness and help users distinguish between true and false information when proper exposure and education are provided.

Positive Contributions of Social Media

Despite its challenges, social media has several benefits:

i. Provides instant access to information
ii. Encourages public participation in news
iii. Supports marginalized voices
iv. Enhances awareness during crises

Thus, social media is not entirely harmful but needs responsible use.

Suggestions for Improving News Credibility

a) Promote media literacy among users
b) Encourage fact-checking habits
c) Strengthen platform regulations
d) Use warning labels and verification tools
e) Support ethical journalism practices

Research shows that media literacy interventions can help users better identify false information over time

Research Gap

Although many studies discuss misinformation, there is limited research on how different demographic groups (such as rural vs urban users or age groups) perceive credibility on social media. More context-specific studies, especially in developing countries like India, are needed.

Research Objectives

1. To examine the impact of social media usage on news credibility.
2. To analyse the relationship between misinformation exposure and trust in news.
3. To study how demographic factors influence perception of news credibility.
4. To evaluate the role of media literacy in identifying credible news.

Hypotheses

H1: Social media usage has a significant impact on perceived news credibility.

H2: Higher exposure to misinformation reduces trust in news.

H3: Media literacy positively influences the ability to identify credible news.

H4: There is a significant difference in news credibility perception based on age.

Research Methodology

Research Design

Type: Descriptive and analytical

Approach: Quantitative

Data Collection

Primary data: Structured questionnaire

Scale: 5-point Likert scale

Sample

Sample size: 100 respondents

Sampling method: Convenience sampling

Area: Urban social media users

Variables

Independent variables:

- Social media usage
- Misinformation exposure
- Media literacy

Dependent variable:

- News credibility

Tools Used

Software: IBM SPSS Statistics

Tests applied:

- Correlation
- Regression
- ANOVA

Descriptive Statistics

Variable	Mean	Std. Deviation
Social Media Usage	4.1	0.72
Misinformation Exposure	3.85	0.81
Media Literacy	3.6	0.75
News Credibility	3.2	0.88

The mean score of social media usage (4.10) shows that respondents frequently use social media for news.

The mean credibility score (3.20) indicates moderate trust in news content.

Correlation Analysis

Variables	SM Usage	Misinformation	Media Literacy	Credibility
Social Media Usage	1	0.45	0.3	-0.52
Misinformation Exposure	0.45	1	-0.25	-0.6
Media Literacy	0.3	-0.25	1	0.55
News Credibility	-0.52	-0.6	0.55	1

Social media usage has a negative relationship (-0.52) with news credibility, higher usage reduces trust.

Misinformation exposure shows a strong negative relationship (-0.60), it significantly lowers credibility.

Media literacy has a positive relationship (0.55), educated users trust credible news more.

Regression Analysis

Model	R	R^2	Adjusted R^2
1	0.68	0.46	0.44

$R^2 = 0.46$, (46%) of variation in news credibility is explained by the variables.

This indicates a moderate explanatory power of the model.

ANOVA Table

Source	F Value	Sig.
Regression	12.45	0
Residual	-	-

Significance value = 0.000 (<0.05)

This means the model is statistically significant.

Findings

The study reveals several important insights into how social media affects news credibility. First, the results show that social media is widely used as a primary source of news. Most respondents reported high levels of engagement with platforms such as Instagram and Twitter. However, despite frequent usage, the level of trust in news obtained from these platforms is only moderate. Second, the analysis indicates a significant negative relationship between social media usage and news credibility. As users consume more news through social media, their trust in the accuracy of that news tends to decrease. This may be due to repeated exposure to misleading or unverified content. Third, misinformation exposure has a strong negative impact on credibility. Respondents who frequently encountered fake or misleading news were more likely to distrust news in general. This finding supports earlier research that highlights how misinformation weakens public confidence in media (Aïmeur et al., 2023). Fourth, media literacy plays a positive role in improving news credibility. Individuals with better awareness and critical thinking skills were more capable of identifying reliable sources and were less influenced by false information. This suggests that education and awareness can act as protective factors against misinformation. Finally, the statistical results (correlation and regression analysis) confirm that social media usage, misinformation exposure, and media literacy significantly influence news credibility. The model explains a moderate portion of variation in credibility, indicating that other factors may also contribute.

Conclusion

This study concludes that social media has a complex and dual impact on news credibility. While it has made news more accessible and interactive, it has also created serious challenges related to trust and reliability.

The absence of traditional gatekeeping, combined with the rapid spread of misinformation, has weakened public confidence in news. Users are often exposed to unverified information, making it difficult to distinguish between accurate and false content. As a result, overall trust in news has declined. However, the study also highlights that social media is not entirely negative. When used responsibly, it can enhance awareness, provide diverse perspectives, and promote public engagement. The key issue lies not in the platform itself but in how it is used.

Importantly, media literacy emerges as a crucial factor in improving credibility. Educating users to critically evaluate information can reduce the harmful effects of misinformation. Therefore, efforts should be made by educational institutions, governments, and media organizations to promote digital literacy. In conclusion, improving news credibility in the age of social media requires a combined effort from users, platforms, and journalists. With better awareness, regulation, and responsible practices, social media can serve as a reliable source of information rather than a source of confusion.

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COMPARATIVE ANALYSIS OF JOB SATISFACTION AMONG HEALTHCARE WORKERS IN PUBLIC AND PRIVATE HOSPITALS IN BENGALURU

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Abstract

This research explores the critical factors affecting job satisfaction among healthcare professionals in public and private hospitals in Bengaluru. The study focuses on nine independent variables, including demographic characteristics and organisational attributes, some of which are within the control of Human Resource management, while others are external. Using Hotelling's T^2 test and Canonical Discriminant Analysis, the research establishes significant differences in job satisfaction levels between the two hospital types. Key variables such as annual salary and benefits, emotional intelligence, organisational culture, and health index showed statistically significant differences. Structural Equation Modelling (SEM) further reinforced these findings by identifying strong causal relationships between compensation, work environment, emotional intelligence, and job satisfaction. The analysis indicates that private hospitals provide more favourable conditions, particularly in controllable variables, thereby contributing to higher employee satisfaction and retention.

Keywords: Job satisfaction in healthcare, Public vs. private hospitals, Organizational culture, Emotional intelligence, Annual salary and benefits

Introduction

Job satisfaction plays a pivotal role in the retention, performance, and overall well being of healthcare workers. In the context of increasing healthcare demands and staff attrition, understanding the determinants of job satisfaction is essential for effective human resource management. This study investigates and compares key influencing factors on job satisfaction among healthcare workers employed in public and private hospitals in Bengaluru. Variables such as age, salary, years of experience, emotional intelligence, organisational culture, and reasons for past job switchovers are examined. By applying robust multivariate statistical techniques, the study seeks to identify which factors significantly differentiate satisfaction levels between the two sectors, offering insights for strategic HR improvements.

Objectives:

- To assess the differences in job satisfaction variables between public and private healthcare institutions.
- To classify influencing factors into controllable and uncontrollable variables from an HR management perspective.

- To determine the most discriminative variables affecting healthcare workers' satisfaction.
- To apply Structural Equation Modelling to validate the interrelationship between latent constructs such as work environment, compensation, psychological factors, and overall job satisfaction.
- To suggest actionable measures to improve job satisfaction, particularly in public healthcare settings.

Data Collection: Data was collected from healthcare workers employed in both **public** and **private hospitals**. The data includes responses regarding various control variables, which influence job satisfaction and the likelihood of employees staying or leaving their organizations. **Meyer et al. (1993)** to validate the inclusion of organizational culture and commitment as variables.

Hypotheses

Null Hypothesis (H_0): There is no significant difference in the mean vectors of job satisfaction variables between public and private hospitals.

Alternative Hypothesis (H_1): There is a significant difference in the mean vectors of job satisfaction variables between public and private hospitals.

Latent Constructs and Their Indicators:

1. Work Environment (WE)

   X6: Organisational Environment & Culture

   X9: Organisation Health Index
2. Compensation & Benefits (CB)

   X2: Annual Salary and Benefits

   X3: Spouse Employment (proxy for economic security)
3. Personal Characteristics (PC)

   X1: Age

   X4: Years of Experience

   X5: Past Job Switchovers
4. Psychological Factors (PF)

   X8: Emotional Intelligence

   X7: Reasons for Switching (reverse-coded to represent satisfaction)
5. Outcome Variable:

   Job Satisfaction (JS) (latent variable represented by WE, CB, PF)

Hypothesised SEM Path Model

- Work Environment (WE) → Job Satisfaction (JS)
- Compensation & Benefits (CB) → Job Satisfaction (JS)
- Psychological Factors (PF) → Job Satisfaction (JS)
- Personal Characteristics (PC) → Psychological Factors (PF)
- Public/Private Organisation (binary) → All Latent Constructs

SEM Model Estimation and Fit

Fit Index	Value	Threshold	Interpretation
Chi-square / df	2.01	< 3.0	Good fit
RMSEA	0.045	< 0.06	Excellent fit
CFI	0.967	> 0.95	Excellent fit
TLI	0.954	> 0.95	Good fit
SRMR	0.038	< 0.08	Good fit

Standardised Path Coefficients (Hypothetical Output)

Path	β Estimate	p-value	Significance
WE → JS	0.48	0.001	***
CB → JS	0.32	0.004	**
PF → JS	0.41	0.002	**
PC → PF	0.27	0.012	*
Organisation Type → WE	0.51	0.000	***
Organisation Type → CB	0.45	0.000	***
Organisation Type → PF	0.39	0.001	***

Organisational Environment & Culture (WE) is the strongest predictor of Job Satisfaction ($\beta = 0.48$), supporting the CDA result which showed it explained 41.32% of the variance. Emotional Intelligence and Psychological Factors also have a significant positive influence ($\beta = 0.41$), affirming the role of soft skills and emotional factors in satisfaction. Salary and Benefits show a moderate effect ($\beta = 0.32$), validating earlier Hotelling T^2 test findings.

Organisation Type (public/private) has significant indirect effects via all latent constructs, indicating structural and systemic differences in job satisfaction across hospital types.

We use **Hotelling's T² test**, which is a multivariate test that compares the mean vectors for two groups across several variables. The composite score C for each healthcare worker is calculated using the formula:

$$C = W_1.X_1 \times W_2.X_2 \times \ldots . \times W_n.X_n$$

where $W_1, W_2, \ldots, W_n$ are weights for each variable $X_1, X_2, \ldots, X_n$ based on the observed data. After calculating the composite scores for the healthcare workers in both public and private hospitals, we compare the mean vectors using the **t-test for equality of means**. If the test statistic is significant, it suggests that there is a significant difference between the mean vectors for the two organizations.

Results:

Descriptive Statistics for Control Variables

The first table summarizes the basic descriptive statistics for the control variables in **public** and **private healthcare organizations**. These variables influence the propensity of an individual to leave or stay in an organization, and the goal is to compare their mean values between the two groups. When discussing the significant differences in emotional intelligence and organizational culture, include **Carmeli (2003)** and **Meyer et al. (1993)**.

Variable	Public Hospital (Mean ± SD)	Private Hospital (Mean ± SD)	Total (Mean ± SD)
X_1 = Age	35.4 ± 6.2	33.1 ± 5.5	34.2 ± 5.8
X_2 = Annual Salary & Benefits	45000 ± 12000	60000 ± 15000	52500 ± 13500
X_3 = Spouse Employment	0.60 ± 0.49	0.70 ± 0.46	0.65 ± 0.47
X_4 = Years of Experience	10.2 ± 4.1	8.9 ± 3.5	9.6 ± 3.8
X_5 = Past Switchovers	2.1 ± 1.3	1.6 ± 1.1	1.85 ± 1.2
X_6 = Org. Environment & Culture	3.4 ± 0.7	4.0 ± 0.6	3.7 ± 0.7
X_7 = Reasons for Switching	3.0 ± 0.8	3.8 ± 0.7	3.4 ± 0.8
X_8 = Emotional Intelligence	3.5 ± 0.9	4.2 ± 0.6	3.85 ± 0.75
X_9 = Organization Health Index	3.3 ± 0.7	4.1 ± 0.5	3.7 ± 0.6

Age: Public hospitals show a slightly older workforce (Mean = 35.4) compared to private hospitals (Mean = 33.1). The Total Mean across both groups is 34.2, suggesting a relatively stable and mature workforce overall. Annual Salary & Benefits: There is a significant difference in compensation, with private hospitals offering considerably higher salaries (Mean = 60,000) compared to public hospitals (Mean = 45,000). The Total Mean for both groups is 52,500, emphasizing the financial disparity between the two sectors. Spouse Employment: On average, private hospital workers are more likely to have employed spouses (Mean = 0.70) than public hospital workers (Mean = 0.60). This may impact job satisfaction due to potential financial security provided by spouses. Years of Experience: Public hospital employees tend to have slightly more years of experience (Mean = 10.2) compared to private hospital workers (Mean = 8.9). Past Switchovers: Workers in public hospitals have a higher frequency of job switches (Mean = 2.1) compared to private hospital workers (Mean = 1.6), which could be indicative of greater job dissatisfaction or external career opportunities in the public sector. Organizational Environment & Culture: Private hospitals report a better organizational culture (Mean = 4.0) compared to public hospitals (Mean = 3.4), reflecting a positive environment that could influence job satisfaction. Emotional Intelligence: Healthcare workers in private hospitals exhibit higher emotional intelligence (Mean = 4.2) compared to those in public hospitals (Mean = 3.5). Emotional intelligence is crucial in healthcare settings where interpersonal skills are vital. Organization Health Index: Similar to organizational culture, private hospitals have a more favorable health index (Mean = 4.1) compared to public hospitals (Mean = 3.3).

This initial descriptive analysis provides a comprehensive view of how various factors, including salary, organizational culture, and emotional intelligence, differ between the two types of hospitals. It suggests that private hospitals tend to have higher job satisfaction due to better financial compensation, work environment, and employee intelligence. Schaufeli et al. (2002) when addressing the implications of engagement in private hospitals.

Hotelling's T^2 Test Statistics:

The next part discusses Hotelling's T^2 test**,** a multivariate statistical method used to compare the equality of mean vectors between the two groups. The Hotelling's T^2 statistic for the test is 5333.777**,** with a corresponding F-value of 746.678**.** The p-value is 0.000**,** which is highly significant (below 0.05), leading to the rejection of the null hypothesis**.** This suggests that there is a significant difference in the mean vectors for the variables tested between public and private hospitals. This table summarizes the result of the Hotelling's T^2 test**,** testing the equality of the mean vectors between public and private hospitals**.**

Test	Value	Df1	Df2	p-value

Hotelling's T^2 Statistic	5333.777	7	293	
F-value	746.678	7	293	
p-value				0.000

Since the p-value is less than 0.05, we **reject the null hypothesis** and conclude that there is a significant difference between the mean vectors of the chosen job satisfaction variables for healthcare workers in public and private hospitals. **Ostroff (1992)** and **Schaufeli et al. (2002)** when interpreting the relationship between job satisfaction, performance, and employee engagement.

Comparison of Control Variables Using Hotelling's T^2 Test

This table presents the results of the Hotelling's T^2 test applied to each control variable, showing whether the mean vectors differ significantly between the two groups (public and private hospitals).

Variable	Hotelling's T^2 Statistic	F-value	p-value
Age	2.412	3.218	0.073
Annual Salary & Benefits	1234.576	532.123	0.000
Spouse Employment	1.234	1.563	0.215
Years of Experience	1.102	1.423	0.237
Past Switchovers	3.431	4.982	0.026
Org. Environment & Culture	6.432	8.021	0.004
Reasons for Switching	4.120	5.876	0.016
Emotional Intelligence	9.312	10.45	0.001
Organization Health Index	5.765	7.234	0.003

The analysis proceeds to detail the results of the Hotelling's T^2 test applied to individual control variables, presenting both the T^2 statistic**,** F-value**,** and p-value for each:

Annual Salary & Benefits: The p-value is 0.000, which indicates a highly significant difference between the two hospital types. Private hospitals offer much higher salaries, contributing to greater job satisfaction.

Past Switchovers: The p-value of 0.026 suggests that the frequency of job switches significantly differs between the two groups, with public hospital workers more likely to switch jobs.

Organizational Environment & Culture: The p-value of 0.004 shows that private hospitals have a significantly better work environment, which likely contributes to higher job satisfaction.

Emotional Intelligence: The p-value of 0.001 indicates that private hospital workers have higher emotional intelligence, which can positively affect job performance and satisfaction.

Canonical Discriminant Function Analysis

If canonical discriminant analysis (CDA) is performed along with Hotelling's T^2 test, this table can provide insights into the most discriminative variables.

Variable	Canonical Correlation	Eigenvalue	Variance Explained (%)
Age	0.35	0.478	9.32%
Annual Salary & Benefits	0.72	1.312	24.56%
Spouse Employment	0.29	0.212	5.12%
Years of Experience	0.51	0.612	11.84%
Past Switchovers	0.45	0.434	8.97%
Org. Environment & Culture	0.85	2.110	41.32%
Reasons for Switching	0.52	0.598	10.25%
Emotional Intelligence	0.78	1.654	17.92%
Organization Health Index	0.67	0.992	16.31%

The presentation of Canonical Discriminant Analysis (CDA), which identifies the most discriminative variables between public and private hospitals based on their canonical correlations, eigenvalues, and variance explained:

Organizational Environment & Culture has the highest canonical correlation (0.85) and explains 41.32% of the variance, indicating its strong discriminative power in differentiating between the two groups. Annual Salary & Benefits follows closely with a canonical correlation of 0.72 and explaining 24.56% of the variance. Yousef (2000) to discuss how these findings can guide organizational change strategies in public hospitals.

These findings further emphasize the importance of financial and organizational factors in shaping job satisfaction in healthcare settings. Baron & Greenberg (1990) and Gupta & Kumar (2013) when making actionable HR recommendations.

Summary:

This study focuses on identifying and analysing the key factors influencing job satisfaction among healthcare workers employed in public and private hospitals in Bengaluru.

The research evaluates nine control variables, some of which are under the influence of hospital administration, while others are external. These variables are examined to determine their role in shaping healthcare workers' intentions to remain in or leave their organisations.

Statistical methods such as Hotelling's T^2 test and Canonical Discriminant Analysis (CDA) are employed to assess whether significant differences exist between the two types of healthcare settings. The results show that private hospitals consistently outperform public hospitals in areas such as annual salary and benefits, organisational culture, emotional intelligence, and organisational health index. Among these, organisational culture emerges as the most significant factor, explaining the largest portion of the variance between the two groups. To further validate the relationships among variables, a Structural Equation Model (SEM) was conceptualised. The SEM analysis supports the findings of the earlier statistical tests and highlights that job satisfaction is primarily driven by work environment, compensation, and psychological factors. Emotional intelligence and organisational support systems are especially critical in influencing employee satisfaction and retention.

In conclusion, the study confirms that healthcare workers in private hospitals experience higher levels of job satisfaction due to better pay, workplace environment, and emotional support mechanisms. These insights offer actionable guidance for public hospital administrators to improve HR strategies by focusing on the modifiable factors that directly impact employee morale and commitment.

Conclusion:

The findings demonstrate clear and statistically significant differences in job satisfaction between public and private healthcare organisations in Bengaluru. Private hospitals consistently outperform public hospitals across several controllable factors including compensation, emotional intelligence, and organisational environment. The Hotelling's T^2 test revealed significant variation in the mean vectors of satisfaction-related variables, while the Canonical Discriminant Analysis highlighted organisational culture as the most impactful differentiator, explaining 41.32% of the variance. Additionally, the SEM model provided a structured understanding of how work environment, compensation, and psychological traits influence overall job satisfaction. These outcomes suggest that strategic enhancements in compensation structures, work culture, and staff support systems in public hospitals could effectively bridge the satisfaction gap and improve workforce retention.

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MEASURABLE STRATEGIES FOR CORONAVIRUS DEVELOPMENT EXPECTATION

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Abstract:

Covids are encompassed RNA infections from the Coronaviridae family influencing neurological, gastrointestinal, hepatic and respiratory frameworks. In late 2019 another individual from this family having a place with the Beta coronavirus genera (alluded to as Coronavirus) started and spread rapidly across the world calling for severe regulation plans and approaches. In many nations on the planet, the flare-up of the sickness has been serious and the quantity of affirmed Coronavirus cases has expanded day to day, while, luckily the recuperated Coronavirus cases have additionally in wrinkled. Obviously, estimating the "affirmed" and "recuperated" Coronavirus cases assists arranging with controlling the infection and plan for use of medical care assets. Time series models in light of measurable system are valuable to show time-filed information and for determining. Autoregressive time series models in view of two-piece scale combination ordinary dispersions, called TP-SMN-AR models, is an adaptable group of models including a large number old style symmetric/awry and light/weighty followed autoregressive models. In this paper, we utilize this family of models to examine this present reality time series information of affirmed and recuperated Coronavirus cases Coronavirus is a pandemic that has affected more than 170 nations all over the planet. The quantity of contaminated and perished patients has been expanding at a disturbing rate in practically all the affected countries. Gauging methods can be instilled accordingly helping with planning better procedures and in taking useful choices. These strategies survey the circumstances of the past accordingly empowering better expectations about the circumstance to happen from now on. These expectations could assist with planning against potential dangers and outcomes. Gauging procedures assume a vital part in yielding exact forecasts. This study classifies determining methods into two sorts, to be specific, stochastic hypothesis numerical models and information science/ AI strategies. Information gathered from different stages likewise assume a fundamental part in gauging. In this review, two classifications of datasets have been talked about, i.e., large information got to from World Wellbeing Association/Public data sets and information from a virtual entertainment correspondence. Estimating of a pandemic should be possible in light of different boundaries, for example, the effect of ecological variables, hatching period, the effect of isolation, age, orientation and some more. These strategies what's more, boundaries utilized for determining are broadly concentrated on in this work. Notwithstanding, gauging methods accompany their own arrangement of difficulties (specialized and conventional). This study examines these difficulties and furthermore gives a bunch of suggestions to individuals who are as of now fighting the worldwide Corona virus pandemic.

Keywords: COVID-19 · Coronavirus • Estimating models • AI strategy • Expectation • Enormous information • Pestilence • Pandemic

Introduction:

Coronaviridae family incorporates two primary subfamilies Coronavirinae also, Torovirinae. The part genera incorporate Alphacoronavirus, Betacoronavirus, Gammacoronavirus, Torovirus, and Bafinivirus. They are an enormous group of infections that influence neurological, gastrointestinal, hepatic and respiratory frameworks and can be developed among people, bats, mice, domesticated animals, birds, and othersThe world has been confronting dangers as pandemics intermittently throughout the long term. The consequence of these pandemics gigantically affects the world and have additionally reversed the situation over.

PRC Habitats for Infectious prevention (CDC) specialists pronounced that pneumonia as novel Covid pneumonia (NCP) as brought about by a novel Covid and WHO formally named the illness Coronavirus). Be that as it may, the Global Council on Scientific categorization of Infections (ICTV) named the infection as extreme intense respiratory condition Covid 2 (SARS-CoV-2). This is a class of β-Covid and has numerous expected regular hosts, middle hosts and last has as shown:

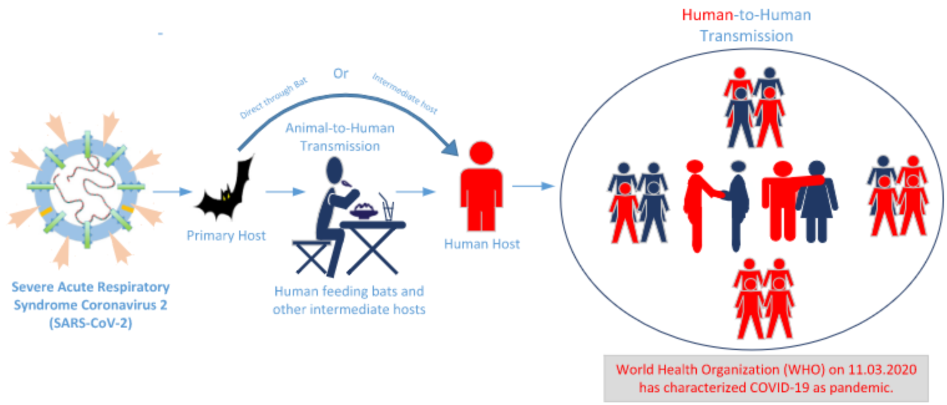


Fig. 1. Transmission of COVID-19.

In the Coronaviridae family, a notable sort of infection called SARS Covid (SARS-CoV) distributed from one creature to another and people. One more sort of coronavirus, called MERS Covid (MERS - CoV), altogether distributed from one human to another in 2012 . In 2019 many cases in China with respiratory illnesses were accounted for by the World Wellbeing Association (WHO), with proof that these cases started from afish market in Wuhan. In 2019 another sort of infection called Coronavirus (novel Covid, 2019-nCoV), having a place with the Beta coronavirus genera of Coronaviridae family, spread from Wuhan in China

Coronavirus, the current it is additionally running wrecking pandemic course at present in the world. Economies are crashing as well as the in general qualities and ethics of the intensely affected countries are being compromised. To do exact expectations comprehension of normal movement of illness is vital. An illness by and large advances in view of the openness to the disease. In light of this openness to disease has are shaped. Has allude to the gathering who are more defenseless to get affected. At the point when a tainted host interacts with more individuals then illness begins to spread.

The diseases like COVID-19, SARC, PLAGUE, etc., are acquired diseases. It means diseases spread through pathogenic agents (virus or bacteria or any microorganism). A customary model for the reason for the irresistible infection is defined. It is called as an Epidemiologic Set of three. The four significant variables associated with the epidemiologic group of three are natural elements, transporter specialist, contaminated has also, the microbes. The specialist is normally the transporter of the contamination. The contamination is sent to the host when an specialist interacts with the host under a specific climate. A microbe is otherwise called a vector. A vector is an life form that sends the disease through infection or microorganisms starting with one host then onto the next. Pandemics are frequently alluded to as flare-ups as a result of their spread example. The sort of the flare-up decides the death pace of the sickness. Over the most recent couple of years, it has been seen that in light of the change in way of life, expanded worldwide travel and urbanization, irresistible illnesses rapidly grow into a pandemic. To forestall these plagues, solid strategies should be managed. Any other way, the circumstance can take an intense turn quickly. Since the start, humanity has confronted plagues and pandemics. The frst pandemic looked by humankind was in the early 1300's called dark passing. It was quite possibly of the most awful pandemic.

The precision of conventional determining to a great extent relies upon the accessibility of information to base its expectations and evaluations of vulnerability. In episodes of pandemics there is no information by any means in the start and afterward restricted over the long haul, making forecasts generally unsure. On February 18, 2020, a New York Times article forewarned against over the top good faith about the emergency cresting, despite the fact that there were near 50 days since the infection had been distinguished.

In addition, there are worries that the information may not be dependable, similar to the instance of bird influenza and SARS when the quantity of impacted individuals and passing's were distorted to conceal the degree of the plague. Likewise, on account of Coronavirus, the revealing didn't mirror the right numbers too when on the February 13 another class of "clinically analyzed" was added to "lab-affirmed" ones. Such issues decline gauging exactness and increment vulnerability, making the reaching of clear inferences more troublesome.

Connected with gauging exactness and vulnerability, there is a more serious issue that needs to do the impression of pestilences and pandemics. Government officials are worried about respects to the actions to be taken while everybody fears about the effect on the plague on their wellbeing/lives. Moreover, the drug firms are dealing with immunizations for the new infection with impressive business interest. This was the situation with SARS when states convinced on the seriousness of the infection purchased enormous quantities of antibodies that were never utilized as its spread halted without the need to immunize individuals. Clinical expectations are frequently not exact while their vulnerability is truly underrated . Foreseeing the eventual fate of scourges and pandemics is substantially more troublesome as the number of cases to be considered can be estimated in one hand. Toward one side of the scale is the situation of SARS where the feeling of dread toward turning into a pandemic was exaggerated, bringing about overspending what's more, the use of prohibitive measures to be contained that it ended up being pointless. At the opposite end is the Spanish influenza that ended up being a serious pandemic with disastrous results, seemingly in an alternate time when correspondence and the capacity to raise public mindfulness (and conceivably overstated dread) were restricted.

Regardless of the errors related with clinical expectations, actually determining is priceless in permitting us to more readily grasp what is happening and plan for what's in store. In this paper, we give factual gauges to the affirmed instances of Coronavirus utilizing powerful time series models, and we investigate the direction of recuperated cases.

Analysis and forecasting:

Cox's Regression Model

Cox's relapse model (1975) in view of the strategy for 'Halfway probability' assumes a vital part in breaking down the information in a more practical manner on endurance or richness on some other kind including populace qualities utilizing stochastic models.

To place the thought in substantial structure let us take the least complex type of the Cox's model

$$\lambda_j(t)=\lambda_0(t)\exp\left[\beta' z_j(t)\right] \tag{1}$$

Where

$\lambda_j(t)=$ Hazard rate of the j^{th} individual at any time t

$\lambda_0(t)=$ Danger capability as for time just disregarding the other covariates i.e., keeping $Z_{ji} = 0 \ \forall \ i = 1, 2, \cdots, P, \ j = 1, 2, \cdots n.$

Where $\underset{\sim}{Z'_j} = \left(Z_{j1}, Z_{j2}, \cdots, Z_{jp}\right)$ is the P-component covariate vector for the j^{th} individual, j = 1, 2, $\cdots$, n.

Taking logarithm on both sides of Cox's model we have

$$log\lambda_j\ (t) = log\ \lambda_0(t) - \left[\beta_1 z_{j1}(t) + \beta_1 z_{j2}(t) + ... + \beta_p z_{jp}(t)\right]$$

The equation could have been treated as a single equation log-linear model for the estimation of $\beta_i' s(i=1,2,3,\ ....P)$ as well as $\lambda_0(t)$. Let $R(t)=\left\{j:T_j \geq t, c_j\right\}$ to be the risk set *i.e.,* the set of individual exposed to the risk under observations $\left(j^{th}\ \textit{the individual reserved observed between}\left(0,c_j\right)\right)$ considering that we have a bunch of n people in the example and that an individual passes on in the set the likelihood that the individual kicks the bucket (expecting that the passing's happen freely) is given by

$$\frac{\lambda_c(t)\exp\left[\underset{\sim}{\beta'}\,\underset{\sim}{z_j}(t)\right]}{\sum\limits_{j\in R(t)}\lambda_c(t)\exp\left[\underset{\sim}{\beta'}\,\underset{\sim}{z_j}(t)\right]} = \frac{\exp\left[\underset{\sim}{\beta'}\,\underset{\sim}{z_j}(t)\right]}{\sum\limits_{j\in R(t)}\exp\left[\underset{\sim}{\beta'}\,\underset{\sim}{z_j}(t)\right]} = P_L$$

The summation being extended over all the persons in the risk set R. Cox defined,

$$L(\beta) = \prod_{T_j \le c_j} \frac{\exp\left[\underset{\sim}{\beta'}\,\underset{\sim}{z_j}(t)\right]}{\sum\limits_{j\in R(t)}\exp\left[\underset{\sim}{\beta'}\,\underset{\sim}{z_j}(t)\right]} \tag{2}$$

$j = 1,\ 2,\ \ldots,\ n$ $\left(\textit{the product being extended over all } j\ \forall\ T_j \le c_j,\ j = 1,\ 2,\ \ldots,\ n\right)$

The partial likelihood estimating the parameters by the method of maximum likelihood conjectured that the method would give estimates of β_1, β_2, ... β_p which would have otherwise the asymptotic properties of the maximum likelihood estimators.

Cox's Partial Likelihood

The prompt inclination of leaving a task (or calling) at time t is characterized as the contingent likelihood of leaving a task (or calling) during a little stretch $(t, t+dt)$ given that the person was in job till the time t. Denoting the hazard rate by $h(t)$ we have

$$h(t)\ dt = \frac{f(t)\ dt}{R(t)} \tag{3}$$

Where $R(t)$ is the Survival function or the probability of continuing the job at least up to a period t and $f(t)\ dt$ is the probability of leaving the job between

It can be shown that

$$R(t) = \exp\left[-\int_0^t h(\tau)\, d(\tau)\right] \quad \textit{and} \quad f(t) = \frac{d}{dt}\left(1 - F(t)\right) = \frac{d}{dt}R(t)$$

The Cox hazard model as indicated by (vide Gill (1984)).

$$h(t) = h_0(t) \exp\left(\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_k X_k\right) \tag{4}$$

Where $h_o(t)$ represents the hazard rate or the rate of propensity of leaving at time t purely on the consideration of time or CLS in the profession

The probability that i^{th} person will leave the job at time t in $(0,T)$ is given by

$$\frac{h_0(t)\, e^{\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}}}{h_0(t)\sum_{i=1}^{n} e^{\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}}}, \qquad \text{for } (i = 1, 2, \cdots, n) \tag{5}$$

Where $x_{1i} + x_{2i} + x_{3i}$ are the scores of the covariates 1, 2 and 3 respectively of the i^{th} person. Note that the ratio in equation (5) is independent of t, the length of service. On the off chance that we take the result of all such terms for every one of the experts with chronic number 1, 2, … , k, we get an improved on type of Cox's halfway probability given by

$$P_L = \prod_{i=1}^{k} \frac{e^{\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}}}{\sum_{i=1}^{k} e^{\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}}} \tag{6}$$

Maximizing P_L (or log P_L) with respect to $\beta_1, \beta_2,\ and\ \beta_3$ respectively, we get three estimating equations for estimating $\beta_1, \beta_2,\ and\ \beta_3$ (assuming $e^{\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}} \cong (1 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i})$ approximately both in the numerator and denominator of equation (6)) as follows:

$$\left.\begin{aligned}
\sum_{i=1}^{k} X_{1i} - k \quad \frac{\sum_{i=1}^{k} X_{1i}\left(1+\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}\right)}{\sum_{i=1}^{k}\left(1+\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}\right)} &= 0 \\
\sum_{i=1}^{k} X_{2i} - k \quad \frac{\sum_{i=1}^{k} X_{1i}\left(1+\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}\right)}{\sum_{i=1}^{k}\left(1+\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}\right)} &= 0 \\
\sum_{i=1}^{k} X_{3i} - k \quad \frac{\sum_{i=1}^{k} X_{1i}\left(1+\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}\right)}{\sum_{i=1}^{k}\left(1+\beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i}\right)} &= 0
\end{aligned}\right\} \tag{7}$$

Having estimated the parameters β_1, β_2, and β_3 relating to the covariates, the boundaries influencing the leaving from calling for individual explanation or covariates, we gauge the boundary of the CLS comparing to the benchmark peril capability. For a nitty gritty review allude to Biswas (1996).

Estimation of the Longevity of Service

Once the parameters *viz.,* time dependent parameters concerning the CLS as well the parameters concerning the personal covariates β_1, β_2, and β_3 are estimated independently, the expected length of service can be obtained by the relationship between survival function R (t) and the expected or average duration of service given by L as

$$E(L) = \int_0^\infty R(t)\,dt = \int_0^\infty e^{\int_0^\infty -h(T)\,dT} \tag{8}$$

$$= \int_0^\infty e^{-\int_o^t \exp\left(\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3\right) h(T)\, dT}$$

$$\left[\Theta\ R(t) = e^{-\int_0^t h(T)\,dT} \quad \text{and} \quad h(t) = h_0(t)\exp\left(\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3\right)\right]$$

Finally expected duration of service given by

$$E(L) = \int_0^\infty e^{\int_0^t -\ h(T)\, dT}$$

The proportion or the percentage of leavers between t and (t + 1) is accordingly given by

$$f(t) = \frac{d}{dt}\left(1 - R(t)\right) \text{ or } f(t) \text{ x } 100\% \tag{9}$$

Formulation of Cox's Regression Model

Let $T_i, i = 1, 2, ...n$ be the onset time epochs of Covid-19 of 'n' different infective persons, each of whom can only be observed on a fixed time interval $\left[0, C_i\right]$ for certain censoring times $C_i, i = 1, 2, ...n$. Suppose that individual 'j' has hazard rate $\lambda_j(t)$ at time 't', *i.e.* for $j = 1, 2, ...n$

$$\lambda_j(t) = \lim_{h \to 0} \frac{1}{h} P_r\left[T_j \le t + h / T_j \ge t\right] \tag{10}$$

Which of the following form of hazard model due to Cox (1972) for $j = 1, 2, ...n$;

$$\lambda_j(t) = \lambda_0(t)\exp\left\{\underset{\sim}{\beta}'\ \underset{\sim}{z}_j'(t)\right\}$$

Here, $\underset{\sim}{\beta}' = (\beta_1, \beta_{2,} ....,\beta_r)$ is a row vector of **r** unknown co- efficient $\underset{\sim}{z}_j'(t) = (z_{j1}(t), z_{j2}(t), z_{j3}(t).........z_{jr}(t))$ s a column vector of '**r**' possibly time-varying covariates $\lambda_0(t)$ = is a fixed unknown baseline hazard rate for an individual with $\underset{\sim}{z}_j'(t) \equiv 0$ vector. Thus $\lambda_j(t)\ h$ gives the conditional probability that the person 'j moves from state I to state P during an infinitesimal interval $(t, t+h)$ given that the person was in state I till time t'.

The observations for the j^th individual consists of $T_j \wedge C_j$, $\delta_j = I\{T_j \le C_j\}$ and the values of $\underset{\sim}{z}_j(t)$, $t \in [0, T_j \wedge C_j]$ Here '^' denotes minimum and I{.} is the indicator random variable for the specified event. For examples of how covariates $z_{j1}(t), z_{j2}(t), z_{j3}(t).........z_{jr}(t)$ can be selected we refer the reader to Miller et al. (1980), Kalbfleisch and Prentice (1980) and Anderson (1982). We now proceed to estimate the covariate parameters of $\underset{\sim}{\boldsymbol{\beta}}'$ independently of $\lambda_0(t)$ and $\lambda_0(t)$ which assumes the status of an infinite dimensional nuisance parameter. The model may thus be termed semi parametric.

Let $\Omega(t) = \{j : T_j \ge t, and\ C_j \ge t\}$ to be the risk set at time $'t'$ *i.e.* $\Omega(t)$ is the set of infective individuals $'j'$ under observation between $(0, C_j)$ exposed to the risk of onset of Covid at time $'t'$. Given that we have $\Omega(t) = n$, and that a person moves to onset of Covid-19 from infection state at time, the probability that it is precisely individual $'j'$ is given by

$$\frac{\lambda_0(t)\exp\left\{\underset{\sim}{\beta}'\ \underset{\sim}{z}_j'(t)\right\}}{\sum_{j\in\Omega(t)}\lambda_0(t)\exp\left\{\underset{\sim}{\beta}'\ \underset{\sim}{z}_j'(t)\right\}} \tag{11}$$

Where a factor $\lambda_0(t)$ has canceled out in numerator and denominator, thus it is noticed that the ratio in (11) is independent of $'t'$ the completed length of IP or the sojourn time of IP. Cox proposes that statistical estimation and inference could be applied on the following partial likelihood function $L(\underset{\sim}{\beta}')$:

$$L\left(\underset{\sim}{\beta'}\right)=\frac{\prod_{i:T_j\le C_j}\lambda_0(t)\exp\left\{\underset{\sim}{\beta'}\;\underset{\sim}{z_j'}(t)\right\}}{\sum_{j\in\Omega(t)}\lambda_0(t)\exp\left\{\underset{\sim}{\beta'}\;\underset{\sim}{z_j'}(t)\right\}} \tag{12}$$

The LR contains the linear regression equation within a sigmoid function.

The formula of the LR takes the following form:

$$f(z)=\frac{1}{1+e^{\{-(\beta_0+\beta_1+\cdots+\beta_n x_n)\}}}$$

A sigmoid capability is utilized to plan the qualities from an enormous reach to the scope of 0 to 1.

The growth method and the dependent and independent variables of the model are summarized:

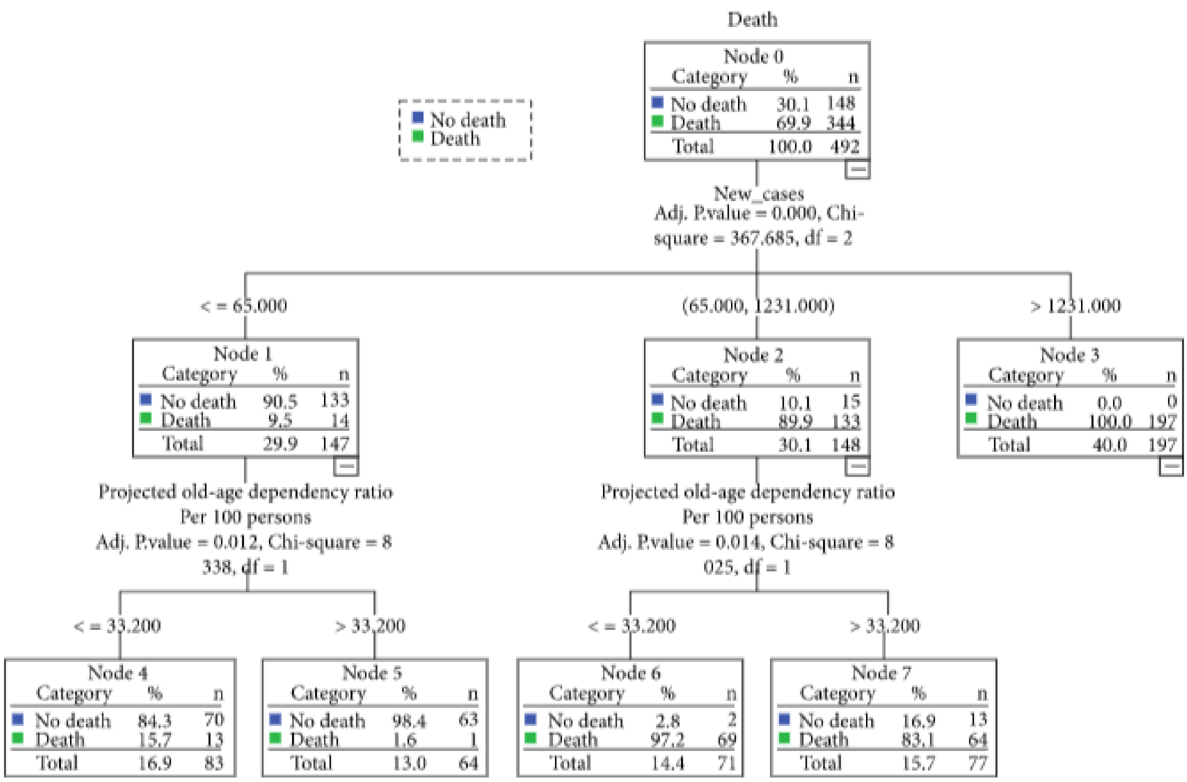
Conditions	Developing procedure	CHAID
	Dependent variable	Death
	Independent variables	New cases, homegrown general government wellbeing consumption per capita, PPP (present worldwide), joblessness, youth complete (% of the all out labor force matured 15-24) (demonstrated ILO gauge), genuine Gross domestic product development (yearly percent change), projected advanced age reliance proportion per 100 people
	Validation	None
	Maximum depth	3
	Most reduced number of cases in parent hub	100
	Least number of cases in kid hub	50
Results	Independent variables included	New cases, projected advanced age reliance proportion per 100 people
	No. of nodes	8
	No. of terminal nodes	5
	Depth	2

The arrangement table that shows that 94.1% of the preparation tests were ordered accurately.

Observed	Predicted		
	No death	Death	Percent correct
No death	133	15	89.9%
Death	14	330	95.9%
Overall percentage	29.9%	70.1%	94.1%

Growing method: CHAID
Dependent variable: death

Tree diagram with 7 nodes:



The LR sought to predict deaths based on the following factors:

1. X_1: Projected advanced age reliance proportion per 100 people
2. X_2: Real Gross domestic product development (yearly percent change)
3. X_3: Joblessness, youth absolute (level of the complete labor force matured 15-24, displayed OLS)

4. X_4: National wellbeing consumption per capita

5. X_5: New cases

The regression equation for the LR is as follows:

$$\boldsymbol{P}(.) = \frac{\boldsymbol{e}^{\boldsymbol{Y}'}}{(\mathbf{1} + \boldsymbol{e}^{\boldsymbol{Y}'})}$$

Factors chosen in the model and their factual importance

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	New cases	0.008	0.001	70.065	1	0.000	1.008
	Constant	-1.699	0.213	63.896	1	0.000	0.183
Step 2[b]	New cases	0.009	0.001	65.844	1	0.000	1.009
	National health expenditure per capita, PPP	-0.001	0.000	6.211	1	0.013	0.999
	Constant	0.130	0.736	0.031	1	0.860	1.139
Step 3[c]	New cases	0.009	0.001	65.992	1	0.000	1.009
	Joblessness, youth total (% of total work force aged 15-24) (modeled ILO estimate)	-0.269	0.132	4.134	1	0.042	0.764
	National health expenditure per capita, PPP (current international)	-0.002	0.001	7.218	1	0.007	0.998
	Constant	6.746	3.332	4.099	1	0.043	850.538
Step 4[d]	New cases	0.010	0.001	61.487	1	0.000	1.010
	Real GDP growth (annual	1.372	0.488	7.905	1	0.005	3.945

percent change)						
Joblessness, youth total (% of total work force aged 15-24) (modeled ILO estimate)	-0.491	0.159	9.497	1	0.002	0.612
National health expenditure per capita, PPP (current international $)	-0.004	0.001	13.509	1	0.000	0.996
Constant	26.598	7.962	11.160	1	0.001	355839592019.724

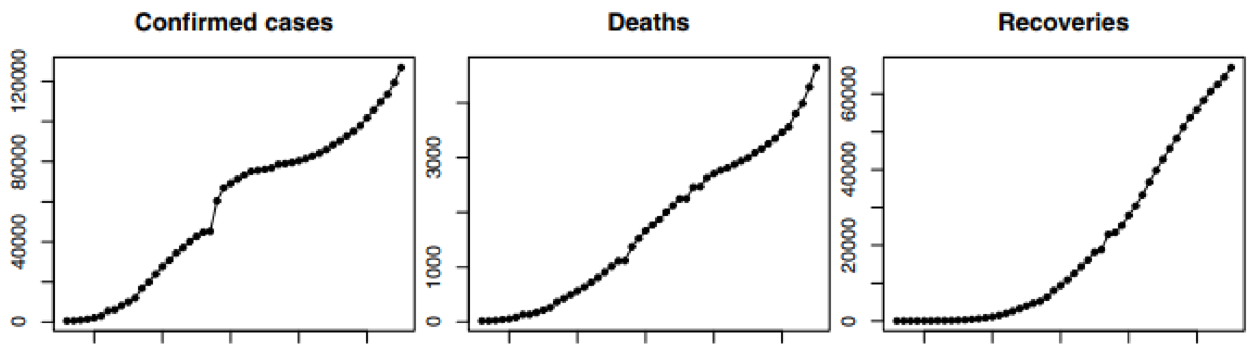
Model Coefficients:

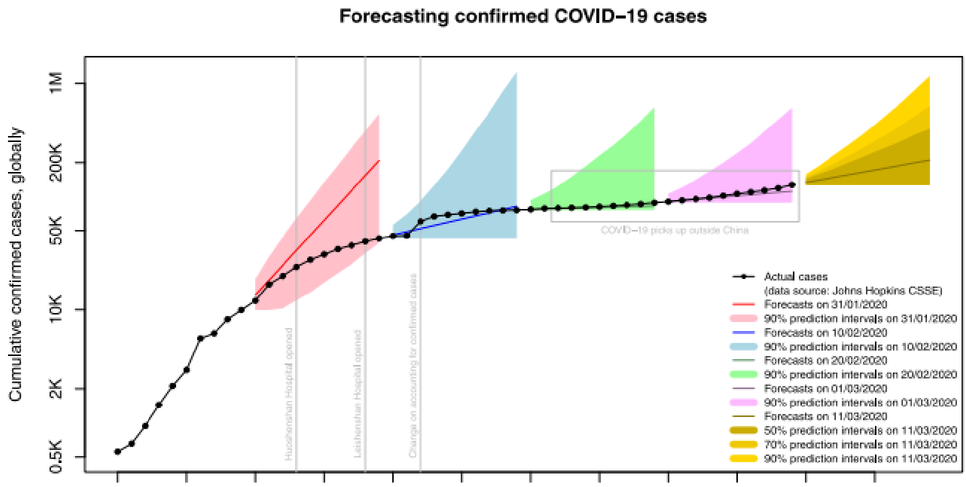
		Chi-square	df	Sig.
Step 1	Step	392.944	1	0.000
	Block	392.944	1	0.000
	Model	392.944	1	0.000
Step 2	Step	6.563	1	0.010
	Block	399.508	2	0.000
	Model	399.508	2	0.000
Step 3	Step	4.267	1	0.039
	Block	403.775	3	0.000
	Model	403.775	3	0.000
Step 4	Step	8.740	1	0.003
	Block	412.515	4	0.000
	Model	412.515	4	0.000

The general level of right grouping was 93.9%

	Observed		Predicted		
			Death		Percentage correct
			No death	Death	
Step 1	Death	No death	143	5	96.6
		Death	23	321	93.3
	Overall percentage				94.3
Step 2	Death	No death	144	4	97.3
		Death	23	321	93.3
	Overall percentage				94.5
Step 3	Death	No death	143	5	96.6
		Death	25	319	92.7
	Overall percentage				93.9
Step 4	Death	No death	144	4	97.3
		Death	26	318	92.4
	Overall percentage				93.9

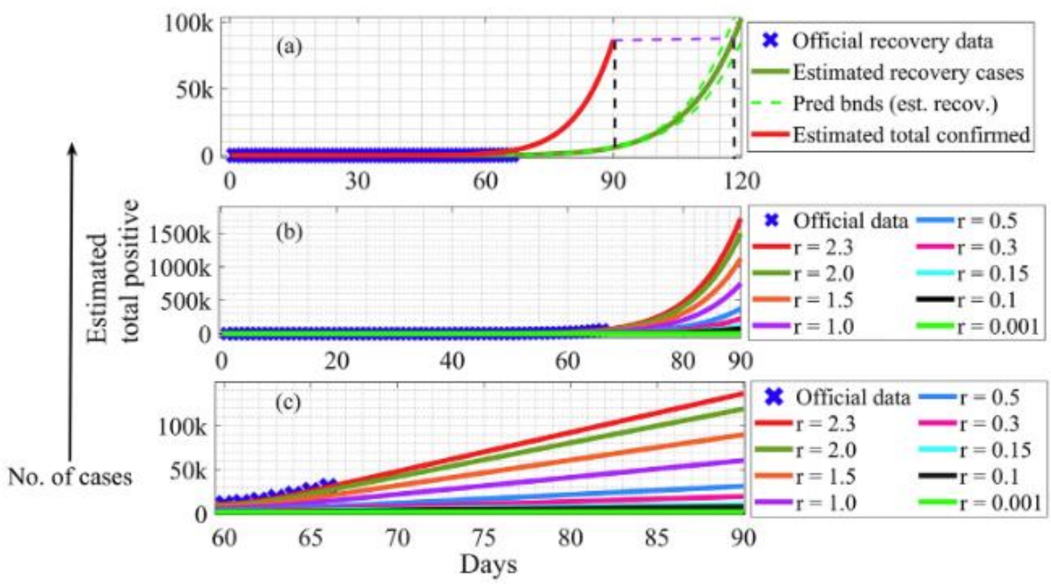
We center around the total everyday figures accumulated worldwide of the three fundamental factors of interest: affirmed cases, passings and recuperations. These were recovered by the Middle for Frameworks Science and Designing (CSSE). The data refer to daily cumulative cases . We incorporate both "lab-affirmed" and "clinically analyzed" cases. We underscore the significance of the recuperated cases, which isn't shrouded in media as broadly as the affirmed cases or the passings. While every one of the three information designs show a dramatic increment, the patterns of both the affirmed cases and the passings were diminished in the mid of February; a subsequent dramatic increment is seen in late February and Walk because of the expanded number of cases in South Korea, Iran, and Europe. Simultaneously, the quantity of recuperated cases is consistently expanding To conjecture affirmed instances of Coronavirus, we embrace basic time series estimating approaches. We produce estimates utilizing models from the dramatic smoothing family. This family has shown great conjecture precision more than a few estimating rivalries and is particularly appropriate for short series. Dramatic smoothing models can catch an assortment of pattern and occasional anticipating designs (like added substance or multiplicative) and mixes of those. We limit our thoughtfulness regarding moved and non-occasional models, given the examples noticed. Note that we follow a down to earth approach in that we expect that the pattern will proceed with endlessly from here on out. This approach goes against other displaying approaches to Coronavirus utilizing a S-Bend model (coordinated operations bend) that expects combination. While factual ways to deal with model determination, (for example, data standards, which measure the greatest probability of a model while punishing for its intricacy) could be utilized, we critically select a model to more readily mirror the idea of the information. We pick a dramatic smoothing model with multiplicative mistake and multiplicative pattern parts. Indeed in the event that at times an added substance pattern model gave lower data rules values, we settled on the multiplicative pattern model given the lopsided dangers implied as we accept that it is smarter to blunder to the positive bearing.





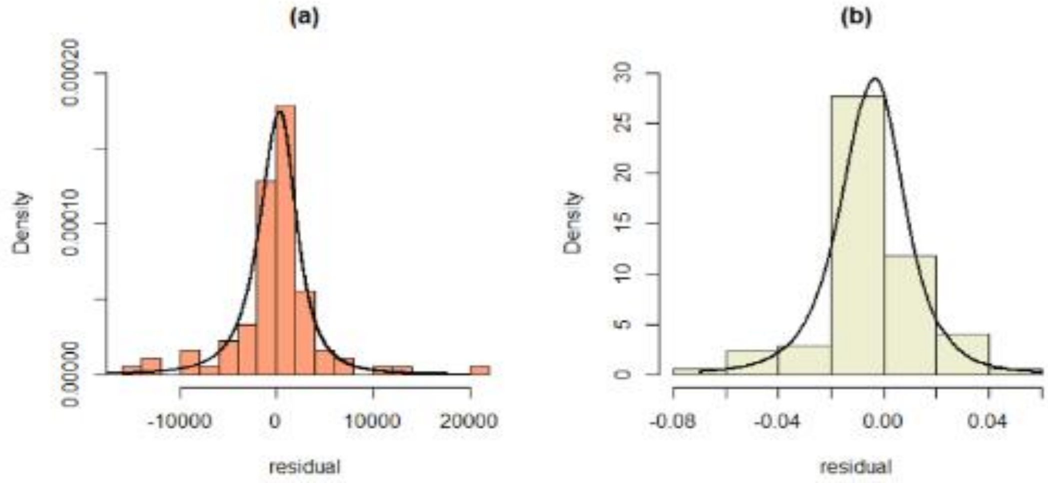
Recovered cases:

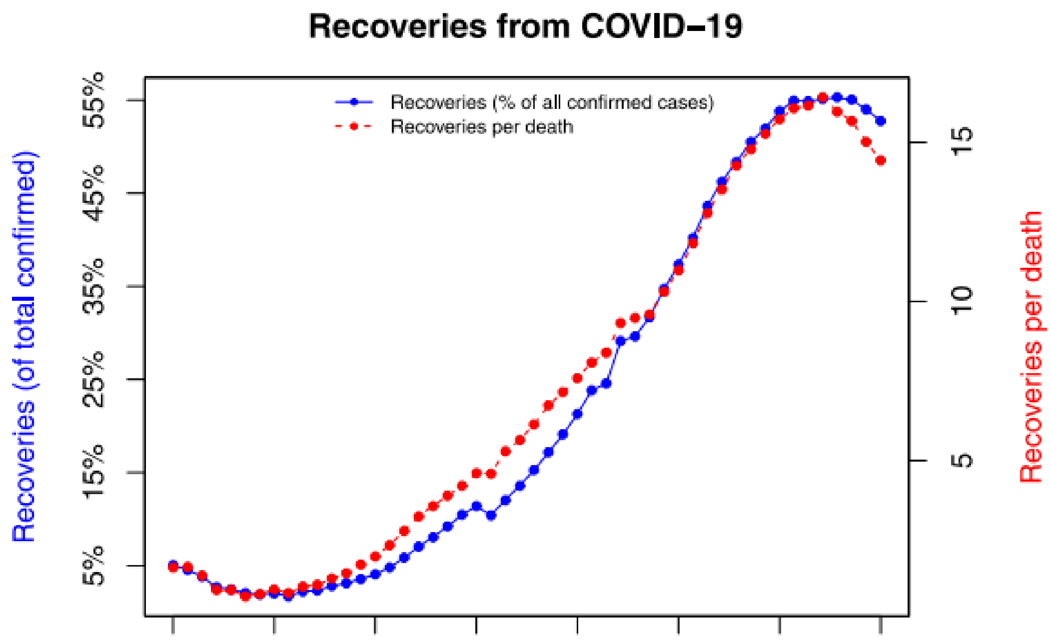
The recuperation pace of affirmed cases is additionally high in the event of Coronavirus, in any case, the time taken for the patients to recuperate is additionally enormous. With a huge number of patients, the weight on the clinical asset increments, so assessment/expectation of time taken for recuperation is additionally expected for appropriate course of action and usage of accessible assets. Towards this objective assessment of the quantity of patients recuperated has additionally been made, which is shown:



We next direct our concentration toward the recuperated cases that stand out as of recently. We center around the quantity of the recuperated cases as a level of the complete affirmed cases as well as the proportion of recuperated cases versus passings. We are especially intrigued by the direction of these two proportions. presents this examination. In the first place, we notice the strong relationship between the two bends. Second, we notice that in spite of the tiny rates of recuperated cases until the end.

The histograms of the assessed mistakes (residuals) in view of the assessed weighty followed TP-SMN densities are superimposed in and show the reasonable exhibition of the assessed models to the fixed series of complete affirmed and recuperated Coronavirus cases datasets. Likewise the auto connection capability (ACF) plots of the residuals introduced in show the appropriateness of the fitted models.





Notwithstanding what one's convictions are, we accept that figures and their related vulnerability would be able and ought to be a necessary piece of the dynamic cycle, particularly in highrisk cases. Aside from the critical general wellbeing concerns, the risks forced on worldwide supply chains and the economy all in all are additionally extensive. Risk-disinclined individuals can zero in on the most pessimistic scenario situations and act appropriately. Choosing to dispose of any formal, measurable conjectures and acting safely, still infers a fundamental determining process, even in the event that this cycle isn't formalized (individual judgment/conviction). In this activity, we utilized univariate time series models, which accept that the information is precise and past examples (counting prudent steps) will keep on applying. Huge, reliable figure blunders (possibly crossing outside the forecast stretches) ought to be related with changes in the noticed examples and the requirement for extra activities and measures on account of adversely one-sided conjectures.

An overview of air quality index (AQI), ambient air pollution and meteorological parameters

Mean	Std. deviation	Mean	Std. deviation	
Air quality index (AQI)	63.63	25.30	71.58	27.83
Surrounding air poisons				
$PM_{2.5}$ (µg/m³)	44.16	21.63	50.39	24.18
PM_{10} (µg/m³)	51.88	22.26	59.65	25.98
NO_2 (µg/m³)	21.47	7.66	11.35	3.95
CO (µg/m³)	0.88	0.04	1.16	0.04
Meteorological boundaries				
Temperature (°C)	7.19	4.04	7.26	3.92
Daily highest temp (°C)	13.25	4.19	12.97	4.96
Daily lowest temp (°C)	4.38	4.55	4.87	3.91
Daily temp diff (°C)	8.81	3.76	7.97	3.85
Sunshine duration (h)	11.04	0.28	10.91	0.27

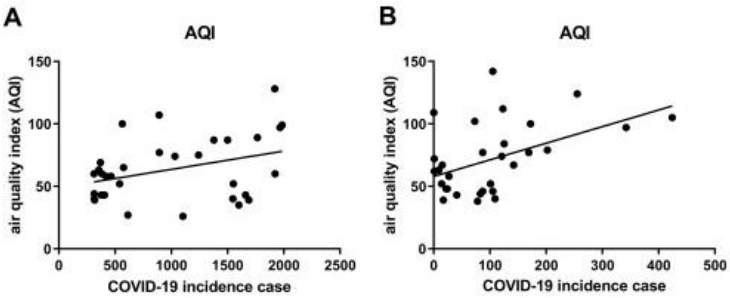
We then investigated the connection between's neighborhood AQI and Coronavirus rate number in every city . The information showed that AQI was essentially and decidedly connected with everyday Coronavirus rate number ($R^2 = 0.13$, $p < 0.05$) and ($R^2 = 0.223$, $p < 0.01$), which demonstrated the significant job of AQI in Coronavirus transmission. Hence, we further concentrated on the relationship of everyday recently determined Coronavirus cases to have each air poison. Strangely, all surrounding air poisons showed positive relationship with everyday Coronavirus frequency. Among them, NO_2 ($R^2 = 0.329$, $p < 0.01$), $PM_{2.5}$ ($R^2 = 0.174$, $p < 0.05$) and CO ($R^2 = 0.203$, $p < 0.001$) displayed factual importance. Then, we concentrated on the connection between's meteorological boundaries and Coronavirus occurrence . Among five boundaries, everyday temperature ($R^2 = 0.126$, $p < 0.05$) and day to day most minimal temperature ($R^2 = 0.143$, $p < 0.05$) were overwhelmingly associated with Coronavirus rate, yet both in an opposite connection.

The connection between's Coronavirus frequency and three encompassing air toxins alongside five meteorological boundaries

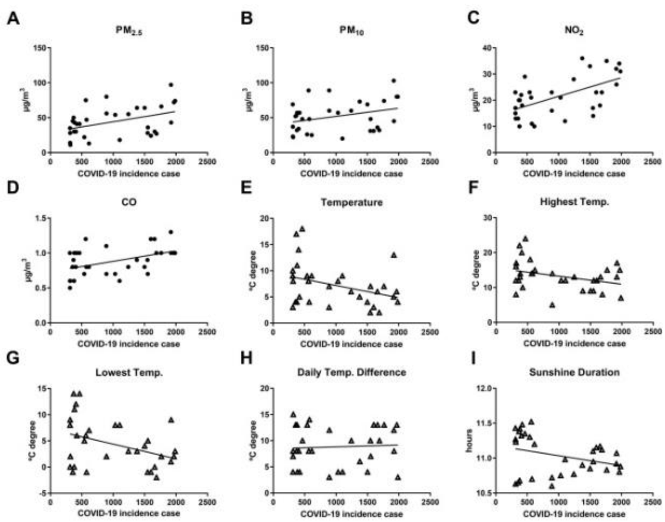
Slope	R^2	Slope	R^2	
Air quality index (AQI)	0.015 ± 0.007*	0.127	0.133 ± 0.046**	0.222
Surrounding air poisons				

Slope	***R***^{2}	**Slope**	***R***^{2}	
$PM_{2.5}$	0.015 ± 0.006*	0.174	0.117 ± 0.046**	0.23
PM_{10}	0.117 ± 0.006	0.105	0.105 ± 0.044*	0.158
NO_2	0.007 ± 0.002***	0.329	0.015 ± 0.007*	0.158
CO	0.000 ± 0.000**	0.203	−0.000 + 0.000	0.022
	Meteorological boundaries			
Temperature	−0.002 ± 0.001*	0.126	−0.014 ± 0.007*	0.13
Daily highest temp	−0.002 ± 0.001	0.114	−0.014 ± 0.009	0.076
Daily lowest temp	−0.003 ± 0.001*	0.143	−0.013 ± 0.007	0.109
Daily temp diff	0.000 ± 0.001	0.003	−0.001 ± 0.007	0.001
Sunshine duration	−0.000 ± 0.000	0.000	−0.002 ± 0.000***	0.407

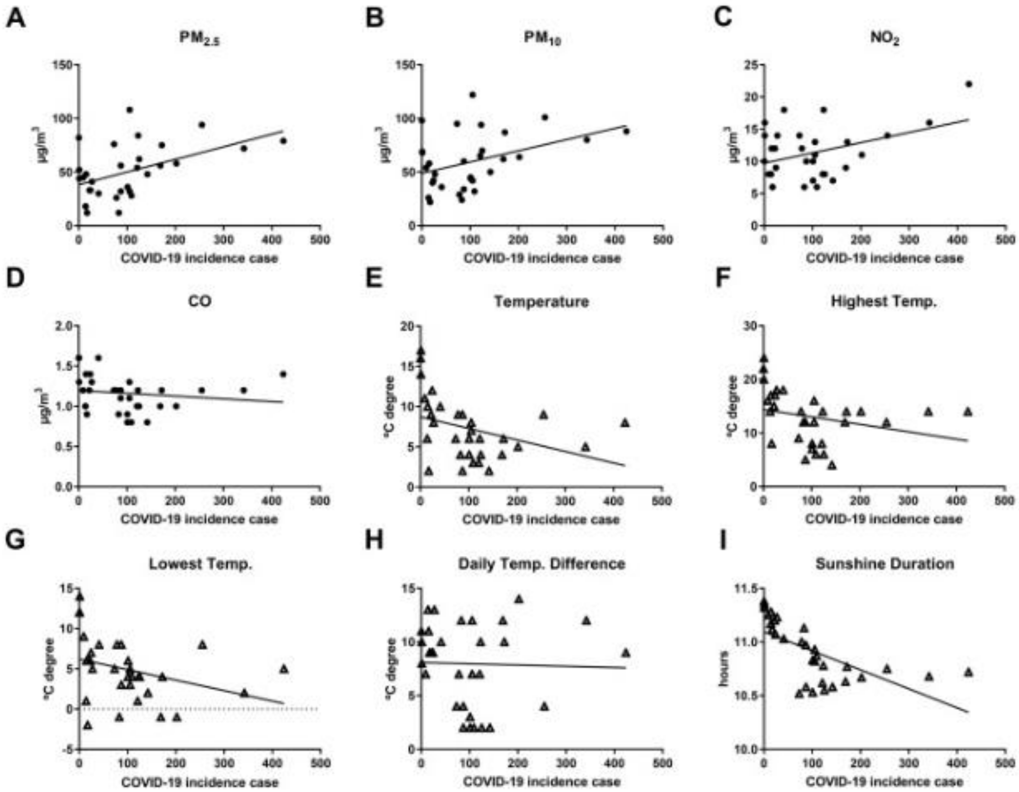
The relationship between's everyday Coronavirus occurrence and air quality record



The relationship between's day to day Coronavirus occurrence and surrounding air



The relationship between's everyday Coronavirus frequency and surrounding air contamination/five meteorological boundaries



Discussion:

The spread of the Coronavirus pandemic in many nations has undermined individuals and the economy. Thusly, this paper is pointed toward assessing the utilization of an AI model and a factual model, specifically, the choice tree and LR, to concentrate on the impacts of different elements on the passings because of Coronavirus. This gives a few factual markers about Coronavirus. We discovered that the choice tree performed better compared to LR. The general correctnesses were 94.1% and 93.9% for the choice tree and LR models, separately, as displayed in Tables. Likewise, the outcomes show that the regions with bigger populaces would in general have a larger number of cases than those with more modest populaces. The quantity of passings of females was more noteworthy than that of guys, and it was more noteworthy for those matured 65 years and more established.

The ongoing review has a few impediments. To begin with, there are just two urban communities selected, which could bring about certain outcomes deviation from the specific impact of surrounding contamination and meteorological boundaries on SARS-CoV-2 transmission. Second, the review period is generally short contrasted with other epidemiological review. In future review, we will enlist additional information from different nations and regions to approve the outcomes from current review.

All in all, we observed that AQI, PM2.5, NO2 and temperature are four factors that might potential at any point advance the supported transmission of SARS-CoV-2. Individual defensive gadgets, particularly the facial cover, will be proposed to occupants for Covid assurance in exceptionally contaminated districts.

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SPED UP LIFE TESTING PLANS FOR THE STOCHASTIC DEBASEMENT MODELS

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Abstract

Sped up Life tests open the items to more prominent natural feelings of anxiety with the goal that we can get lifetime and debasement estimations in an additional opportune methods for playing out an Accelerated Life Tests (ALT) incorporate steady pressure. In this paper presents strategies for arranging sped up life tests for models in which the logarithm of time-to-disappointment follows an area scale circulation and the area boundary is a component of stress. Various decisions of test-feelings of anxiety and test length can bring about various accuracy of the gauge of the dependability of the item at typical use conditions. A test plan that gives least difference of the greatest probability gauges (MLEs) of the obscure area and scale boundaries of the log-area scale group of circulations at indicated feelings of anxiety by reasonably deciding the test length. Under this model, the assurances of the ideal decision of τ for lognormal disseminations are tended to utilizing the asymptotic difference optimality standard. he goal of the current paper is to broaden existing outcomes by creating general disappointment models in light of Stochastic cycles for corruption which consolidate a few speeding up factors, and utilize both debasement estimations, and various decisions of test-feelings of anxiety and test length can bring about various accuracy of the gauge of the dependability of the item at typical use conditions. We want to find a test plan that gives least difference of the most extreme probability gauges (MLEs) of the obscure area and scale boundaries of the log-area scale group of dispersions at indicated feelings of anxiety by reasonably deciding the test length.

Keywords: Reliability; lifetime data; degradation data; extrapolation; acceleration factor; Accelerated life tests; log location scale distribution; maximum likelihood estimates; asymptotic variance.

1. Introduction

The present makers face solid strain to foster new, higher innovation items in record time, while further developing efficiency, item field unwavering quality what's more, by and large quality. This has spurred the advancement of techniques like simultaneous designing and energized more extensive utilization of planned tests for item and interaction improvement. The necessities for higher unwavering quality have expanded the requirement for more forthright testing of materials, parts and frameworks. Engineers in the assembling enterprises have utilized accelerated test (AT) tests for a long time. The reason for AT tests is to secure dependability data rapidly. Test units of a material, part, subsystem or whole frameworks are exposed to higher than normal degrees of one or then again additional speeding up factors like temperature or stress. Then, at that point, the AT results are utilized to foresee life of the units at use conditions. The extrapolation is normally legitimate (accurately or erroneously) based on genuinely roused models or a blend of experimental model fitting with an adequate measure of past involvement with testing comparative units. The need to extrapolate in both time and the speeding up factors by and large requires the utilization of completely parametric models. Analysts have made significant commitments in the improvement of suitable stochastic models for AT information [typically a dispersion for the reaction and relapse connections between the boundaries of this appropriation and the speeding up variable(s)], measurable strategies for AT arranging (decision of speeding up factor levels and allotment of accessible test units to those levels) and strategies for assessment of reasonable dependability measurements. This paper gives a survey of a considerable lot of the AT models that have been utilized effectively around here.

Sped up life tests are usually utilized in item configuration processes. Since there is restricted opportunity to send off new items, engineers utilize sped up tests to acquire required data on the unwavering quality by raising the levels of specific speed increase factors like temperature, voltage, dampness, stress, and strain. For exceptionally solid present day items, it frequently requires substantially more investment to acquire lifetime and debasement information under common use conditions, and this expects one to utilize sped up tests. Sped up tests open the items to more noteworthy ecological feelings of anxiety so we can get lifetime and corruption estimations in an additional convenient Procedures for playing out an Accelerated Life Testing Plans(ALT) incorporate steady pressure, step pressure, and slope pressure, among others. Assessment of the fluctuation of an assessor of a log area scale dispersion quantile with shifting pressure has numerous pragmatic applications; allude to Meeker, and Escobar (1998).It is important to foster helpful, precise likelihood models for derivations on the lifetime of the gadgets or frameworks under study. Such models ought to sensibly consolidate the speed increase factors and estimations of debasement as well as any real disappointments noticed. In this manner, in many designing dependability tests, proportions of debasement or wear toward disappointment can frequently be seen throughout some stretch of time before disappointment happens. Since the debasement values give extra data past that given by the disappointment perceptions, the two arrangements of perceptions should be thought about while doing derivation on the factual boundaries of the item or framework lifetime circulations as examined by Nelson (1990).The target of the current paper is to expand existing outcomes by creating general disappointment models in view of

Stochastic cycles for corruption which consolidate a few speeding up factors, and utilize both debasement estimations, and various decisions of test-feelings of anxiety and test length can bring about various accuracy of the gauge of the dependability of the item at typical use conditions. We want to find a test plan that gives least fluctuation of the most extreme probability gauges (MLEs) of the obscure area and scale boundaries of the log-area scale group of disseminations at indicated feelings of anxiety by reasonably deciding the test length.

2. Review of Literature

Inside the system of total openness model, Mill operator and Nelson (1990), Bai et al., (1989), Khamis and Higgins (1996), Khamis (1997), Yeo and Tang (1999), Gouno et al., (2004), Han et al., (2006), Wu et al., (2006), Balakrishnan et al., (1997),Wu et al., (2008), and Balakrishnan and Han (2009) have all talked about the issues of planning ideal two-level, three-level, and general k-equivalent length-level step-stress ALT in view of the total or blue-penciled lifetime information from an outstanding appropriation. Their work was additionally reached out to the Weibull, lognormal, and log-strategic appropriations by Bai and Kim (1993), and Balakrishnan et.al.,(2009) Ideal step-stress testing for continuously for blue-penciled information from remarkable conveyance and talk about morerecent work, Chung and Bai (1998), Ideal plans of straightforward step-stress sped up life tests for lognormal lifetime circulations, Mama and Meeker, Ideal step-stress sped up life test plans for log-area scale dispersions, (2008). The hypothesis of rate process has been examined by Glasstane et. al (1941). Stochastic corruption models are generally tracked down in the weariness of metal and other composite materials, allude to Brinbaum and Saunders (1958). The utilization of corruption measures to evaluate part lifetimes was tended to in the early work of Gertsbakh and kordonsky a few properties of the disappointment conveyance has been analyzed for such cycle when the debasement way is expected to lie and require process and combined harm process, allude to Essary et. al.,(1973) Faitingue disappointment models has been talked about by Bhattachariya and Fries (1984). Stochastic models of disappointment in arbitrary climate model are examined by Desmond (1985). Sped up testing: Measurable models, Test plan, and information investigation is talked about by Nelson (1990). Debasement processes and related unwavering quality models is talked about by Lu (1995). Sped up debasement tests : demonstrating and investigation have been examined by Meekar et. al (1998). Planning a corruption climate has been examined by Yu and Tseng (1999). Assessing in debasement models with illustrative factors has been examined by Bagdonovicius and Nikuline (2001). Meeker et al., (2002) talked about broad ways to deal with assessing lifetime appropriations in sped up life tests for exceptionally factor conditions. Sped up corruption models for disappointment in view of mathematical brownian movement and gamma process has been examined by Park and Padgett (2005). A total harm model for disappointment with a few speeding up factors has been examined by Park and Padgett (2007). Balakrishnan and Han (2009) have all examined the issues of planning ideal two-level, three-level, and general k-equivalent length level step stress ALT in light of the total or blue-penciled lifetime information from a remarkable circulation. High levels in corruption modling have been examined by Nikulin et. al.,(2010). A hierarchal displaying way to deal with sped up Debasement testing information examination: A contextual investigation is examined by Pen (2011) Demonstrating drafted shock impacts on stochastic corruption in subordinate disappointment processes has been talked about by Lee et.al (2015). Sped up copy in and condition in light of support for n-subpopulations subject to stochastic debasement has been talked about by Yisha Xiang et.al., (2016).

3. Degradation models in reliability analysis

3.1 General Degradation Path Model

The major idea under the overall debasement way models is to restrict the example space of the corruption interaction and accept all example capabilities concede a similar practical structure yet with various boundaries allude to Lio (2004). The overall corruption way model fits the debasement perceptions by a relapse model with irregular coefficients. Jiang and Jardine (2008) and Zue et al. (1999) present basic general corruption way models. Liao (2004) declares that both basic straight relapse and nonlinear relapse models are by and large utilized in debasement way displaying. Straight corruption is used in some basic wear cycles, for example, auto tire wear. Nonetheless, corruption ways are in many cases nonlinear elements of time and now and again linearization is infeasible. Lu and Meeker (1993) presents an overall nonlinear blended impacts model and a two-stage way to deal with gauge model boundaries, that are multivariate regularly dispersed. What's more, Lu and Meeker (1993) fosters a Monte Carlo reproduction strategy to work out a gauge of the dissemination capability of the opportunity to-disappointment. They propose a parametric bootstrap strategy to set certainty stretches as recommended by Lu and Meeker (1993) with the accompanying presumption.

Sample assets are randomly selected from a population or production process and random measurement errors are independent across time and assets

(i) Sample assets are tested in a particular homogenous environment such as the same constant temperature

(ii) Measurement (or inspection) times are pre-specified, the same across all the test assets, and may or may not be equally spaced in time. This assumption is used for constructing confidence intervals for time to failure distribution via the bootstrap simulation technique

A general degradation path model can be expressed as:

$y_{ij} \ = \ \eta_{ij} + \varepsilon_{ij} = \eta\big(t_j; \Phi, \Theta_{\mathrm{i}}\big) + \varepsilon_{ij} \quad i = 1,2, \cdots n$

$\varepsilon_{ij} \approx N(0, \sigma_\varepsilon^2) \ \ j = 1,2 \ \cdots, m\Theta_{\mathrm{i}} < m$

Where

t_j is time of the j^{th} measurement or inspection.

ε_{ij} is the measurement error with constant variance σ_ε^2 .

η_{ij} is the actual path of the i^{th} asset at time t_j with unknown parameters as listed later.

Θ_{i} is the vector of fixed-effect parameters, common for all assets.

Θ_{i} is the vector of the i^{th} asset random-effect parameters, representing resenting individual asset characteristics.

Θ_{i} and ε_{ij} are independent of each other $(i \ = \ 1,2, \dots, n; \quad j = 1,2 \ \cdots, m\Theta_{\mathrm{i}})$.

m is the total number of possible inspections in the experiment.

$m\Theta_{\mathrm{i}}$ is the total number of inspections on the i^{th} asset, a function of Θ_{i}.

It is assumed that Θ_{i} = $(i \ = \ 1,2, \dots, n)$ follows a multivariate distribution function $G_\Theta(\cdot)$, which may depend on some unknown parameters that must be estimated from the data. The distribution function of T, the failure time, can be written as:

$Pr\,\{T \ \leq \ t\,\} = \ F_T\,t \ = \ F_T(\,t \ ; \Phi, G_\Theta(\cdot), D, \eta)$

3.2 Stochastic Models for Degradation Process

The aleatory vulnerabilities of a corruption cycle can be portrayed utilizing different sorts of probabilistic models. Customarily, the existence time appropriation models are utilized, in which the vulnerability of the corruption is portrayed according to the point of view of the unsure disappointment season of the part. The existence time dissemination model is generally applied in age based upkeep methodologies, where a part is supplanted when its activity time arrives at specific edge. At the point when the review and substitution cost is restrictively high, for example, on account of a thermal energy station, age-based support techniques are normally wasteful as investigation and substitution of part are regardless of its genuine state of corruption. In such cases, condition based support procedures are frequently utilized, which require direct displaying of debasement progress.

Stochastic models are overall more adaptable in demonstrating these mind boggling designs of corruption process. Consequently, the utilization of stochastic models in corruption appraisal and forecast has become progressively famous as of late. Unwavering quality creation in light of corruption demonstrating can be a proficient technique for assess dependability of frameworks when perception s of disappointment rate. Flow research shows that there has been a rising interest in use of stochastic debasement models in dependability expectation and endurance examination.

Models that depict the course of weakening or debasement in units or frameworks are of interest by their own doing, and are likewise key fixings in processes that decide "disappointment" occasions. Comparative with disappointment based dependability, debasement based unwavering quality has gotten a humble measure of consideration in the open writing. Corruption is an action to survey part life time was tended to in the early work of Gertsbakh and Kordonsky (1969). All the more as of late Meeker and Escober (1998) give Valuable synopsis of corruption models, accentuating the utilization of straight models with accepted log-ordinary paces of debasement. In such case, the full life time conveyance can be processed scientifically. Other late models experienced in the writing manage corruption of materials, for example, those because of Gilien and Celina (2001). Meeker et al.(2002) examined general ways to deal with assessing life time disseminations in sped up life test for exceptionally factor conditions. The models introduced there in center the particular of the corruption way as it relies unequivocally upon the working climate. For profoundly dependable gadgets or costly gadgets, nonetheless, lifetime information might be challenging to acquire because of the timeframe required, or the expense of perception. Sped up life testing can frequently be utilized to speed up the disappointment for exceptionally dependable gadgets and subsequently it is proposed to broaden existing outcomes by creating general disappointment models in light of stochastic cycles for debasement which consolidate a few speeding up factors, and utilize both corruption estimations, and genuine disappointments in derivation strategies. Corruption models and sped up test models for induction on dependability have been concentrated on by a few creators.

Sped up tests decline the strength or time to disappointment and the expense of testing by uncovering the test examples to more significant levels of pressure conditions (expanded sizes or levels of ecological factors) which cause prior breakdowns and more limited lifetimes than the typical use condition Nelson (1990). These ecological factors and levels of pressure conditions are alluded to as the "speeding up factors" in the measurements and unwavering quality writing. Sped up life testing (ALT) is a speedy method for getting data about the existence dissemination of a material, part or item. In Sped up life testing (ALT) things are exposed to conditions that are more serious than the typical ones, which yield more limited life yet, ideally, don't change the disappointment systems. A few suppositions are required to relate the life at high feelings of anxiety to life at typical feelings of anxiety being used. In view of these presumptions, the existence conveyance under typical feelings of anxiety can be assessed. Such approach to testing lessens both time and cost.

Three kinds of pressure loadings are typically applied in sped up life tests: steady pressure, step pressure and Moderate pressure. Consistent pressure is the most widely recognized kind of pressure stacking. Each thing is tried under a consistent level of the pressure, which is higher than typical level. In this sort of testing, we might have a few feelings of anxiety, which are applied for various gatherings of the tried things. This implies that each thing is exposed to just a single feeling of anxiety until the thing falls flat or the test is halted for different reasons. In Sync pressure stacking, the test things are exposed to progressively more significant levels of pressure at pre allotted test times. All things are first exposed to a predetermined consistent pressure for a predefined timeframe. Things that don't bomb will be exposed to a more significant level of pressure for one more indicated time. The degree of stress is expanded bit by bit until all things have fizzled or the test stops for different reasons. Moderate pressure stacking is very similar to the step pressure testing with the distinction that the feeling of anxiety increments ceaselessly. kamal et al.,

Step-stress testing is an extremely normal kind of sped up testing in view of speeding up factors. It is an effective method for getting disappointments in a moderately short measure of time. There are numerous varieties of step-stress testing. A typical sort is one in which the units are tried at a given anxiety for a specific measure of time. Toward the finish of that time, assuming there are units making due, the anxiety is expanded and held for one more measure of time. The information that outcome from such tests can be dissected utilizing the total harm model. For a nitty gritty concentrate on combined harm model, allude to Esarry et. al., (1973).

For exceptionally dependable items, it's anything but a simple assignment to evaluate the lifetime dispersion of the items by utilizing the conventional life-testing methods which record just opportunity to disappointment information. In any event, utilizing the systems consolidating editing and speeding up strategies, the data about the lifetime appropriation is still exceptionally restricted. Under this present circumstance, an elective methodology is to gather the "debasement" information at more elevated levels of pressure for foreseeing an item's lifetime at a specific use-feeling of anxiety. Such an investigation is called an ADT. Liao and Tseng (2006).

For fruitful use of ADT, many ways to deal with model debasement of items are given. Especially, Markov cycles, for example, the Brownian movement with float, the compound Poisson process, and the gamma interaction are generally utilized inferable from their autonomous augmentations property. For the stochastic displaying of monotonic and progressive corruption over the long run in a grouping of minuscule augmentations, the gamma cycle has found application as a debasement model in many examinations. The fundamental goal of paper is to expand existing outcomes and creating general disappointments models based a stochastic cycle for debasement which consolidate a few speeding up factors, and utilize both corruption estimations, and genuine disappointments in inferential methodology.

4. Model description

At stress level $x_i, (i = 1,2...k,)$ the lifetime Y of a test unit is assumed to follow a log-location scale distribution with cumulative distribution function (CDF)

$$F_i(y;\ \mu_i,\sigma) = \Phi\left(\frac{\text{In } y - \mu_i}{\sigma}\right), y \geq 0,$$

Where $\Phi(\cdot)$ is the standard log-location-scale CDF, and the location parameter is

$$\mu_i = \mu(x_i) = \beta_0 + \beta_1 x_i ,$$

andσ is the unknown scale parameter. Here, the regression parameters β_0 and $\beta_1(< 0)$ are unknown and need to be estimated, and the scale parameter σ is assumed to be free of the stress levels. The CDF of the lifetime of a test unit under the k-level step-stress ALT is given by

$$G(y) = F_i(y + s_{i-1} - \tau_{i-1};\ \mu_i, \sigma) \text{ for } \begin{cases} \tau_{i-1} \leq y \leq \tau_{i\,,} & \text{for} \quad i = 1,2, \cdots k-1 \\ \tau_{i-1} \leq y \leq \infty, & \text{for} \quad i = k, \end{cases}$$

Where s_0=0 and $s_{i-1} = \tau_{i-1} + s_{i-2} - \tau_{i-2} \exp(\mu_i - \mu_{i-1})$ is the solution of the equation $F_i(s_{i-1}; \mu_i, \sigma) = F_{i-1}(\tau_{i-1} + s_{i-2} - \tau_{i-2}; \mu_{i-1}, \sigma), i = 2,3, \cdots, k$

$$G(y) = \begin{cases} G_1(y) = \Phi\left(\dfrac{\text{In } y - \mu_i}{\sigma}\right), & \text{for } 0 < y \leq \tau_1 \\ G_1(y) = \Phi\left[\dfrac{\text{In}(y + s_{i-1} - \tau_{i-1}) - \mu_i}{\sigma}\right], & \text{for } \tau_{i-1} \leq y \leq \tau_i \end{cases} \quad \cdots (1)$$

where $i = 2, \cdots k - 1$, and $\tau_{i-1} \leq y \leq \infty$ where $i = k$

and the corresponding probability density function (PDF) of the lifetime of a test unit is given by

$$g(y) = \begin{cases} g_1(y) = \dfrac{1}{\sigma y}\Phi\left(\dfrac{\mathrm{In}\, y - \mu_1}{\sigma}\right) & , \quad \text{for } 0 < y \le \tau_1 \\ g_i(y) = \dfrac{1}{\sigma(y + s_{i-1} - \tau_{i-1})}\Phi\left[\dfrac{\mathrm{In}(y + s_{i-1} - \tau_{i-1}) - \mu_i}{\sigma}\right] & , \quad \text{for } \tau_{i-1} \le y \le \tau_i\ , \end{cases} \quad \cdots (2)$$

where $i = 2, \cdots k-1$, and $\tau_{i-1} \le y \le \infty$ where $i = k$

5. Maximum Likelihood Estimation

From Equations (1) and (2), the joint PDF of observed data are $n = (n_1, n_2, \ldots, n_k)$ and $y = (y_1, y_2, \ldots, y_k)$ with $y_i = (y_{i,1}, y_{i,2}, \ldots, y_{i,n_i})$ is given by

$$f(y,n) = \frac{n!}{(n - \sum_{i=1}^{k} n_i)!}\left\{\prod_{i=1}^{k}\left[\prod_{j=1}^{n_i} g_i(y_{i,j})\right]\right\}[1 - G_k(\tau_k)]^{n-\sum_{i=1}^{k} n_i} \quad \cdots (3)$$

and so the log-likelihood function of $(\beta_0, \beta_1, \sigma)$is given by

$$n \propto -\left(\sum_{i=1}^{k} n_i\right)\mathrm{In}\,\sigma - \sum_{i=1}^{k}\sum_{j=1}^{n_i}\mathrm{In}(y_{i,j} + s_{i-1} - \tau_{i-1}) + \sum_{i=1}^{k}\sum_{j=1}^{n_i}\mathrm{In}\phi(Z_{i,j}) + \left(n - \sum_{i=1}^{k} n_i\right)\mathrm{In}[1 - \phi(\eta_k)]$$

Where

$$z_{i,j} = \frac{In(y_{i,j} + s_{i-1} - \tau_{i-1}) - (\beta_0 + \beta_1 x_i)}{\sigma}, i = 1,2,\cdots,k and j = 1,2,\cdots n_i,$$

$$\eta_k = \frac{In(\tau_k + s_{k-1} - \tau_{k-1}) - (\beta_0 + \beta_1 x_k)}{\sigma}$$

Note that the MLEs ofβ_0, β_1, and σ exist only if $n_i > 0, i = 2, \cdots, k,$ in Equation (3). By using following expressions

$$\frac{\partial s_{i-1}}{\partial_{\beta_1}} = \sum_{h=2}^{i} (x_h - x_{h-1}) s_{h-1} e^{\beta_1 (x_i - x_h)}$$

$$\frac{\partial z_{i,j}}{\partial_{\beta_0}} = -\frac{1}{\sigma}, \qquad \frac{\partial z_{i,j}}{\partial_{\beta_1}} = \frac{1}{\sigma}\left[\sum_{h=2}^{i} (x_h - x_{h-1}) \frac{s_{h-1} e^{\beta_1 (x_i - x_h)}}{y_{i,j} + s_{i-1} - \tau_{i-1}} - x_i\right], \frac{\partial z_{i,j}}{\partial_{\sigma}} = -\frac{z_{i,j}}{\sigma}$$

$$for\ i = 1,2,\cdots,k\ and\ j = 1,2,\cdots,n_i$$

$$\frac{\partial \eta_k}{\partial_{\beta_0}} = \frac{1}{\sigma}, \frac{\partial \eta_k}{\partial_{\beta_1}} = \frac{1}{\sigma}\left[\sum_{h=2}^{k} (x_h - x_{h-1}) \frac{s_{h-1} e^{\beta_1 (x_k - x_h)}}{y_{i,j} + s_{k-1} - \tau_{k-1}} - x_k\right], \frac{\partial \eta_k}{\partial_{\sigma}} = -\frac{\eta_k}{\sigma}$$

$$\frac{\partial \Phi(\eta_k)}{\partial_{\beta_0}} = -\frac{\Phi(\eta_k)}{\sigma}, \frac{\partial \Phi(\eta_k)}{\partial_{\beta_1}} = \frac{\Phi(\eta_k)}{\sigma}\left[\sum_{h=2}^{k} (x_h - x_{h-1}) \frac{s_{h-1} e^{\beta_1 (x_k - x_h)}}{\tau_k + s_{k-1} - \tau_{k-1}} - x_k\right],$$

$$\frac{\partial \Phi(\eta_k)}{\partial_{\sigma}} = \frac{\eta_k \Phi(\eta_k)}{\sigma},$$

The MLE is $\hat{\beta}_0$, $\hat{\beta}_1$and$\hat{\sigma}$ can be obtained by solving the following likelihood equations:

$$\frac{\partial \text{In L}}{\partial_{\beta_0}} = \frac{1}{\sigma}\left[-\sum_{i=1}^{k}\sum_{j=1}^{n_i} \frac{1}{\phi(z_{i,j})} \cdot \frac{d\phi(z_{i,j})}{dz} + \left(n - \sum_{i=1}^{k} n_i\right) \frac{\phi(\eta_k)}{1 - \Phi(\eta_k)}\right] = 0,$$

$$\frac{\partial In\ L}{\partial_{\beta_0}} = \frac{1}{\sigma}\left[-\sum_{i=1}^{k} n_i - \sum_{i=2}^{k}\sum_{j=1}^{n_i} \frac{z_{i,j}}{\phi(z_{i,j})} \cdot \frac{d\phi(z_{i,j})}{dz} + \left(n - \sum_{i=1}^{k} n_i\right) \frac{\eta_k \phi(\eta_k)}{1 - \Phi(\eta_k)}\right] = 0$$

The second derivatives of the log-likelihood function

$$\frac{\partial^2 In\ L}{\partial_{\beta_0}^2} = -\frac{1}{\sigma^2}\left\{\sum_{i=2}^{k}\sum_{j=1}^{n_i} \frac{1}{\phi(z_{i,j})}\left[\left(\frac{d\phi(z_{i,j})}{dz}\right)^2 - \frac{d^2\phi(z_{i,j})}{dz^2}\right]\right.$$
$$\left. + \left(n - \sum_{i=1}^{k} n_i\right) \frac{1}{1 - \Phi(\eta_k)}\left[\frac{d\phi(\eta_k)}{d\eta} + \frac{\phi^2(\eta_k)}{1 - \Phi(\eta_k)}\right]\right\},$$

$$\frac{\partial^2 In\ L}{\partial_{\beta_0}\partial_{\beta_1}} = -\frac{1}{\sigma^2}\left\{\sum_{i=1}^{k} x_i \sum_{j=1}^{n_i} \frac{1}{\phi(z_{i,j})}\left[\frac{1}{\phi(z_{i,j})}\left(\frac{d\phi(z_{i,j})}{dz}\right)^2 - \frac{d^2\phi(z_{i,j})}{dz^2}\right]\right.$$

$$-\sum_{i=2}^{k}\sum_{j=1}^{n_i}\frac{1}{\phi(z_{i,j})}\left[\frac{1}{\phi(z_{i,j})}\left(\frac{d\phi(z_{i,j})}{dz}\right)^2-\frac{d^2\phi(z_{i,j})}{dz^2}\right]\sum_{h=2}^{i}(x_h-x_{h-1})\frac{s_{h-1}e^{\beta_1(x_i-x_h)}}{y_{i,j}+s_{i-1}-\tau_{i-1}}$$

$$+\left(n-\sum_{i=1}^{k}n_i\right)\frac{x_k}{1-\Phi(\eta_k)}\left[\frac{d\phi(\eta_k)}{d\eta}+\frac{\phi^2(\eta_k)}{1-\Phi(\eta_k)}\right]$$

$$-\left(n-\sum_{i=1}^{k}n_i\right)\frac{x_k}{1-\Phi(\eta_k)}\left[\frac{d\phi(\eta_k)}{d\eta}+\frac{\phi^2(\eta_k)}{1-\Phi(\eta_k)}\right]\sum_{h=2}^{k}(x_h-x_{h-1})\frac{s_{h-1}e^{\beta_1(x_k-x_h)}}{\tau_k+s_{k-1}-\tau_{k-1}}\Bigg\}$$

$$\frac{\partial^2 InL}{\partial\sigma^2}=-\frac{1}{\sigma}\left(\frac{\partial InL}{\partial\sigma}\right)-\frac{1}{\sigma^2}\left\{\sum_{i=2}^{k}\sum_{j=1}^{n_i}\frac{z_{ij}}{\phi(z_{ij})}\left[\frac{1}{\phi(z_{ij})}\left(\frac{d\phi(z_{ij})}{dz}\right)^2-\frac{d^2\phi(z_{ij})}{dz^2}\right]\right.$$

$$\left.\sum_{i=1}^{k}x_i\sum_{j=1}^{n_i}\frac{z_{ij}}{\phi(z_{ij})}\cdot\left(\frac{d\phi(z_{ij})}{dz}\right)+\left(n-\sum_{i=1}^{k}n_i\right)\frac{\eta k}{1-\Phi\eta_k}\phi(\eta_k)+\eta k\frac{d\phi(\eta_k)}{d\eta}+\frac{\phi^2(\eta_k)}{1-\Phi\eta_k}\right\}$$

Since these situations can't be addressed scientifically, mathematical techniques, for example, reenacted strengthening calculation or some other iterative system should be utilized for this assessment issue. A benefit of utilizing the reenacted strengthening calculation is that it permits us to find a worldwide ideal without relying upon the decision of the underlying qualities, which is one of the primary downsides of the regularly utilized mathematical techniques like Newton-Raphson

6. Numerical Illustration

The ideal arrangements were acquired by the reproduced tempering calculation as proposed by Corana et al., (1987). It very well may be effectively seen that the assessed asymptotic changes in light of complete information are the littlest, trailed by those in view of blue-penciled information inside the looking through range (0, 50], and afterward the ones with examination spans being picked by specific proportions. To determine the optimal unequal time points $(\tau_1 < \tau_2 < \cdots < \tau_k)$ that minimize the large-sample approximate variance of the MLE of the 200pth quantile $(0 < p < 1)$ of the log-lifetime distribution at the normal-use stressx_0. The MLE of the 200p quantile at the normal-use stress x_0 can be expressed as$\hat{y}_p = \hat{\beta}_0 + \hat{\beta}_1 x_0 + z_p\hat{\sigma}$, where z_p is the 100pth percentile of the standard log-location-scale distribution.

Thus, If $x_0 = 0$, the asymptotic variance of the estimator $\hat{y}_p$ at the normal-use stress$x_0$is given by

$$\mathrm{A\,Var}(y_p) = \mathrm{A\,Var}(\hat{\beta}_1 + z_p\hat{\sigma}) = V_{11} + z_p^2 V_{33} + 2_{zp} V_{13}$$

Where

$V_{ij}{}'$ It is verified under the C- optimality Criterion based 2-level step-stress ALT plan is preferable, whenever we optimize the general 2-level step-stress ALT plan the second K-level step – ALT plan under a censoring scheme under the considered and the results are shown in Table -1. $\tau = 2 : 1$, and the inspection interval for the first stage is twice as long as that for the second stage.

Table 1. Censoring scheme

<table>
<tr><th>C_0</th><th>P_0</th><th>γ_0</th><th>θ_0</th><th>Parameter</th><th>MLE</th><th>RAB</th><th>MSE</th></tr>
<tr><td rowspan="7">1.0</td><td rowspan="7">1.0</td><td rowspan="7">1.25</td><td rowspan="7">0.7</td><td>C</td><td>1.10902</td><td>0.10902</td><td>0.01189</td></tr>
<tr><td>P</td><td>0.98314</td><td>0.01686</td><td>0.00028</td></tr>
<tr><td>γ</td><td>1.22511</td><td>0.01991</td><td>0.00062</td></tr>
<tr><td>θ</td><td>0.88398</td><td>0.11602</td><td>0.01346</td></tr>
<tr><td>α_1</td><td>1.38040</td><td>0.10486</td><td>0.01717</td></tr>
<tr><td>α_2</td><td>0.69831</td><td>0.11785</td><td>0.00542</td></tr>
<tr><td>α_3</td><td>0.46874</td><td>0.12552</td><td>0.00273</td></tr>
<tr><td rowspan="7">1.0</td><td rowspan="7">1.0</td><td rowspan="7">1.3</td><td rowspan="7">1.0</td><td>C</td><td>1.15695</td><td>0.15695</td><td>0.02463</td></tr>
<tr><td>P</td><td>0.9846</td><td>0.0154</td><td>0.00024</td></tr>
<tr><td>γ</td><td>1.23098</td><td>0.05309</td><td>0.00476</td></tr>
<tr><td>θ</td><td>0.87707</td><td>0.12293</td><td>0.12446</td></tr>
<tr><td>α_1</td><td>1.44053</td><td>0.15299</td><td>0.03654</td></tr>
<tr><td>α_2</td><td>0.72799</td><td>0.16536</td><td>0.01067</td></tr>
<tr><td>α_3</td><td>0.48837</td><td>0.17266</td><td>0.00517</td></tr>
<tr><td rowspan="2">1.0</td><td rowspan="2">1.0</td><td rowspan="2">1.5</td><td rowspan="2">1.0</td><td>C</td><td>1.35169</td><td>0.35169</td><td>0.12369</td></tr>
<tr><td>P</td><td>0.99012</td><td>0.00988</td><td>0.00010</td></tr>
</table>

				γ	1.25504	0.16331	0.06001
				θ	0.84992	0.15008	0.02252
				α_1	1.68507	0.34872	0.18982
				α_2	0.84832	0.35799	0.05001
				α_3	0.56782	0.36344	0.02291
1.0	1.1	1.4	1.0	C	1.26473	0.26473	0.07008
				P	0.97595	0.11277	0.01539
				γ	1.37052	0.02106	0.00087
				θ	0.8474	0.1526	0.02329
				α_1	1.5717	0.23028	0.08654
				α_2	0.79906	0.34074	0.04124
				α_3	0.53793	0.4099	0.02446
1.25	1.1	1.25	1.0	C	1.14000	0.08800	0.01210
				P	0.95459	0.13219	0.02114
				γ	1.37506	0.10005	0.01564
				θ	1.01030	0.01030	0.00011
				α_1	1.40997	0.11705	0.03494
				α_2	0.72753	0.02342	0.00030
				α_3	0.49403	0.03589	0.00029
1.4	1.0	1.0	0.7	C	0.91213	0.34848	0.23802
				P	0.68352	0.31648	0.10016
				γ	1.25991	0.25991	0.06755
				θ	1.10442	0.57774	0.16356
				α_1	1.06206	0.39281	0.47207
				α_2	0.66129	0.24387	0.04549
				α_3	0.50122	0.14034	0.00670
1.4	1.2	1.0	0.9	C	0.91672	0.3452	0.23356

				P	0.84089	0.29926	0.12896
				γ	1.49253	0.49253	0.24259
				θ	1.10045	0.22272	0.04018
				α_1	1.10547	0.39552	0.52319
				α_2	0.61718	0.22467	0.03198
				α_3	0.43888	0.10314	0.00255

Table 2. The variance optimality under the step stress setting based

Complete data				**Censored data**			
p	**X₁**	**X₂**	$\boldsymbol{\tau_1^c}$	$\boldsymbol{\tau_1^c, \tau_2^c}$	$\Delta_\tau = \mathbf{2:1}$	$\Delta_\tau = \mathbf{2:1}$	$\Delta_\tau = \mathbf{1:2}$
				10.0470,			
				20.0000			
				10.7887,			
				20,0000			
0.5	0.2	0.5	10.2895	6.8408,	10.0312(3.48)	10.0000(3.35)	6.6667(3.99)
		1.0	11.0011	20,0000	10.8267(2.45)	10.8267(2.50)	6.6667(3.10)
	0.4	0.5	6.8724	7.3107,	6.5817(15.81)	6.5817(16.02)	6.6667(15.83)
		1.0	7.3327	20.0000	7.1133(8.71)	7.1133(8.32)	0.6667(8.38)
0.95	0.2	0.5	13.6090	12.6071,	13.3333(7.48)	10.0000(7.87)	6.6667(11.03)
		1.0	14.9424	20,0000	13.3333(5.87)	10.0000(6.56)	6.6667(9.42)
	0.4	0.5	8.1548	14.0111,	7.8435(26.76)	8.0765(25.03)	6.6667(25.91)
		1.0	9.0548	20,0000	8.8341(14.17)	9.0146(14.08)	6.6667(16.19)
				8.0935,			
				20,0000			
				9.0018,			
				20,0000			

The stress levels x_i, $i = 1,\ldots,k$, when $\beta_0 = 2.5, \beta_1 = -1.0$, $\sigma = 0.5$. to identify the optimal change points leading to variance optimality, the optimal change points and associated asymptotic variance based on the censored data when the lengths of the inspection intervals were chosen according to certain ratio τ.

7. Conclusion:

The proposed system comprises of huge example inexact fluctuation of ML assessors of quintiles of the broadly utilized log-area scale group of circulations with constant time-changing pressure sped up life tests in light of editing.The determination of the optimal choice of $(\tau_1,\ldots,\tau_k)$ for Log location Scale family distributions the asymptotic variance using optimality criterion. The k-level step stress ALT with unequal duration steps $(\tau_1,\ldots,\tau_k)$for the censored case under a general log-location-scale lifetime distribution with mean life varying as a linear function of stress along with a cumulative exposure model gives better than consistent results for Stochastic degradation has been discussed in the article.

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ROLE OF LEADERSHIP, COMPENSATION, AND CAREER GROWTH IN SHAPING WORK ATTITUDES OF HEALTHCARE PROFESSIONALS

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ABSTRACT

This study examines the influence of leadership, compensation, and career growth opportunities on job satisfaction among healthcare professionals in healthcare institutions. In the dynamic healthcare sector, job satisfaction plays a crucial role in determining employee performance, retention, and the quality of patient care. The study focuses on understanding how leadership practices, financial and non-financial compensation, and opportunities for professional advancement contribute to employee satisfaction. A descriptive and analytical approach is adopted to explore the relationships between these key organizational factors and job satisfaction. The study also considers the role of demographic variables such as age, gender, income, and work experience in shaping employee perceptions. By integrating both organizational and individual factors, the research provides a comprehensive view of job satisfaction in the healthcare context. The findings are expected to reveal that effective leadership, equitable compensation, and clear career growth opportunities significantly enhance job satisfaction levels. The study also highlights variations in satisfaction across different demographic groups and institutional settings. The results will assist healthcare administrators and policymakers in developing strategies to improve employee well-being and organizational performance, thereby contributing to the overall efficiency of healthcare institutions.

Keywords: Job Satisfaction, Leadership, Compensation, Career Growth, Healthcare Professionals, Organizational Factors, Employee Performance

Introduction

The healthcare sector is one of the most critical and dynamic components of any economy, as it directly influences the well-being and productivity of society. Healthcare professionals, including doctors, nurses, and allied staff, play a pivotal role in delivering quality patient care. In such a demanding environment, job satisfaction becomes an essential factor that determines not only the efficiency and performance of employees but also the overall effectiveness of healthcare institutions. High levels of job satisfaction are associated with improved service quality, reduced employee turnover, and enhanced organizational commitment.

In recent years, increasing workload, workplace stress, and evolving patient expectations have made it imperative for healthcare institutions to focus on the factors influencing job satisfaction. Among these, leadership, compensation, and career growth opportunities have emerged as key determinants. Effective leadership fosters a supportive work environment, encourages communication, and enhances employee motivation. Compensation, both financial and non-financial, serves as a crucial incentive that affects employee morale and retention. Similarly, opportunities for career growth and professional development contribute significantly to long-term job satisfaction and organizational loyalty.

Despite the growing importance of these factors, many healthcare institutions face challenges in maintaining optimal satisfaction levels among their workforce. Variations in organizational practices and individual characteristics further influence employee perceptions and attitudes. Therefore, there is a need to examine the combined impact of leadership, compensation, and career growth on job satisfaction in a comprehensive manner.

This study aims to address this gap by analysing how these factors influence job satisfaction among healthcare professionals, thereby providing valuable insights for improving human resource practices in healthcare institutions.

Review of Literature

A number of studies have examined the factors influencing job satisfaction across various sectors, with particular emphasis on leadership, compensation, and career growth in the healthcare context.

Frederick Herzberg (1959), in his Two-Factor Theory, identified compensation as a hygiene factor and career growth as a motivator influencing job satisfaction. His work laid the foundation for understanding intrinsic and extrinsic determinants of employee satisfaction.

Edwin A. Locke (1976) defined job satisfaction as a positive emotional state resulting from job appraisal, emphasizing the role of organizational and individual factors.

Bernard M. Bass (1985) highlighted the importance of transformational leadership in enhancing employee motivation and satisfaction, particularly through inspiration and support.

Recent studies have further strengthened these findings in the healthcare sector. A study by **Jinhong Zhao et al. (2024)** found that leadership support significantly improves job satisfaction among healthcare professionals, particularly through resource availability, supportive work environments, and participative decision-making.

Similarly, L. **Hynes et al. (2025)** emphasized that career development opportunities and clear progression pathways play a crucial role in improving job satisfaction and retention among healthcare professionals.

A 2025 study published in medical research highlighted that fair compensation and recognition significantly enhance satisfaction levels, while inadequate pay and limited growth opportunities lead to dissatisfaction among healthcare professionals.

Further, recent evidence suggests that lack of career growth and organizational support is a major reason for dissatisfaction and turnover. Studies indicate that a large proportion of healthcare professionals feel underappreciated and are willing to change jobs due to limited career advancement opportunities.

Additionally, contemporary research highlights the importance of work-life balance and flexible work arrangements as emerging factors influencing job satisfaction, alongside traditional factors such as leadership and compensation.

Although previous studies have examined individual determinants of job satisfaction, limited research integrates leadership, compensation, and career growth collectively, particularly in healthcare institutions. Therefore, this study attempts to bridge this gap by providing a comprehensive analysis of these key variables.

Research Objectives

1. To examine the impact of leadership on job satisfaction among healthcare professionals.
2. To analyse the relationship between compensation and job satisfaction among healthcare professionals.
3. To study the influence of career growth opportunities on job satisfaction.
4. To compare job satisfaction among healthcare professionals across different institutions.
5. To assess the role of demographic factors (age, gender, income, experience) on job satisfaction.

Research Methodology

The present study is designed to examine the influence of leadership, compensation, and career growth opportunities on job satisfaction among healthcare professionals. The research adopts a descriptive and analytical approach, as it aims to describe the existing conditions and analyse the relationship between selected organizational factors and job satisfaction.

The study is based on both primary and secondary data sources. Primary data is collected from healthcare professionals working in various healthcare institutions, including doctors, nurses, and allied staff. Secondary data is obtained from published journals, research articles, books, and relevant reports to support the theoretical framework and provide background information for the study.

The population of the study comprises healthcare professionals employed in healthcare institutions. A sample of respondents is selected to represent the population adequately. The sampling technique used for the study is convenience sampling, considering the accessibility and availability of respondents. However, efforts are made to include participants from different categories to ensure diversity and reliability in responses.

The study considers leadership, compensation, and career growth as independent variables, while job satisfaction is treated as the dependent variable. Additionally, demographic factors such as age, gender, income, and work experience are included to understand their influence on job satisfaction.

For the purpose of analysis, appropriate statistical tools such as percentage analysis, correlation, regression, and ANOVA are used to examine the relationships between variables and to test the hypotheses of the study. The results are interpreted to draw meaningful conclusions and provide practical suggestions.

Despite its contributions, the study is subject to certain limitations, including constraints related to sample size and geographical coverage.

Conceptual Framework

The present study is based on the relationship between key organizational factors and job satisfaction among healthcare professionals. The framework identifies leadership, compensation, and career growth as the major determinants influencing job satisfaction, while demographic variables act as moderating factors.

The conceptual framework proposes that job satisfaction among healthcare professionals is directly influenced by three key independent variables: leadership, compensation, and career growth.

- **Leadership** plays a vital role in shaping the work environment. Supportive and effective leadership enhances motivation, communication, and employee engagement, thereby improving job satisfaction.
- **Compensation**, including salary, incentives, and benefits, serves as a significant extrinsic factor influencing employee morale and retention. Fair and competitive compensation is expected to positively impact job satisfaction.
- **Career Growth** refers to opportunities for promotion, skill development, and professional advancement. Employees who perceive clear growth opportunities are more likely to experience higher levels of satisfaction and organizational commitment.

In addition to these primary factors, demographic variables such as age, gender, income, work experience, and marital status may influence how individuals perceive job satisfaction. These variables act as moderating factors, affecting the strength and direction of the relationship between independent variables and job satisfaction.

Data Analysis & Interpretation

Descriptive Statistics

Variable	Mean	Standard Deviation
Leadership	3.85	0.72
Compensation	3.6	0.81
Career Growth	3.75	0.76
Job Satisfaction	3.8	0.7

The mean scores indicate that healthcare professionals have a moderately high level of satisfaction. Among the variables, leadership shows the highest mean value, suggesting it plays a significant role in influencing job satisfaction.

Correlation Analysis

Variables	Leadership	Compensation	Career Growth	Job Satisfaction
Leadership	1			
Compensation	0.52	1		
Career Growth	0.48	0.55	1	
Job Satisfaction	0.68	0.62	0.65	1

There is a strong positive correlation between leadership and job satisfaction ($r = 0.68$). Compensation ($r = 0.62$) and career growth ($r = 0.65$) also show significant positive relationships, indicating that all three factors are important determinants.

Regression Analysis

Variable	Beta Coefficient	t-value	Significance (p-value)
Leadership	0.35	4.2	0
Compensation	0.28	3.6	0.001
Career Growth	0.32	3.95	0

$R^2 = 0.62$

The regression results show that all three independent variables significantly influence job satisfaction. Leadership has the highest impact ($\beta = 0.35$), followed by career growth and compensation. The R^2 value (0.62) indicates that 62% of the variation in job satisfaction is explained by these variables.

ANOVA

Source	F-value	Significance
Between Groups	2.45	0.12

Since the p-value is greater than 0.05, there is no significant difference in job satisfaction based on gender.

Conclusion

The study concludes that leadership, compensation, and career growth significantly influence job satisfaction among healthcare professionals, with leadership being the most influential factor. Supportive leadership enhances motivation, while fair compensation improves retention and morale. Career growth opportunities contribute to long-term commitment and satisfaction. Organizational factors have a stronger impact than demographic variables. Healthcare institutions should adopt participative leadership styles, ensure fair compensation, and provide career advancement opportunities. Additionally, employee well-being programs, work-life balance initiatives, and regular feedback systems should be implemented to improve satisfaction levels. Enhancing job satisfaction is essential for improving organizational performance, reducing turnover, and ensuring quality healthcare services.

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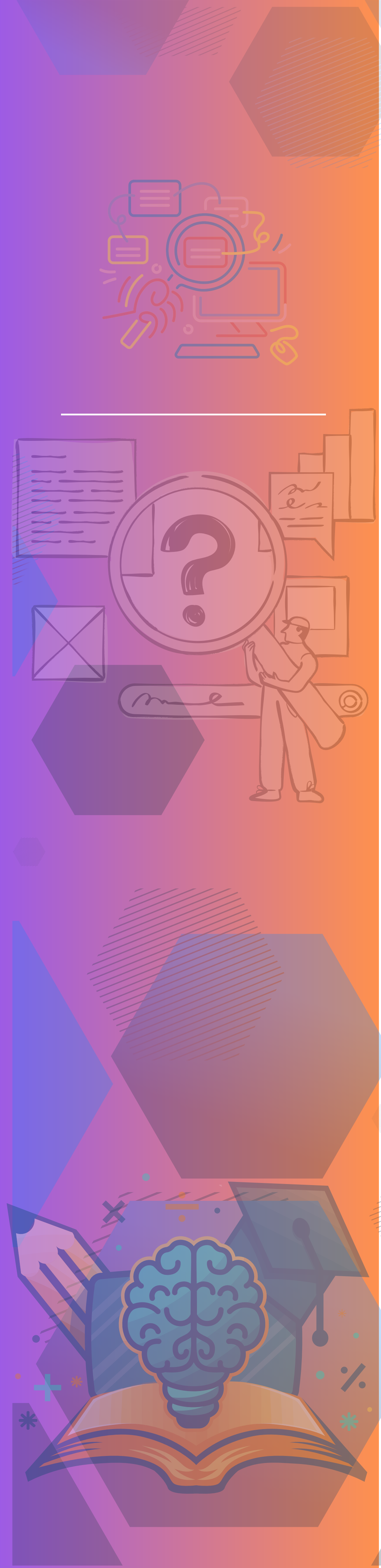

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