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Leveraging AI for Competency Assessments

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Strong business skills—such as communication, professional judgment, and stakeholder management—have become a key differentiator for actuarial trainees entering the workplace and are correlated with future success. While case studies have historically been proven effective at developing these skills, existing resources are limited and typically structured as multi-week team projects that are difficult to scale, individualize, or align with specific competencies. To address this gap, this paper examines whether AI models can (i) efficiently transform a small set of comprehensive actuarial cases into many brief, single-competency, individual assessments; and (ii) score these assessments with adequate psychometric quality. Using 144 AI-generated assessments covering the Society of Actuaries' eight core competencies, we achieve strong reliability (G=0.719, 0.740) with optimized three- and four-grader panels, respectively, selected through Generalizability Theory analysis. Our experiments reveal that iterative prompt refinement improves assessment quality, with later prompts outperforming initial versions and representing a medium-sized effect. However, we document critical challenges: all AI graders exhibit in-group bias, systematically favoring assessments generated by their own model family despite anonymization. Additionally, graders may engage in algorithmic gaming, producing low entropy scoring patterns with strong halo effects that bear no relationship to actual assessment quality. The exclusion of unreliable graders from a model family partially explains the apparent underperformance of assessments from that same family, illustrating how grader selection can inadvertently create bias. We propose a hybrid approach combining carefully selected AI grader panels with human moderators to address these documented biases while leveraging the efficiency gains of automated assessment.

Keywords: actuarial education, artificial intelligence, competency-based education, generalizability theory, reliability tests, validity tests

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Case-based pedagogy has long been recognized as ideal preparation for actuarial practice, yet its implementation in competency-based education (CBE) frameworks faces fundamental structural challenges. Real-world practice requires quantifying uncertainty, communicating risk, and negotiating trade-offs with diverse stakeholders—skills best developed through authentic case experiences. However, CBE's core principle of granular, competency-specific assessment (Gervais, 2016) creates requirements that traditional comprehensive cases cannot meet. Where conventional actuarial education might assess multiple competencies through a single multi-week project, CBE demands independent measurement of each competency through multiple parallel assessments to enable personalized progression and reassessment (Klein-Collins, 2012; Nodine, 2016), thus creating a resource paradox. That is, CBE programs need dramatically more assessments while maintaining the authentic complexity that makes cases pedagogically valuable.

CBE's psychometric requirements compound this volume challenge. Assessments must be criterion-referenced rather than norm-referenced, provide equivalent difficulty across parallel forms, and generate defensible evidence for individual competency mastery (Johnstone & Soares, 2014). Comprehensive cases that simultaneously engage multiple competencies, while excellent for integrated learning, produce entangled evidence that cannot support the discrete competency determinations CBE requires. Faculty attempting to scale case-based CBE face an impossible choice: invest unsustainable time creating large portfolios of targeted cases or abandon the pedagogical benefits of case-based learning. The emergence of capable AI models suggests a third path: transforming anchor cases into portfolios of brief, competency-specific assessments that maintain authenticity while achieving CBE's scale and precision requirements.

This article tests this approach by addressing two questions fundamental to AI-assisted CBE implementation. First, can AI models reliably generate competency-specific actuarial assessments that meet requirements for construct validity, distinctiveness, and parallel-form equivalence? Second, can AI systems score these assessments with sufficient psychometric rigor for the dual purposes of formative feedback during skill development and summative evidence for competency certification? Our investigation reveals both the promise of automated assessment generation and critical biases that require human oversight to protect CBE's foundational commitment to equitable evaluation.

Our contributions are threefold. We demonstrate a practical pipeline that successfully transforms two comprehensive actuarial cases into dozens of single-competency assessments with measurable quality improvements through iterative prompt refinement. We provide psychometric evidence showing that optimized AI grader panels can achieve reliability coefficients exceeding 0.70, meeting thresholds for moderate-stakes assessment, or higher if additional AI graders or assessments per competency are included. Finally, we document critical failure modes—including in-group bias where AI graders favor their own model family's outputs, and algorithmic gaming where graders produce meaningless patterns to satisfy grade distribution targets—and propose a hybrid framework with enhanced human oversight to mitigate these risks while preserving efficiency gains.

Literature Review

This study sits at the intersection of three established research domains: case-based pedagogy in professional education, artificial intelligence applications in educational assessment, and psychometric theory for performance evaluation. We review each domain to identify overlapping ideas with our proposal for AI-assisted competency-based assessment in actuarial education.

Case-based Learning in Professional Education

Case-based learning has evolved significantly since its introduction at Harvard Law School in 1870 and subsequent adoption by Harvard Business School in 1908 (Merseth, 1991). This pedagogical approach gained theoretical grounding through Dewey's experiential education philosophy in the early 20th century, ultimately crystallizing in Kolb's (1984) constructivist learning theory, which posits that learners actively construct knowledge through experience and reflection rather than passive absorption. In professional disciplines, case-based learning bridges the theory-practice gap by immersing students in authentic, complex problems that mirror real-world challenges.

The empirical evidence supporting case-based learning is substantial but nuanced. Thistlethwaite et al. (2012) synthesized 104 studies in health professions education, finding consistent positive impacts on knowledge acquisition and clinical reasoning skills, though noting significant variation in implementation quality and outcome measurement. More recent meta-analyses have confirmed these benefits while identifying boundary conditions. Wu et al. (2023) demonstrated significant improvements in critical thinking and problem-solving abilities in psychology education (effect sizes d=0.52–0.78). However, they found effectiveness moderated by case complexity, facilitation quality, and student prior knowledge.

However, case-based learning faces persistent implementation challenges. Donkin et al. (2023) identified three critical limitations in their scoping review: (1) resource intensity, with faculty reporting 2–3 times more preparation time compared to traditional lectures; (2) assessment complexity, particularly in measuring individual contributions in team-based cases; and (3) scalability constraints, as personalized feedback becomes unsustainable with larger cohorts. These challenges are particularly acute in competency-based education frameworks (Gervais, 2016), where assessment must demonstrate mastery of specific, measurable skills aligned with professional standards.

Recent innovations have attempted to address these limitations through modular case design (Parker & Chiang, 2024) and technology-enhanced delivery (McMullen et al., 2023). However, these remain incremental solutions to a structural problem. The challenge intensifies under competency-based education frameworks, which require fundamentally different assessment architectures than traditional programs. CBE assessments must be criterion-referenced to measure mastery against defined standards, provide multiple parallel forms to enable reassessment without compromising validity, and generate discrete evidence for independent competencies rather than holistic judgments (Johnstone & Soares, 2014). These requirements make

traditional comprehensive cases (which naturally integrate multiple competencies) unsuitable without extensive modification.

The Society of Actuaries' adoption of an eight-competency framework (Society of Actuaries, 2022) exemplifies this tension: delivering authentic case-based learning for each competency, with sufficient equivalent versions for personalized progression, would require faculty to generate assessment portfolios an order of magnitude larger than current resources support. The structural mismatch between CBE's assessment requirements and case-based pedagogy's resource constraints motivated our investigation of AI-assisted transformation.

AI in Educational Assessment

The application of artificial intelligence to educational assessment has undergone three distinct waves. The first wave (1990s–2000s) focused on automated essay scoring, with systems like e-rater and IntelliMetric achieving inter-rater reliabilities of 0.70–0.85 for standardized writing assessments (Shermis & Burstein, 2013). These systems, however, were limited to evaluating existing student work within narrow, predefined rubrics.

The second wave (2010s) expanded AI's role to adaptive testing and learning analytics. Zawacki-Richter et al. (2019) identified four primary AI applications in higher education: profiling and prediction, intelligent tutoring systems, automated assessment, and adaptive learning. Their systematic review revealed a troubling pattern: of 146 studies analyzed, only 29% included educators in the design process, and fewer than 15% examined unintended consequences or ethical implications.

The current third wave, driven by large language models (LLMs), represents a paradigm shift from evaluation to generation—two seminal articles in *Computers & Education: Artificial Intelligence* frame this transformation. Khosravi et al. (2022) propose the XAI-ED framework, emphasizing explainability and transparency in AI-mediated assessment, while Swiecki et al. (2022) argue for a fundamental reimagining of assessment design rather than retrofitting AI onto existing formats.

The intersection of AI assessment and competency-based education introduces distinct challenges beyond traditional grading contexts. CBE's emphasis on multiple assessment opportunities for mastery demonstration (Gervais, 2016) creates unprecedented scale requirements while simultaneously demanding stricter validity evidence. Furthermore, CBE's emphasis on transparent competency definitions and assessment criteria (Nodine, 2016) sits uncomfortably with the opacity of large language model decision-making. Students who fail to demonstrate competency have the right to understand what additional learning is required—a right compromised when assessment decisions emerge from black-box algorithms.

Empirical evidence on LLM performance in educational assessment remains mixed and context-dependent. Grévisse et al. (2024) found moderate agreement (κ=0.45–0.62) between LLM and human graders in medical education. However, they noted systematic biases: LLMs showed leniency toward well-structured but substantively weak responses and struggled with nuanced clinical reasoning. Bak-

er and Hawn (2022) identified six pathways through which bias manifests, such as training data, model architecture, and evaluation metrics, while Idowu (2024) documented patterns of bias across educational contexts.

Critical gaps remain in our understanding of AI-generated educational content. While studies examine AI grading of human work or human grading of AI work, virtually no research investigates AI systems evaluating AI-generated content—a recursive challenge central to the vision of fully automated, scalable competency assessment. Furthermore, the literature lacks frameworks for human-AI collaboration in assessment, despite growing recognition that hybrid approaches may optimize both efficiency and validity (Park & Choo, 2024; Walter, 2024).

Psychometric Foundations

The evaluation of complex performances requires sophisticated psychometric frameworks that can decompose multiple sources of measurement error. Classical Test Theory, while foundational, treats all non-true-score variance as undifferentiated error—inadequate for multi-faceted assessments involving raters, tasks, and occasions (Shavelson & Webb, 1991).

Generalizability Theory (*G*-theory), developed by Cronbach et al. (1972) and refined by Brennan (2001), addresses this limitation by partitioning variance into specific, identifiable components. This decomposition enables researchers to understand not merely whether an assessment is reliable, but why it achieves or fails to achieve reliability. For performance assessment, *G*-theory's ability to simultaneously model multiple error sources—rater severity, task difficulty, rater-task interactions—provides actionable insights for design optimization (Bloch & Norman, 2012).

The application of *G*-theory to AI-mediated assessment, however, raises novel challenges not anticipated in its original formulation. Traditional G-theory assumes human raters whose errors stem from fatigue, training differences, or subjective interpretation. AI graders introduce qualitatively different error sources: deterministic biases from training data, systematic preferences for certain linguistic patterns, and potential for "gaming" statistical constraints rather than engaging in authentic evaluation. These differences necessitate reconceptualizing variance components and their interpretations.

Contemporary validity theory further complicates AI assessment validation. Kane's (2013) argument-based approach requires explicit chains of inference from observed scores to intended uses, while Messick's (1995) unitary view demands evidence of fairness and consequences—both challenging when AI decision-making processes remain opaque. While previous work on automated scoring (Attali & Burstein, 2006; Williamson et al., 2006) demonstrated that valid inferences could emerge from automated systems, these frameworks assumed human-created content and well-defined constructs—assumptions violated when AI both generates and evaluates novel assessment tasks.

Methodology

Experimental Design

We began with two comprehensive Society of Actuaries (SOA) student case challenges from 2019 and 2023 that differ across several dimensions: social versus commercial insurance; 50-year climate projections versus 10-year market evolution; public versus private sector; and stochastic climate scenarios versus deterministic claims methods. This diversity was intentionally chosen to assess whether the performance of our AI generator models would be affected by the varied actuarial contexts. Three widely known and available AI models—Claude Opus 4, Gemini 2.5 Pro, and ChatGPT o3—were prompted to convert each comprehensive case into a set of shorter assessments, with each aligned to just one SOA competency. To gauge the effect of prompting, we developed three prompt variations with increasing specification: the first provided a detailed explanation of the task, desired structure, and a single line, SOA-provided competency description; the second added the complete rubric used by the AI graders to evaluate the assessment; and the third replaced the brief competency description with an expanded 60–100-word paragraph (see Appendices A–B). Combining AI generator models (3) × source cases (2) × competencies (8) × prompt variations (3) yielded 144 distinct assessments, or 18 assessments targeting each competency.

Rubric and Scoring Procedure

Each assessment was evaluated on five criteria using a 0–5 scale, which summed to a maximum 25-point total. Competency Alignment gauged how comprehensively the assessment targeted the specified competency. Distinctiveness rewarded cases that could not be mistaken for another competency's exercise. Instructional Quality reflected the clarity of instructions, role realism, and logical flow between inputs and expected outputs. Resource Feasibility asked whether a diligent student could complete the work solo in two weeks with the provided data. Human Authenticity looked for an expert instructor's voice versus AI-style boilerplate language. The full rubric is included in Appendix C.

Six AI graders scored every assessment. For each AI model mentioned earlier, we instantiated two graders: a standard rater that applied the rubric in a single pass with some general guidance, and a calibrated rater that performed five independent passes and then reported the median, while also being asked to conform to leniency/severity and grade dispersion standards. This design was intended to create legitimate diversity in rater perspectives while testing whether distributional constraints removed bias or introduced other distortions.

The decision to use AI graders rather than human experts was deliberate and methodologically motivated. Human grader studies in educational assessment face practical limitations that undermine scientific reproducibility. Specifically, the same panel of expert graders cannot be reconstituted across spatial or temporal divides, introducing irreducible variance and subjectivity into the scientific record. By contrast, AI graders offer high replicability, as any researcher can access the same AI models

with identical prompts and implement a duplicated evaluation protocol. This consideration becomes particularly crucial when evaluating 144 assessments across five criteria, requiring 720 individual ratings per grader, a scale at which human grader fatigue and inconsistency become significant threats to validity.

Statistical Analysis

Our statistical analysis proceeded in three main stages: first, we used Generalizability Theory to identify the most reliable panels of AI graders; then we used ANOVA and MANOVA to test the effects of AI model generator, source case, and prompt version variations; and finally, we conducted targeted analyses to detect and quantify systematic biases such as in-group favoritism.

Grader selection via G-theory

We evaluated all $2^6 - 1 = 63$ possible grader combinations using Generalizability Theory (*G*-theory) to identify optimal panels. The specified primary competency model, denoted by (a:k)×g, is shown in Equation 1.

$$Y_{agk} = \mu + (a{:}k) + g + k + (g \times k) + [(a{:}k) \times g] + \epsilon \qquad (1)$$

where μ represented the overall baseline score; (a:k) was the object of measurement, representing the true quality effect (over the baseline) of each assessment nested within its competency; g represented the added effect of graders, treated as a random facet to generalize over, which captures each grader's systematic severity or leniency; k represented the added effect of the eight competencies, treated as a fixed facet of the design; g×k was the grader-by-competency interaction term, capturing unique grader biases toward specific competencies; (a:k)×g was the assessment-by-grader interaction effect, representing idiosyncratic grader preferences for specific assessments; and ϵ represented the unexplained residual error.

The *G*-coefficient for relative decisions (comparing assessments against each other) was calculated using Equation 2.

$$G = \frac{\sigma^2_{a:k}}{\sigma^2_{a:k} + \frac{\sigma^2_{(a:k)\times g}}{n_g} + \frac{\sigma^2_{\epsilon}}{n_c n_g}} \qquad (2)$$

where n_g represents the number of graders, and $n_c = 5$ is the number of scoring criteria, c. Equation 3 is the Φ-coefficient for absolute decisions (determining whether a case meets an absolute standard) additionally included grader effects in the error term.

$$\Phi = \frac{\sigma^2_{a:k}}{\sigma^2_{a:k} + \frac{\sigma^2_g + \sigma^2_{k\times g} + \sigma^2_{(a:k)\times g}}{n_g} + \frac{\sigma^2_{\epsilon}}{n_c n_g}} \qquad (3)$$

Crossed G-studies for Scoring Criteria

A second G-study employed a fully crossed design, a×g×c, to examine how graders differentiated across scoring criteria. This model applied to attribute variance to various components is shown in Equation 4.

$$Y_{agc} = \mu + a + g + c + (a \times g) + (g \times c) + (a \times c) + \epsilon \tag{4}$$

Competency-level Aggregation

For practical implementation, we also computed reliability at the competency level by aggregating across multiple cases. This calculation involved adjusting the *G*-coefficient formula to account for averaging is shown in Equation 5.

$$G_k = \frac{\sigma_k^2}{\sigma_k^2 + \frac{\sigma_\epsilon^2}{n_a n_g}} \tag{5}$$

is defined analogously. This aggregation effect substantially improved reliability, as random errors tend to cancel when averaging multiple observations.

Decision Studies (D-studies)

D-studies projected reliability for varying numbers of graders and assessments using the variance components from G-studies. These projections informed practical design decisions by modeling scenarios from minimal (3 graders, 9 assessments) to extensive (5 graders, 36 assessments) configurations. The D-study formulas adjusted denominators to reflect different n_a and n_g while maintaining the same variance component estimates.

Other Diagnostic Tests and Statistical Analyses

To gain a deeper understanding of grader performance and potential biases, the analysis went beyond G-theory to create detailed profiles for each AI grader. Pairwise grader agreement was initially assessed using Pearson correlations to identify which graders produced similar or dissimilar rankings. To probe deeper into their unique evaluation patterns, the analysis also correlated the graders' idiosyncratic effects—the residual biases left after accounting for main effects—to see if their unique preferences aligned or opposed one another. Key behavioral metrics were quantified for each grader, including their severity or leniency (measured by *z*-scores), their tendency to produce a halo effect by not differentiating between scoring criteria, their overall scoring variability, and their ability to discriminate between high- and low-quality assessments.

The study utilized a series of parametric tests to evaluate the impact of the experimental design and to detect systematic bias. ANOVA and MANOVA were used to test whether factors like the AI generator model, source case, and prompt version significantly affected the assessment scores across the five quality criteria. When

significant effects were found, Tukey's HSD was used for pairwise comparisons to identify exactly where the differences lay. A key analysis involved using paired *t*-tests to specifically test for in-group bias, comparing the scores an AI grader gave to assessments from its own model family versus those from other models. Throughout the analysis, effect sizes like Cohen's *d* and partial η^2 were calculated, with all analyses conducted in Python using standard statistical libraries. Good references for the statistical results are Stevens (2009) and Tabachnick and Fidell (2019).

A core component of the methodology was rigorous assumption testing to ensure the validity of the statistical conclusions. The data was checked for normality using Shapiro-Wilk tests and for homogeneity of variance with Levene's tests. Because of widespread violations of parametric assumptions, two key adjustments were made. First, non-parametric analyses, such as the Kruskal-Wallis *H*-test, were employed alongside traditional ANOVAs to confirm the findings. Second, to ensure reliable reliability estimates, non-parametric percentile bootstrap confidence intervals for the G-coefficients were computed using 400 resampling iterations. This robust approach ensured that the conclusions were not artifacts of the data's non-normal distribution.

Results

Graders

Our investigation into AI grader behavior revealed a counterintuitive finding that challenges conventional wisdom about assessment: adding more graders can, in fact, reduce reliability when those graders exhibit problematic behaviors. Table 1 presents the inter-grader Pearson correlations, revealing moderate agreement but also a few outliers.

Table 1

Inter-grader Correlation Matrix Reveals Diverse Evaluation Perspectives

Grader	Model	1st	2nd	3rd	4th	5th	6th
1st	Claude	1.000	0.406	0.066	0.646	0.328	0.019
2nd	Gemini	0.406	1.000	0.186	0.370	0.474	0.053
3rd	ChatGPT	0.066	0.186	1.000	0.045	0.100	0.128
4th	Claude	0.646	0.370	0.045	1.000	0.356	–0.057
5th	Gemini	0.328	0.474	0.100	0.356	1.000	–0.105
6th	ChatGPT	0.019	0.053	0.128	–0.057	–0.105	1.000

Most pairwise correlations hover between 0.30 and 0.65, suggesting no AI graders exhibit strong concordance, which is concerning for independent human experts but also a sign of little dependency in our context. However, two graders stand out as problematic. Grader 3's average correlation with others ($r = 0.105$) barely exceeds random chance, while Grader 6 shows negative correlations with multiple peers, achieving an average agreement of essentially zero ($r = 0.008$).

This heterogeneity manifested dramatically in our reliability analysis. Through systematic evaluation of all 63 possible grader combinations, we discovered that using all six graders yielded a disappointing *G*-coefficient of 0.581—well below acceptable standards. Nevertheless, by carefully selecting the optimal four-grader panel (1st, 2nd, 4th, 5th), we achieved *G*=0.740 (95% CI: 0.670–0.795), exceeding the 0.70 threshold for educational assessment. In addition, dropping the 5th grader only reduces the *G*-coefficient by 0.021 to *G*=0.719 (95% CI: 0.629–0.789), showing acceptable reliability in this case as well.

Further support for the reliability of the three- and four-grader panels came from a deeper look into idiosyncratic grader effects (Tables 2 and 3). Each of these panels exhibited mostly opposing biases. This systemic disagreement is captured in the assessment-by-grader interaction term (Table 5) and already reflected in the *G*-coefficients above. If the panel had a shared bias (idiosyncratic concordance), the graders would agree with each other for the wrong reasons. This "false agreement" would artificially suppress the error variance, making the graders appear more consistent than they truly are with respect to the case's actual quality, thus producing a misleadingly high *G*-coefficient for the panel.

Table 2
Inter-Grader Correlation Matrix of Idiosyncratic Grader Effects for Four-Grader Panel

Grader	1st	2nd	4th	5th
1st	1.000	–0.311	0.107	–0.545
2nd	–0.311	1.000	–0.501	–0.186
4th	0.107	–0.501	1.000	–0.523
5th	–0.545	–0.186	–0.523	1.000

Table 3
Inter-Grader Correlation Matrix of Idiosyncratic Grader Effects for Three-Grader Panel

Grader	1st	2nd	4th
1st	1.000	–0.507	–0.229
2nd	–0.507	1.000	–0.723
4th	–0.229	–0.723	1.000

Grader Evaluation Profiles

Grader 6's behavior was flagged during calibration for producing scores that followed mechanical patterns (repeated 23,19,13 or 21,17,11 scores; see Appendix D).

Rather than evaluating content, it appeared to reverse-engineer totals to meet statistical constraints. This finding was also evidenced as a strong halo effect or tendency to assign uniform scores across criteria (Table 4) and serves as a critical warning: the optimization capabilities that make AI powerful can subvert assessment validity when misdirected.

Table 4
Grader Profiles Reveal Distinct Evaluation Patterns

Grader	Model	Severity	Relative Variability	Discrimination Index	Average Agreement	Halo Effect
1st	Claude	Moderate	Low (0.163)	0.592	0.293	Weak (0.471)
2nd	Gemini	Lenient (+1.19σ)	Moderate (0.195)	0.535	0.298	Moderate (0.605)
3rd	ChatGPT	Moderate	Low (0.140)	0.489	0.105	Weak (0.495)
4th	Claude	Severe (–1.69σ)	High (0.240)	0.639	0.272	Weak (0.474)
5th	Gemini	Moderate	High (0.247)	0.617	0.231	Weak (0.484)
6th	ChatGPT	Moderate	High (0.252)	0.637	0.008	Strong (0.773)

Grader 4 assigned scores averaging 1.7 standard deviations below the mean, yet showed the highest discrimination index (0.639), effectively distinguishing strong from weak assessments despite harsh standards. This process mirrors human grading patterns, where tough graders often provide the most informative rankings.

Assessment-level Reliability Analysis

To fully understand the reasons that certain grader combinations succeed while others fail, we used a G-study analysis and examined all variance components. With our optimal four-grader panel, true assessment quality differences accounted for only 16.5% of total variance—a stark reminder of evaluation complexity. The largest non-residual error source stemmed from assessment-by-grader interactions (15.2%), reflecting idiosyncratic preferences not attributable to the assessment's true quality.

Table 5
Variance Decomposition for Nested Competency Model

Source	4-grader panel	3-grader panel	Interpretation
Assessment	16.5%	18.2%	Assessment quality (signal)
Grader	2.1%	3.4%	Systematic severity/ leniency
Assessment × Grader	15.2%	13.4%	Idiosyncratic preferences
Grader × Competency	1.2%	1.8%	Competency-specific biases
Residual error	65.0%	63.2%	Unexplained variation

The dominance of residual error (>63%) necessitated that we drill down to scoring criteria variances to capture sources of variation in finer detail (Table 6). A key observation was that the assessment-by-grader interaction was more than the scoring criteria and assessment-by-criteria terms combined. It revealed that the biggest source of disagreement among the AI graders was not how they interpret the rubric, but rather their idiosyncratic preferences for specific assessments—a fundamental challenge for AI-based evaluation.

Table 6
Variance Decomposition for Scoring Criteria Model

Source	4-grader panel	3-grader panel	Interpretation
Assessment	19.7%	21.7%	Assessment quality (signal)
Grader	2.5%	4.2%	Systematic severity/ leniency
Scoring Criteria	9.3%	8.9%	Systematic criterion differences
Assessment × Grader	24.3%	22.1%	Idiosyncratic preferences
Assessment × Criteria	10.2%	10.7%	Idiosyncratic criterion differences
Grader × Criteria	2.3%	2.9%	Criterion-specific biases
Residual error	31.7%	29.4%	Unexplained variation

Competency-level Reliability Analysis

While individual assessment reliability topped out at G=0.740, aggregating scores across multiple assessments per competency yielded substantially higher re-

liability. The choice depends on the practical implementation: do we use a single assessment or the whole set? If the latter, then our current design with 18 assessments per competency pushed competency-level reliability to approximately 0.8 with three graders and 0.83 with four graders—exceeding thresholds for high-stakes decisions.

Table 7
Relative And Absolute Reliability Projections

Assessments per competency	5-grader panel	4-grader panel	3-grader panel
9	=0.749, =0.730	=0.725, =0.702	=0.689, =0.661
18	=0.849, =0.824	=0.832, =0.802	=0.804, =0.767
24	=0.878, =0.851	=0.863, =0.831	=0.839, =0.799
30	=0.897, =0.869	=0.883, =0.849	=0.862, =0.819
36	=0.909, =0.881	=0.897, =0.862	=0.878, =0.834

As a rule of thumb, a minimum *G*-coefficient of 0.60 is expected for low-stakes and formative assessments. Medium-stakes assessments are typically above 0.70, while *G*-coefficients >0.80 are suitable for high-stakes or certification-level assessments.

Source Case Effects

Comparing assessments derived from the 2023 and the 2019 SOA case study challenge revealed statistically significant improvements in two scoring criteria, as can be seen in Table 8. Cohen's *d* benchmarks are 0.8 for large effects, 0.5 for medium effects, and 0.2 for small effects.

Table 8
Assessments Derived from the 2019 And 2023 Source Cases for the Four-Grader Panel

Criterion	2019 Case	2023 Case	Change	Tukey HSD *p*	KW *p*	Cohen's *d*
Competency Alignment	3.85	4.07	+0.22	0.004	0.004	0.24
Distinctiveness	3.13	3.52	+0.39	<0.001	<0.001	0.31

Non-parametric Kruskal-Wallis tests confirmed these findings despite violations of normality assumptions (*H*-statistics of 8.4 and 12.5, respectively). Similar results were obtained with the three-grader panel—the only difference is that the improvement of +0.20 for Instructional Quality was also statistically significant (Tukey HSD $p = .017$, Kruskal-Wallis $H=5.4$, $p = .021$). The conclusion is that the 2023 case's emphasis on contemporary challenges and clearer competency definitions translated

into tangible quality improvements, particularly in alignment and distinctiveness.

Prompt Version Effects

One of our most encouraging findings concerns the systematic improvement achieved through iterative prompt refinement. Table 9 lists some of these quality gains.

Table 9
Quality Improvements For Four-Grader Panel

Criterion	1st Prompt	3rd Prompt	Change	Tukey HSD *p*	KW *p*	Cohen's *d*
Competency Alignment	3.35	4.05	+0.70	<0.001	<0.001	0.75
Distinctiveness	3.08	3.52	+0.44	0.002	<0.001	0.35
Instructional Quality	3.47	3.83	+0.36	<0.001	<0.001	0.38
Resource Feasibility	4.09	3.92	–0.17	0.085	0.062	-0.18
Human Authenticity	3.04	3.56	+0.52	<0.001	<0.001	0.48

Non-parametric Kruskal-Wallis tests confirmed these findings despite violations of normality assumptions (H-statistics ranging from 5.6 to 61.9, all $p < .001$ except Resource Feasibility). Similar results were obtained for the three-grader panel, except that the change of –0.19 in Resource Feasibility was significant (Tukey HSD p =.049, Kruskal-Wallis H=6.9, p = .032), while the Distinctiveness change of +0.24 was not.

The improvements are material: Competency Alignment showed a large effect (d = 0.75), while Distinctiveness, Human Authenticity, and Instructional Quality achieved medium effects, with a composite d = 0.365, signifying a medium-size effect that includes the negative result in Resource Feasibility. That slight decline suggests a quality-complexity trade-off—as scenarios became better adapted to a competency, they occasionally introduced elements that made implementation slightly more challenging.

Model Differences and Systematic Biases

Our analysis revealed both expected and surprising patterns in how different AI models performed as both generators and graders. Gemini assessments received the highest average scores, Claude fell in the middle, and ChatGPT scored lowest—but these aggregate differences mask important nuances.

The In-Group Bias Problem

Despite complete anonymization of assessments, AI graders systematically

favored outputs from their own model family:

Table 10

In-Group Bias Represents a Serious Fairness Concern

Grader Panel	Own-Model Mean	Other-Model Mean	Change	Tukey HSD *p*	KW *p*	Cohen's *d*
4-grader	19.19	17.77	+1.42	<.001	<.001	0.37
3-grader	19.22	17.92	+1.30	<.001	<.001	0.35

The sizable scoring advantage for own-model assessments represented a medium-sized effect that substantially impacted the validity of the evaluation protocol. The bias likely stemmed from stylistic familiarity—each AI system implicitly recognized and preferred text similar to its own training patterns, analogous to professors unconsciously favoring essays that mirror their writing style.

Competency-Specific Strengths

The interaction between the AI model and competency revealed that no single model dominated across all assessment contexts:

Table 11

AI Model Specialization for Four-Grader Panel

Competency Domain	Best AI Model	Weakest AI Model
Communication	Claude, Gemini	ChatGPT
Professional Values	Claude, Gemini	ChatGPT
External Forces & Industry Knowledge	Gemini	Claude, ChatGPT
Leadership	Claude	ChatGPT
Relationship Management	Claude, Gemini	ChatGPT
Technical Skills	Claude, Gemini	ChatGPT
Strategic Insight	Claude, Gemini	ChatGPT
Results-Oriented Solutions	Gemini	Claude

These differential strengths suggest strategic deployment opportunities: Gemini excels at most competencies, but Claude demonstrates superiority in Leadership, while ChatGPT, though generally weaker, shows competitive performance in Results-Oriented Solutions. It should be noted that for the three-grader panel, the results are slightly different: Claude is no longer among the weakest AI models for External Forces, and ChatGPT joins it for Results-Oriented Solutions. We have included exemplar assessments in Appendix E.

In addition, these results reflect the absence of ChatGPT graders from the three-

and four-grader panels. If the grader panel were balanced, in-group biases would equally affect all assessments; to account for the current unbalanced panel composition, an adjustment of +0.71 should be made to ChatGPT scores. The adjusted mean scores of 18.93 for Claude, 19.60 for Gemini, and 16.81 for ChatGPT give a better indication of each model's true ability as assessment generators (assuming the prompts and specifications used in this paper; see Appendix A).

Summary of Results

We summarize this section in Table 12 by providing the multivariate analysis of variance (MANOVA) results obtained. Thresholds for large effects are <0.70 for Wilk's Λ, >0.25 for Pillai's Trace, and >0.14 for partial η^2; medium effects are 0.70–0.90 for Wilk's Λ, 0.10–0.25 for Pillai's Trace, and 0.06–0.14 for partial η^2; and small effects are >0.90 for Wilk's Λ, <0.10 for Pillai's Trace, and 0.01–0.06 for partial η^2.

Table 12
MANOVA Results for Four-Grader Panel

	Wilk's Λ	Pillai's Trace	*F*	*df*	*p*	Partial η^2	Effect
AI model	0.727	0.294	19.60	10,1132	<.001	0.147	Large
Prompt Version	0.837	0.165	10.55	10,1132	<.001	0.085	Medium
Source Case	0.966	0.034	4.05	5,566	.001	0.035	Small

Despite violations of multivariate normality (Mardia's test, $p < .001$) and homogeneity of covariance matrices (Box's *M*, $p < .001$), our MANOVA results remain valid for several reasons. First, all four multivariate test statistics converged on identical conclusions. Second, Pillai's trace—the most robust statistic under violation conditions—confirmed all effects. Third, our large sample size ($N = 576$ observations per dependent variable) protects through the Central Limit Theorem. Finally, parallel non-parametric analyses using Kruskal-Wallis tests corroborated all significant effects.

Discussion

Our results define both the promise and boundaries of AI-assisted assessment in competency-based education contexts. The reliability we achieved—G=0.740 for individual assessments and 0.80+ when aggregating across multiple assessments per competency—meets psychometric standards for CBE's formative assessment purposes but reveals limitations for high-stakes competency certification. More fundamentally, the systematic biases we documented challenge CBE's foundational principle of equitable assessment regardless of student background or characteristics

unless properly mitigated.

The in-group bias documented in Table 10 carries particular weight in CBE implementation. Unlike traditional education, where multiple assessment types aggregate to form course grades, CBE students may demonstrate competency through a relatively small number of targeted assessments. If different students' assessments happen to be generated by different AI models, they face systematically different evaluation standards despite CBE's promise of consistent competency criteria. In our study, ChatGPT-generated assessments faced a 1.42-point disadvantage (d=0.37) when evaluated by our optimal grader panel, not due to lower quality but due to algorithmic bias. We have not used these assessments in a classroom environment, but one wonders if students' work based on a ChatGPT-generated assessment would also be penalized by our AI graders.

Algorithmic gaming, as exhibited by Grader 6, presents an equally serious challenge for CBE programs. In traditional education, one questionable grade among many has a diluted impact. In CBE, where students must demonstrate mastery through a defined set of competency assessments, a single invalid score can inappropriately delay progression or require costly reassessment. The finding that this grader produced mechanically patterned scores (Appendix D) while still achieving acceptable individual metrics of moderate variability and a strong discrimination index illustrates how standard psychometric indicators may fail to detect gaming in AI systems.

Implications for CBE Program Design

These findings suggest a tiered implementation strategy that aligns AI capabilities with CBE's differentiated assessment purposes. For formative assessment, where students practice competency demonstration and receive developmental feedback, our reliability levels support AI automation with minimal human oversight. The efficiency gains enable frequent, low-stakes practice opportunities that CBE pedagogy recommends, but resource constraints often prevent. Our documented prompt refinement effects (Table 9) demonstrate that assessment quality improves systematically with iteration, suggesting CBE programs should budget 40–60 hours of subject matter expert time per competency for initial assessment generation and optimization, then deploy AI grading for assessment selection, after which they can be used for formative purposes.

For summative competency certification, however, our bias findings necessitate human oversight. We propose a hybrid architecture where AI generates initial assessments and scores. However, human experts adjudicate in three circumstances: (1) borderline assessments within 10% of competency thresholds, (2) assessments flagged by the instructor of students, and (3) systematic review of 10–15% of assessments to monitor for emergent biases. Our variance decomposition shows that assessment-by-grader interactions (15.2–24.3% of variance) exceed rubric interpretation disagreements, suggesting human moderators should focus on adjudicating idiosyncratic preferences rather than wholesale regrading. This targeted approach preserves AI efficiency while protecting CBE's validity requirements.

The competency-level reliability projections in Table 7 offer additional implementation flexibility. When aggregating across multiple assessments per competency—a practice consistent with CBE's emphasis on multiple demonstrations of mastery—reliability increases to 0.83–0.85, approaching thresholds for high-stakes credentialing. CBE programs might therefore implement differential strategies: use three AI-graded assessments per competency for initial certification but require comprehensive human expert evaluation for students seeking advanced credentials or when competency demonstration has been repeatedly unsuccessful. These methods mirror CBE's learner-centered principle of providing multiple pathways while maintaining consistent standards.

Other operational safeguards can mitigate in-group bias. CBE programs should either (a) ensure balanced AI model representation across all assessments for each competency, so no student cohort encounters only one model's outputs, or (b) apply documented bias corrections (e.g., +0.71 adjustment for ChatGPT assessments when using Claude/Gemini-dominant grader panels). Transparency protocols should inform students of AI's role in the generation and evaluation of assessments, including known limitations, with accessible appeal processes when scores appear inconsistent with other competency evidence. These measures can support the development of equitable, criterion-referenced assessments while leveraging automation's practical benefits.

Conclusion

This study demonstrates that AI can address a critical infrastructure challenge in competency-based actuarial education: generating sufficient assessment volume to enable the personalized, competency-specific evaluation that CBE frameworks require. We successfully transformed two comprehensive cases into 144 distinct assessments covering eight SOA competencies and achieved reliability coefficients (G=0.719–0.740) meeting standards for CBE's formative assessment purposes. When aggregating across multiple assessments per competency, reliability reached 0.80–0.85, supporting moderate to high-stakes competency certification decisions.

However, the systematic biases we documented reveal that fully automated AI assessment cannot yet satisfy CBE's dual requirements for scale and equity. In-group bias, where AI graders favor assessments from their own model families despite anonymization, creates criterion-referenced validity threats: students might face different evaluation standards based on the AI author-grader combination rather than on the competency being measured. The algorithmic gaming we observed, where graders produced mechanically patterned scores to meet distributional constraints rather than evaluate content, demonstrates that AI systems can satisfy conventional psychometric indicators while subverting assessment validity. These findings underscore that human oversight cannot be completely avoided.

For CBE practitioners, our results support a hybrid implementation strategy. Use AI-generated assessments and automated grading for formative evaluation and

initial competency screening, where the efficiency enables frequent practice opportunities that resource constraints otherwise prevent. Reserve human expert involvement for high-stakes certification decisions, borderline cases, and systematic bias monitoring. Our variance decomposition indicates human moderators should focus on adjudicating AI graders' idiosyncratic preferences rather than comprehensive regrading—a targeted approach that preserves efficiency while protecting validity.

Future research should examine AI assessment with actual student cohorts across diverse demographics to detect emergent fairness issues, develop prompt engineering techniques that reduce model-specific biases, and establish algorithmic auditing protocols for CBE contexts. The empirical validation of AI-generated assessments with student performance data would strengthen validity arguments beyond the psychometric evidence we provide. As AI capabilities advance, the question for competency-based education is not whether automation will transform assessment, but how we harness its scale advantages while safeguarding the equity and transparency principles that define competency-based learning.

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Appendices

Appendix A: Prompts

Assessment Generation Prompts
[Text in italics appears in the second prompt; underlined text appears in the third prompt]

The document at [LINK] pertains to a multi-week group case study competition focusing on actuarial and data analysis. You are asked to adapt this case study to make it suitable for individual completion within a shortened timeframe and to target a specific competency of the SOA competency framework.

The targeted competency is [COMPETENCY AND <u>EXPANDED</u> DESCRIPTION]

Generate a simplified case study that contains an overview, project objectives, parameters, explicit data, and deliverables. Only include relevant aspects from the original case study and add other contextual information as needed to effectively assess the targeted competency. Use concise bullet points with action verbs for clear student directions, but provide enough context so that the simplified case study can stand on its own. Ensure it is around 1000 words, completable within two weeks, with a maximum 5-page deliverables report. *Here is the rubric the individual case studies will be evaluated on: [ATTACHMENT]*

Initial Grading Prompt

You are an actuarial science professor and an expert in actuarial education. You have exacting standards—your average grade is a 70% and you do not award perfect scores to more than 1 or 2 of the materials you are reviewing. You would like to score the attached set of case studies (18 cases) on the attached rubric. This set focuses on the [NUMBER] competency in the SOA competency framework at https://www.soa.org/professional-development/competency-framework/

The origin of these cases has been two SOA case studies: https://www.soa.org/491e40/globalassets/assets/files/static-pages/research/opportunities/2019-student-research-case-study.pdf and https://www.soa.org/48f4cc/globalassets/assets/files/static-pages/research/opportunities/2023-student-research-case-study.pdf

Additional guidance on using the rubric:

- Competency alignment and distinctiveness aim to measure bias and variance: how well the case hits its intended target, and how concentrated each series (A or B, or C) is around it
- Instructional quality means that the case forces students to engage in the kind of thought and discovery that builds their skill level in the specific competency. Clarity is definitely a huge plus, but there is space for constructive or deliberate ambiguity.

- For resource feasibility, consider whether the data and deliverables support completing this work in a satisfactory manner within two weeks, i.e., around 15–20 hours of work.
- For human authenticity, consider whether the case study has a human voice, is engaging, and does not sound robotic. Excessive lists of bullet points give clarity (may be a plus for instructional design), but tend to break the flow and do not sound human. Errant links, leftover remarks, or weird use of British English (e.g., "analyse") may also detract from the goal of sounding human.

Present your grading in a master table that contains granular scores and totals for each case. Produce a short justification for each case. Also, give highlights: cases that are scored extremely high and the reasons, and conversely, cases that scored low.

Calibrated Grading Prompt

You are an actuarial science professor and need to grade case studies that target different competencies. Use the attached rubric to score each of the 18 cases (indexed by series A/B/C, version F/S/T, and type 3,9) in the attached set across the 5 rubric criteria (competency alignment, distinctiveness, instructional quality, resource feasibility, and human authenticity). To ensure high standards, follow the 5-step algorithm below:

Step 1. Read each case deeply and carefully weigh its merits and areas for improvement. Compare with every other case in the set before proceeding. Do not penalize cases for formatting, use of British English spelling, links, or titles as "simplified case study," which have no bearing on the case's true merits. Do not penalize cases that share a theme. No case is a derivative of another case in the set.

Step 2. Grade each case and justify all scores. Apply the rubric to the best of your understanding and strive for fairness across the board.

Step 3. Check the mean total score and standard deviation of total scores. Low-quality sets of cases should have a mean total score in [15,17]. High-quality sets of cases should have a mean total score in [17,19]. The mean total score should never drop below 15 nor exceed 19, and the standard deviation of total scores within a set should be at least 4 to guarantee proper differentiation between great and poor cases.

Step 4. If the calibration parameters of step 3 are not satisfied, then refine your understanding of the rubric criteria and adjust your grading style to be more lenient/strict as needed. Then go back to step 1.

Step 5. If the calibration parameters have been satisfied, repeat steps 1–4 another four times and take the median of the five scores for each rubric criterion—these will be your final scores. This process will help minimize the effect of random noise and help produce consistent grading.

Present your final granular scores in a tabular form organized as follows: first, all cases of type 3 ordered alphabetically; then all cases of type 9 ordered alphabetically. Provide a short justification for the grade given to each case. Also, compute the mean total score and the standard deviation of the total scores for the whole set to help me check your calibration. If you are outside the calibration parameters set on

step 3, regrade all cases in the set.

Note that every case study in this set targets [COMPETENCY AND DESCRIPTION]

AI System Specifications

Anthropic Claude Opus 4 (web version with Extended thinking mode enabled; normal style). Temperature not user exposed.

Google Gemini 2.5 Pro (web version with Canvas mode enabled). Temperature not user exposed.

ChatGPT o3 (web version with Study and learn mode enabled). Temperature not user exposed.

Appendix B: Expanded Competency Descriptions

Communication. Developing the listening, writing, and speaking skills that are needed to address diverse technical and non-technical audiences in formal and informal settings and across different cultural contexts. Emphasizing clarity, timeliness, and appropriateness of actuarial communication for the intended users. Disclosing any uncertainties, conflicts of interest, reliance on other sources, or assumptions and methods used. Taking steps to prevent misuse of communications by unintended parties.

Professional Values. Becoming aware of the standards of professional conduct and practicing how to adhere to them with integrity, honesty, and impartiality. Meeting prescribed qualification standards based on education and experience, and discharging duties with care and competence. Protecting the public interest and the reputation of the actuarial profession with your conduct on and off work. Safeguarding confidential or proprietary information and complying with regulations and the law.

External Forces and Industry Knowledge. Incorporating global and local economic trends, market fluctuations, and financial indicators in actuarial models and risk assessments. Staying abreast of evolving insurance and financial regulations, compliance requirements, and legal frameworks that impact actuarial practices and product design. Recognizing the long-term impact of changes in population demographics, social behaviors, and cultural trends. Understanding how emerging technologies, data analytics, and digital transformation can transform actuarial methodologies and industry-wide processes and products.

Leadership. Articulating a clear and compelling vision for actuarial projects or teams and creating strategic plans to achieve long-term goals and organizational success. Leading high-performing teams and effectively managing diverse personalities and skill sets to maximize collective potential. Influencing decision-making processes across different levels of an organization. Adapting leadership styles to meet evolving industry challenges and team needs, demonstrating sound and ethical decision-making under pressure.

Relationship Management and Interpersonal Collaboration. Fostering an environment of open dialogue and mutual respect to facilitate collaborative problem-solving. Maintaining strong professional relationships within and outside the organization, creating a network of resources and partnerships to enhance actuarial work and professional growth. Bridging gaps between actuarial teams and other departments (e.g., underwriting, claims, finance, IT) to streamline processes, improve information flow, and achieve organizational objectives more efficiently. Recognizing and managing emotions effectively to build positive relationships and successfully resolve conflicts through negotiation skills.

Technical Skills and Analytical Problem-Solving. Applying statistical techniques and mathematical models to interpret intricate data sets, forecast trends, and quantify risks across various insurance and financial domains. Demonstrating expertise in industry-specific software tools and programming languages (e.g., R, Python,

SQL) due to a growth mindset and continuous upskilling. Adjusting theoretical models to address real-world scenarios that do not perfectly align with textbook cases and making sound judgments in the face of incomplete or inconsistent data. Examining model assumptions and stress-testing model results to ensure a whole range of possible outcomes is being considered.

Strategic Insight and Integration. Internalizing the broader business context and organizational goals, aligning actuarial practices with corporate strategies, and translating actuarial calculations into value-added business recommendations. Sharing knowledge and best practices from across the company to broaden perspectives and build a culture of excellence. Building cross-functional teams that are responsible for operationalizing strategic priorities and initiatives. Anticipating potential industry disruptors and emerging threats, and formulating proactive strategies and action plans.

Results-Oriented Solutions. Designing customized actuarial solutions that directly address identified needs, considering practical constraints, available resources, short-term results vs. long-term sustainability, and potential implementation challenges. Evaluating key performance indicators to monitor the effectiveness of implemented solutions, and iteratively refining approaches to maximize results and value delivery. Breaking down business problems into manageable components and synthesizing findings to provide actionable insights and recommendations to stakeholders. Claiming ownership of the entire lifecycle of a solution, from initial concept through design, implementation, and post-implementation review, ensuring continuity and accountability throughout the process.

Appendix C: Quality Assessment Rubric

Evaluation Criteria and Scoring Guide	5 points	4 points	3 points	2 points	1 point	No points
Competency Alignment	Laser-focused on a specific competency; every element reinforces the target skill	Strong competencies focus with minor generic elements	Moderate alignment, but some off-target content	Weak alignment with significant off-target content	Minimal competency focus; mostly generic content	No clear competency target
Distinctiveness	Completely unique approach; impossible to confuse with other competency cases	Clearly distinct with minor overlaps	Moderately distinct, but some common elements with other cases	Limited distinction; could apply to multiple competencies	Barely distinguishable from other competency cases	Indistinguishable; generic case study
Instructional Quality	Perfect student level; crystal clear what to do; logical flow; appropriate context provided	Well-written with minor clarity issues; mostly appropriate level	Generally clear, but some confusing elements or level mismatches	Multiple unclear instructions; inappropriate difficulty assumptions	Frequently confusing; poor writing for the target audience	Incomprehensible or completely wrong level
Resource Feasibility	Realistic data needs; achievable in 2 weeks; appropriate complexity for individual work	Mostly reasonable with minor time/data pressures	Adequate but pushing the limits of the timeframe or data availability	Excessive demands requiring shortcuts or unrealistic effort	Requires "crazy amounts" of data or research	Completely impossible resource requirements
Human Authenticity	Reads like expert instructor created it; natural flow; contextual expertise evident	Mostly natural with minor formulaic elements	Generally authentic but some AI-generated feel	Noticeably formulaic; lacks instructor insight	Obviously, AI-generated, mechanical approach	Completely artificial; no human expertise evident
Scoring Interpretation	**20-25 points**	**15-19 points**	**10-14 points**	**5-9 points**	**0-4 points**	
	Excellent transformation ready for implementation	Good transformation requiring minor refinements	Adequate transformation needing moderate revision	Poor transformation requiring major rework	Failed transformation needing complete redesign	

Appendix D: Evidence of Algorithmic Gaming

Relationship Management Case Set – Grading Results

Rubric used: Competency Alignment (CA), Distinctiveness (Dist), Instructional Quality (IQ), Resource Feasibility (RF), and Human Authenticity (HA) – each 05; totals out of 25.
Guiding rubric definitions are taken from the uploaded file

Type 3 cases (alphabetical)

Case	CA	Dist	IQ	RF	HA	Total	Key justification
5AF3	5	5	5	4	4	**23**	Explicitly requires building consensus among four stakeholder blocs and gives a clear two-week workflow; stretches resources a little but remains feasible
5AS3	4	4	4	4	3	**19**	Variant of Storslysia brief adds a cultural-sensitivity layer; solid but less novel than AF3; instructions remain clear and doable
5AT3	3	3	3	2	2	**13**	"Interdepartmental war" scenario is engaging yet sprawling; multiple conflicts & dual ministers push workload beyond two-week scope, lowering feasibility and authenticity
5BF3	5	5	4	5	4	**23**	Smart-Driver telematics pilot tightly ties data findings to relationship tasks and supplies concrete email/memo artefacts for students
5BS3	4	5	4	4	2	**19**	Winery-risk product is distinctive; instructions clear, but wildfire/heat data volatility adds realism that may intimidate novices, slightly reducing authen-ticity
5BT3	3	3	3	2	2	**13**	Wearable-discount case repeats familiar conflict triad; IT lead's cost memo shows feasibility strain, and aggressive marketing claims hurt authenticity
5CF3	5	5	4	4	5	**23**	Relocation-insurance brief balances technical cost model with rich stakeholder plan and phased schedule; highly authentic governmental context
5CS3	4	4	4	4	3	**19**	Safelife AV launch plan offers a unique autonomy angle but shares structure with earlier Fseries; guidance keeps workload reasonable
5CT3	3	3	3	2	2	**13**	SmartRide "Collaboration Sprint" repeats many elements from the BT-series; broad KPI set and negotiation brief exceed 5-page limit risk

Type 9 cases (alphabetical)

Case	CA	Dist	IQ	RF	HA	Total	Key justification
5AF9	5	4	4	4	4	**21**	AV-insurance launch maintains strong competency link; slightly longer 90-day regulator window increases task realism without overstretching
5AS9	4	3	4	3	3	**17**	Adds consumer-advocacy angle but otherwise mirrors AF9; some instructions duplicate earlier text, reducing distinctiveness and authenticity
5AT9	2	3	3	2	1	**11**	Competing manufacturers & eight-week timeline make workload heavy; authenticity suffers from generalized language and a lack of concrete data sets
5BF9	5	4	4	4	4	**21**	Critical-illness product balances simple dataset with clear stakeholder mapping and communication requirements; good resource fit
5BS9	4	3	4	3	3	**17**	SafeRider discount pilot is practical but echoes BF3 structure; feasible yet less distinctive and slightly formulaic
5BT9	2	3	3	2	1	**11**	AU "black-box" concerns interesting, but integration with legacy mainframe (12-month build) overshoots 2-week limit; template language lowers human feel
5CF9	5	4	4	4	4	**21**	Follow-on relocation brief keeps a tight scope and adds new sensitivity-analysis task; good balance of novelty and feasibility
5CS9	4	3	4	3	3	**17**	Evergreen Insurance silo-breaking case distinct yet shares format with CT9; clear objectives but moderate novelty
5CT9	2	3	3	2	1	**11**	Similar to CS9 but with less data and broad deliverables, stretching the 5-page limit; language feels templatedriven

Calibration check

Mean total score: **17.3**
Standard deviation: **4.4**
Both parameters meet the Step3 requirements (mean within 15-19; SD ≥ 4), so no regrading is necessary.

Notes on algorithm application

The five-round median scoring converged quickly; scores above reflect the median values. Attention was paid to balancing high-quality flagship cases (Fseries) with deliberately lighter or templatelike variants (Tseries) to preserve differentiation across the set.

Feel free to let me know if you would like deeper commentary on any individual case or a different statistical view.

Appendix E: Exemplar Assessments

The following five assessments were ranked top-6 by both the four-grader and the three-grader panels. They generally received consistent scores ≥ 23.

E.1 Claude's Leadership assessment (4-AT3)

Leadership in Crisis: Strategic Response to Storslysia's Climate Catastrophe
Overview

You are the newly appointed Chief Risk Officer (CRO) at Storslysia National Insurance Corporation (SNIC), the country's largest insurance provider covering 60% of the population. Three days into your role, a Category 4 hurricane has devastated the eastern coastal region, displacing 150,000 residents. The government has activated emergency protocols, and SNIC faces unprecedented claims while simultaneously being tasked to lead the design of a permanent relocation insurance framework.

As CRO, you must lead a cross-functional crisis response team while developing a strategic vision for long-term climate resilience. Your leadership will be tested as you navigate conflicting stakeholder interests, manage a diverse team under extreme pressure, and influence critical decisions that will impact millions of citizens.

Project Context

Immediate Crisis Situation

- 150,000 displaced residents requiring immediate assistance
- Estimated $2.5 billion in claims (40% of SNIC's annual revenue)
- Government pressure for immediate action
- Public outcry over delayed responses
- Team morale is at historic lows following previous leadership failures

Your Crisis Response Team

You inherit a 12-person team with the following composition:

- 3 Actuaries: Technical experts but resistant to rapid change
- 2 Claims Managers: Overwhelmed and showing signs of burnout
- 2 Government Relations Officers: Politically connected but risk-averse
- 2 Data Scientists: Innovative but lack insurance industry experience
- 2 Customer Experience Leaders: Passionate but often clash with technical staff
- 1 Communications Director: New hire with strong media skills but unfamiliar with insurance

Key Stakeholders

- Minister of Finance: Demands cost containment (maximum 10% GDP impact)
- Minister of Environment: Advocates for proactive relocation incentives
- Board of Directors: Focused on shareholder value and reputation
- Displaced Citizens Groups: Demanding immediate relief and long-term security
- Media: Highly critical of insurance industry response
- Regulatory Chief: Threatening intervention if the private sector fails

Project Objectives

Lead your team to develop and execute a dual-mandate strategy:

1. Immediate Response Leadership (Week 1)
    - Stabilize team dynamics and restore morale
    - Influence the board to approve emergency measures
    - Create a communication strategy for multiple stakeholder groups
    - Make ethical decisions on claims prioritization
2. Strategic Vision Development (Week 2)
    - Articulate a compelling vision for a climate-resilient insurance model
    - Design organizational structure for long-term program management
    - Develop an influence strategy for government partnership
    - Create a leadership succession plan for program sustainability

Available Data and Resources

Crisis Dashboard Data

- Current displacement: 150,000 residents (see demographic breakdown in Appendix A)
- Claims pipeline: 45,000 filed, 105,000 expected
- Processing capacity: 2,000 claims/day with current staff
- Team satisfaction scores: 3.2/10 (critical level)
- Media sentiment: 78% negative

Historical Context

- Previous climate events: 5 major events in the past decade
- Average displacement duration: 18 months
- Voluntary relocation uptake: <5% despite incentives
- Government relations history: 3 failed partnership attempts

Resource Constraints

- Budget authority: $10 million discretionary spending
- Hiring freeze, except for critical roles (maximum 5 new hires)
- Board meetings: Emergency session available with 48-hour notice
- Government access: 30-minute slots with Ministers weekly

Deliverables

Prepare a 5-page Strategic Leadership Report addressing:

1. Leadership Philosophy & Approach (1 page)
    - Articulate your leadership vision for crisis response
    - Identify leadership style adaptations for each stakeholder group
    - Describe your approach to building team cohesion under pressure
    - Explain the ethical framework for decision-making
2. Immediate Crisis Leadership Plan (1.5 pages)
    - Present the team reorganization strategy with a clear rationale
    - Outline stakeholder influence map with engagement tactics
    - Develop a 7-day action plan with specific leadership interventions

- Define success metrics for the immediate response phase

3. Strategic Vision & Organizational Design (1.5 pages)
    - Articulate a compelling 3-year vision for climate-resilient insurance
    - Design organizational structure balancing agility and expertise
    - Create a talent development strategy for key leadership roles
    - Establish a governance model for stakeholder collaboration
4. Influence & Communication Strategy (1 page)
    - Develop differentiated messaging for each stakeholder group
    - Create influence tactics for securing government partnership
    - Design internal communication plan to maintain team morale
    - Outline media strategy to rebuild public trust

Specific Requirements:

- Use action-oriented bullet points for all strategic elements
- Include one influence scenario demonstrating your approach to a resistant stakeholder
- Provide ethical justification for at least two difficult decisions
- Create a visual leadership model (one-page diagram) showing your integrated approach

Evaluation Focus

Your leadership effectiveness will be assessed on:

- Ability to create a unified vision from competing interests
- Skill in adapting leadership style to diverse audiences
- Strategic thinking in organizational design
- Influence tactics for multi-level stakeholder management
- Ethical decision-making under extreme pressure
- Team development despite crisis conditions

Time Constraint

Complete this individual assignment within two weeks, simulating the compressed timeframe of crisis leadership where strategic decisions cannot wait for perfect information.

Note: This case study assesses your ability to lead through complexity, influence without authority, and create strategic vision under pressure—core competencies for actuarial leaders in an era of increasing climate uncertainty.

Appendix F: Displacement Demographics

Affected Population Breakdown (150,000 total)

- High-risk coastal zone: 85,000 (57%)
    - Low income: 45,000
    - Middle income: 30,000
    - High income: 10,000
- Moderate-risk areas: 50,000 (33%)
    - Elderly (65+): 20,000
    - Families with children: 25,000
    - Young professionals: 5,000
- Voluntary evacuees: 15,000 (10%)
    - Proactive movers: 3,000
    - Temporary evacuees: 12,000

Insurance Coverage Status

- SNIC policyholders: 90,000 (60%)
- Competitor coverage: 40,000 (27%)
- Uninsured: 20,000 (13%)

Claim Severity Estimates

- Total loss (home destroyed): 30%
- Major damage: 45%
- Minor damage: 25%
- Average claim value: ₱185,000

Processing complexity: 40% require field assessment

E.2 Gemini's Communication Assessment (1-BS3)

Individual Case Study: Communicating Wildfire Risk

Overview

You are a junior actuarial analyst at Golden State Mutual (GSM), a mid-sized insurer specializing in California homeowners' insurance. Recently, GSM's advanced analytics team developed a new predictive model to better understand the factors influencing wildfire-related property claims. This model analyzes how property characteristics and policyholder mitigation efforts impact the frequency and severity of losses.

Your manager has tasked you with a critical project: to analyze the model's findings and communicate them effectively to key stakeholders across the company. Your ability to translate complex technical results into clear, actionable insights for different audiences will directly influence GSM's underwriting strategy, agent training, and policyholder discount programs for the upcoming year. This is not a modeling exercise; it is an assessment of your ability to synthesize and communicate pre-existing analytical results.

Project Objectives

The primary goal of this case study is to assess your ability to communicate technical actuarial concepts to diverse audiences. You will:

- Interpret the key findings from a summary of GSM's new wildfire risk model.
- Synthesize these findings into distinct messages tailored for three different internal audiences.
- Develop clear, concise, and professional documents that effectively convey the appropriate level of technical detail for each audience.
- Formulate strategic recommendations based on your interpretation of the data.
- Demonstrate strong written communication skills, including clarity, organization, and persuasive reasoning.

Project Parameters

- Timeline: Two (2) weeks from the date of receipt.
- Format: Individual project.
- Deliverable: A single report, submitted as a PDF, with a maximum length of five (5) pages (excluding a title page).
- Focus: The evaluation will be based on the clarity, appropriateness, and effectiveness of your communication, not on the development of new models or analysis. You must use only the data provided below.

Context and Data Provided

The analytics team has provided you with the following summary table, which highlights the most significant findings from their analysis of 100,000 policies over a five-year period. The model's "Risk Relativity" score indicates how much more or less risky a particular characteristic is compared to a baseline property. A relativity greater than 1.0 indicates higher risk, while a value less than 1.0 indicates lower risk.

Baseline Property Profile:

- Construction: Wood Frame
- Roofing: Asphalt Shingles
- Defensible Space: Standard (meets minimum state requirements)
- Policyholder Mitigations: None

Characteristic Category	Factor	Average Claim Frequency (per 1,000 policies)	Average Claim Severity (per claim)	Combined Risk Relativity
Construction Type	Wood Frame (Baseline)	12.5	$250,000	1.00
	Stucco / Masonry	9.0	$235,000	0.68
	Fiber Cement Siding	7.5	$220,000	0.53
Roofing Material	Asphalt Shingles (Baseline)	12.5	$250,000	1.00
	Metal	6.2	$210,000	0.42
	Clay / Concrete Tile	5.0	$205,000	0.33
Defensible Space	Standard (Baseline)	12.5	$250,000	1.00
	Enhanced (cleared 100 ft)	8.5	$240,000	0.65
	Premium (cleared 100 ft + fire-resistant landscaping)	6.0	$225,000	0.43
Policyholder Mitigations	External Sprinkler System	-	-	0.75
	Class A Fire-Rated Vents	-	-	0.85

*Note: The "Policyholder Mitigations" relativities are multiplicative and apply on top of other characteristics. For example, a Wood Frame home with a Metal Roof (0.42 relativity) and an External Sprinkler System (0.75 relativity) would have a final relativity of approximately 0.315 (0.42 * 0.75).*

Project Deliverables

Your final 5-page report must contain the following three distinct parts, clearly labeled and tailored to the specified audience.

Part 1: Executive Summary for Senior Leadership (Approx. 1 page)

- Audience: GSM's CEO and Chief Financial Officer. They have limited time and a strategic, high-level focus. They are not actuaries.
- Task:
    - Write a concise, high-level summary of the project's purpose and key findings.
    - Avoid technical jargon. Translate concepts like "relativity" into business impacts (e.g., "homes with metal roofs represent less than half the risk of those with standard shingles").
    - Conclude with two to three clear, actionable business recommendations regarding underwriting strategy or potential new premium discount programs.
    - Focus on the financial and strategic implications for the company.

Part 2: Technical Memo for Actuarial Management (Approx. 2 pages)

- Audience: The Head of Actuarial Pricing. This person is an experienced actuary who understands the technical details and will challenge your assumptions.
- Task:

- Provide a detailed interpretation of the data table.
- Discuss the interactions between different risk factors (e.g., how mitigation credits should be applied with different construction types).
- Propose a specific, justifiable rating structure for these factors. For example, suggest specific percentage discounts or surcharges for each characteristic.
- Identify at least one potential limitation of the provided data or one question you would ask the analytics team for further clarification.

Part 3: Informational Brief for Insurance Agents (Approx. 1 page)

- Audience: GSM's independent insurance agents. They need to explain to current and potential policyholders why their premiums are changing and how they can save money.
- Task:
  - Create a clear, easy-to-understand brief that agents can use as a reference.
  - Develop a "talking points" section that translates the model findings into simple, persuasive language. For example, "Did you know that upgrading to a metal or tile roof could significantly lower your insurance costs? Let us talk about how."
  - Create a simple checklist or visual guide that a homeowner could use to identify potential safety upgrades that lead to premium discounts.
  - Focus on empowering agents to have productive conversations with policyholders about wildfire risk and mitigation.

E.3 Gemini's Relationship Management and Interpersonal Collaboration assessment (5-BF3)

Individual Case Study: The 'Smart-Driver' Program Stakeholder Alignment

Competency Focus: Relationship Management and Interpersonal Collaboration. *This case study assesses your ability to use strategic communication to achieve a common goal, build mutually beneficial relationships, and develop effective work processes with diverse stakeholders.*

1. Overview

You are a new Actuarial Analyst at Lemonade Stand Insurance (LSI), a mid-sized personal auto insurance carrier. For the past year, LSI has been piloting a new telematics program called "Smart-Driver." The program uses a smartphone app to collect data on driving behaviors like acceleration, braking, cornering, and phone usage. LSI's data science team has used this data to create a proprietary "Driver Safety Score."

The pilot program is at a critical juncture. Preliminary analysis suggests the Driver Safety Score is highly predictive of accidents, even more so than some traditional rating factors like credit score or age. Leadership is excited about the potential to create more accurate pricing, improve profitability, and offer discounts to safe drivers.

However, the initiative is facing internal friction. Different department leaders have conflicting perspectives, concerns, and objectives. The Head of Product Development wants to launch the program nationwide immediately to gain a competitive edge. The Chief Risk Officer is hesitant, raising concerns about data privacy, potential for biased results, and the reliability of the app-based data collection. The Marketing team is unsure how to explain this complex program to customers without causing confusion or backlash.

Your manager has tasked you with a crucial role: Develop a communication and collaboration strategy that aligns these key stakeholders. Your goal is not to re-do the statistical analysis, but to interpret the existing results and use them to build consensus, manage relationships, and create a clear path forward.

2. Project Objectives

Your primary objective is to develop a plan that demonstrates how targeted communication can bridge the gap between technical analysis and business strategy. You will:

- Analyze the perspectives and concerns of various internal stakeholders.
- Develop a tailored communication plan that addresses the specific needs of each stakeholder group.
- Create sample communications that translate complex analytical findings into clear, actionable insights for different audiences.
- Propose a work process to foster ongoing collaboration between the actuarial, product, and marketing teams.
- Articulate how your communication strategy builds trust and supports mutually beneficial relationships to achieve the company's goals.

3. Project Parameters

- Timeline: Two weeks from receipt of this document.
- Format: Individual project.
- Deliverable: A single report, maximum of 5 pages (excluding a title page).
- Your Role: Actuarial Analyst responsible for facilitating stakeholder alignment.
- Key Stakeholders:
    - Priya, Head of Product Development: Enthusiastic and focused on innovation and market share. Non-technical background. Wants to know the bottom-line business impact.
    - David, Chief Risk Officer (CRO): Cautious and analytical. Responsible for the company's financial stability and regulatory

compliance. Concerned about model bias, data security, and unforeseen risks.

- Maria, Marketing Team Lead: Customer-focused. Needs a simple, positive story to tell. Worried about how customers will perceive being "monitored."

4. Data and Preliminary Analysis Summary

You have been provided with the following summarized findings from the data science team's pilot analysis. You must accept this analysis as fact; do not attempt to re-analyze or question the data.

Dataset Snapshot: A simplified sample of the pilot data is provided for context.

Driver Segment	Traditional Risk Tier	Avg. Driver Safety Score (1-100)	Actual Accident Frequency (per 100 vehicles)
Urban, Under 25	High	65	8.2
Urban, 25-50	Medium	78	4.5
Suburban, 25-50	Low	85	2.1
Rural, Over 50	Low	92	1.5
Urban, Under 25 (Low Income Zip)	High	64	8.5

Key Findings from the Full Analysis:

- High Predictive Power: The Driver Safety Score is 40% more predictive of claim frequency than the company's current rating plan.
- Behavioral Insights: Hard braking and late-night driving are the two strongest predictors of accidents.
- Data Integrity Concern: 15% of pilot users had periods of data loss, often due to the app being turned off. The data science team "imputed" this missing data using statistical methods.
- Potential Bias Flagged: The Driver Safety Score appears to be correlated with certain non-driving factors. For example, drivers in dense urban areas with poor road quality tend to have lower scores due to frequent, necessary hard-braking events. This could disproportionately impact drivers in lower-income zip codes.
- Positive Correlation: Drivers with higher Safety Scores also have a higher policy renewal rate (8% higher than the control group).

5. Deliverables

Structure your 5-page report to include the following four sections:

1. Stakeholder Analysis and Communication Plan
    - Present a table that identifies each key stakeholder (Priya, David, Maria).
    - For each stakeholder, complete the following:
        - Primary Interest/Goal: What is their main objective regarding the Smart-Driver program?
        - Primary Concern: What is their biggest reservation or fear?
        - Key Message: What is the single most important message you need to convey to them?
        - Communication Method & Cadence: How and how often will you communicate with them (e.g., weekly email summary, bi-weekly one-on-one meeting, formal presentation)? Justify your choice.

2. Sample Communications
    - Draft three distinct pieces of communication based on the analysis provided:
        - An Email to David (CRO): Write a professional email that proactively addresses his concerns about data integrity (the 15% data loss) and potential bias (the urban driver issue). Use the provided findings to suggest a path forward that mitigates these risks, such as a phased rollout or specific adjustments.
        - A "Talking Points" Memo for Priya (Product): Create a bulleted list of 3-5 talking points for a meeting with her. Frame the results in terms of business opportunities (e.g., profitability, market leadership) while also clearly and concisely explaining the challenges that need to be managed before a full launch.
        - A "Marketing Message" Paragraph for Maria (Marketing): Write a brief, customer-friendly paragraph (50–75 words) that Maria's team could use as a starting point for a webpage or brochure. It should explain the benefit of the Smart-Driver program from a customer's perspective, focusing on fairness, rewards, and safety without using technical jargon.

3. Proposed Collaboration Process
    - Outline a simple, sustainable work process for the next six months to ensure the Actuarial, Product, and Marketing teams remain aligned.
    - Describe the purpose of at least two recurring meeting types or reporting structures (e.g., a "Monthly Program Check-in").
    - Explain how this process will ensure that business decisions are informed by data and that analytical insights are translated into effective business actions.

4. Concluding Reflection
   - Write a short, concluding paragraph explaining how your proposed communication plan and collaboration process are designed to build trust and foster mutually beneficial relationships among the stakeholders, ultimately contributing to the success of the project.

E.4 ChatGPT's Strategic Insight assessment (7-CT9)

Below is a stand-alone case study (≈1,000 words) designed for a single student to complete in ≤ 14 days with a 5-page maximum report. It zeroes in on the SOA competency Strategic Insight & Integration—helping you practice turning actuarial analysis into forward-looking, enterprise-level recommendations.

1 | Executive Overview

TrueNorth Life & Benefits (TNL&B) is a mid-sized U.S. insurer writing group life, voluntary accident, and short-term disability. Over the past five years, disability frequency has fallen while life claims have edged up, leaving mixed profit signals. Meanwhile, several insurtechs are bundling "Financial Wellness Platforms" (FWPs): cloud-based portals that combine micro-savings, student-loan counseling, and on-demand life coverage sold payroll-deduction via employers.

TNL&B's board wants to know whether acquiring a six-year-old FWP startup called BrightPath (see data below) will (a) advance its "digital partner" strategy and (b) create measurable enterprise value. You are the *sole* actuarial strategist assigned to craft a two-year integration plan and quantify the impact on company value.

2 | Project Objectives

By the end, you will be able to internalize business context, align actuarial work with strategy, and translate numbers into actionable business moves. Specifically:

1. Diagnose the strategic fit between BrightPath and TNL&B's stated goals.
2. Quantify expected financial/actuarial impacts (earnings, capital strain, embedded value).
3. Integrate cross-functional perspectives—pricing, IT, distribution, HR—to build a realistic roadmap.
4. Recommend go/no-go and, if "go," a two-year phased rollout that anticipates potential disruptors (e.g., Big-Tech HR platforms, embedded insurance).

3 | Parameters & Explicit Data

3.1 Company Snapshots *(all amounts USD millions unless noted)*

Metric (2024 YE)	TNL&B	BrightPath*
In-force premium	1 200	75
# employer groups	3 800	160
Net income	82	-3 (loss)
RBC ratio	425 %	n/a (SaaS)
Persistency (life)	88 %	97 % (opt-in)
Tech OPEX / premium	4 %	18 %
Valuation ask (price)	—	$95 mm

*BrightPath sells monthly life coverage on demand; keeps 6 % platform fee; passes mortality risk to carrier partners (TNL&B would assume the risk post-acquisition).

3.2 Assumptions to Use

- Discount rate 8 % (hurdle).
- Cost of capital 10 %.
- Mortality table: 2015 VBT, age-salted down 2 %.
- Capital required = 150 % of the NAIC company action level on the net amount at risk.
- Integration expected to reduce combined IT cost by 20 % over two years.
- Synergy uplift: +12 % premium growth on TNL&B legacy block if platform cross-sell succeeds.

3.3 Market Signals

- Two competitors launched similar portals last year; one achieved 25 % enrollment, the other 11 %.
- A major payroll software vendor announced an embedded life product slated for launch in 18 months.

4 | Student Tasks & Deliverables

Limit your report to 5 pages (excl. exhibits). Use the headings below.

A. Strategic Fit (≈1 page)

- Map BrightPath's capabilities to TNL&B's three published strategic pillars (Digital Partner, Workforce Wellbeing, Capital Discipline).
- Identify at least two cultural or process frictions that could derail integration.
- Assess how the deal positions TNL&B against the upcoming payroll-vendor threat.

B. Financial & Actuarial Impact (≈1.5 pages)

- Project BrightPath's stand-alone earnings before and after risk-transfer to TNL&B (show simple 3-year projection).
- Estimate acquisition-year capital strain and RBC impact under baseline and stress (shock 15 % enrollment drop).
- Calculate the NPV of expected free cash flow and compare with $95 mm

asking price.
- Quantify the embedded value uplift on the legacy block from the assumed 12 % cross-sell growth.

C. Integration Roadmap (≈1 page)
- Outline a two-year timeline with quarterly milestones spanning pricing, IT migration, HR change-management, and distribution training.
- Assign cross-functional owners (e.g., CIO, Chief Distribution Officer) for each work-stream.
- Embed contingencies for two emerging disruptor scenarios (payroll-vendor launch exceeds 30 % market share; new regulatory sandbox caps platform fees).

D. Recommendation & KPI Dashboard (≈0.5 page)
- Conclude with a clear *Go / No-Go / Go-Lite* recommendation and rationale.
- Select 4–6 leading KPIs (e.g., monthly active users, IT cost per policy) and set target ranges for the first 24 months.

E. Executive Summary (≤250 words, counts toward 5 pages)
- Translate actuarial findings into plain English, C-suite language, focusing on value creation, risk, and strategic position.

5 | Working Guidance
- Data sufficiency: Use only data provided plus *publicly available* industry benchmarks—no proprietary datasets.
- Modeling: Spreadsheet or R/Python acceptable; keep formulas readable for a non-actuarial reviewer.
- Time-boxing: Allocate ≈3 days research, 4 days modeling, 3 days drafting, 2 days refinement & peer shadow-review (optional).
- Assumption testing: Perform one deterministic sensitivity you deem "most material" and *explain why* you chose it.
- Citation: Footnote any external figures; APA or SOA style fine.

6 | Evaluation Alignment (Rubric Snapshot)

Rubric Dimension	How to Max Score (5 pts)
Competency Alignment	Thread every section back to how it advances TNL&B's corporate strategy; spotlight decisions that integrate actuarial insight with business objectives.
Distinctiveness	Lean heavily on *strategic integration* (not pure pricing, not pure leadership). Avoid generic M&A templates.
Instructional Quality	Follow bullet cues exactly; keep math transparent; write with executive clarity.
Resource Feasibility	Stick to the explicit data and 2-week plan above; resist adding outside data hunts.
Human Authenticity	Use a professional, conversational tone—sound like a seasoned actuary advising the Board.

7 | Submission Checklist
☐ ≤ 5 pages (incl. summary, excl. appendices).
☐ Excel/R/Python file with labeled tabs or scripts.
☐ Cover email with one-sentence recommendation & KPI table (optional bonus).

Quick Start Question

To anchor your thinking, which single metric—other than NPV—do you expect will most sway TNL&B's Board, and why? (Jot down your answer before you dive in; revisit after modeling to see if it changes.)

Good luck—enjoy merging strategy with actuarial analytics!

E.5 Gemini's Results-Oriented Solutions assessment (8-BT3)

Individual Case Study: Designing a Resilient Agricultural Risk Solution
Competency Focus: Results-Oriented Solutions

1. Overview

Context: Veridia Farms is a large, family-owned agricultural enterprise on the fictional Isle of Vertia, a region experiencing increasingly volatile weather patterns. For generations, they have specialized in growing a unique, high-value grain. Historically, Veridia has relied on traditional indemnity-based crop insurance to manage risk. However, recent years have seen more frequent and severe droughts and floods, leading to significant crop losses. Consequently, their insurance premiums have skyrocketed, and the claims process has become slow and burdensome, creating cash flow crises when they need capital most.

The Challenge: Veridia Farms' Chief Financial Officer (CFO) has concluded that their current risk management strategy is no longer financially sustainable. The farm is caught in a cycle of paying unaffordable premiums for coverage that is slow to respond to their needs. They have engaged you, an actuarial consultant, to analyze their situation and design a new, customized risk solution. The goal is to move beyond a simple insurance policy to a comprehensive, results-oriented strategy that ensures the farm's long-term financial health and operational stability.

2. Project Objective

Your primary objective is to develop a practical and effective risk management solution for Veridia Farms that directly addresses their needs and constraints. This is not just an analytical exercise; you are expected to claim ownership of the entire solution lifecycle.

- Analyze the business problem by breaking down Veridia Farms' historical financial and weather data to quantify the shortcomings of their current approach.
- Design a customized actuarial solution that directly addresses their need for timely, affordable, and sustainable financial protection. Your design must consider practical constraints, such as the farm's budget and the trade-offs between short-term results and long-term viability.
- Recommend a clear, actionable path forward for stakeholders. This includes synthesizing your findings into a compelling business case for your proposed solution.
- Propose a framework for monitoring the solution's effectiveness post-implementation, using key performance indicators (KPIs) to measure value and guide iterative refinements.

3. Parameters and Constraints

- Timeline: This project is to be completed individually within two weeks.
- Deliverable: Your final submission must be a professional report directed to the CFO of Veridia Farms. The report must not exceed 5 pages (12-point font, single-spaced), excluding a title page and any appendices.
- Data Usage: Your analysis and recommendations must be based exclusively on the data provided below. Do not use external data or research.
- Focus: The core of your evaluation will be on the design, justification, and implementation plan for your solution, not just the technical accuracy of the calculations.

4. Provided Data

You have been given the following data covering the last 20 years of Veridia Farms' operations.

Table 1: Historical Weather and Crop Yield Data (2004-2023)

Year	Annual Rainfall (mm)	Average Summer Temperature (°C)	Actual Crop Yield (as % of Expected)
2004	1,150	22.1	100%
2005	980	23.5	95%
2006	850	24.2	80%
2007	1,210	22.5	100%
2008	1,350	21.8	90%
2009	790	25.1	65%
2010	1,100	22.9	100%
2011	950	23.8	90%

2012	1,450	21.5	75%
2013	820	24.8	70%
2014	1,050	23.1	100%
2015	750	25.5	55%
2016	1,180	22.6	100%
2017	1,510	21.2	60%
2018	990	24.0	98%
2019	800	25.3	60%
2020	1,080	23.3	100%
2021	720	26.1	45%
2022	1,480	21.4	65%
2023	920	24.5	85%

Note: The expected crop value at 100% yield is consistently $10,000,000.

Table 2: Traditional Insurance Performance (2014-2023)

Year	Annual Premium Paid	Financial Loss from Reduced Yield	Insurance Payout Received	Net Financial Impact (Payout - Premium - Loss)
2014	$250,000	$0	$0	($250,000)
2015	$280,000	$4,500,000	$3,500,000	($1,280,000)
2016	$350,000	$0	$0	($350,000)
2017	$380,000	$4,000,000	$3,000,000	($1,380,000)
2018	$450,000	$200,000	$0	($650,000)
2019	$500,000	$4,000,000	$3,200,000	($1,300,000)
2020	$600,000	$0	$0	($600,000)
2021	$750,000	$5,500,000	$4,000,000	($2,250,000)
2022	$850,000	$3,500,000	$2,500,000	($1,850,000)
2023	$900,000	$1,500,000	$500,000	($1,900,000)

5. Deliverables: Report Structure

Structure your 5-page report to the CFO with the following sections:

1. Executive Summary:
    - Provide a concise overview of the problem, your proposed solution, and its expected value to Veridia Farms.
    -
2. Problem Analysis:
    - Use the provided data to quantify the financial inefficiency and risk of the current insurance program.

    - Analyze the relationship between weather events (e.g., rainfall) and crop yield to identify the primary drivers of loss.
    - Clearly illustrate why the status quo is unsustainable.
3. Proposed Solution Design:
    - Present your customized solution. A strong proposal will likely be a form of parametric (or index-based) insurance, but you are free to justify another innovative approach.
    - Justify your design choices. Explain the specific parameter(s) you chose (e.g., a rainfall index), the trigger levels for payout, and the payout amounts. Connect these directly to the data and Veridia's need for rapid, predictable capital.
    - Explain how your solution balances cost-effectiveness (the new premium) with risk reduction (the protection offered). Address the concept of basis risk (the potential for the index not to match the farm's actual loss) and how you would manage it.
4. Implementation and Monitoring Plan:
    - Outline the key steps and timeline to transition from the current insurance to your proposed solution.
    - Define 3–4 Key Performance Indicators (KPIs) to monitor the solution's effectiveness over the first three years. Examples could include "Premium Stability," "Speed of Payout," and "Basis Risk Ratio."
    - Describe how you would use these KPIs to iteratively refine the solution (e.g., adjust the trigger levels or payout structure) after each year to ensure it continues to deliver maximum value.
5. Conclusion:

Summarize why your solution is the optimal, results-oriented choice for Veridia Farms and reiterate the value it will deliver.