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Review of BLS Employment Projection Methodologies: Foundations, Current Practices, and Opportunities for Enhancement

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Abstract: *This paper provides a comprehensive review of the U.S. Bureau of Labor Statistics (BLS) employment projection methodologies as documented in official BLS publications, including the Handbook of Methods, Monthly Labor Review articles, and technical documentation. The BLS Employment Projections program produces essential long-term forecasts of the labor force, industry output, and occupational employment that inform national policy and workforce development strategies. This review systematically examines the core methodological components: labor force projections using demographic models, macroeconomic projections of GDP and its components, industry output and employment projections using input-output analysis, and occupational employment projections based on industry staffing patterns. We analyze key technical documents including the occupational separations methodology, gross flows estimation frameworks, Bayesian inference for survey estimation, hedonic quality adjustment methods, multiple imputation techniques for missing data, and productivity measurement approaches. The review synthesizes findings from recent methodological innovations published in the Monthly Labor Review and working paper series, identifying strengths, limitations, and opportunities for enhancement. This comprehensive examination serves as a foundation for understanding how BLS methodologies might evolve to address emerging measurement challenges while maintaining historical continuity and statistical rigor.*

Keywords*:* Bureau of Labor Statistics; Employment Projections; Handbook of Methods; Monthly Labor Review; Occupational Separations; Gross Flows Estimation; Input-Output Analysis; Occupational Employment Statistics; Current Population Survey; Labor Force Projections; Industry Projections; Methodological Review; Statistical Infrastructure; Official Statistics

I. INTRODUCTION

The U.S. Bureau of Labor Statistics (BLS) Employment Projections program represents one of the most comprehensive and long-standing statistical endeavors in federal labor market measurement. For decades, the program has produced detailed projections of the labor force, economic growth, industry output and employment, and occupational employment and openings that serve as foundational inputs for educational planning, career guidance, and workforce development policy at federal, state, and local levels [1], [2].

The methodological framework underlying these projections is documented extensively in the BLS Handbook of Methods [3], [4], technical documentation [5], [6], [7], and numerous articles in the Monthly Labor Review [8], [9], [10]. This body of work represents decades of methodological refinement, incorporating advances in economic theory, statistical techniques, and data collection while maintaining the consistency and comparability essential for time series analysis.

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This paper provides a comprehensive review of BLS employment projection methodologies as documented in official sources. The review is organized around the core components of the projection system: labor force projections, macroeconomic projections, industry output and employment projections, and occupational employment projections. We examine the underlying data infrastructure, including the Current Population Survey (CPS), Occupational Employment and Wage Statistics (OEWS), O*NET database, Quarterly Census of Employment and Wages (QCEW), and American Time Use Survey (ATUS). We then review key methodological innovations documented in recent BLS publications, including gross flows estimation [11], Bayesian inference for survey estimation [12], hedonic quality adjustment [13], multiple imputation methods [14], and productivity measurement frameworks [15], [16]. The review synthesizes findings across these documents to identify strengths, limitations, and opportunities for methodological enhancement.

II. THE BLS EMPLOYMENT PROJECTIONS PROGRAM: OVERVIEW AND CORE COMPONENTS

A. Program Mission and Products

The BLS Employment Projections program develops long-term projections of the labor force, economic growth, industry output and employment, and occupational employment and openings [8]. These projections are published biennially with a 10-year horizon, providing stakeholders with consistent, comparable forecasts for planning and policy development.

As documented in the Employment Projections Frequently Asked Questions [1], the primary products include:

- Labor force projections by age, gender, race, and ethnicity
- Macroeconomic projections of GDP, productivity, and related aggregates
- Industry output and employment projections for detailed industries
- Occupational employment projections for over 800 detailed occupations
- Occupational openings projections, including replacements needs and growth
- Education and training assignments by occupation

B. Overview of BLS Statistics by Occupation

The Overview of BLS Statistics by Occupation [2] describes the comprehensive system of occupational statistics that supports the projections program. This includes:

- Occupational Employment and Wage Statistics (OEWS) providing current employment and wage estimates
- Current Population Survey (CPS) providing demographic and labor force characteristics
- American Time Use Survey (ATUS) providing detailed time-use data by occupation
- O*NET providing occupational task descriptions and skill requirements

C. Data Sources for Employment Projections

The Data Sources documentation [17] details the extensive statistical infrastructure underlying the projections program:

- **Current Population Survey (CPS)**: Monthly household survey of approximately 60,000 households, providing the primary source of labor force statistics
- **Current Employment Statistics (CES)**: Monthly establishment survey providing industry employment, hours, and earnings
- **Quarterly Census of Employment and Wages (QCEW)**: Administrative data from state unemployment insurance systems covering over 95% of U.S. jobs
- **Occupational Employment and Wage Statistics (OEWS)**: Semi-annual survey of establishments providing occupational employment and wage estimates
- **National Compensation Survey (NCS)**: Provides compensation cost trends and detailed benefit provisions
- **American Time Use Survey (ATUS)**: Measures time spent in work, leisure, and other activities
- **Consumer Expenditure Survey (CE)**: Provides data on consumer spending patterns

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- **O*NET Database**: Occupational information network providing task-level descriptions

III. LABOR FORCE PROJECTIONS METHODOLOGY

A. Demographic Projection Framework

The labor force projections methodology, documented in the Handbook of Methods [3], employs a demographic cohort approach. The civilian noninstitutional population is projected by age, gender, race, and ethnicity using Census Bureau population projections as a starting point. Labor force participation rates are projected for each demographic group using time series models that incorporate historical trends and expected changes in behavior.

The basic projection equation can be expressed as:

$$LF_t = \sum_{d \in D} P_{d,t} \times PR_{d,t}$$

Where:

- LF_t = labor force in year t
- $P_{d,t}$ = population for demographic group d in year t
- $PR_{d,t}$ = labor force participation rate for demographic group d in year t
- D = set of demographic groups defined by age, gender, race, and ethnicity

B. Historical Trends and Model Specification

The methodology incorporates historical data from the CPS to estimate participation rate trends. Time series models account for cyclical effects, structural changes, and cohort effects that may influence future participation. The models are specified separately for each demographic group to capture differential trends in labor force attachment.

IV. MACROECONOMIC PROJECTIONS METHODOLOGY

A. Overview of Macroeconomic Framework

The macroeconomic projections, described in the Calculation documentation [5], [6], provide the aggregate economic context for industry and occupational projections. The framework integrates:

- GDP projections by major expenditure category (consumption, investment, government, net exports)
- Productivity projections affecting output per worker relationships
- Price level projections affecting real vs. nominal relationships
- Interest rate and exchange rate assumptions affecting international competitiveness

B. GDP, GDI, and GDO in Productivity Analysis

[16] provides a detailed evaluation of alternative output measures for productivity analysis. The paper examines GDP (Gross Domestic Product), GDI (Gross Domestic Income), and GDO (Gross Domestic Output) as alternative measures of economic activity, finding that these measures diverge in ways that affect productivity calculations. For employment projections, which depend on forecasts of industry output per worker, the choice of output measure has cascading effects on projected labor demand.

The paper recommends careful consideration of measurement discrepancies when using output measures for productivity analysis, particularly in sectors undergoing rapid technological change where output quality improvements may be imperfectly captured in standard measures.

C. Productivity Measurement and Output Choice

[15] examines whether output choice matters for productivity measurement, finding that the selection among alternative output proxies generates materially different productivity estimates. This has direct implications for employment projections, as projected labor demand depends critically on assumed productivity growth rates.

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The paper reviews alternative output measures including:

- Sectoral output (gross output less intra-sector sales)
- Gross output (total production value)
- Value-added output (gross output less intermediate inputs)

Each measure captures different aspects of production and yields different productivity estimates, requiring careful matching of output measures to the economic questions being addressed.

V. INDUSTRY OUTPUT AND EMPLOYMENT PROJECTIONS

A. Input-Output Framework

The industry projections, documented in [8] and the Handbook of Methods [3], employ an input-output framework that captures inter-industry relationships. The approach begins with final demand projections for major categories (personal consumption, investment, government, exports), then uses input-output coefficients to derive industry output requirements.

The basic input-output relationship can be expressed as:

$$X = (I - A)^{-1}F$$

Where:

- X = vector of industry outputs
- F = vector of final demands
- A = matrix of input-output coefficients
- $(I - A)^{-1}$ = Leontief inverse matrix

B. Industry Growth Patterns Analysis

[10] provides comprehensive analysis of industry growth patterns from 1990 to 2024, examining output, productivity, and hours worked. This historical analysis reveals:

- Differential growth rates across major industry sectors
- Changing relationships between output and employment over time
- Productivity growth patterns varying by industry and time period
- Cyclical sensitivity differences across industries

This historical context is essential for validating projection methodologies and understanding how structural changes affect industry-employment relationships.

C. Industry Employment Projections

Industry employment projections are derived from output projections and productivity assumptions. For each industry, employment is projected as:

$$E_{i,t} = \frac{Q_{i,t}}{P_{i,t}}$$

Where:

- $E_{i,t}$ = employment in industry i in year t
- $Q_{i,t}$ = output in industry i in year t
- $P_{i,t}$ = productivity (output per worker) in industry i in year t

Productivity trends are projected using historical patterns modified by expected technological and organizational changes.

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VI. OCCUPATIONAL EMPLOYMENT PROJECTIONS

A. Staffing Pattern Approach

The occupational employment projections, detailed in [8] and the Calculation documentation [5], [6], use industry staffing patterns to allocate industry employment to occupations. The approach can be summarized as:

$$O_{j,t} = \sum_{i} E_{i,t} \times S_{i,j,t}$$

Where:

- $O_{j,t}$ = employment in occupation j in year t
- $E_{i,t}$ = employment in industry i in year t
- $S_{i,j,t}$ = staffing pattern coefficient (share of industry i employment in occupation j in year t)

Staffing patterns are derived from OEWS survey data and are projected forward using trend analysis and expected technological and organizational changes.

B. Occupational Separations Methodology

The Occupational Separations Methodology [7] provides the framework for estimating worker flows out of occupations. This is essential for projecting replacement needs, which often exceed growth-related openings in determining total job opportunities.

The methodology distinguishes between:

- **Separations due to labor force exits**: Workers leaving the labor force due to retirement, disability, or other reasons
- **Occupational transfers**: Workers moving to different occupations while remaining in the labor force

Separation rates are estimated using CPS data on worker transitions, with separate rates calculated by occupation, age, and other characteristics. The basic relationship is:

$$R_{j,t} = E_{j,t} \times (r_{j,t}^{exit} + r_{j,t}^{transfer})$$

Where:

- $R_{j,t}$ = replacement needs in occupation j in year t
- $E_{j,t}$ = employment in occupation j in year t
- $r_{j,t}^{exit}$ = labor force exit rate for occupation j in year t
- $r_{j,t}^{transfer}$ = occupational transfer rate for occupation j in year t

C. Gross Flows Estimation

[11] presents a detailed methodology for estimating gross flows from matched Current Population Survey data. Gross flows measure the dynamic transitions of workers between labor force states (employed, unemployed, not in labor force) and between occupations, capturing the underlying dynamics that net change measures obscure.

The methodology involves:

1. Matching CPS records for individuals across consecutive months
1. Applying population weights to produce nationally representative estimates
2. Using Stasny-Fienberg reconciliation methods to produce consistent gross flows tables
3. Estimating variances through replication methods (balanced repeated replication or jackknife)

The paper produces estimated gross flows tables for CPS from 2003-2023, providing a valuable resource for understanding labor market dynamics and validating projection methodologies.

D. Occupational Case Studies

[9] presents occupational case studies examining how AI impacts might be incorporated into BLS employment projections. The case studies examine specific occupations where technological change is likely to have significant effects, including:

- Software developers
- Customer service representatives
- Legal occupations
- Healthcare practitioners

For each occupation, the analysis examines:

- Current task structure from O*NET
- Historical employment trends
- Expected technological impacts
- Potential modifications to projection methodology

These case studies provide a foundation for developing systematic approaches to incorporating technology impacts into occupational projections.

VII. O*NET AND TASK-LEVEL ANALYSIS

A. O*NET Database Structure

The O*NET database, described in the Handbook of Methods [4], provides the primary source of occupational task information for BLS projections. The database includes:

- Task statements describing work activities
- Importance ratings for each task within occupations
- Skill, knowledge, and ability requirements
- Work context and work style information

O*NET data are collected through surveys of workers and occupational analysts, with updates on a rotating basis across occupational groups.

B. Integration with Employment Projections

O*NET data are used in employment projections primarily for:

- Validating occupational classifications
- Assessing skill requirements for education and training assignments
- Understanding task composition for technology impact assessment
- Supporting occupational separations analysis through task similarity measures

VIII. ADVANCED STATISTICAL METHODOLOGIES IN BLS PUBLICATIONS

A. Bayesian Inference for Informative Sampling

[12] develops a Bayesian inference framework for repeated measures under informative sampling. This is particularly relevant for labor market surveys where inclusion probabilities may be correlated with outcomes of interest. The framework accounts for:

- Complex survey designs with stratification and clustering
- Informative sampling where selection probabilities depend on the outcome variable
- Repeated measurements over time with potential panel attrition
- Hierarchical modeling to borrow strength across domains

The methodology has important applications for reducing bias in occupational wage and employment estimates, particularly for fast-changing sectors where response rates may vary systematically.

B. Hedonic Quality Adjustment Methods

[13] evaluates hedonic methods of quality adjustment under static pricing conditions, with application to PPI microprocessors. Hedonic methods adjust prices for quality changes by regressing prices on product characteristics, then using the estimated coefficients to value quality differences.

Key findings include:

- The relative performance of alternative hedonic specifications depends on sample size
- For small product samples (typical for rapidly changing products like microprocessors), time-dummy hedonics have lower variance than more flexible specifications
- The choice of functional form matters less than the stability of implicit prices over time

These insights are relevant for measuring AI-driven quality changes in labor inputs and outputs, where traditional price measures may not capture productivity improvements.

C. Multiple Imputation Methods for Missing Data

[14] investigates alternatives to current cell mean imputation procedures for missing price data in the Producer Price Index. The study examines:

- CART (Classification and Regression Trees)
- Random Forest imputation
- AMELIA multiple imputation
- Hybrid methods combining cell mean and random forest techniques

The simulation results demonstrate that multiple imputation methods can outperform traditional cell mean imputation, particularly when missing data patterns are complex and auxiliary information is available. These approaches could be adapted for imputing missing employment and wage data in occupational surveys.

D. Labor Market Concentration Analysis

[18] provides detailed analysis of concentrated labor markets in the United States using OEWS microdata. Key findings include:

- Labor market concentration is primarily a characteristic of small labor markets, whether defined by geographic area or by occupation
- More concentrated labor markets are associated with slightly lower wages, but only within the private sector
- Concentration measures vary significantly across areas and occupations, with implications for understanding market power and wage determination

[19] develops measures of the occupational homogeneity of employers as indicators of outsourcing. The analysis finds that wages are strongly related to occupational homogeneity, particularly for workers in low-wage occupations, suggesting that outsourcing and organizational structure affect wage outcomes.

E. Time Series Analysis of Price Index Weights

[20] presents time series analysis of Consumer Price Index products and weights, examining how consumption patterns evolve over time and how weight updates affect index measurements. The methodology for detecting structural breaks and trend changes in weight series has applications for dynamic updating of occupational weights in response to labor market changes.

IX. HISTORICAL DATA AND TREND ANALYSIS

A. Industry Growth Patterns 1990-2024

[10] provides comprehensive historical analysis of industry growth patterns, examining:

- Output growth by major industry sector
- Productivity trends and their determinants

- Hours worked and employment patterns
- Relationships between output, productivity, and employment over time

This historical record is essential for validating projection methodologies and understanding how structural changes affect industry-employment relationships.

B. Growth Trends in Automation-Risk Occupations

[21] examines growth trends for selected occupations considered at risk from automation. The analysis provides baseline data for understanding how automation-risk occupations have evolved historically, informing projections of how AI may accelerate or alter these trends.

C. Productivity and Progress Literature Review

[22] reviews the literature on productivity and progress, examining how productivity measurement has evolved and how technological change affects productivity trends. This historical perspective informs current understanding of how AI might affect productivity measurement and employment projections.

X. ASSESSING NEW TECHNOLOGY IMPACTS

A. Congressional Report on Technology Assessment

[23] provides key constructs, gaps, and data collection strategies for assessing the impact of new technologies on the labor market. This report, prepared for Congress, identifies:

- Current BLS capabilities for measuring technology impacts
- Data gaps that limit understanding of technology-labor relationships
- Potential strategies for enhancing data collection and analysis
- Priority areas for methodological development

B. Measuring Effects of New Technologies

The associated documentation [24] elaborates on the data collection strategies needed to better measure technology impacts, including:

- Longitudinal tracking of technology adoption within establishments
- Linked employer-employee data connecting firm-level technology investment to worker outcomes
- Enhanced occupational task data capturing technology use
- Real-time indicators of emerging technology adoption

XI. SYNTHESIS AND DISCUSSION

A. Strengths of Current BLS Methodologies

The review reveals several significant strengths in current BLS employment projection methodologies:

1. **Comprehensive framework**: The multi-stage projection system integrates labor force, macroeconomic, industry, and occupational projections into a coherent whole, ensuring consistency across levels of analysis.
2. **Rich data infrastructure**: The combination of household surveys (CPS), establishment surveys (OEWS, CES), administrative data (QCEW), and specialized surveys (ATUS, O*NET) provides multiple perspectives on labor market phenomena.
3. **Methodological rigor**: Advanced statistical methods, including Bayesian inference for survey estimation, gross flows analysis, and multiple imputation techniques, address complex measurement challenges.
4. **Historical continuity**: Consistent methodologies over time enable reliable trend analysis and validation of projection accuracy.
5. **Transparency**: Detailed documentation in the Handbook of Methods, technical papers, and Monthly Labor Review articles ensures that methodologies are accessible to researchers and stakeholders.

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6. **Ongoing innovation**: Recent publications demonstrate active methodological development addressing emerging challenges.

B. Limitations and Challenges

Several limitations emerge from the review:

1. **Temporal lags**: Survey-based data collection introduces delays between economic changes and their measurement, limiting responsiveness to rapid technological shifts.
2. **Aggregate occupational categories**: Standard occupational classifications may mask substantial heterogeneity in technology exposure at the task level.
3. **Correlational frameworks**: Projection methods rely primarily on historical relationships that may not hold when technology fundamentally alters production processes.
4. **Static skill assumptions**: Occupational skill requirements are updated infrequently, potentially missing rapid changes in skill demands.
5. **Limited real-time indicators**: The current system lacks high-frequency indicators of emerging technology adoption and labor market adjustment.
6. **Geographic aggregation**: National projections may obscure significant regional variation in technology impacts and labor market conditions.

C. Opportunities for Enhancement

Building on existing BLS infrastructure, several enhancement opportunities emerge:

1. **Enhanced task-level analysis**: Leverage O*NET task data more intensively for technology exposure assessment, building on occupational case study approaches in [9].
2. **Expanded gross flows analysis**: Extend the gross flows methodology of [11] to track technology-induced transitions specifically.
3. **Dynamic skill updating**: Adapt the time series reweighting methods of [20] for more frequent occupational skill profile updates.
4. **Multiple imputation for missing data**: Implement the hybrid imputation approaches demonstrated in [14] for occupational employment estimation.
5. **Productivity measurement refinement**: Apply hedonic quality adjustment methods from [13] to better capture technology-driven quality improvements.
6. **Bayesian bias reduction**: Implement the informative sampling frameworks from [12] to reduce bias in estimates for fast-changing sectors.
7. **Geographic disaggregation**: Develop place-based projection components using OEWS microdata and labor market concentration analysis from [18].
8. **Validation using historical data**: Leverage the comprehensive historical series in [10] for rigorous backtesting of enhanced methodologies.

TABLE 1: SUMMARY OF BLS METHODOLOGICAL DOCUMENTATION REVIEWED

Methodology Area	Key Documents	Primary Contributions	Year
Employment Projections Framework	[5], [6], [8]	Industry-occupational matrix approach, staffing patterns	2024
Handbook of Methods	[3], [4], [25]	Comprehensive methodology documentation	Ongoing
Gross Flows Estimation	[11]	Stasny-Fienberg reconciliation, CPS matched data	2023
Occupational Separations	[7]	Replacement needs estimation, transition rates	Current
Bayesian Inference	[12]	Informative sampling adjustment, bias reduction	2024
Hedonic Quality Adjustment	[13]	Quality adjustment under static pricing	2024

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Methodology Area	Key Documents	Primary Contributions	Year
Multiple Imputation	[14]	CART, Random Forest, AMELIA methods	2024
Labor Market Concentration	[18], [19]	OEWS-based concentration analysis	2023-2024
Productivity Measurement	[15], [16]	Output measure evaluation, productivity analysis	2024-2026
Industry Growth Analysis	[10]	Historical growth patterns 1990-2024	2025
Technology Impact Assessment	[23], [24]	Data gaps, collection strategies	2024
Occupational Case Studies	[9]	AI impact incorporation frameworks	2025
Price Index Methods	[20]	Dynamic weight updating, time series analysis	2024
Automation-Risk Trends	[21]	Historical trends in automation-risk occupations	2024
Productivity Literature	[22]	Historical review of productivity research	2017
Data Sources	[2], [17]	Comprehensive data infrastructure description	Current

XII. CONCLUSION

This comprehensive review of BLS employment projection methodologies, drawing exclusively on official BLS publications and documentation, reveals a sophisticated statistical infrastructure developed over decades of methodological refinement. The multi-stage projection system integrates labor force demographics, macroeconomic aggregates, industry input-output relationships, and occupational staffing patterns into a coherent framework that has served policymakers, educators, and workforce development professionals effectively for generations.

The review documents the rich methodological foundation underlying BLS projections, including:

- Demographic cohort models for labor force projections
- Input-output analysis for industry output and employment relationships
- Staffing pattern approaches for occupational employment allocation
- Occupational separations methodology for replacement needs estimation
- Gross flows estimation for capturing labor market dynamics
- Advanced statistical methods including Bayesian inference, hedonic quality adjustment, and multiple imputation
- Comprehensive data infrastructure spanning household surveys, establishment surveys, administrative records, and specialized data collections

Recent methodological innovations documented in BLS publications demonstrate ongoing commitment to improvement:

- Enhanced gross flows estimation using matched CPS data [11]
- Bayesian inference frameworks for informative sampling [12]
- Multiple imputation methods for missing data handling [14]
- Hedonic quality adjustment for rapidly changing products [13]
- Occupational case studies for technology impact assessment [9]
- Time series methods for dynamic weight updating [20]

The review also identifies opportunities for methodological enhancement that build naturally on existing BLS infrastructure:

1. Enhanced task-level analysis leveraging O*NET data for technology exposure assessment
2. Expanded gross flows analysis distinguishing technology-induced transitions
3. Dynamic skill weight updating using price index methodology adaptations
4. Multiple imputation implementation for occupational employment estimation
5. Productivity measurement refinement capturing technology-driven quality improvements

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6. Bayesian bias reduction for fast-changing sector estimates
7. Geographic disaggregation using OEWS microdata and concentration analysis
8. Historical validation using comprehensive industry growth series

These enhancements would maintain continuity with BLS historical data while improving the system's ability to capture rapid technological change. The foundation established through decades of methodological development provides a solid basis for evolution, ensuring that BLS employment projections continue to serve as reliable guides for workforce development and education policy in an era of technological transformation.

Future research should focus on operationalizing these enhancements within the existing BLS framework, validating their performance against historical data, and developing implementation strategies that maintain the consistency and comparability essential for time series analysis. The rich methodological literature documented in this review provides ample foundation for such development, ensuring that BLS projection methodologies can evolve to meet emerging challenges while preserving their core strengths.

DECLARATION

The views expressed are those of the author and do not represent any affiliated institutions. This work is conducted as part of independent research. This is a review paper drawing exclusively on published BLS documentation and official sources. All findings and proposals are derived from the cited literature. The author's work was to review, organize, and synthesize existing BLS methodological documentation.

Portions of this manuscript were drafted with the assistance of AI writing tools to improve clarity and organization. All AI-generated content was reviewed, edited, and verified by the author. The LaTeXcode was developed with the assistance of GitHub Copilot and edited through DeepSeek. Final responsibility for all content, including any errors or omissions, rests solely with the author.

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