

Artificial intelligence (AI) is becoming a cornerstone in strategic decision-making across industries. When presenting AI-driven insights to boards, the integrity of those insights rests heavily on the quality of assumptions underpinning the models. Properly documenting AI assumptions in board decks is not just good practice — it's essential for establishing trust, enabling auditability, and fostering robust strategic discussions.



This post delves into best practices for documenting AI assumptions in board-ready reporting, focusing on four critical themes:

- **DCI as an audit signal:** Using Data, Context, and Interpretation frameworks to surface assumptions clearly.
- **Model disagreement as useful friction:** Embracing, explaining, and highlighting divergent model outputs.
- **Provenance and traceability to source documents:** Maintaining clear lineage from inputs to forecasts.
- **Variance across runs and across models:** Reporting variability to set realistic expectations.

Why Documenting AI Assumptions Matters for Boards

Boards rely on concise, vetted information to make high-stakes decisions. AI models, while powerful, introduce layers of complexity and uncertainty that can obscure how results were derived. Poorly documented assumptions lead to blind spots, reduce confidence, and expose organizations to risks during audits or due diligence.

Beyond regulatory scrutiny, well-documented assumptions elevate strategic conversations. They enable board members to:

- Understand the foundation and limitations of AI-driven forecasts.
- Challenge or validate insights with evidence-backed rigor.
- Identify areas requiring sensitivity analysis or further investigation.

With that context, let's unpack how to embed thorough, board-ready documentation of AI assumptions into your reporting workflows.

1. DCI: Data, Context, and Interpretation as Audit Signals

The *DCI* framework provides a structured yet flexible approach to communicate assumptions clearly in your board decks.

Data: What Inputs Were Used?

Detailing the data behind AI models creates the foundation for traceability. Key points to capture include:

- **Sources:** Specify origin (e.g., internal CRM, third-party market data, public datasets).
- **Timestamp:** When was the data pulled or updated? Versioning matters.
- **Preprocessing:** Summarize cleaning, normalization, or feature engineering steps.
- **Data quality indicators:** Missingness rates, outlier treatment, or sampling biases.

Example snippet for travispyuj085.raidersfanteamshop.com a board deck:

"Forecast models use sales transaction data from internal ERP systems collected through Q1 2024, encompassing 120,000 customer interactions after outlier filtering and imputation for 3% missing values."

Context: Business and Environmental Assumptions

Context frames the "why" behind the AI model's design and assumptions:



- Market conditions affecting the data period (e.g., inflation, seasonality, regulatory shifts).
- Strategic initiatives or constraints embedded in the model.
- Known risks or uncertainties factored in explicitly or implicitly.

Example:

"The model assumes stable input costs post-April 2024, reflecting current supplier contracts but excluding anticipated raw material shortages flagged by procurement."

Interpretation: How Outputs Should Be Read

Clarify assumptions & limitations impacting how board members interpret forecasts or categorizations:

- Confidence intervals or error margins attached to predictions.

- Highlighting known blind spots (e.g., insufficient data from emerging markets).
- Use case specifics – whether outputs are directional guidance or precise estimates.

Example:

“Growth projections have a 95% confidence interval of $\pm 3\%$, reflecting variance introduced by forecasting model parameter tuning and supply chain volatility.”

2. Model Disagreement as Useful Friction

Contrary to impulse for consensus, differences between AI models or multiple runs are valuable signals rather than errors to average away blindly.

Why embrace disagreement?

- **Surface hidden assumptions:** Diverging outputs often illuminate differing assumptions—be it economic scenarios, customer behavior, or data inclusion criteria.
- **Encourage scrutiny:** Presenting friction opens the door for board members to challenge and validate assumptions rather than accept polished, homogenized figures.
- **Risk identification:** Wide gaps can reflect genuine uncertainty, signaling need for contingency plans.

Practical ways to display disagreement in board decks:

- Use *side-by-side tables* showing outputs from competing models with key assumption differences annotated.
- Visualize *variance ranges* as shaded bands or boxplots rather than single-point forecasts.
- Call out any known structural reasons for divergence, e.g., “Model A includes recent consumer survey data; Model B relies solely on historical sales.”

Example table:

Model	Annual Revenue Growth Assumption	Customer Churn Rate Assumption	Q3 2024 Forecast	Key Difference
Model A	5.0%	12%	\$10.5M $\pm$ 0.3M	Includes consumer sentiment data
Model B	4.3%	15%	\$9.8M $\pm$ 0.5M	Excludes recent survey data

3. Provenance and Traceability to Source Documents

As a seasoned due diligence professional, I cannot overemphasize that all numbers and claims must be *directly traceable* to an underlying authoritative source. Without provenance, assumptions become unverifiable and room for executive summaries to slip into jargon and empty assertions widens.

How to build provenance into your board deck?

1. **Link every key assumption back to its source data or rationale:** Attach or cite specific CSV exports, original PDFs, or contractual documents.
2. **Maintain an audit trail:** Version control for datasets, model code snapshots, and assumptions logbooks that track changes and approvals.
3. **Embed documentation in appendix or interactive supplemental material:** For example, include hyperlinked footnotes or QR codes linking to primary source repositories.
4. **Use unique IDs or timestamps:** To correlate model runs with exact data snapshots.

Tips:

- Never accept assumptions or figures offhand without requesting a direct source file or document.
- Document any manual adjustments or overrides with justification and date/time stamps.
- For external data, note vendor name, version, and date of acquisition.

4. Variance Across Runs and Across Models

AI models typically incorporate probabilistic elements and may update dynamically when retrained on new data. Reporting a single deterministic output hides uncertainty and misleads board members.

Key considerations for variance reporting:

- **Across runs variance:** How much do outputs fluctuate when retraining with newly ingested data or tweaking hyperparameters? Cache recent run results to compare.
- **Across models variance:** Differences resulting from architectural choices, algorithms, or input scope.
- **Presentation:** Confidence intervals, standard deviations, or scenario ranges help boards contextualize reliability.

Example illustrative statement:

"Over five consecutive weekly model retrainings, quarterly sales forecasts fluctuated between \$10.1M and \$10.9M, indicating inherent model sensitivity to recent market inputs. Combined with alternative forecasting techniques, overall variance is +/- 6%."

Putting It All Together: A Checklist for Board-Ready AI Assumptions

Checklist Item	Why It Matters	How to Implement	Explicitly state each key assumption	Enables transparent evaluation by board and auditors
Use bullet points or callouts tied to model components	Ensures verifiability and audit trail integrity	Hyperlink footnotes; maintain folder and version controls	Highlight differences across models/runs	Stimulates critical review of model robustness
Display comparative tables & visualizations	Include confidence intervals and variance explanations	Frames realistic expectations of forecast accuracy	Present alongside key KPIs; add interpretive notes	Document data preprocessing and transformation steps
Prevents hidden biases or errors during audit	Summary tables and methodology appendixes	Register known limitations and unknowns	Mitigates overconfidence; prompts further due diligence	Explicit disclosure slides or memo sections

Conclusion

Trustworthy, board-ready reporting of AI-driven insights hinges not just on impressive outputs, but on rigorous, transparent documentation of assumptions. By embedding **DCI audit signals**, embracing **model disagreement as constructive friction**, ensuring unbroken **provenance and traceability**, and reporting **variance across runs and models**, organizations dramatically improve governance, strategic clarity, and audit readiness.

Executives and board members deserve no less than memos and decks that don't just say "*optimized for growth*," but show exactly how, why, and where such assumptions hold or may break down.

Equip your next board deck with this rigor and watch AI insights translate to confident decisions and durable trust.