

INSTITUTE OF ACTUARIES OF INDIA

SA3 - General Insurance

May 2026 Examination

INDICATIVE SOLUTION

Introduction:

The indicative solution has been written by the Examiners with the aim of helping candidates. The solutions given are only indicative. It is realized that there could be other points as valid answers and examiners have given credit for any alternative approach or interpretation which they consider to be reasonable.

Solution 1**i) Key characteristics of health insurance:**

- Health insurance protects financially against medical expenses such as hospitalization, surgeries, and treatments.
- Expenses before and after hospitalization (like tests, medicines, follow-ups) are often covered for a specified period.
- a fixed amount (premium) periodically (monthly, quarterly, or yearly) is paid to keep the policy active.
- Sum insured is maximum amount the insurer will pay for your medical expenses during a policy year.
- Cashless Treatment- Many insurers allow treatment at network hospitals without upfront payment (the insurer settles bills directly with the hospital)
- Certain illnesses (like pre-existing diseases or specific treatments) are covered only after a waiting period.
- Diseases you already have before buying the policy are covered after a defined waiting period.
- You may have to pay a portion of the claim amount (co-pay) or a fixed deductible before insurance kicks in.
- Exclusions and non-covered claims- Certain conditions or treatments (like cosmetic surgery, self-inflicted injuries, etc.) are not covered.
- Occurrence vs. claims-made: most ELI is written on an occurrence basis tied to the date of hospitalization
- Claims have short reporting and settlement delays
- Claim size tends to be small to medium-sized
- Claims frequency is likely to be moderate to high
- There will be significant accumulations of claims from adverse epidemic conditions
- Accumulations might occur from same product or same geographic region
- If a disease is widespread, e.g.- COVID, then the insurer could face several years of high losses.
- Short tail hence low impact from general claims inflation but maybe subject to high medical inflation
- Potential for disputes regarding pre-existing diseases, coverages under a product.

[8]**ii) Individual health insurance**

- Age
- Gender
- Smoking status
- Geographic location
- Medical history
- Individual v/s Family composition
 - Sum Insured - fixed vs floating
 - Optional Covers opted
 - Deductibles /excess chosen

Group health insurance

- Group size
- Group demographics- age, gender, dependent mix
- Industry
- Geographic mix of employees
- Groups claims experience
- Plan design

[5]**iii)**

- Unusually light / heavy experience. Claims experience fluctuates over time. An example in health insurance is covid claim. If the experience of the base period does not appear typical the insurer must choose another base period, aggregate more years experience or apply an adjustment factor to the affected base year. Exclude or normalize such events.
- Large / exceptional claims. Have to decide whether to leave claims in, truncate them or remove them. This will depend on the extent to which claims of this type are expected to occur in future. Examples in health insurance would be a large cancer claim. It can cap (limit) or remove large claims and replace them with an average value

- Trends in claims experience. Investigate any trends in base data to see if they are likely to occur in future. If so need to project the trend and include. If not likely to occur in future then exclude. Rate of increase of cost of healthcare cost is likely to be a trend in health insurance. In that case, inflate past claims to present/future cost levels.
- Changes in risk over time can be very difficult to deal with. Could be dealt with as trends. Or may separate them out, project and combine with explicit assumptions about the future mix of these risks. This will also need to be done for different types of claims if the mix of claims is changing significantly. Example is that due to Age, gender, and health profile impact claim frequency and severity. If the average age of the insured group increases from 30 to 40, claims are expected to rise → adjust upward.
- Changes in cover can also be difficult to allow for. If perils are no longer insured the insurer may be able to exclude from the base data all claims that wouldn't be covered in future. Example if the new policy includes maternity benefits (not present earlier), expected additional claims must be added. Modify claims to reflect current policy benefits. Here, internal data or external data will need to be used such as market stats, government data or consumer stats.
- If the change is to the level of limits or excesses then it is more complicated. May be possible to allow for increases in these by looking at individual claims e.g. Introducing a 20% co-pay reduces insurer liability → claims cost is adjusted downward.
 - Adjustment for PED exclusion, waiting period, expected renewal rate
 - Expected change in litigation level
 - Changes in medical advancements / procedures and impact on frequency (early detection) and severity
 - Currency rate (for imported medicines etc.)
- Past data may not be fully reliable (especially for small groups).

If a small group has volatile claims, only 40% weight may be given to its experience and 60% to standard rates.

Adjustment: Blend past experience with industry benchmarks.

- If the detailed claims information is not available then an approximation will have to be made using the claims cost distribution. Many insureds will not inform the insurer of losses that occur below the excess point.
- Changes in the impact of reinsurance will need to be allowed for e.g. cat XL retention changes assuming the calculations are performed net of reinsurance.
- Not all claims that occurred during the period have been reported yet. Add an estimate for unreported claims
- Claims already reported may increase (or sometimes decrease) as they are settled-Develop claims to their ultimate value.

[15]

iv)

- A small number of very large claims can make the historical average claims cost look much higher (or lower) than what is “typical” for most policies.
- Rate indications may become overly influenced by outliers, leading to overpricing or under-pricing for the underlying risk
- Large individual claims and catastrophes often arise from rare, different mechanisms (e.g., unusual circumstances, weather-related events, clustering in time/area).
- The frequency model may be intended to reflect the “normal” claim generation process; extreme events may not follow the same pattern as ordinary claims.

- Catastrophes are concentrated in particular periods (e.g., certain months/years). If that period is included in the dataset, experience could be temporarily elevated.
- For pricing, the company wants a forecast of future conditions, not just the recent spike caused by one event.
- Catastrophes may affect specific geographical areas or policy clusters more than others.
- If the company's exposure mix changes over time (e.g., business growth/withdrawal in certain areas), raw historical claims can lead to biased estimates of expected frequency
- Extreme claims increase the variance of claim estimates, making models harder to calibrate and less stable.
- Adjusting large claims helps produce more reliable estimates, particularly when there is limited data for certain segments.
- Various individual claims arising from a catastrophe may develop at a similar speed to non-catastrophe claims
- they may bias the average date of occurrence
- The inflationary effect on a large claim is likely to be different to that on smaller claims

[7]

v)

$$\text{Design matrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

[2]

vi)

$$\begin{aligned} Y &= \begin{bmatrix} 700/1400 \\ 600/1000 \\ 400/1000 \\ 420/1200 \end{bmatrix} \\ &= \begin{bmatrix} 0.5 \\ 0.6 \\ 0.4 \\ 0.35 \end{bmatrix} \end{aligned}$$

[2]

vii)

$$0.5 = \beta_1 + \beta_2 + 0.35 + E_1$$

$$\rightarrow E_1 = 0.15 - \beta_1 - \beta_2$$

$$0.6 = \beta_1 + 0.35 + E_2$$

$$\rightarrow E_2 = 0.25 - \beta_1$$

$$0.4 = \beta_2 + 0.35 + E_3$$

$$\rightarrow E_3 = 0.05 - \beta_2$$

$$0.35 = 0.35 + E_4$$

$$\rightarrow E_4 = 0$$

$$SSE = (0.15 - \beta_1 - \beta_2)^2 + (0.25 - \beta_1)^2 + (0.05 - \beta_2)^2$$

$$dSSE/d\beta_1 = -2(0.15 - \beta_1 - \beta_2) - 2(0.25 - \beta_1) = 0$$

$$0.8 = 4\beta_1 + 2\beta_2$$

$$\beta_1 = 0.2 - 0.5\beta_2$$

$$\beta_1 = 0.2 - 0.5(0.1 - 0.5\beta_1)$$

$$\beta_1 = 0.2$$

β_1 is the difference in average claim frequency between male policyholders and female policyholders

keeping Territory fixed. Hence adding “male” changes the expected claim frequency by 0.2

$$dSSE/d\beta_2 = -2(0.15 - \beta_1 - \beta_2) - 2(0.05 - \beta_2) = 0$$

$$0.4 = 2\beta_1 + 4\beta_2$$

$$\beta_2 = 0.1 - 0.5\beta_1$$

$$\beta_2 = 0$$

β_2 is the difference in average claim frequency between vehicles in Territory A and vehicles in Territory B keeping gender fixed. Hence adding “Territory A” changes the expected claim frequency by 0

[6]

viii) Frequency is non-negative, so normal distribution is a poor fit. A multiplicative relationship fits frequency better than additive relationship.

The Poisson structure is more apt for this data use for a frequency model because:

- Values for frequency are restricted to positive values; normality violates these assumptions

- Normality assumes a fixed variance while Poisson structure allows the variance to increase with mean (more weight to observations at left of the distribution)

[2]

ix)

A GLM is often more interpretable than many machine learning models because it is built around a fixed, explicit statistical structure:

- a) Model has a simpler, transparent story- Many machine learning methods can learn very complex patterns—sometimes so complex that it's hard to explain them in plain language.

With GLMs, the model assumes a *specified kind of relationship* between inputs and the outcome (for example, “log-odds change linearly with X” in logistic regression). Because the form is simpler and specified ahead of time, you can explain the results more straightforwardly. GLMs specify that the expected outcome is linked to predictors through a known link function (e.g., log link for frequency), so the model form is transparent: changes in predictors translate to clear changes in the linear predictor.

- b) Parameters have direct meaning: Each coefficient corresponds to a quantifiable effect (e.g., a coefficient represents the multiplicative effect on the mean response via the link). For example, with a log link, exponentiated coefficients can be interpreted as relative risk / rate relativities.
- c) Interpretability is about explanations-With appropriate variable encoding, GLM coefficients correspond to specific factors (e.g., territory, gender) and their main effects—so actuaries can read the model in terms of underwriting variables.

A GLM is often better at producing results that can be communicated clearly—like effect sizes and direction of influence—rather than only “the model is accurate.” Eg- "How does each factor affect the outcome?", "What is the practical meaning of this feature?", "Is the effect consistent and understandable?"

- d) Controlled functional form: Because the model is intentionally restricted to (often) main effects and selected interactions, it avoids “black-box” complexity. Any nonlinearity must be introduced explicitly (e.g., polynomial terms, spline basis), which keeps interpretation aligned with chosen actuarial features.

GLMs are made to show what variables matter and how

In a GLM, the effect of each input (like age, income, or advertising spend) is expressed with a clear mathematical pattern. Eg-"Which factors are associated with higher/lower outcomes?", "Whether the relationship is positive or negative?", "How strong is the relationship?"

- e) GLMs can still be flexible without becoming opaque- Uncertainty and diagnostics are standard: GLMs naturally support inference tools (standard errors, confidence intervals, hypothesis tests, deviance/AIC) that help justify which effects are significant and whether the model is well calibrated.

The performance can be improved while staying interpretable in GLMs by doing things like:

- adding carefully chosen transformations (e.g., age groups)
- using interaction terms (“X matters more when Y is high”)
- using regularization (which can help stability)

One can get “good enough” performance with clearer explanations.

In contrast, many ML methods (e.g., random forests, neural networks) learn flexible nonlinear relationships, so individual predictors' effects are harder to summarize into simple, stable coefficients, making interpretation less direct.

[5]
[52 Marks]

Solution 2:

i) Technical reserves estimated by a reserving actuary

- Incurred but not enough reported
 - Individual case estimates set by claims handlers to cover expected future payments on reported claims (including future payments for indemnity, expenses, legal costs)
 - Includes reserves for reopened claims and adjustment of existing reserves.
- IBNR Reserves (Incurred But Not Reported)
- Reserve for claims that have occurred but not yet been reported at valuation date. Often split into:
 - Pure IBNR (unreported claims)
 - IBNER (Incurred But Not Enough Reported) — reserve for development on reported claims beyond case reserves.
- UPR and PDR (Unearned Premium Reserve and Premium Deficiency Reserve)

While primarily a premium/solvency item, actuaries often assess Unearned Premium Reserve to ensure premium adequacy relative to future claims (especially for short-tail lines). PDR is created if UPR is insufficient to meet future claims, policy maintenance costs and claim related costs

- Reserves for Bulk/IBNR for Specific Risks
- Large-loss reserves (separately monitored for individual large claims).
- IBNR for specific risks/peculiarities eg- clean cut feature in reinsurance

Claims Handling/Settlement Expenses (Future Claims Costs / Expense Reserve)

- Provision for future internal & external claims handling costs related to outstanding and IBNR claims.

Reserving for Reinsurance Recoverables and Counterparty/default risk

- Gross reserves supplemented by estimates of reinsurance recoverables; allowances for recoverability and timing risk (bad debts, reinstatement premiums).
- Reserves for Premium Refunds- free look reserve/policy cancellation within free look period requiring premium refund
- Separate estimates for expected salvage/subrogation and associated recoveries if needed; conservative provisioning for uncertain recoverables.
- Explicit risk margin needs to be estimated as required by regulation

Provision for Adverse Deviations (PAD)

- Explicit margins in reserves as may be prescribed by regulations

[7]

ii)

- the run-off pattern is the same for each origin period (as for the chain-ladder)
- incremental claim amounts are stochastically independent
- the variance of the incremental claim amounts is proportional to the mean
- incremental claims are positive for all development periods

iii)

- a) The ODP method may not be suitable for latent claims like asbestos claims, since they are only able to reflect the variability in the claims data available and this may have not occurred.

A possible approach around this is to use an exposure-based method whereby assumptions concerning the volatility around the number of future claims, and the average cost of future claims, are made.

- b) Sparse data set in case of cyber liability can be problematical for stochastic methods.
In particular, small changes in numbers can lead to significant changes in the distribution of outcomes, and the results can be quite sensitive to individual points.
- c) Data peculiarities, such as this missing data in case of truncation can be problematical for stochastic methods. Coping with individual data peculiarities is a matter of individual actuarial judgement; judgement forms as important a part of stochastic reserving as best estimate reserving.
- d) For some purposes, stochastic reserving is used extensively for determining the extreme tail of the distribution of possible outcomes. However, the distribution is parameterised on a finite amount of historic data, which may not be representative of the tail. In addition, most stochastic methods make some simplifying assumptions, which may be approximately correct for the bulk of the distribution of outcomes, but which may significantly break down at the extremes. It follows that great care needs to be taken when estimating the tail of a claims distribution which is important to understand the large claims such as the catastrophe claims.

[8]

- iv) Operational risk is the risk of loss arising from inadequate or failed internal processes, people, systems, or from external events.

It includes things like:

- System failures or cyber issues
- Human errors or fraud
- Poor process design or controls
- Failures by third-party vendors

This could lead to financial loss, regulatory penalties, reputational damage, or incorrect financial reporting (especially critical under IND AS 117).

[2]

- v) Outsourcing Risk (Third-Party Failure)

Since the system design and installation are outsourced, the insurer depends heavily on the vendor.

Risk:

- Vendor may deliver a poor-quality system
- Delays in implementation
- Lack of understanding of IND AS 117 requirements
- Data security breaches

Mitigation:

- Conduct thorough due diligence before selecting the vendor
- Use well-defined contracts and SLAs (Service Level Agreements) with penalties
- Regular project monitoring and audits
- Include data security and confidentiality clauses

System Implementation / Integration Risk

The new system may not integrate properly with existing policy and claims systems.

Risk:

- Data migration errors (loss or corruption of data)
- System incompatibility leading to operational disruption
- Incorrect financial reporting under IND AS 117

Mitigation:

- Perform extensive testing (unit, integration, and user acceptance testing)
- Use phased implementation instead of a full switch-over
- Maintain backup systems and rollback plans
- Ensure strong data validation and reconciliation processes

Staff / Change Management Risk

Employees may not understand or properly use the new system.

Mitigation:

- Provide training programs
- Develop clear documentation and user guides
- Run systems in parallel during transition

Data Migration Risk

Risk:

Errors while transferring historical policy and claims data to the new system can lead to incorrect financial reporting.

Example:

Incorrect mapping of policy liabilities could result in misstated reserves under IND AS 117.

Mitigation:

- Perform data cleansing before migration
- Run parallel systems (old vs new) for validation
- Conduct reconciliation checks post-migration

Regulatory Compliance Risk

Risk:

The system may fail to fully comply with IND AS 117 requirements, leading to reporting errors or regulatory penalties.

Example:

Incorrect calculation of Contractual Service Margin (CSM).

Mitigation:

- Involve actuarial and finance experts in design
- Perform compliance testing and audits
- Keep system flexible for regulatory updates

Cybersecurity Risk

Risk:

New systems and third-party involvement increase exposure to cyber threats and data breaches.

Example:

Unauthorized access to sensitive customer health data.

Mitigation:

- Implement strong encryption and access controls
- Conduct penetration testing
- Ensure vendor follows robust cybersecurity standards

Project Management Risk**Risk:**

Poor planning or coordination can lead to cost overruns, delays, or incomplete implementation.

Example:

Missing deadlines for IND AS 117 compliance.

Mitigation:

- Establish a dedicated project management team
- Use milestones and progress tracking tools
- Regular stakeholder reviews

[12]
[31 Marks]

Solution 3:**i) Review types of arrangements:**

- Proportional (quota share, surplus)
- Non-proportional (excess of loss, stop loss)
- Assess:
 - Retentions vs limits
 - Layer exhaustion patterns
 - Coverage gaps or overlaps

Compare Gross v/s ceded experience:

- Gross claims vs ceded recoveries
- Net retained losses

Analyze:

- Proportion of risk transferred
- Stability of net results post-reinsurance

Investigate recoveries:

- Actual recoveries vs expected recoveries
- Delays in recovery receipts

Identify:

- Outstanding recoverables (case reserves, IBNR)
- Bad debt or disputed recoveries

Compare pricing adequacy:

- Reinsurance premiums paid vs expected claims recoveries

Calculate:

- Loss ratios (ceded and net)
- Cost of reinsurance vs benefit received

Assess whether reinsurance is:

- Cost-effective
- Appropriately priced

Review large loss and catastrophe claims:

- Individual large claims ceded
- Catastrophe event recoveries

Check:

- Adequacy of catastrophe protection
- Clustering of losses in specific layers

Review profit commission and sliding scale features:

- Profit commissions earned/paid
- Sliding scale commissions

Assess:

- Impact on net profitability

Credit Risk

analysis by credit rating of reinsurer and domicile of reinsurer - this will help gauge credit risk

Analyze trends over time:

- Ceded ratios
- Recoveries
- Loss ratios

Identify:

- Deterioration or improvement in performance

[7]

ii) Strengthen application and underwriting controls (prevention)

- Check policy cover dates against date of accident
- Look for multiple claims from the same claimant.
 - Enhanced identity verification: require multi-factor identity checks (document upload + electronic identity verification, database cross-checks). Rationale: reduces first-party fraud and ghost policies.
 - Automated business-rule checks on applications: flag inconsistencies (age vs driving license issue date, address mismatches, implausible vehicle usage). Implement as real-time rules with risk scores.
 - Mandatory disclosure prompts and attestations: require clear, digitally logged attestations for key risk factors (previous claims, modifications). Legal deterrent and better audit trail.
 - Use external data enrichment at quote time: credit/insurance databases, sanctions lists, vehicle history, telematics enrolment prospects. Helps detect misrepresentation before binding.
- Check previous claims history of the policyholder at inception

Use pricing and contract design to reduce moral hazard (prevention / mitigation)

- Deductible structures and excesses: higher deductibles reduce opportunistic small claims. Offer transparent voluntary excess discounts linked to claim-free history.
- No-claims bonuses and experience-rated pricing: stronger long-term financial incentives for honest behaviour; consider bonus-protection products with costs that reflect moral hazard.
- Policy design excluding often-fraudulently-abused coverages where appropriate, or tightening sub-limits and evidential requirements for high-risk coverages.
- Underwriting conditionality: link acceptance to verifiable data (e.g., vehicle security devices, telematics) with premium discounts to encourage honest disclosure and better risk alignment.

Expand data sources and risk scoring (early detection)

- Integrate internal and external data: claims history, payment patterns, credit data, social media (where lawful), repairer/tow provider lists, vehicle telematics, CCTV/ADAS data, and public records.
- Use unsupervised / anomaly detection for novel fraud: clustering, autoencoders, isolation forest to find atypical claims outside labelled patterns.

Improve claim intake and triage processes (early containment)

- Standardised digital claim submission with mandatory structured fields and guided prompts to reduce misreporting and enable automated screening.
- Fast automated triage: route low-risk claims to quick settlement, high-risk/medium-risk to specialist investigation. Reduces cost and preserves resources for suspicious cases.
- Capture and preserve digital evidence at intake: photos with geotags and timestamps, raw telematics snippets, CCTV uploads. Make chain-of-custody policies explicit.

Use telematics, IoT, and digital forensics (evidence & deterrence)

- Telematics/black-box devices or smartphone telematics: provide objective evidence of accident severity, speed, location, and occupant counts.
- Encourage adoption via premium discounts or product variants; use data for crash reconstruction and behaviour-based pricing.
- Incorporate image/video forensics (metadata, tamper detection) and tools to validate photo authenticity.

Customer communication and behavioural nudges (deterrence)

- Educate customers clearly on fraud consequences: clear messaging in policy docs and claim channels about legal penalties and recoveries.
- Behavioral nudges at claim time: require declarations that false claims are punishable; show “honesty reminders” proven to reduce false reporting.
- Transparency in anti-fraud measures and benefits to honest customers (lower premiums, faster service).

Governance, performance measurement and cross-functional operating model (sustainability)

- Centralized anti-fraud unit with strong analytics, legal and claims investigation integration; clear escalation and KPIs.
- Fraud KPIs: detection rate, savings recovered, time-to-detect, false positive rate, cost per investigation, and return on investment.
- Regulatory and privacy compliance: ensure data use and investigative processes comply with local laws (GDPR, insurance regulations), retaining legal counsel involvement early.

[10]
[17 Marks]
