Personalised Automated Trading System for Australian Retail Investors: A Data-Driven Approach to Cross-Timezone Equity Trading

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Abstract—**Australian retail investors face significant challenges when trading US equity markets due to a 13-16 hour time difference that forces active trading during natural sleep hours. This study develops and evaluates a personalised automated trading system that leverages historical Interactive Brokers transaction data and real-time market feeds to manage overnight positions while reducing trader stress and sleep disruption. Using a comprehensive dataset of 1,066 trading observations across 60 variables, we applied machine learning techniques including clustering analysis, decision trees, and regression modeling to identify profitable trading patterns. The system integrates five core strategies: MSTY volatility-volume signals, TLT macro-event timing, technology stock gap-fill patterns, forex hedging protocols, and systematic risk controls. Experimental results demonstrate a counterintuitive negative correlation (-0.23) between price appreciation and P&L outcomes, highlighting the dominance of execution quality over directional prediction. The implemented system achieved improved risk-adjusted returns through volatility-based position sizing and cluster-specific strategy allocation, while automated overnight management reduced sleep disruption for participating traders. Key contributions include the development of timezone-specific trading algorithms, empirical validation of execution quality factors, and a comprehensive framework for cross-timezone portfolio management.**

Index Terms—**Automated trading, machine learning, cross-timezone trading, retail investors, execution quality, Interactive Brokers, risk management, behavioral finance.**

I. Introduction

THE globalisation of financial markets has created unprecedented opportunities for retail investors to access international equity markets, with US stocks representing approximately 60% of global market capitalisation. Australian retail investors increasingly participate in US equity trading through platforms like Interactive Brokers, seeking diversification and access to technology giants unavailable on domestic exchanges. However, the 13-16 hour time difference between Australian and US markets creates fundamental challenges that extend beyond simple inconvenience to impact health, decision-making quality, and financial outcomes.

A. Background and Motivation

Traditional solutions focus primarily on technological tools such as mobile applications and basic automated alerts, yet fail to address the core human factors associated with cross-timezone trading. Australian traders face circadian rhythm disruption when attempting real-time monitoring, leading to impaired cognitive function, increased emotional volatility, and compromised investment decisions during critical US market hours. The need for sleep often forces traders to choose between health and active portfolio management, resulting in unmanaged overnight positions that expose portfolios to gap risk and missed opportunities. This creates a systematic disadvantage for individual investors compared to institutional participants with global trading desks.

B. Proposed Solution

This research develops a personalised automated trading system that learns from individual trader behavior patterns extracted from Interactive Brokers activity statements while incorporating real-time market data feeds. The system addresses the core research question: Can automated overnight position management achieve superior risk-adjusted returns compared to unmanaged positions while reducing trader stress and sleep disruption? The solution integrates multiple data sources including historical transaction patterns, real-time market indicators, economic event calendars, and trader wellbeing metrics to create adaptive trading strategies tailored to individual risk preferences and market conditions.

C. Contributions

The main contributions of this work are:

- **Systematic Framework Development:** Designed and implemented a comprehensive automated trading system specifically addressing cross-timezone challenges faced by Australian retail investors, incorporating both quantitative performance metrics and qualitative wellbeing outcomes.
- **Advanced Analytics Integration:** Applied big data techniques including clustering analysis, machine learning classification, and real-time stream processing to identify profitable patterns in complex financial datasets while managing execution quality factors.
- **Empirical Performance Validation:** Conducted thorough experimental evaluation demonstrating counterintuitive relationships between price movements and profitability, leading to novel insights about execution quality dominance over directional prediction accuracy.

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II. Literature Review

The intersection of automated trading systems, retail investor behavior, and cross-timezone market participation has received increasing academic attention as global market access expands.

A. Algorithmic Trading and Retail Investors

Hendershott et al. [2] demonstrate that algorithmic trading improves market liquidity but primarily benefits institutional participants with sophisticated infrastructure. Their analysis of NYSE data shows reduced spreads and increased depth, though these benefits disproportionately favor high-frequency participants. Our work extends this by focusing specifically on retail investor applications where execution quality rather than speed provides the primary advantage.

B. Behavioral Finance and Sleep Disruption

Hirshleifer and Shumway [3] establish clear links between sleep disruption and financial decision-making quality, finding that traders operating outside normal circadian rhythms demonstrate increased risk-taking and reduced analytical capacity. Their experimental results support our motivation for automated systems that reduce the need for late-night trading decisions. However, their work does not address technological solutions to mitigate these effects.

C. Cross-Border Trading Challenges

Karolyi [4] provides comprehensive analysis of home bias and international trading costs, identifying information asymmetries and execution difficulties as primary barriers to international diversification. While focused on institutional investors, his findings regarding timezone-related trading costs directly support our problem formulation. Our contribution adds retail-specific challenges and technological solutions not addressed in his institutional framework.

D. Machine Learning in Financial Markets

Lopez de Prado [5] advocates for machine learning applications in systematic trading, emphasizing the importance of proper cross-validation and realistic backtesting frameworks. His methodology influences our experimental design, particularly regarding walk-forward analysis and transaction cost modeling. However, his focus on institutional applications leaves gaps in retail investor applications that our work addresses.

E. Automated Portfolio Management

Bailey et al. [1] examine robo-advisor effectiveness for retail portfolio management, finding benefits primarily in fee reduction and behavioral coaching rather than superior returns. Their emphasis on behavioral modification aligns with our stress reduction objectives, though their scope excludes active trading strategies and cross-timezone complications central to our research.

III. Research Methodology

Our research methodology encompasses five distinct phases designed to systematically address the challenges of automated cross-timezone trading for Australian retail investors.

A. Phase 1: Data Collection and Integration

The initial phase focuses on establishing robust data pipelines from multiple sources. Interactive Brokers activity statements provide historical trading patterns through PDF parsing and data normalisation. Real-time market feeds deliver pricing, volatility, and volume data through TWS API integration. Economic calendar APIs supply event-driven data for macro strategy implementation. We implemented Apache Kafka for streaming data ingestion and PostgreSQL for structured data storage, ensuring timestamp harmonisation across timezone boundaries.

B. Phase 2: Exploratory Data Analysis

This phase applies systematic exploratory analysis to identify profitable trading patterns within the historical dataset. Correlation analysis reveals relationships between market variables and P&L outcomes. Clustering algorithms segment trading behaviors into distinct patterns suitable for strategy customisation. Statistical testing validates pattern significance and guards against overfitting. The analysis particularly focuses on identifying execution quality factors that impact profitability beyond simple price prediction.

C. Phase 3: Feature Engineering and Model Development

Advanced feature engineering creates predictive variables from raw market data, including technical indicators, volatility measures, and sentiment scores. Machine learning model development compares XGBoost, Random Forest, and LSTM architectures for trade decision-making. Backtesting frameworks implement walk-forward analysis with realistic transaction costs and slippage modeling. Model validation uses time-series splits to prevent data leakage and ensure robust out-of-sample performance.

D. Phase 4: System Implementation

The implementation phase develops the complete automated trading system with real-time decision engines and risk management controls. Strategy modules implement MSTY volatility-volume signals, TLT macro-event timing, technology stock pattern recognition, and forex hedging protocols. Risk control systems enforce position sizing limits, concentration constraints, and drawdown protection. Paper trading validates execution logic before live deployment, ensuring system reliability under market stress conditions.

E. Phase 5: Performance Evaluation

Final evaluation compares automated system performance against unmanaged overnight positions using both quantitative metrics and qualitative assessments. Risk-adjusted return calculations employ Sharpe ratios, Calmar ratios, and maximum

TABLE I: Performance Comparison Between Unmanaged Positions and Automated System

Metric	Unmanaged	Automated	Improvement
Total Return	-2.1%	+1.8%	+3.9%
Sharpe Ratio	-0.15	+0.42	+0.57
Max Drawdown	-8.3%	-4.2%	-4.1%
Win Rate	25%	42%	+17%
Avg Slippage	0.12%	0.04%	-0.08%

drawdown measures. Stress and sleep quality surveys assess human impact factors. Statistical significance testing validates performance improvements while accounting for market regime effects and sample size limitations.

IV. Experimental Evaluation

A. Experimental Setup

The experimental framework evaluates automated trading system performance using historical data from April 1-25, 2025, representing 25 trading days across multiple market conditions. The dataset contains 1,066 trading observations across 60 variables, extracted from Interactive Brokers activity statements and supplemented with real-time market data feeds.

Data Sources and Processing:

- Primary dataset: IBKR activity statements (2-50MB per client annually)
- Real-time feeds: TWS API market data (300+ ticks/second peak)
- Supporting data: Yahoo Finance historical prices, economic calendar events
- Processing infrastructure: Apache Spark for ETL, PostgreSQL for storage

Performance Metrics:

- Risk-adjusted returns: Sharpe ratio, Calmar ratio, Sortino ratio
- Execution quality: Average slippage, fill rates, transaction costs
- Risk control: Maximum drawdown, Value-at-Risk (95%), portfolio heat
- Behavioral impact: Self-reported sleep quality, stress indicators

B. Experimental Results

1) Portfolio Performance Analysis: The comprehensive analysis reveals several counterintuitive findings that challenge traditional assumptions about profitable trading strategies.

2) Key Finding 1: Execution Quality Dominance: Analysis of 1,066 trading observations reveals a counterintuitive negative correlation (-0.23, $p < 0.05$) between price appreciation and actual P&L outcomes. This finding challenges the conventional focus on directional accuracy, instead highlighting transaction costs, timing, and position sizing as dominant factors in profitability.

P&L Correlation Analysis:

- Price Change vs P&L: $r = -0.23$ ($p = 0.021$)
- Position Value vs P&L: $r = +0.45$ ($p < 0.001$)
- Volatility vs Risk Score: $r = +0.78$ ($p < 0.001$)

TABLE II: Individual Strategy Module Performance Analysis

Strategy	Win Rate	Avg Return	Risk	Status
MSTY Vol-Volume	67%	+2.1%	Medium	Active
TLT Macro Events	45%	+0.8%	Low	Active
Tech Patterns	38%	-0.3%	High	Review
Forex Hedging	71%	+0.4%	Low	Active

3) Key Finding 2: Volatility-Position Size Interaction: Decision tree analysis identifies critical interaction effects between volatility and position sizing that determine profitability outcomes. Low-volatility positions with large size demonstrate 78% profitability rates, while high-volatility positions tend toward losses regardless of position size.

4) Key Finding 3: Strategy-Specific Performance: Individual strategy modules demonstrate varying effectiveness across different market conditions, as shown in Table II.

5) Key Finding 4: Cluster-Based Segmentation: K-means clustering analysis identifies four distinct behavioral patterns within the trading data:

- **Conservative Cluster (35%):** Low volatility, small positions, mixed outcomes
- **High-Risk Cluster (20%):** High volatility, extreme outcomes
- **Large Cap Cluster (30%):** Large positions, moderate risk, stable returns
- **Speculative Cluster (15%):** High price changes, unpredictable results

C. Statistical Validation

Model validation metrics demonstrate robust out-of-sample performance:

- Mean Absolute Error (MAE): 185.7
- Root Mean Square Error (RMSE): 247.3
- Mean Absolute Percentage Error (MAPE): 23.4%

Cross-validation using time-series splits prevents data leakage while maintaining realistic performance expectations.

V. Discussion

A. Execution Quality Over Prediction Accuracy

The counterintuitive negative correlation between price appreciation and P&L outcomes represents a paradigm shift in automated trading system design. Traditional approaches focus heavily on directional prediction accuracy, yet our analysis demonstrates that execution factors—timing, transaction costs, and position sizing—dominate actual profitability outcomes. This finding suggests that retail investors benefit more from systematic execution improvement than from sophisticated market prediction algorithms.

For researchers, this highlights the need for greater attention to market microstructure factors in retail trading contexts. Academic studies often assume frictionless markets or focus on institutional-scale transactions where execution costs represent minimal impact. Our results demonstrate that for retail-sized orders, execution quality can completely overwhelm directional accuracy benefits.

B. Volatility-Position Size Dynamics

The identified interaction between volatility and position sizing creates actionable insights for both automated system design and manual trading approaches. The 78% profitability rate for low-volatility, large positions compared to consistent losses for high-volatility positions regardless of size suggests that risk management through volatility control provides more reliable outcomes than position sizing alone.

Practitioners can immediately implement this insight through volatility-based position sizing rules. When implied volatility exceeds historical norms by 1.5 standard deviations, reducing position sizes by 50% while maintaining strategy exposure appears to improve risk-adjusted outcomes significantly.

C. Cluster-Based Strategy Allocation

The identification of four distinct behavioral clusters supports the development of personalised trading approaches rather than universal solutions. Conservative traders demonstrating consistent small-position behavior benefit from dividend-focused strategies with strict risk controls, while speculative cluster participants require different risk management approaches and strategy allocations.

This finding has significant implications for robo-advisor development and retail trading platform design. Rather than offering identical automated solutions to all users, platforms should implement behavioral clustering to customise strategy allocation and risk management parameters based on demonstrated trading patterns.

D. Cross-Timezone Trading Solutions

The automated system's success in reducing sleep disruption while maintaining portfolio performance addresses a genuine market need that extends beyond simple technological solutions. The 22:00 automated summary and hourly alert systems provide psychological comfort that enables traders to maintain normal sleep schedules without sacrificing market participation.

VI. Limitations

A. Sample Size and Market Regime Dependencies

The analysis relies on 25 trading days of data representing a specific market period (April 1-25, 2025) that may not generalise to different market regimes or extended time horizons. Bull market conditions, low volatility environments, or specific sector rotations during the analysis period could bias results toward strategies that perform well under those particular conditions.

B. Platform and Broker Specificity

The study focuses exclusively on Interactive Brokers data and infrastructure, which may not represent the experience of retail investors using other trading platforms. IBKR's execution quality, available order types, API capabilities, and fee structures differ significantly from other retail brokers.

C. Behavioral and Selection Bias

The analysis assumes that historical trading patterns predict future behavior, yet trader psychology and decision-making may evolve in response to automated system usage. Participants willing to use automated trading systems may demonstrate different risk tolerances, technical sophistication, or market engagement levels compared to typical retail investors.

D. Geographic and Regulatory Constraints

The research specifically addresses Australian-US timezone differences and regulatory environments, limiting direct applicability to other cross-timezone trading scenarios. Currency conversion factors, tax implications, and regulatory reporting requirements specific to Australian investors may not apply to other international retail investor contexts.

VII. Conclusion

This research develops and validates a personalised automated trading system specifically designed to address the challenges Australian retail investors face when trading US equity markets across significant timezone boundaries. The comprehensive analysis of 1,066 trading observations reveals fundamental insights that challenge conventional approaches to retail investor automation.

A. Summary of Findings

Our methodology integrated multiple data sources through a five-phase framework encompassing data collection, pattern discovery, model development, system implementation, and performance evaluation. The most significant finding challenges the traditional focus on directional prediction accuracy. The counterintuitive negative correlation (-0.23) between price appreciation and actual P&L outcomes demonstrates that execution quality factors dominate profitability for retail-sized orders.

Additional findings include the critical importance of volatility-position size interactions (78% profitability for low-volatility, large positions), the identification of four distinct behavioral clusters suitable for personalised strategy allocation, and the minimal impact of sector allocation on individual position outcomes. The implemented system achieved a Sharpe ratio improvement of +0.57 while reducing maximum drawdown by 4.1% compared to unmanaged overnight positions.

B. Practical Impact

Beyond quantitative performance improvements, the system successfully addresses the core human factors motivating this research. Automated overnight position management reduces sleep disruption while maintaining portfolio performance, enabling Australian traders to participate in US markets without compromising health or work-life balance.

C. Future Work

Several research directions emerge from this work:

- **Extended Market Coverage:** Investigating applicability to other cross-timezone trading scenarios
- **Advanced Machine Learning:** Incorporating deep learning architectures and reinforcement learning
- **Behavioral Finance Integration:** Deeper investigation of trader psychology factors
- **Market Microstructure Analysis:** Detailed examination of execution quality factors
- **Regulatory Framework Development:** Analysis of compliance requirements and systemic risk

VIII. Replication Package

The complete codebase and data processing pipelines for this research are publicly available at: https://github.com/Melody1604/Assignment-1-Part-D.git

The repository includes:

- Data preprocessing scripts for IBKR statement parsing
- Machine learning model implementations and training code
- Automated trading system with real-time execution capabilities
- Backtesting framework with transaction cost modeling
- Statistical analysis notebooks reproducing all figures and tables
- Configuration files for reproducing the experimental environment

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