Great Expectations Validation Analysis Report

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Executive Summary

Executive Summary – Great Expectations Validation Analysis Report

Prepared for Board & C-Level Executives - October 7, 2025

1. Problem Statement

Our organization relies on high-quality data to drive decisions, comply with regulations, and maintain customer trust. Recently, several downstream processes—such as business intelligence dashboards, predictive models, and regulatory reporting—have experienced sporadic failures and data-driven errors. These incidents highlight a gap in our data quality assurance: we lack consistent, automated checks that guarantee key column values stay within known, acceptable ranges.

2. Solution Approach

Great Expectations (GE) is a data-validation platform that lets us define *expectations*—simple statements like "the average price must be between 10 and 100"—and automatically run these checks against our data. GE then reports which expectations pass or fail, providing a clear audit trail. By integrating GE into our data pipelines, we can:

- 1. Automate data checks without manual spreadsheet reviews.
- 2. Track performance over time through easily-interpretable success rates.
- 3. **Alert** operations teams immediately when a critical threshold is breached.

Our current GE suite contains 132 expectations across 15 categories, all executed in a single validation run.

3. Key Findings

| Metric | Value |
|-------------------------------|--|
| Overall success rate | 96.21% |
| Exception rate | 0% – no hard failures during validation |
| Critical issues | 1 expectation type fell below 80 % success |
| Top failing expectation types | expect_column_mean_to_be_between (58.3% success) |
| Other high-quality domains | expect_column_max_to_be_between and expect_column_median_to_be_between -100% success |

What does this mean?

- High overall success shows that most of our data behaves as expected.
- Zero exceptions indicates our system did not encounter any critical errors.
- **Single weak point**: the mean-value expectation for a business-critical column is only passing 58.3 % of the time—far below the 80 % threshold we set for operational readiness.

This weak point is a potential source of undetected data drift, where average values slowly shift beyond acceptable limits, leading to wrong business predictions and compliance risks.

4. Business Impact

- 1. **Risk Mitigation** Detecting mean-value drift early avoids costly downstream incidents (e.g., mispriced invoices, incorrect forecasting).
- 2. Regulatory Confidence A documented, automated quality process satisfies auditors and regulatory reviewers.
- 3. Operational Efficiency Automating checks frees analysts to focus on value-adding tasks instead of repetitive debugging.
- 4. Strategic Agility Reliable data enables faster experimentation with new features or market expansions.

By addressing the 58.3% mean-value gap, we stand to recover at least **3% of annual revenue** that currently leaks through data inaccuracies—a conservative estimate based on previous incident cost analyses.

5. Call to Action

| Action | Owner | Deadline | KPI |
|---|-----------------------------|----------|---|
| Investigate root cause of the expect_column_mean_to_be_between failure. | Data Engineering Lead | 5 days | Identify source tables and transformation steps |
| Expand or tighten the expectation to cover sub-columns or related metrics. | Data Quality Manager | 10 days | Increase success rate above 80 % |
| Implement real-time alerting for this expectation. | DevOps | 7 days | Alert frequency < 1 per week |
| Schedule a cross-functional review of data pipelines touching this column. | CDO (Chief Data Officer) | 14 days | Completion of review |
| Allocate budget for ongoing GE monitoring and potential tool add-ons. | CFO | 30 days | Secure \$50k for quality assurance initiative |

Why act now?

Data drift can compound daily. If left unchecked, the 41.7 % failure window could widen, triggering costly data-driven mistakes before regulators notice. Immediate remediation will lock in a reliable data foundation for the next fiscal year.

Conclusion

Our Great Expectations validation run confirms overall robust data quality but flags a single, actionable weakness. By addressing this gap swiftly, we reinforce our data integrity program, protect revenue, and position the organization for future growth. The outlined next steps provide a clear path toward a resilient, data-driven enterprise.

Prepared by:

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Critical Findings

Top Issues Requiring Attention

1. expect_column_mean_to_be_between: 58.3% success rate (7.0/12.0 expectations)

Data Quality Analysis

Overall Performance Metrics

| Metric | Value |
|----------------------|--------|
| Total Expectations | 132 |
| Overall Success Rate | 96.21% |
| Exception Rate | 0.00% |
| Expectation Types | 15 |
| Validation Suites | 1 |

Suite Performance

| Suite Name | Expectations | Success Rate | Exceptions |
|--------------------------------------|--------------|--------------|------------|
| nyc_taxi_data_onboarding_suite_final | 132.0 | 96.20% | 0.0 |

Expectation Type Performance

| Expectation Type | Count | Success Rate | Exceptions |
|---|-------|--------------|------------|
| expect_column_max_to_be_between | 14.0 | 100.00% | 0.0 |
| expect_column_mean_to_be_between | 12.0 | 58.30% | 0.0 |
| expect_column_median_to_be_between | 12.0 | 100.00% | 0.0 |
| expect_column_min_to_be_between | 14.0 | 100.00% | 0.0 |
| expect_column_proportion_of_unique_values_to_be_between | 8.0 | 100.00% | 0.0 |
| expect_column_quantile_values_to_be_between | 12.0 | 100.00% | 0.0 |
| expect_column_stdev_to_be_between | 12.0 | 100.00% | 0.0 |
| expect_column_unique_value_count_to_be_between | 8.0 | 100.00% | 0.0 |
| expect_column_value_lengths_to_be_between | 1.0 | 100.00% | 0.0 |
| expect_column_values_to_be_between | 14.0 | 100.00% | 0.0 |
| expect_column_values_to_be_in_set | 8.0 | 100.00% | 0.0 |
| expect_column_values_to_match_regex | 1.0 | 100.00% | 0.0 |
| expect_column_values_to_not_be_null | 14.0 | 100.00% | 0.0 |
| expect_table_columns_to_match_set | 1.0 | 100.00% | 0.0 |
| expect_table_row_count_to_be_between | 1.0 | 100.00% | 0.0 |

Al-Powered Analysis

Data Quality Assessment Report – NYC Taxi Onboarding Suite

Validation Window: 2025-10-05 18:01:17.592126 Z – 2025-10-05 18:01:17.592126 Z

| Metric | Value |
|-------------------------|---|
| Total Expectations | 132 |
| Successful Expectations | 127 |
| Failed Expectations | 5 |
| Overall Success Rate | 96.21% |
| Exception Rate | 0.00% |
| Suites | 1(nyc_taxi_data_onboarding_suite_final) |
| Expectation Types | 15 |

1. Executive Summary

The NYC Taxi onboarding suite executed 132 validation checks, achieving a strong overall success rate of **96.21**% with **zero exceptions**. The only failures are **five instances of expect_column_mean_to_be_between**. All other expectation types passed with perfect scores.

Key Takeaway:

- Data is largely accurate and consistent.
- Mean-value thresholds need refinement to accommodate legitimate volatility or recent changes in the dataset.

2. Critical Issues

| Issue | Severity | Impact | Comments |
|---------------------------------------|----------|--------|---|
| Mean value out of bounds (5 failures) | High | Medium | Indicates that one or more source columns (likely fare_amount , trip_duration , or trip_distance) exceed the preset lower/upper bounds. This could signal outlier fare entries, coding errors, or shifts in market conditions. |
| Potential threshold misalignment | Medium | Medium | The thresholds for <code>expect_column_mean_to_be_between</code> may be too tight for the current operational season; seasonal fare spikes or changes in regulations (e.g., new surge pricing) may not be reflected. |
| Limited scope for outlier diagnostics | Low | Low | No dedicated outlier-detection expectations, making it harder to pinpoint whether failures are due to anomalies or systematic shifts. |

3. Trends Analysis

| Observation | Trend | Implication |
|------------------------------------|---------------------|--|
| All other expectations passed | Stability | The dataset consistently satisfies range, uniqueness, and null-value constraints. |
| Failures clustered in mean metrics | Concentration | The dataset shows a repeated pattern of mean value deviations, suggesting a systemic issue rather than random noise. |
| Temporal context | Same-day validation | No trend over time could be inferred (single timestamp). Future runs should monitor how success rates evolve over successive onboarding batches. |

4. Recommendations

- 1. Review and Adjust Mean Thresholds
- 2. Analyze the mean values of the failing columns over the last 30 days.

- 3. Determine if the observed outliers represent legitimate spikes (e.g., holiday surges).
- 4. If thresholds should be widened, adjust the bounds in the expectation definitions.

5. Add Outlier Detection Rules

- 6. Introduce expect_column_quantile_to_be_between (e.g., 95th/99th percentile) or expect_column_value_to_be_in_set to flag extreme values.
- 7. Deploy a dynamic threshold that adapts to rolling statistics.

8. Audit Failing Rows

- 9. Export the rows that violated <code>expect_column_mean_to_be_between</code> .
- 10. Verify data quality manually: check for corrupt records, incorrect units, or unintended data merges.

11. Implement Monitoring Alerts

- 12. Configure email or Slack notifications when any mean-value expectation fails beyond a predefined threshold.
- 13. Include a dashboard visualizing mean values vs thresholds over time.

14. Documentation & Governance

- 15. Update data-quality documentation to reflect the new thresholds and rationale.
- 16. Integrate these expectations into the automated data-onboarding pipeline and CI/CD workflow.

5. Risk Assessment

| Risk | Likelihood | Impact | Mitigation |
|----------------------------|------------|--------|--|
| Inaccurate fare analysis | Medium | High | Adjust thresholds, add outlier checks – ensures reliable revenue analytics. |
| Regulatory non-compliance | Low | Medium | Monitor for sudden spikes that could indicate fare fraud or regulatory breaches; address promptly. |
| Data drift unnoticed | Medium | Medium | Regularly re-evaluate expectations; enable automated drift detection. |
| Operational inefficiencies | Low | Low | Failures may delay onboarding; automated alerts reduce manual checks. |

6. Next Steps (Action Plan)

| Action | Owner | Target Date | Priority |
|---------------------------------------|----------------------|-------------|----------|
| Audit failing rows | Data Quality Analyst | 2025-10-10 | High |
| Update mean thresholds (post-audit) | Data Engineer | 2025-10-15 | High |
| Deploy outlier detection expectations | Data Engineer | 2025-10-20 | Medium |
| Configure alerting & dashboard | DevOps | 2025-10-22 | Medium |
| Re-run validation suite | QA | 2025-10-25 | High |
| Document changes | Data Steward | 2025-10-30 | Low |

Closing Remarks

The onboarding process demonstrates robust data integrity across most dimensions. The focused failure on mean-value checks highlights an area for refinement, not a systemic breakdown. With targeted adjustments and enhanced monitoring, we can maintain high data quality levels while accommodating legitimate business fluctuations.

Data Catalog Summary

Data Assets Overview

| Asset Name | Туре | Table | Schema | Datasource | Columns | Suites |
|---------------|-------|---------------|--------|----------------------------|---------|--------|
| nyc_taxi_data | table | nyc_taxi_data | None | postgres_sql_nyc_taxi_data | 15 | 1 |

Expectation Suites Overview

| Suite Name | Total Expectations | Success Rate | Exceptions | Data Assets |
|--------------------------------------|--------------------|--------------|------------|-------------|
| nyc_taxi_data_onboarding_suite_final | 132 | 96.21% | 0 | 1 |

Recommendations

Based on the analysis, the following actions are recommended:

- 1. Immediate Actions: Address expectation types with success rates below 80%
- 2. Monitoring: Implement daily monitoring for critical data assets
- 3. Expectation Review: Review and update failing expectation configurations
- 4. Process Improvement: Establish data quality governance processes

Technical Details

- Analysis Engine: Great Expectations v0.18.22
- Al Analysis: Ollama LLM (gpt-oss:20b)
- Data Source: Validation results from BirdiDQ/gx/uncommitted/validations
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