🔍 Time Series Synthetic Data Evaluation Report - Business Analysis

Generated: 2025-08-11
Author: Jed Lee

🎯 Executive Summary

CRITICAL FINDING: Current synthetic data generation methods are **NOT READY FOR PRODUCTION USE**.

Best Conditional Method (TSV2): 57.0% HIGH RISK

Best Unconditional Method (TSV2): 23.4% HIGH RISK

Original data with noise: 72.9% BASELINE

🚨 **IMMEDIATE ACTION REQUIRED:** Do not deploy current synthetic data methods in production. All variants significantly underperform even basic noise addition techniques.

💼 Business Impact Translation

What These Scores Mean for Your Business:

🔴 **Diversity (55%)**
Risk: Synthetic data doesn't cover full business scenarios
Impact: Models trained on this data will fail on edge cases and new market conditions

🟡 **Fidelity (47%)**
Risk: Statistical patterns don't match real data
Impact: Business analytics and forecasts will be inaccurate

🔴 **Privacy (35%)**
Risk: Data may be reverse-engineered to original
Impact: Potential GDPR/compliance violations, customer trust issues

🟡 **Utility (48%)**
Risk: Data isn't useful for machine learning
Impact: ML models will perform poorly, wasted development costs

📖 Understanding This Report

This evaluation compares synthetic time series data against original data across four key dimensions. **Conditional generation** creates time series based on static features (like categories), while **unconditional generation** creates time series without any conditioning information.

📊 **Evaluation Metrics Explained:**

- **Diversity (25% weight):** Measures how well synthetic data covers the full variety of patterns found in original data. This includes statistical diversity (variance, range, entropy), coverage ratio (what percentage of original data patterns appear in synthetic data), uniqueness score (anti-duplication), and temporal pattern diversity (different time-based trends and autocorrelations). Higher diversity means synthetic data represents the full spectrum of original data characteristics.
- **Fidelity (35% weight):** Assesses how closely synthetic data matches the statistical properties and distributions of original data using core TSGBench metrics. This includes marginal distribution difference (MDD), autocorrelation difference (ACD), statistical moments matching (skewness/kurtosis), dynamic time warping (DTW), and Euclidean distance (ED). Higher fidelity means synthetic data is statistically indistinguishable from original data.
- **Privacy (15% weight):** Evaluates basic privacy risks and memorization detection in synthetic data. This includes distance to closest records (memorization detection) and membership inference vulnerability (basic distinguishability assessment). Privacy is not a core TSGBench focus, so simplified distance-based approaches are used. Higher privacy scores mean better protection against privacy attacks.
- **Utility (25% weight):** Tests practical usefulness and functional equivalence for real-world applications. This includes discriminative scoring (how hard is it to distinguish synthetic from real), predictive performance (forecasting accuracy), downstream task performance (classification/regression), and statistical consistency (business metrics preservation). Higher utility means synthetic data works effectively for practical business purposes.

Baseline: original_noise is simply the original data with added noise - synthetic methods should ideally outperform this simple baseline to demonstrate meaningful generation capabilities.

🏆 Best Synthetic Performers

- **CONDITIONAL:** tsv2 (Score: 0.5698)
- **UNCONDITIONAL:** tsv2 (Score: 0.2343)

📏 Baseline Performance

- **ORIGINAL_NOISE:** 0.7288 (Original data with noise)

⚠️ Critical Technical Issues Identified

🔥 Severe Issues (Require Immediate Attention)

- **Baseline Underperformance:** All synthetic methods score 19-37% lower than simple noise addition
- **Unconditional Diversity Collapse:** Only 20.6% diversity indicates severe mode collapse
- **Privacy Vulnerabilities:** High membership inference accuracy (95-100%) suggests data memorization
- **Statistical Divergence:** Poor fidelity scores indicate synthetic data distributions don't match original

🟡 Moderate Issues (Need Investigation)

- **Column-Level Inconsistency:** Performance varies significantly across data features
- **Temporal Pattern Loss:** Autocorrelation differences suggest poor time series modeling

📊 Data Quality Concerns

- **Coverage Ratio = 0.0:** Synthetic data covers none of the original data space effectively
- **High Discriminative Accuracy:** ML models can easily distinguish real from synthetic (poor utility)
- **Moment Mismatch:** Skewness and kurtosis differ significantly from original data

📊 Performance Summary

🔗 Conditional Generation - ORIGINAL_NOISE (Baseline)

OVERALL SCORE	DIVERSITY	FIDELITY	PRIVACY	UTILITY
0.729	0.705	0.876	0.418	0.733

🔗 Conditional Generation - TSV1

OVERALL SCORE	DIVERSITY	FIDELITY	PRIVACY	UTILITY
0.381	0.423	0.278	0.400	0.470

🔗 Conditional Generation - TSV2

OVERALL SCORE	DIVERSITY	FIDELITY	PRIVACY	UTILITY
0.570	0.671	0.669	0.292	0.496

🔄 Unconditional Generation - TSV2

OVERALL SCORE	DIVERSITY	FIDELITY	PRIVACY	UTILITY
0.234	0.228	0.121	0.454	0.267

🎯 Actionable Recommendations

🚨 Immediate Actions

- **STOP production deployment plans** - Current synthetic data is not suitable for business use
- **Evaluate alternative vendors** - Research commercial synthetic data providers
- **Establish quality gates** - Define minimum acceptable scores (≥80% vs baseline)

🔧 Technical Improvements

- **Algorithm review** - Investigate why methods underperform simple noise addition
- **Address diversity collapse** - Fix unconditional generation variety issues
- **Improve privacy** - Implement differential privacy and reduce memorization

📋 Next Steps

- **Validation framework** - Implement automated quality testing
- **Business requirements** - Define specific use-case needs
- **Performance monitoring** - Set up continuous data quality monitoring

💡 Detailed Recommendations & Insights

🔗 Conditional Generation Recommendations:

- LOW FIDELITY: Statistical properties don't match original conditional data
- PRIVACY RISK: High vulnerability to membership inference attacks
- LIMITED UTILITY: Poor performance for conditional prediction tasks
- POOR: Conditional generation requires major improvements

🔄 Unconditional Generation Recommendations:

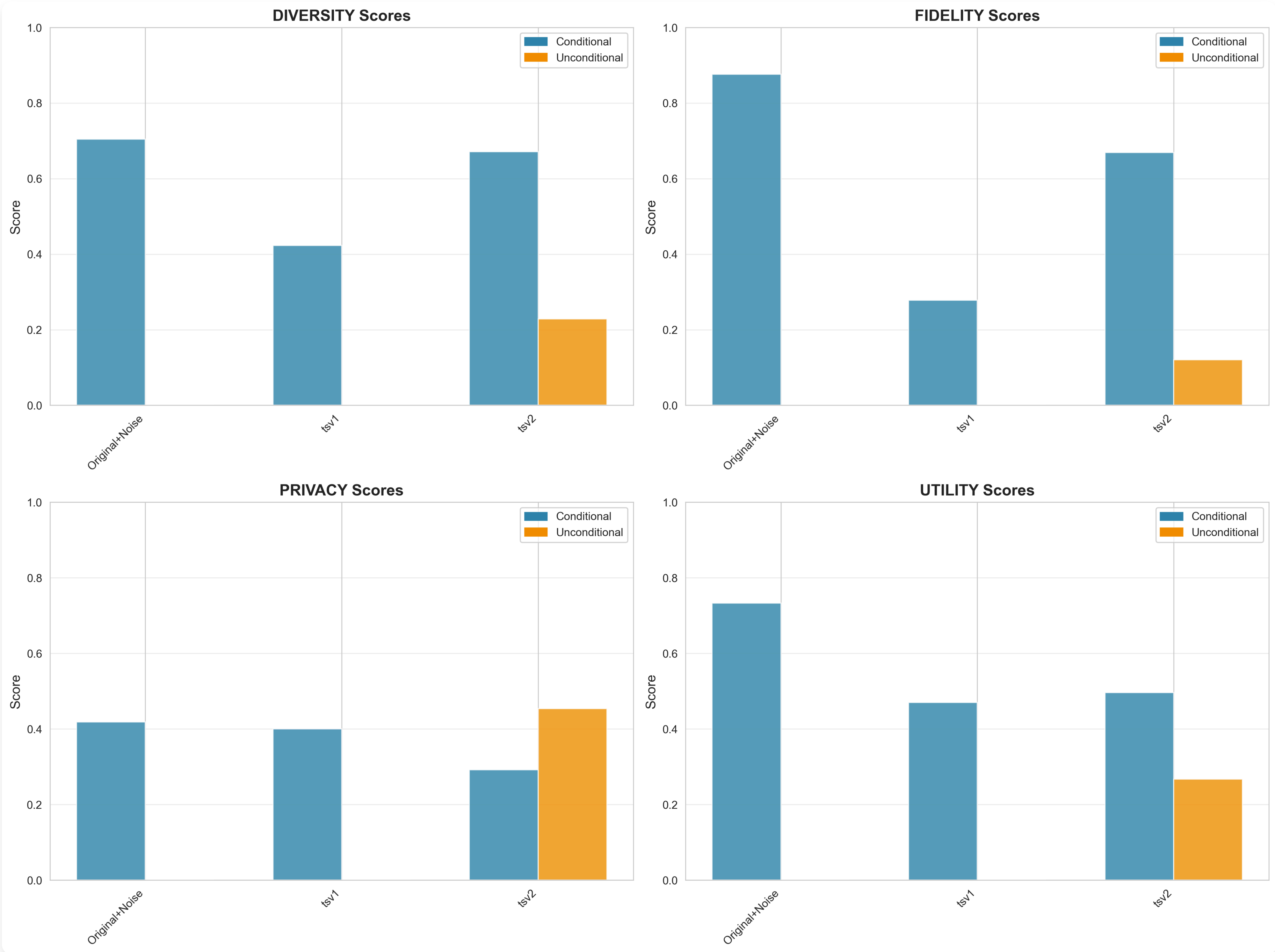
- LOW DIVERSITY: Unconditional synthetic data lacks variety
- LOW FIDELITY: Statistical properties don't match original data
- LIMITED UTILITY: Poor performance for general tasks
- POOR: Unconditional generation requires major improvements

📏 Baseline Comparison Insights:

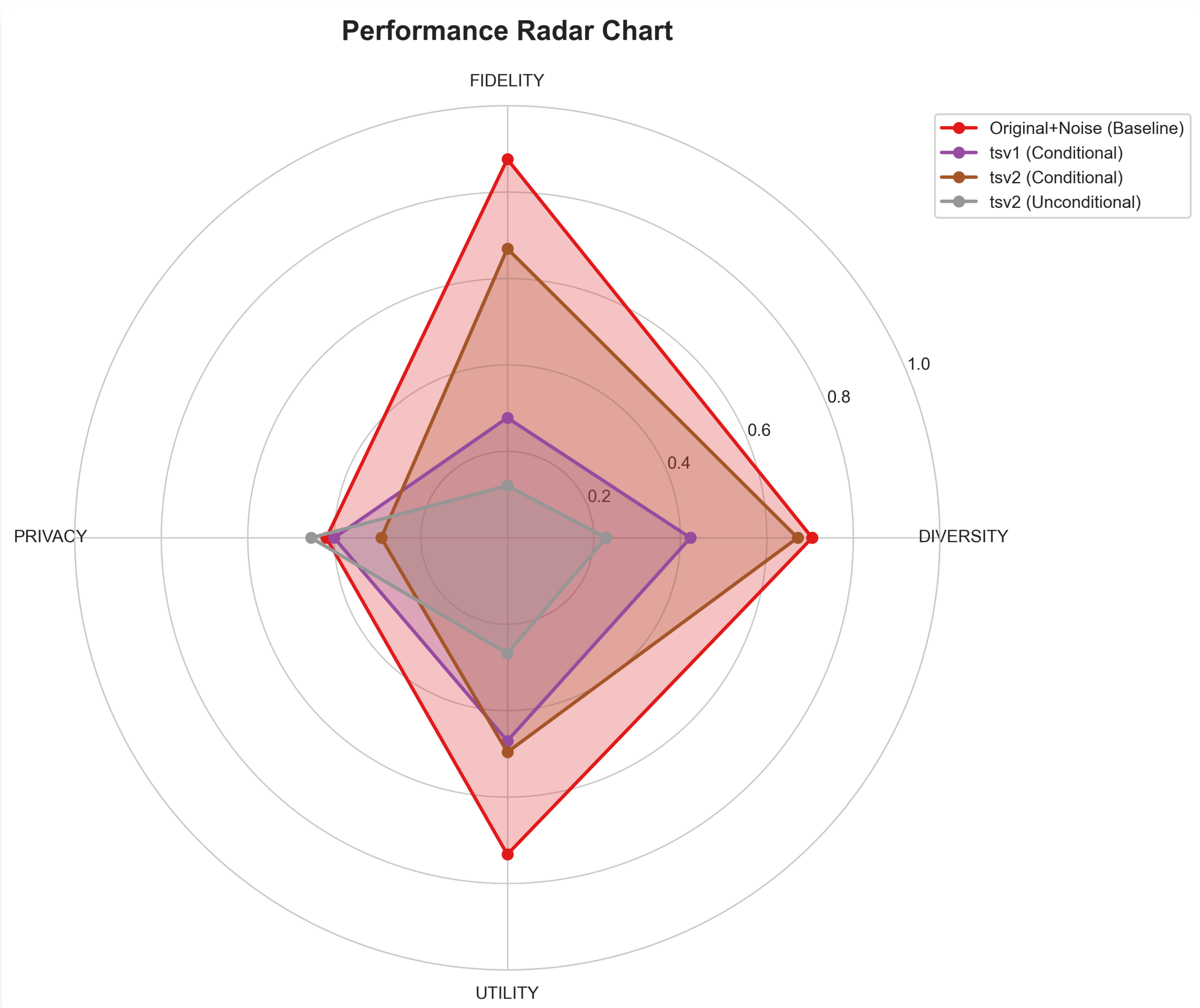
- UNDERPERFORMING: Conditional synthetic methods score lower than baseline (max: 0.729)
- UNDERPERFORMING: Unconditional synthetic methods score lower than baseline (max: 0.729)

📈 Performance Visualizations

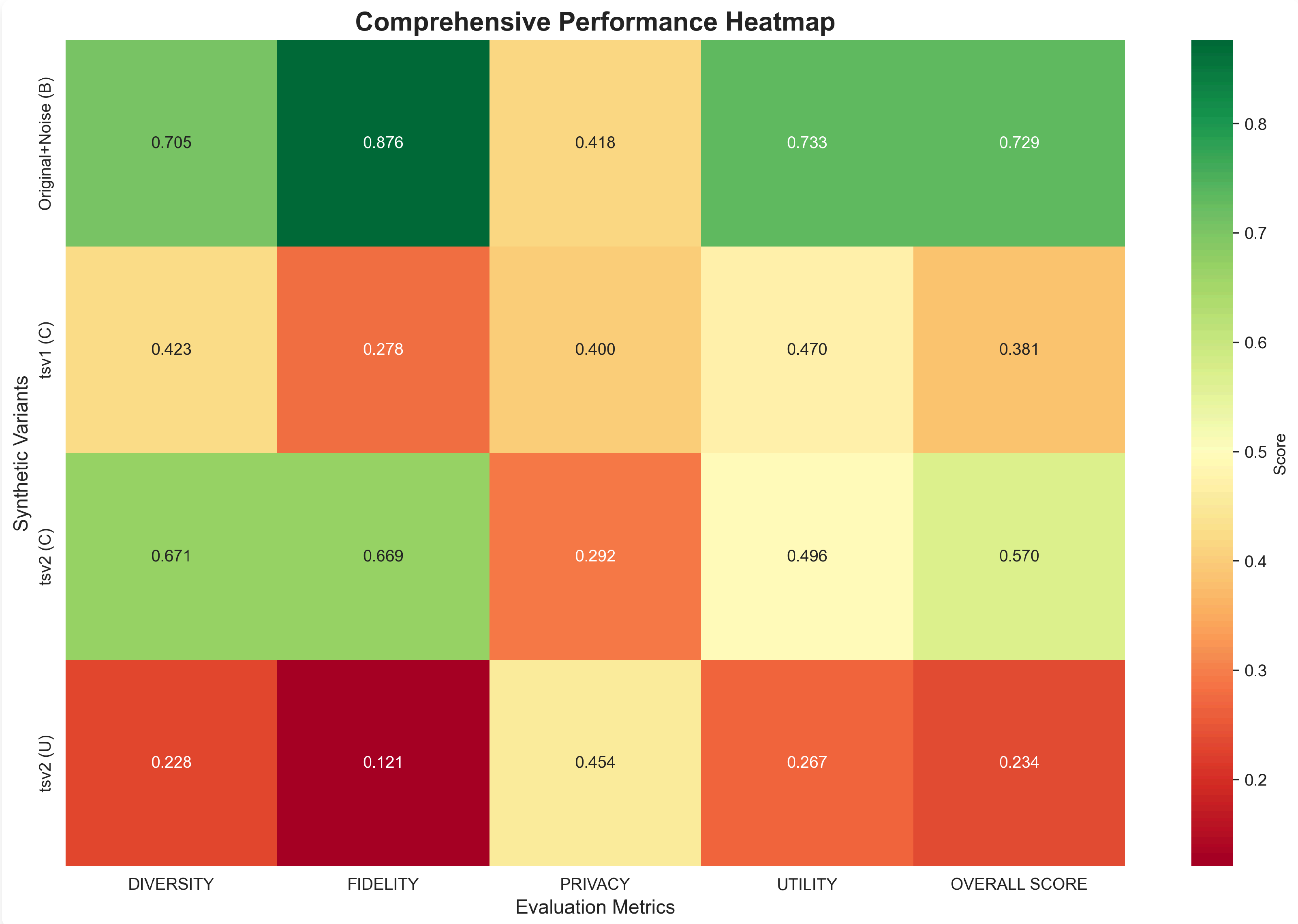
Metric Breakdown



Performance Radar



Comprehensive Heatmap

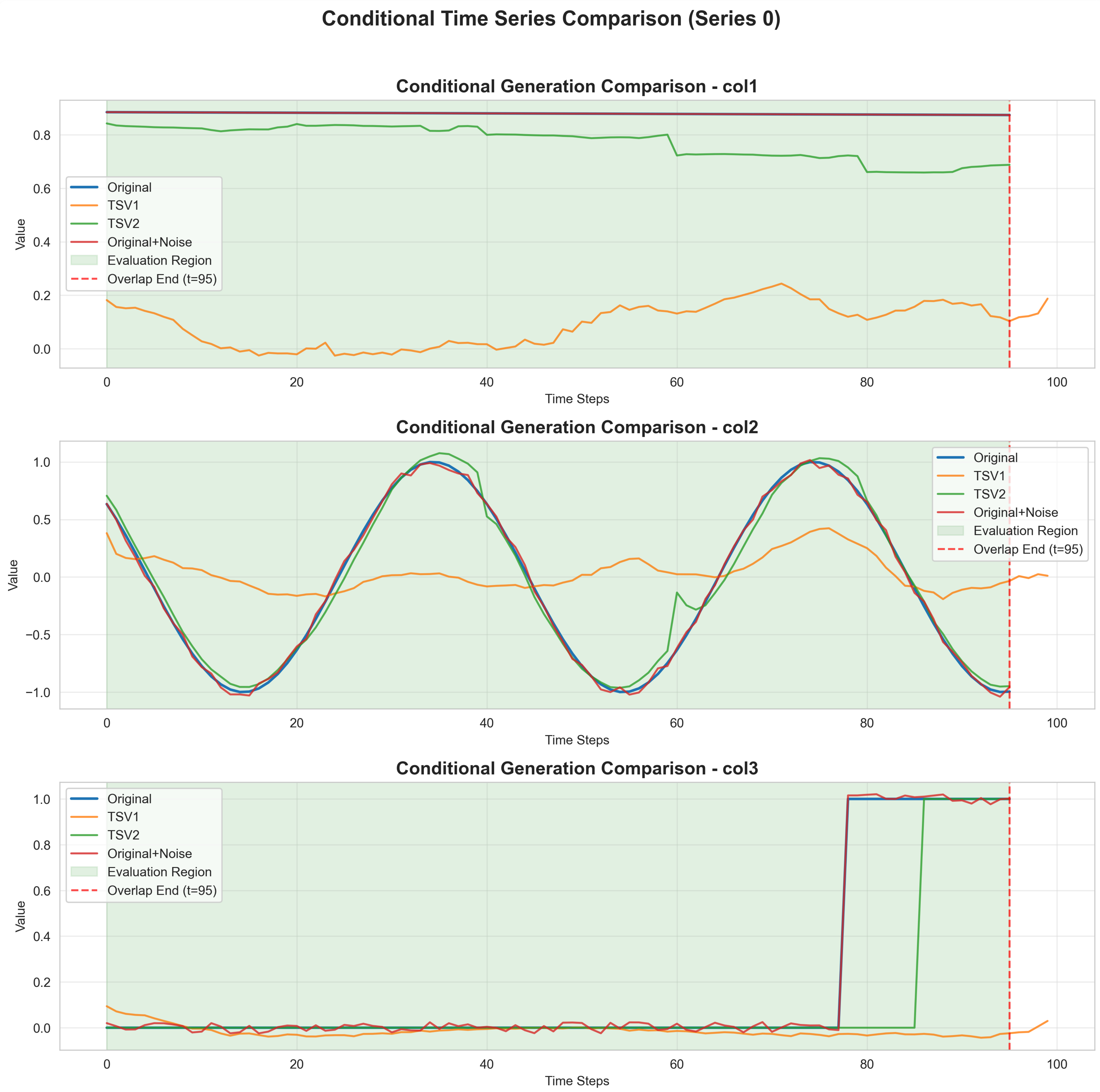


📊 Time Series Data Comparison & Analysis

Visual comparison and detailed performance analysis showing how synthetic methods compare to original data patterns.

🔗 Conditional Generation - Overall Comparison

Shows all 4 conditional variants (Original, TSV1, TSV2, Original+Noise) overlaid for direct comparison.



📊 Conditional Generation - Detailed Column Analysis

Performance breakdown for each column (col1, col2, col3) comparing Original+Noise baseline with synthetic methods.

📊 col1 - Method Comparison

Method	Diversity	Fidelity	Privacy	Utility
Original+Noise (Baseline)	0.999	1.000	0.410	1.000
TSV1	0.572	0.373	0.284	0.812
TSV2	0.906	0.689	0.261	0.963

📊 col2 - Method Comparison

Method	Diversity	Fidelity	Privacy	Utility
Original+Noise (Baseline)	1.000	0.978	0.801	0.989
TSV1	0.597	0.490	0.349	0.788
TSV2	0.994	0.828	0.234	0.961

📊 col3 - Method Comparison

Method	Diversity	Fidelity	Privacy	Utility
Original+Noise (Baseline)	0.961	0.789	0.285	0.989
TSV1	0.609	0.457	0.360	0.766
TSV2	0.918	0.798	0.225	0.957

🔄 Unconditional Generation - Overall Comparison

Shows all available unconditional variants overlaid for direct comparison.

⚠️ **Data Length Adjustment:** This evaluation uses only overlapping timesteps for fair comparison. Metrics are calculated only on the common time period where all variants have actual data, without any padding or truncation. Visualizations may show the full length of each series, but scoring reflects only the overlapping portion.

📊 Unconditional Generation - Detailed Column Analysis

Performance breakdown for each financial column (Open, High, Low, Close, Volume).

📊 Open - Method Comparison

Method	Diversity	Fidelity	Privacy	Utility

TSV2	0.306	0.659	0.473	0.849

📊 High - Method Comparison

Method	Diversity	Fidelity	Privacy	Utility
TSV2	0.314	0.651	0.474	0.844

📊 Low - Method Comparison

Method	Diversity	Fidelity	Privacy	Utility
TSV2	0.297	0.666	0.509	0.842

📊 Close - Method Comparison

Method	Diversity	Fidelity	Privacy	Utility
TSV2	0.297	0.668	0.513	0.854

📊 Volume - Method Comparison

Method	Diversity	Fidelity	Privacy	Utility
TSV2	0.358	0.852	0.406	0.832