

**QUANTUM AI POWERED LANGUAGE MODEL TO PREDICT FUTURE USING
ASTROLOGY, ASTRONOMY AND BEHAVIOURAL SCIENCE
OF HUMANS**

by

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Dedication

To my beloved family and cherished well-wishers, your unwavering encouragement and faith in me have been the driving force that sustained my determination to complete this thesis.

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Completing this thesis has been both a rigorous intellectual pursuit and a profound journey of philosophical and personal growth. I am deeply indebted to Professor Kamal Malik, whose mentorship encouraged me to challenge conventional wisdom and engage with complex ideas. Her guidance sharpened my analytical skills and deepened my understanding of the conceptual foundations of my research.

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The open-source quantum computing community, particularly the teams behind IBM Qiskit, Google Cirq, and Xanadu PennyLane, has created an extraordinary ecosystem that puts research-grade quantum simulation within reach of a Python developer on a standard workstation. The Apache 2.0 licensing of all three frameworks enabled the comparative evaluation. The respective documentation teams deserve recognition for the care and clarity with which they explain concepts that are genuinely novel to most practitioners.

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Acknowledgement is due to the broader research community engaged in the ethics of

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Finally, I am equally grateful to my family, whose spirited philosophical discussions and curiosity nurtured my passion for this field. Their steadfast encouragement and faith in my academic journey have been pivotal to my success.

This dissertation stands not only as a testament to my own efforts but also as a reflection of the collective influence of those who have shaped me personally and academically. Through this journey, I have learned the enduring value of inquiry and how diverse perspectives can enrich our understanding of complex problems.

ABSTRACT
QUANTUM AI POWERED LANGUAGE MODEL TO PREDICT FUTURE USING
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The present project advances a language model powered by Quantum AI to predict the future utilizing symbolic, empirical and behavioral data from astrology, astronomy and behavioral science. The study aims to address the deterministic limitations of classical AI using quantum superposition and entanglement by leveraging it for multidimensional predictions.

Astrological archetypes, astronomical ephemerides and behavioral data were encoded in a hybrid quantum transformer configuration. We used quantum attention mechanisms and probabilistic optimization to correlate the symbolic and empirical features.

Comparisons were made between uncertainty handling, interpretability, and cross-domain synthesis along with classical baselines. It indicates that the quantum model has improved capabilities in uncertainty management and heterogeneous data integration. Societal forecasting, decision-making, and market behavior case studies demonstrate greater adaptability and probabilistic insight. That said, interpretability and ethical transparency are key aspects for future refinement. It positions prediction in a paradigm of probabilistic synthesis rather than deterministic forecasting, to cross between scientific accuracy and symbolic significance.

The study establishes quantum AI as a transformative framework for understanding uncertainty, mapping future possibilities by uniting the cosmic, cognitive, and computational dimensions. This interdisciplinary approach expands on both theoretical and applied approaches that would be used to build a robust foundation of responsible, culturally attuned predictive intelligence.

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List of Abbreviations

S No	Abbreviation	Description
01	ADQL	Astronomical Data Query Language
02	AI	Artificial Intelligence
03	API	Application Programming Interface
04	AerSimulator	Aer Quantum Circuit Simulator (IBM Qiskit)
05	CNOT	Controlled-NOT quantum gate
06	CPU	Central Processing Unit
07	DEI	Diversity, Equity, and Inclusion
08	DOB	Date of Birth
09	DSR	Design Science Research
10	DXA	Device-Independent Extended Attribute (unit of measurement)
11	EAD	Ethically Aligned Design (IEEE framework)
12	ECL	Ecliptic Longitude (helio- or geocentric)
13	ESA	European Space Agency
14	GDR3	Gaia Data Release 3
15	GFI	Galactic Flux Index
16	GPU	Graphics Processing Unit
17	HDR	Hadamard gate (quantum)
18	HF	Hugging Face
19	HTML	HyperText Markup Language
20	IBM	International Business Machines
21	IEEE	Institute of Electrical and Electronics Engineers
22	IST	Indian Standard Time (UTC+5:30)
23	J2000	Julian Date Epoch 2000.0 (astronomical reference)
24	JPL	Jet Propulsion Laboratory (NASA/Caltech)
25	JSON	JavaScript Object Notation

26	LLM	Large Language Models
27	MAE	Mean Absolute Error
28	MD5	Message Digest Algorithm 5 (hash function)
29	ML	Machine Learning
30	MSE	Mean Squared Error
31	NASA	National Aeronautics and Space Administration
32	NLP	Natural Language Processing
33	OSF	Open Science Framework (Psychology Data Repository)
34	PyPI	Python Package Index
35	QIPLM	Quantum Interdisciplinary Predictive Learning Model
36	QML	Quantum Machine Learning
37	QASM	Quantum Assembly Language
38	QPU	Quantum Processing Unit (real quantum hardware)
39	QNLP	Quantum Natural Language Processing
40	QNode	Quantum Node (PennyLane differentiable circuit)
41	REST	Representational State Transfer
42	RL	Reinforcement Learning
43	RMSE	Root Mean Square Error
44	RY	Rotation-Y quantum gate
45	SAD	Seasonal Affective Disorder
46	SRO	Specific Research Objective
47	SQL	Structured Query Language
48	SWS	Slow-Wave Sleep (deep sleep stage)
49	TAP	Table Access Protocol (astronomical query standard)
50	UCI	University of California
51	UI	User Interface
52	UNESCO	United Nations Educational, Scientific and Cultural Organization

53	UTC	Coordinated Universal Time
54	UUID	Universally Unique Identifier
55	VQC	Variational Quantum Circuit
56	VSOP87	Variations Séculaires des Orbites Planétaires 1987 (ephemeris model)
57	YD	Yerkes-Dodson (arousal-performance principle)

CHAPTER 1

INTRODUCTION

1.1 Introduction

The merger of **quantum artificial intelligence (AI)**, **astronomy**, **astrology**, and **behavioral science** offers an exciting opportunity for future predictive modelling. Traditional AI models, however advanced and powerful, are still limited to classical computation and linear data structures. Quantum AI uses superposition and entanglement to process information in multidimensional situations, enabling unprecedented powers of pattern recognition and probabilistic inference. This paradigm shift presents an opportunity to create language models that not only comprehend large datasets but also generate detailed predictions about human behaviour and cosmic phenomena.

Astronomy supplies the empirical foundation for such an approach - namely, it provides rigorous observations of the stars and data to base predictive structures on scientific reality. Astrology, being viewed as symbolic rather than empirical, has a cultural and interpretive layer to it and adds a dimension to human meaning-making that embeds itself into the predictive process. In combination with behavioral science, the latter being interested in cognition, decision-making, and social processes, we create a model to integrate symbolic traditions, empirical science, and human psychology through a common predictive framework.

For this cross-disciplinary synthesis of theories and data science, **a quantum AI-facilitated language model** would run on such an intersection where symbolic reasoning meets empirical analysis. It might process astronomical databases to predict cosmic phenomena, make sense of astrological symbolism to map human experience, and use behavioral science to predict behavior patterns. Such a system would do so, not only by predicting, but by generating in its totality insight into both measurable phenomena and stories of culture. This approach crosses boundaries that have long been drawn between science and tradition, suggesting a computational and cultural hybrid model for forecasting.

The importance of these efforts is that it has the potential to fundamentally reshape

predictive modelling. By merging quantum AI's computational capabilities with astronomy's empirical precision, astrology's symbolic forms, and behavioral science's psychological underpinnings, the project seeks to be a first step towards paving the way for a new class of language models that can predict future trends across cosmic, cultural, and human realms. We will not only reach a technical frontier with AI but also grapple with themes such as meaning, identity, and foresight within human experience.

1.2 Background and Motivation

The pursuit of understanding and predicting future developments has remained a hallmark of human civilization. From the ancient wisdom of astrology that sought meaning in celestial alignments to sophisticated astronomical techniques that track planetary cycles accurately, humanity has sought to decipher the rhythms of the universe for millennia. Parallel to these cosmic inquiries, behavioral science has shed light on how humans think and make decisions, and the mechanisms through which they make decisions and the things we are collectively making changes about. Each of the three sub-disciplines - astrology, astronomy, and behavioral science provides different perspectives about prediction, but as a result are still mostly siloed in their methodology and epistemology.

Forecasting - in the broad sense of generating structured anticipations of future states based on systematically gathered evidence has been a preoccupation of human thought since antiquity. The astronomical observations of Babylonian and Hellenistic scholars, the seasonal harvest projections of early agricultural societies, and the probabilistic actuarial tables of seventeenth-century London coffeehouses all reflect the same underlying aspiration: to reduce uncertainty by grounding expectations in evidence. What distinguishes contemporary computational forecasting from these predecessors is not the aspiration but the scale, speed, and formal rigour of the tools available.

The past two decades have produced an extraordinary expansion in personalized forecasting capabilities, driven by the convergence of ubiquitous personal data collection, statistical machine learning, and cloud computing infrastructure. Recommendation systems at Netflix, Spotify, and Amazon predict individual preferences with remarkable precision. Wearable health platforms forecast cardiovascular events, sleep patterns, and glucose trajectories from continuous biometric streams. Financial advisory systems generate personalized investment

portfolios calibrated to individual risk tolerance and time horizons. These applications share a common architecture: large-scale historical data, statistical pattern recognition, and individual-level personalization through demographic or behavioral profiling.

Yet a persistent and underacknowledged limitation runs through virtually all of these systems: they model human life as a phenomenon that is, in principle, fully predictable from historical patterns, ignoring the fundamentally non-deterministic and contextual nature of human psychological states. A person's decision-making capacity on a given morning is not merely a function of demographic variables and historical purchase behavior; it is a function of how they slept last night, what cognitive biases are currently activated by their stress level, where they are in their circadian energy cycle, and what emotional carry-over they bring from yesterday's interactions. These factors are well-documented in behavioral science literature but are almost absent from production forecasting systems.

Artificial intelligence (AI) has revolutionized predictive modelling as machines can now manipulate large datasets, observe associations, and produce forecast probabilities. But classical AI systems have computational limitations, limits on computation, and deterministic systems built on deterministic architectures. Quantum artificial intelligence (QAI), in stark contrast, relies on quantum mechanics' principles of superposition, entanglement, and probabilistic computation to step beyond such limitations. This shift in paradigms creates new opportunities for combining symbolic, empirical, and psychological data to construct integrated predictive tools.

Quantum mechanics, meanwhile, has spent the past four decades developing a mathematically rigorous framework for reasoning about systems whose states cannot be described by classical probability theory. The qubit - the quantum analogue of the classical bit - can exist in a superposition of $|0\rangle$ and $|1\rangle$ states whose measurement probabilities are given by the squared moduli of complex probability amplitudes. This is not merely a computational trick; it is a fundamentally different ontological framework for describing systems in which multiple possible states coexist until a measurement event collapses the system into a definite outcome. The parallel to human psychological states - which genuinely coexist in ambiguous, contextually sensitive superpositions until a decision event resolves them is more than metaphorical (Busemeyer and Bruza, 2012).

Simultaneously, the practice of astrology encompasses three major computational traditions, each offering a different framework for relating birth-time configurations to personality tendencies and life-domain strengths. Western tropical astrology uses a Sun-sign system anchored to the vernal equinox and has been studied in relation to Big Five personality dimensions (Mayo, White, and Eysenck, 1978; Eysenck and Nias, 1982). Vedic Jyotish uses a sidereal zodiac corrected by the Lahiri ayanamsa ($\sim 23.85^\circ$) and prioritizes the Moon sign (Janma Rashi) and Nakshatra over the Sun sign. Chinese BaZi (Four Pillars of Destiny) maps the birth year, month, day, and hour to the traditional sixty-year Jiazi cycle, identifying the Day Master as the individual's core elemental nature (Lip, 1988). The QIPLM takes a deliberately agnostic position on astrological causality, treating each tradition as a culturally grounded symbolic framework. This model implements all three in parallel, enabling users to select the most consonant tradition with their cultural background.

This thesis aims to achieve new potential in generating prediction insight based on a **Quantum AI-powered language model**, combining astrology, astronomy, and behavioral science in a probabilistic manner on future events. Embedding symbolic astrological archetypes, astronomical cycles, and behavioral variables in a quantum-enhanced language model will give researchers the opportunity to discover if interdisciplinary integration can bring new insights.

The convergence of these three research streams - quantum probability theory, precision astronomical computation, and behavioral science into a single personalized forecasting framework is the central intellectual opportunity that motivates this research. No prior work, to the author's knowledge, has attempted this integration at the level of rigor, completeness, and formal ethics evaluation that this thesis presents. The QIPLM is the result.

1.3 Research Problem

Advances in **quantum artificial intelligence** (AI) and large language models (LLMs) have also created opportunities for predictive modelling across diverse domains. But the methods are still siloed:

- **Astronomy** serves as a rich source of empirical data for prediction of cosmic events, though its incorporation into AI systems is typically for scientific purposes.

- Albeit representing a culturally significant and symbolically rich body of knowledge, **Astrology** is often excluded from computational models due to its non-empirical foundations.
- **Behavioural science** can bring a more human perspective to cognition as well as decision-making and social dynamics yet existing AI models cannot integrate emotional and psychological dimensions as well as symbols and empirical data.

The challenge is a coherent framework to integrate these varied knowledge systems - empirical astronomy, symbolic astrology and behavioural science through a quantum AI driven language model. Conventional AI models do not have the computational complexity necessary to mediate on symbolic traditions and empirical science, whereas quantum AI is under-developed in interdisciplinary forecasting.

This gap sets up many questions:

- How do quantum AI language models combine astronomical data with astrological and behavioural-science symbolism to generate consistent predictive results?
- What approaches can assure scientific trustworthiness without disregarding cultural sensitivity and human interpretive approaches?
- How will the system reconcile probabilistic analysis and symbolic thought, free from reductive thinking, with meaningful vision?

Without tackling such challenges, predictive modelling could risk remaining fragmented, scientifically rigorous but culturally disconnected, symbolically rich but empirically weak. As such, the research problem is the absence of an interdisciplinary, quantum-enhanced language model that unifies the empirical, symbolic, and behavioural components of prediction.

1.4 Problem Statement

The development of Artificial Intelligence (AI) has emerged into this pivotal moment with the advent of **quantum AI and complex language models**. These systems are said to offer unparalleled potential for data processing, probability determination, and symbolic inferential thinking. But, for all these potentials, predictive modelling in interdisciplinary fields is still pieced together and not done up to date.

- **Astronomy** provides rigorously vetted empirical data from the heavens; however, its role in AI systems is more limited to scientific predictions without extensive cultural or behavioural context.
- **Astrology** is a cultural motif that is frequently belittled even in scientific settings, but it remains fundamental to global cultural narrative framing, human identity construction, and decision-making. The symbolism underlying prediction is underused for computational modelling.
- **Behavioural science** does contribute insight to human cognition, biases, social dynamics, etc., whereas many AI systems fail to integrate these psychological factors, even with the available empirical and symbolic information.

In essence, the problem of synthesizing these disparate knowledge systems - empirical astronomy, symbolic astrology, and behavioural science into a quantum AI-based prediction framework which can be applied as a complete predictive tool is central to this discussion. Traditional AI architectures are not well trained to interface symbolic traditions with empirical science; quantum AI applications not explored in the interdisciplinary forecasting context.

This gap creates multiple challenges.

1. **Integration Challenge:** How should quantum AI language models bridge astronomical datasets with astrological symbolism and behavioural science knowledge?
2. **Validity Challenge:** How to sustain scientific credibility of a system with respect to cultural sensitivity and symbolic traditions?
3. **Methodological Challenge:** What computational approaches would allow for both the probabilistic inference and the symbolic reasoning to avoid reductionism and at the same time permit operative foresight?
4. **Ethical Challenge:** How can predictive models ensure responsible use, avoiding deterministic interpretations of human behaviour and cultural traditions?

Besides above, the fundamental problem driving this research can be stated in one sentence: existing personalised forecasting systems are simultaneously too narrow in their theoretical foundations, too imprecise in their astronomical computations, too shallow in their psychological modelling, too opaque in their quantum-inspired components, and too unaccountable in their ethical governance to serve as credible, trustworthy, or scientifically valid tools for personalised life forecasting.

This composite problem decomposes into five specific deficiencies, each of which are documented independently below and each of which the QIPLM directly addresses:

1.4.1 Deficiency One: Stochastic Inconsistency

Any system that incorporates stochastic elements - random number generators, probabilistic sampling, quantum measurement simulation - faces the problem of inconsistency: the same inputs, processed on different occasions, will produce different outputs. For a weather forecasting system or a financial model generating aggregate statistics, this is acceptable because the system's outputs are expected to vary with changing real-world conditions. For a personalised advisory system that claims to provide meaningful individual-level guidance, it is not: a user who receives dramatically different forecasts on Tuesday versus Wednesday, using the same birth data and the same self-reported inputs, will justifiably conclude that the system is generating noise, not signal.

The solution adopted in this research is deriving the quantum random seed from a deterministic hash of the user's birth data and stable self-report inputs guarantees that the system produces identical outputs for identical inputs regardless of when it is run. This is, in principle, straightforward; in practice, it requires careful identification of every source of non-determinism in the pipeline and the systematic elimination or seeding of each one.

1.4.2 Deficiency Two: Astronomical Imprecision

The computation of a person's tropical zodiac sign from their birth date is, in principle, a straightforward astronomical calculation: compute the Sun's geocentric ecliptic longitude at the moment of birth, divide by thirty, and take the floor to obtain the sign index. In practice, virtually all software implementations contain a subtle but

consequential error. The author's investigation of multiple Python implementations, including the erroneous version present in an earlier iteration of the QIPLM itself, revealed that the use of `ephem.Observer` with `obs.epoch = ephem.J2000`, followed by reading `sun.hlong`, returns not the geocentric apparent ecliptic longitude but Earth's heliocentric ecliptic longitude in the J2000 inertial reference frame.

For modern epoch dates, Earth's J2000 heliocentric longitude is approximately 45 degrees, placing it consistently in the Taurus sector of the zodiac. Consequently, any system using this algorithm returns Taurus as the zodiac sign for virtually every person born in the contemporary era, regardless of their actual birth date. This error is not merely an academic curiosity: it propagates through every downstream computation that depends on zodiac sign, rendering all area modifier scores, trait descriptions, and monthly variation calculations incorrect.

1.4.3 Deficiency Three: Behavioural Science Shallowness

Most personalised AI systems that incorporate psychological state variables rely on a single scalar measure, typically a self-reported stress level or mood score to characterise the user's current psychological state. This approach ignores three decades of behavioural science research demonstrating that psychological decision-making capacity is a multi-factorial, dynamic, and context-sensitive phenomenon. A person's stress level alone does not determine their decision quality; it must be understood in relation to their position in the circadian cycle, their accumulated sleep debt, their current affective state, and the specific cognitive biases that are activated by their current stress and sleep conditions.

The QIPLM incorporates a ten-component behavioural model - Borbely's two-process model, Walker's sleep debt curve, Rosenthal's SAD modifier, Yerkes-Dodson optimisation, and ten specific cognitive bias activation functions that produces a substantially more nuanced and scientifically grounded characterisation of the user's current decision-making state.

1.4.4 Deficiency Four: Quantum Model Opacity

The marketing of systems as 'quantum-inspired' or 'quantum-enhanced' has proliferated in commercial AI contexts, but rigorous comparative evaluation of different quantum circuit implementations is rare. A system that uses IBM Qiskit for one function and

claims quantum advantage without comparing it to the PennyLane or Cirq equivalent on the same circuit architecture is not providing a scientifically credible basis for its quantum-inspired claims. The present research addresses this by implementing all four backends on the identical Ry-Hadamard-CNOT circuit and evaluating them across three independent metrics: measurement fidelity, stability across repeated runs, and shot convergence rate.

1.4.5 Deficiency Five: Ethics Accountability Gap

Personalised AI systems that provide advice, recommendations, or forecasts relating to health, financial decisions, relationship choices, or professional development carry a non-trivial ethical responsibility to the individuals they serve. Despite the availability of internationally recognised ethics frameworks - UNESCO's Recommendation on the Ethics of Artificial Intelligence (2021) and the IEEE Ethically Aligned Design (2019) the vast majority of personalised AI systems are deployed without any documented ethics evaluation. This is not merely an oversight; it represents a systematic failure of accountability that the AI ethics community has repeatedly identified as one of the most pressing challenges in the field (Jobin, Ienca and Vayena, 2019; Floridi et al., 2018).

1.5 Purpose of the Study

This study aims to design and conceptualize a **quantum AI-powered language model** that combines **astronomy, astrology, and behavioral science** into a unified predictive framework. The research aims at mediating between empirical science, symbolic traditions, and human psychology via the computational power of quantum AI to produce holistic and culturally resonant foresight.

1. To investigate the application of quantum AI capabilities in predictive modelling

Building on the principles of quantum computing, for example, superposition and entanglement for a better processing capability of language models towards multidimensional data processing and the making of probabilistic inference.

2. To incorporate astronomy into AI-powered predictions with astronomical data

Based on scientifically validated astronomical datasets, provide scientifically

grounded predictions of celestial phenomena and their potential influence on human systems.

3. By integrating astrology as a symbolic interpretive framework to embrace astrology as a symbolic perspective

The use of some astrological traditions in the language model that incorporates astrological traditions to relate prediction systems with cultural narratives and personal identity to contextualize predictions in cultural narratives and identity, to increase the richness of interpretation with interpretive depth. A key element of the research focus.

4. To make predictions based on behavioral science for humans

Leverage behavioral science uses psychological and cognitive models for predicting human decision-making, biases, social dynamics, etc., to create predictions including variability of behaviour.

5. Focused on developing a methodology for synthesis that is interdisciplinary

Formulating computational approaches incorporating empirical data, symbolic reasoning and behavioral insights in a quantum-enhanced language model.

Broader Purposes

This study aims to establish a new class of predictive systems to cross-disciplinary boundaries. Drawing on the empirical precision of astronomy, the symbolic richness of astrology, and the psychological insights of behavioral science, this study attempts to:

- Promote discovery of high-impact quantum AI applications in interdisciplinary contexts.
- Develop a holistic forecasting instrument which is scientifically rigorous and culturally sensitive.
- Offer to add to the ethical debate on AI by showing how symbolic traditions and human behavior can be responsibly integrated in computational models.
- Deliver practical applications in fields including cosmic event forecasting,

personalized decision-support systems and behavioral trend analysis.

1.6 Significance of the Study

The significance of this proposed study resides in the fact that an **interdisciplinary predictive framework** is introduced that connects quantum AI and astronomy, astrology and behavioral science in a way that has historically occupied separate spaces. Its importance extends to several dimensions:

1. Theoretical Significance

- **Promoting Quantum AI Research:** This paper advances the theoretical exploration of quantum-augmented natural language processing and predictive models with natural language models after applying this same quantum computing framework.
- **Interdisciplinary Integration:** It is the new fusion by creating a one-in-a-generation combination of empirical science (astronomy), symbolic traditions (astrology) and behavioural paradigms, blurring the lines of just what predictive AI can handle.
- **Epistemological Contribution:** The study challenges traditional academic/literary divides and proposes a new model that respects the empirical basis of knowledge and cultural understanding.
- The most fundamental theoretical contribution of this research is the establishment of a formal mapping between qubit probability amplitudes and psychological state variables. Busemeyer and Bruza (2012) proposed a quantum cognition framework in which quantum probability theory provides a better model of human decision-making under uncertainty than classical Bayesian inference, particularly for phenomena such as the conjunction fallacy, the order effect in surveys, and disjunction effect violations of the sure-thing principle. The present research operationalises this insight in a working computational system, providing the first implementation of quantum cognition principles within a personalised forecasting architecture.
- The entanglement of the energy qubit ($|q0\rangle$) and mood qubit ($|q1\rangle$) through the CNOT gate is particularly significant from this perspective. Classical

probability theory would represent energy and mood as independent variables multiplied to obtain their joint probability: $P(\text{high energy AND high mood}) = P(\text{high energy}) \times P(\text{high mood})$. The quantum CNOT entanglement creates a correlation that cannot be decomposed this way - the joint measurement probability $P(|11\rangle)$ encodes a genuine non-classical correlation between the two states. This is empirically appropriate: Watson, Clark and Tellegen (1988) demonstrated in their seminal PANAS study that positive affect (mood) and energetic arousal (energy) share substantial common variance that classical product probability theory cannot capture.

2. Practical Significance

- **Forecasting Cosmic Events:** Using astronomical datasets in quantum AI models improves scope and certainty for the prediction of celestial events.
- **Human Behavioural Prediction:** By incorporating behavioural science, the model can predict human decision-making cycles, social processes, and cognitive biases, rendering predictions to be more focused on human-centric models.
- **Personalized Decision Support:** The astrological symbolism delivers culturally relevant insights and could be applied to personalized forecasting, identity exploration, and decision support systems.
- The corrected zodiac sign algorithm represents a methodologically significant contribution to the domain of computational astronomy and its applications. The systematic error documented in prior implementations was the misuse of the J2000 heliocentric frame via `obs.epoch = ephem.J2000 + sun.hlong`, which is not mentioned in any published computational astrology paper or software documentation that I've been able to locate. Its correction, documented in detail in subsequent Chapters, provides a replicable standard for precision tropical zodiac computation that future researchers and developers can adopt.
- The QIPLM is delivered as a fully functional, documented, and open-architecture Jupyter Notebook implementation across seven functions. This makes it immediately usable as a research prototype, an educational

demonstration of quantum computing principles, or a foundation for further development. The integrated ethics evaluation, person vitality validation, and PDF report generation components give it a completeness that distinguishes it from most published quantum computing demonstrations, which typically focus on circuit mechanics in isolation from system-level functionality.

3. Ethical and Cultural Significance

- **Cultural Sensitivity in AI:** The research illustrates how a cultural tradition such as astrology may be respectfully incorporated into a computational model without undermining the legitimacy of research.
- **Ethical Forecasting:** In contrast, through the integration of the two sources of knowledge: probabilistic inference and symbolic reasoning, the model is free of deterministic reasoning of human action, which leads toward ethical foresight.
- **Global Relevance:** As astrology and astronomy are deeply rooted in multiple cultures, the study is cross-cultural and has global relevance, which will enhance predictive AI that will contribute to a more global and inclusive approach.
- The formal application of the UNESCO 2021 and IEEE EAD v2 ethics frameworks to a quantum-AI personalised system establishes a precedent for ethics-by-design in quantum computing applications. The four-dimensional evaluation - human values, fairness, privacy and transparency provides a replicable protocol that other researchers and developers can apply to their own quantum-AI systems. The finding that all four backends achieve compliance in local simulation mode, but that IBM Qiskit and Google Cirq become conditional in cloud deployment, is a practically important result for system architects choosing between backend options.

4. Academic and Societal Impact

- **Contribution to Scholarship:** The research contributes to the scholarly debate in AI, computational sciences, and interdisciplinary research and provides a foundation for future studies that leverage symbolic and empirical understanding.

- **Societal Applications:** Applications might include forecasting, improvement of cultural awareness and promotion of cross-disciplinary curriculum.
- **Innovation in Predictive Systems:** It proposes that quantum AI-based language models are revolutionizing technology for science and culture, helping humanity to reconsider foresight.

1.7 Research Objectives

Specifically, this study aims to build a quantum AI-powered language model, which merges the understanding of astronomy, astrology, and behavioral science and applies them as one coherent prediction system.

The overarching aim of this research is to design, implement, and evaluate the QIPLM in a manner that resolves each of the five deficiencies identified above. This aim is operationalized through six specific research objectives (SROs), each with defined outputs and evaluation criteria:

Table 1.1: Research Objectives, Output and Evaluation Criterion

SRO	Objective	Output	Evaluation Criterion
SRO 1	Design and implement a multi-source astronomical data pipeline integrating NASA Exoplanet Archive, ESA Gaia DR3, and JPL Horizons ephemerides	Functional Layer 2 with live API queries and embedded fallbacks	API availability > 80%; luminosity index and galactic flux index computed
SRO 2	Implement a tropically correct zodiac sign computation algorithm using ephemeris. Ecliptic conversion with UTC-corrected birth time and geographic coordinates	zodiac_sign() function in Layer 3	100% accuracy on 12 cusp-date test cases; prior algorithm accuracy documented
SRO 3	Develop a ten-component behavioural science model incorporating circadian rhythm, sleep debt, seasonal affective patterns, Yerkes-Dodson arousal, and ten cognitive bias activation functions	compute_beh_scores() and compute_bias_scores() in Layer 3	Internal consistency across 24 test profiles; YD peak at stress=0.45

SRO	Objective	Output	Evaluation Criterion
SRO 4	Implement and comparatively evaluate four quantum circuit backends (NumPy, IBM Qiskit, Google Cirq, PennyLane) on an identical Ry-Hadamard-CNOT architecture across fidelity, stability, and convergence	run_all_models() in Layer 4 with all four backends	Accuracy score > 80/100 for at least two backends; convergence below MSE 0.005 at 4096 shots
SRO 5	Construct a deterministic, birth-data-seeded six-month prediction matrix across seven life areas with a full consistency guarantee	build_matrix() in Layer 6 with det_seed_birth()	Identical output on a minimum of 3 independent re-runs with the same inputs
SRO 6	Formally evaluate all four quantum models against the UNESCO 2021 and IEEE EAD v2 frameworks across four ethics dimensions.	Ethics compliance table in Layer 5 report	Minimum two models COMPLIANT without qualification; all four models documented

Specific Objectives

1. For understanding the role of quantum AI in predictive modelling

- Investigate how quantum principles of superposition, entanglement and quantum parallelism could improve the performance of language models on multidimensional and probabilistic data.
- Evaluate the strengths of quantum AI over traditional AI on interdisciplinary forecasting.

2. To incorporate astronomical datasets into language models

- Leverage validated astronomical observations and datasets for empirical grounding of predictive outputs.
- Create algorithms for incorporating astronomy-based knowledge into quantum-boosted language models to accurately predict cosmic events.

3. For astrology to be used as a symbolic interpretive framework

- Explore how the astrological conventions and system of symbols can be incorporated and calculated in language models.
- Establish devices to frame predictions within cultural and symbolic narratives, giving interpretative depth to the data in combination with empirical data.

4. To include behavioral science to work for human-oriented predictions

- Incorporate psychological and cognitive models into the language model to predict human cognition, decision-making, and social processes, biases and dynamics in the language model.
- Consider how behavioral science can help to add more contextually relevant and applicable knowledge of predictive outputs with relevance to real-world applications.

5. To develop an interdisciplinary synthesis methodology

- Construct computational solutions that fuse empirical astronomy, symbolic astrology and behavioral science in a quantum AI paradigm.
- Utilize a statistical method that combines probabilistic inference with symbolic reasoning without reductionism, allowing for practical foresight.

6. How to deal with ethical and cultural issues in predictive AI

- Explore the ethical dimension of infusing our symbolic traditions with empirical science in AI for prediction.
- Recommend practices for use with consideration of cultural values, inclusivity, and for not falling into deterministic interpretations of humans.

1.8 Research Questions

Core Research Question

1. Can a quantum-inspired AI framework that fuses precision astronomical ephemerides, evidence-based behavioural science inputs, and quantum circuit probability estimation produce deterministic, ethically compliant, and epistemically meaningful personalised six-month forecasts?

This question embeds three key claims that must each be addressed: (a) the framework must be demonstrably deterministic - same inputs must produce same outputs; (b) it must be evaluable as ethically compliant under at least one recognised international framework; and (c) its outputs must be epistemically meaningful, meaning that the scores it produces can be traced to specific, documented, theory-grounded input components rather than to opaque model internals.

Subsidiary Research Questions

Quantum AI and Computational Framework

2. How do quantum computing principles (e.g., superposition, entanglement, quantum parallelism) improve the predictive capacity of language models compared to classical AI architectures?
3. What computational methodologies can balance probabilistic inference with symbolic reasoning in interdisciplinary forecasting?
4. Which quantum circuit backend - NumPy Ry-H-CNOT, IBM Qiskit AerSimulator, Google Cirq, or PennyLane default qubit, achieves the highest composite accuracy score on the identical three-qubit Ry-Hadamard-CNOT circuit architecture, and what accounts for the observed differences?

Astronomy Integration

5. How do we include validated astronomical datasets to run on quantum AI language models to further improve cosmic event forecasting?
6. What frameworks for evaluating the reliability of astronomy-informed

predictions in AI systems work best?

Astrology as Symbolic Framework

7. How can astrological symbolism and traditions be computationally represented within language models without compromising scientific validity?
8. How to extend interpretive layers of predictive models to astrology, by situating the realizations in cultural and personal narratives?
9. To what degree does birth time and geographic coordinate correction affect zodiac sign determination accuracy on cusp dates, and what is the mechanism of the error in prior implementations?
10. How does a birth-data-derived deterministic seed guarantee prediction consistency across unlimited re-runs, and what are its computational security implications?

Applications in Behavioural Science

11. How can behavioural science insights (cognition, biases, social dynamics, etc.) be harnessed in predictive models so we better predict human decision-making processes?
12. What impact does behavioural variability have on the precision of interdisciplinary predictions?
13. What proportion of the ten modelled cognitive biases are activated under high-stress, sleep-deprived, and mood-extreme input conditions, and how does the activation rate vary with stress level?

Ethical and Cultural Aspects

14. What ethical challenges arise when combining empirical science, symbolic traditions, and behavioural frameworks within predictive AI?
15. How may we ensure cultural sensitivity and inclusivity when constructing and applying these interdisciplinary language models?
16. To what degree do the four quantum models satisfy UNESCO 2021 and IEEE

EAD v2 ethics compliance criteria, and which evaluation dimension produces the greatest between-model variance?

All these questions combined can:

- Define the technical feasibility of quantum AI-powered language models.
- Investigate the incorporation of diverse knowledge systems (astronomy, astrology, behavioural science).
- Address ethical and cultural issues of interdisciplinary predictive modelling.
- Create a cross-disciplinary general framework for forecasting.

1.9 Scope and Limitations

Scope of the Study

In this paper, we describe and prototype a quantum AI-guided language model that marries astronomy, astrology and Behavioural Science within a convergent predictive system. The definition of the scope is as follows:

1. Quantum AI Application

- Investigating principles of quantum computing (superposition, entanglement, quantum parallelism) in augmenting language model performance.
- Use of natural language processing with quantum technology for multidimensional data integration.

2. Astronomy Integration

- Evidence-based predictive outputs based on validated astronomical datasets.
- Developing ways to embed astronomy-based knowledge in language models for predicting cosmic events.

3. Astrology Incorporation

- Representation of astrological symbolism and traditions in a computational framework.

- Adaptation of predictions through cultural narratives and identity-based interpretation.

4. Application of Behavioral Science

- The integration of psychological and cognitive models to predict human decision-making abilities, biases, and behaviour to predict human social processes.
- Assessment of behavioural diversity, predictability and use of the data.

5. Ethical and Cultural Considerations

- Exploring the morality of the merger of empirical science and symbolic traditions.
- Recommendations for responsible and culturally sensitive predictive AI use.

Limitations of the Study

The research is ambitious in scope, but it admits to several limitations:

1. Data Integration Challenges

- Though the astronomy datasets are well documented, astrology, with no scientific consensus, is dependent on symbolic traditions. Incorporating these diverse datasets may promote interpretive bias.
- Data in behavioural science are context-dependent and may not generalize across cultures or populations.

2. Computational Constraints

- Quantum AI is still a developing field and has limited access to scalable quantum hardware. Instead, the work may be based on simulations or hybrid quantum-classical models rather than fully developed quantum phenomena.
- Real quantum hardware: all four quantum backends are operated in classical simulation mode. No real quantum processing unit (QPU) hardware is employed, and no quantum computational speedup is achieved or claimed. The

choice to use simulation reflects the research objective of comparative backend evaluation on identical circuit architecture, which would be confounded by the variable noise profiles and gate error rates of different QPU hardware.

3. Interpretive Bias

- The symbolic frameworks of astrology, which may be seen as subjective or culturally specific, can challenge accepting them in strictly scientific communities.
- Forecasts may differ in interpretive depth based on cultural context and how it is perceived by the audience.
- Causal astrological claims: The QIPLM uses zodiac sign traits as a symbolic-psychological modifier matrix. No causal claims are made about the relationship between birth-time, astronomical or calendar configurations and subsequent personality development or life outcomes. The computation is rigorous and precise; the interpretive mapping is acknowledged as a cultural-symbolic framework for all three supported traditions (Western, Vedic, Chinese).
- Biometric data: the system operates exclusively on self-reported inputs. No biometric sensors, wearable devices, or physiological measurements are incorporated. The sleep hours, stress level, and mood inputs rely entirely on user self-report, which introduces recall bias and social desirability effects.

4. Ethical Concerns

- Risk of deterministic interpretations of human behaviour if the predictions are not applied correctly.
- Potential abuse of culturally sensitive data or symbolic traditions used for certain purposes, potentially diminishing inclusivity.

5. Scope Boundaries

- It's exploratory and conceptual and not fully functional - it proposes frameworks and prototypes, not a full-fledged predictive system.
- Only astronomy, astrology, and behavioural science are selected; other fields of

predictive modelling would be excluded (e.g., economics, climate science).

- Longitudinal validity: the prediction matrix scores generated by the QIPLM are not validated against actual life outcomes over the six-month prediction horizon. Such validation would require a prospective study of a minimum 12 months duration with a participant pool of several hundred individuals providing continuous self-report data - a study of considerable ethical, logistical, and financial complexity. The absence of longitudinal validation is acknowledged as the most significant limitation of the current research.
- Geographic comprehensiveness: While the India database contains 1,582 entries, it cannot claim complete coverage of all inhabited settlements across the globe. Rural populations in states with sparse administrative records may find their nearest major town listed rather than their precise birth settlement.
- Language: the entire system is implemented and documented in English. Adaptation for non-English-speaking populations would require localisation of the user interface, description texts, and potentially the zodiac trait vocabulary.

Summary

This study is a very wide-scale and comprehensive one, linking the empirical, symbolic and the behavioural for quantum AI-based prediction. Its constraints capture the fact that quantum computing is simply a new form of computation; astrology has always been difficult; interpretive complexities are significant, and behavioural science can vary from case to case depending on the context of observation. These boundaries help ensure that the research remains focused, feasible and ethically responsible and allows to open a door for developments in future research.

1.10 Thesis Outline

Chapter 1: Introduction

This chapter presents the topic of the research, the problem statement, and the objectives and significance of the study. It is complete with a description of the research questions and aims, the scope and what the study will be unable to focus on, and a clear sketch of the thesis.

Chapter 2: Review Of Literature

The literature review will investigate the related research and scholarly works, Quantum Artificial Intelligence, Astronomy and AI integration, Astrology and Symbolic Systems, Behavioural Science and AI, Ethical and Cultural considerations and review the research gaps in the literature.

Chapter 3: Proposed Methodology

This chapter describes the research design and conceptual framework of the Quantum AI-Powered Language Model. It explains the data sources, computation, evaluation metrics, ethical considerations and process for modelling the proposed framework and using it.

Chapter 4: Results Analysis

The fourth chapter includes the Performance of the Quantum AI model, Predictive Accuracy in Astronomy Forecasting, Astrology Integration, Interpretive Depth, Behavioural Science Contributions to Human-Centric Predictions, Comparative Analysis and Classical AI Models, Ethical and Cultural Evaluation.

Chapter 5: Discussion

These insights are situated in an interpretation of findings, theoretical contributions to quantum AI and interdisciplinary forecasting, practical applications in scientific and societal domains, ethical considerations and cultural sensitivities, study limitations and future research avenues.

Chapter 6: Summary, Implications, And Recommendations

Summarizes the major findings and conclusions. Contributions to knowledge, Implications for AI, Astronomy, Astrology and Behavioural Science, and Closing Reflections.

CHAPTER 2

REVIEW OF LITERATURE

This chapter presents a systematic and critical review of four bodies of literature that together provide the theoretical and technical grounding for the QIPLM: (1) quantum computing and quantum-inspired machine learning; (2) astronomical ephemerides and computational astronomy; (3) behavioural science models for personalised AI; and (4) AI ethics frameworks. A fifth section analyses the gap in the literature that motivates the integrated framework proposed in this thesis. The review draws on peer-reviewed journal articles, conference proceedings, technical reports, and official documentation from international standards bodies.

The review strategy followed the PRISMA framework for systematic literature reviews (Page et al., 2021), adapted for a computational science context. Database searches were conducted across ACM Digital Library, IEEE Xplore, Google Scholar, arXiv, and NASA/ADS, using Boolean combinations of primary terms (quantum computing, astronomical ephemerides, behavioural science AI, ethics AI) combined with secondary terms (personalised forecasting, zodiac computation, circadian rhythm AI, UNESCO AI ethics). Papers were included if they were published in peer-reviewed venues, directly relevant to at least one of the four domains, and available in English. Historical foundational papers (pre-2000) were included where they represent seminal contributions that continue to shape the field.

2.1 Quantum Artificial Intelligence

Quantum AI brings together the principles of quantum computing - superposition, entanglement, and quantum parallelism with machine learning and natural language processing. Academics like Nausheen et al. (2025) provide an extensive survey of Quantum Natural Language Processing (QNLP), highlighting its potential to revolutionize semantic representation and inference. Similarly, Arlt et al. (2026) illustrate how language models can design quantum experiments, underscoring the synergy between quantum systems and AI.

These works form the theoretical basis for quantum-enhanced predictive modelling. Nevertheless, the existing research is largely technical and domain-specific, and emphasis is placed on computational efficiency instead of interdisciplinary synthesis.

There is limited exploration of how quantum AI can unify empirical science, symbolic traditions, and behavioural frameworks into holistic predictive systems.

Nausheen, F., Ahmed, K., Khan, M.I. and Riaz, F. (2025). Quantum Natural Language Processing: A Comprehensive Review of Models, Methods, and Applications. <https://arxiv.org>.

Annotation: This paper surveys quantum natural language processing (QNLP), highlighting models and applications. It is directly relevant as it provides the theoretical foundation for applying quantum AI to language modelling in interdisciplinary contexts.

Arlt, S., Duan, H., Li, F., Xie, S.M., Wu, Y. and Krenn, M. (2026) ‘Meta-designing quantum experiments with language models’, *Nature Machine Intelligence*, 8(2), pp. 148–157. doi:10.1038/s42256-026-00874-1.

Annotation: Demonstrates how language models can design quantum experiments, showing the synergy between quantum systems and AI. This supports my thesis by illustrating how quantum AI can be applied beyond traditional computation.

2.1.1 The Qubit and Quantum State Space

The mathematical object at the foundation of quantum computing is the qubit - a two-state quantum system whose state is described by a normalised vector in a two-dimensional complex Hilbert space $\mathbb{C}^2$. Unlike a classical bit, which is deterministically in state 0 or state 1, a qubit exists in a superposition $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$, where $\alpha, \beta \in \mathbb{C}$ and $|\alpha|^2 + |\beta|^2 = 1$. The quantities $|\alpha|^2$ and $|\beta|^2$ are the probabilities of measuring the qubit in state $|0\rangle$ or $|1\rangle$, respectively - a principle known as the Born rule (Born, 1926). The qubit state can be visualised geometrically on the Bloch sphere, where the north pole represents $|0\rangle$, the south pole represents $|1\rangle$, and all intermediate states on the surface represent superpositions with different probability amplitudes (Bloch, 1946).

The R_y rotation gate, used extensively in the QIPLM circuit, rotates the qubit state by angle θ around the Y-axis of the Bloch sphere: $R_y(\theta)|0\rangle = \cos(\theta/2)|0\rangle + \sin(\theta/2)|1\rangle$. The measurement probability after R_y rotation is therefore $P(|1\rangle) = \sin^2(\theta/2)$. By setting $\theta = \text{score} \times \pi$ where $\text{score} \in [0, 1]$, the QIPLM encodes classical input scores as qubit rotation angles in a monotonically increasing, naturally bounded mapping that respects

the probabilistic interpretation. A score of 0 maps to $\theta = 0$, giving $P(|1\rangle) = 0$; a score of 0.5 maps to $\theta = \pi/2$, giving $P(|1\rangle) = 0.5$; a score of 1.0 maps to $\theta = \pi$, giving $P(|1\rangle) = 1.0$. This is the canonical data encoding strategy for variational quantum circuits (Schuld, 2021).

Table 2.1: Qbit State Representation and Gate Transformations

$ 0\rangle$ Classical 0 (North pole)	$R_y(\theta)$ Rotation gate $0 \leq \theta \leq \pi$	$ \psi\rangle = \alpha 0\rangle + \beta 1\rangle$ Superposition (equator)	Hadamard H Equal weights $ +\rangle$ state	$ 1\rangle$ Classical 1 (South pole)
Pure ground state $P(0\rangle)=1.0$	Encodes score s $\theta = s \times \pi$	$P(1\rangle)= \beta ^2$ Born rule	Creates a spread over basis states	Pure excited state $P(1\rangle)=1.0$
CNOT Gate — Entanglement Control (energy qubit) $ q0\rangle \rightarrow$ If $ q0\rangle= 1\rangle$, flip target Target (mood qubit) $ q1\rangle \rightarrow q1\rangle \oplus q0\rangle$ (XOR) <i>Result: $P(11\rangle) =$ entangled joint probability</i>			Born Rule — Score Extraction $P(1\rangle) = \beta ^2$ (single qubit) $P(11\rangle) = \text{sum}(\text{shots}=11)/n_shots$ <i>At 4096 shots: std error ≤ 0.008 for all p</i>	

2.1.2 The Hadamard Gate and Superposition

The Hadamard gate $H = (1/\sqrt{2})[[1, 1], [1, -1]]$ is one of the most important single-qubit gates in quantum computing. Applied to the ground state $|0\rangle$, it creates the uniform superposition $|+\rangle = (1/\sqrt{2})(|0\rangle + |1\rangle)$; applied to $|1\rangle$, it creates $|-\rangle = (1/\sqrt{2})(|0\rangle - |1\rangle)$. Its crucial property for the QIPLM circuit is that it converts between the Z-basis (computational basis) and the X-basis, effectively distributing the qubit's amplitude across basis states in a way that amplifies sensitivity to small input variations near the midpoint of the score range. The combined Ry-H operation produces a probability $P(|1\rangle)$ that is a smooth, S-shaped function of the input score - more sensitive near the middle of the range (where decisions are genuinely uncertain) and less sensitive at the extremes (where the score already strongly indicates the outcome). This matches the psychometric expectation for personality and state assessment instruments (De Boeck and Wilson, 2004).

2.1.3 Entanglement and the CNOT Gate

Quantum entanglement, the phenomenon by which the state of one qubit cannot be described independently of another, is the resource that most sharply distinguishes quantum from classical computation. Bell (1964) proved that no local hidden variable theory can reproduce the correlations predicted by quantum mechanics for entangled states, establishing that quantum entanglement is a genuinely non-classical phenomenon. In the QIPLM, entanglement is used to model the empirically documented correlation between human energy and mood states.

The CNOT gate (Controlled-NOT) acts on two qubits as follows: if the control qubit $|q_0\rangle$ is in state $|1\rangle$, the target qubit $|q_1\rangle$ is flipped (X gate applied); if $|q_0\rangle$ is in state $|0\rangle$, $|q_1\rangle$ is unchanged. The CNOT matrix in the computational basis is $[[1,0,0,0],[0,1,0,0],[0,0,0,1],[0,0,1,0]]$. Applied after Ry-H rotations on both qubits, the CNOT creates a two-qubit entangled state whose joint probability $P(|11\rangle)$ depends on both input scores in a non-separable way — it cannot be written as $f(\text{energy}) \times g(\text{mood})$ for any functions f and g . The resulting emotional alignment score encodes the statistical dependence between energy and mood that Watson, Clark and Tellegen (1988) documented in their foundational PANAS studies.

2.2 Astronomy, Astronomical Ephemerides and Coordinate Systems

Astronomy has historically relied on computational models to handle large datasets of celestial observations. Recent breakthroughs in AI now speed up this process. Li et al. (2025) developed an astronomical question-answering dataset to assess large language models, whereas de Haan et al. (2025) proposed AstroMLab, a specific astronomy-oriented LLM performing at GPT-4o level. Wu et al. (2024) also suggested evaluation models for testing AI in astronomy studies.

These works showcase the empirical capacity of AI in astronomy, leading to accurate forecasts of cosmic occurrences and enhancing scientific progress. However, astronomy-focused AI remains disconnected from cultural and behavioural contexts and, as such, has limited relevance for predictive modelling with a wider human-centred lens.

Li, J., Zhao, F., Chen, P., Xie, J., Zhang, X., Li, H., Chen, M., Wang, Y. and Zhu, M. (2025) ‘An astronomical question answering dataset for evaluating large language

models', Scientific Data, 12(447), pp. 1–12. doi:10.1038/s41597-025-0447-0.

Annotation: Introduces a dataset for testing LLMs in astronomy, providing empirical grounding for AI-driven cosmic forecasting. This is crucial for integrating astronomy into my predictive framework.

de Haan, T., Ting, Y-S., Ghosal, T., Nguyen, T.D., Accomazzi, A., Wells, A., Ramachandra, N., Pan, R. and Sun, Z. (2025). AstroMLab 3: Achieving GPT-4o Level Performance in Astronomy with a Specialized 8B-Parameter Large Language Model. <https://arxiv.org>.

Annotation: Presents a specialized astronomy-focused LLM, showing how domain-specific models can outperform general-purpose AI. This informs my thesis on integrating astronomy datasets into quantum AI.

2.2.1 History and Development of Ephemerides

The word ephemeris derives from the Greek ἐφήμερος (ephemerous, 'daily'), reflecting the original function of these tables: to provide the daily positions of astronomical objects for use in navigation, calendaring, and astrological interpretation. The transition from hand-calculated astronomical tables, the Alfonsine Tables of 1252, Kepler's Rudolphine Tables of 1627, to computational ephemerides began in the mid-twentieth century with the advent of electronic computers. The first numerical integration of the outer planets' equations of motion using a computer was performed at the Institute for Advanced Study in Princeton in the 1950s; the JPL Developmental Ephemeris series, beginning with DE69 in 1969 and currently at DE441 (Park et al., 2021), represents the culmination of seventy years of progressively refined numerical integration.

The practical accuracy of modern ephemerides is extraordinary. The DE441 ephemeris achieves positional accuracy better than one metre for the inner planets over timescales of a century, and better than one kilometre over millennia. This precision far exceeds what is required for zodiac sign computation - a precision of approximately 0.1 degrees of ecliptic longitude is sufficient to correctly determine the sign even on cusp dates, but it provides a scientific grounding that distinguishes the QIPLM's astronomical component from the approximate lookup tables used by most astrological software.

2.2.2 Coordinate Systems: Tropical vs Sidereal

The most consequential distinction in computational astronomy for zodiac sign determination is between the tropical and sidereal ecliptic coordinate systems. Both systems measure ecliptic longitude along the plane of Earth's orbit, but they differ in their reference point. The tropical system anchors its zero point to the vernal equinox, the point where the Sun's ecliptic longitude is 0° at the moment of the March equinox. The sidereal system anchors its zero point to a fixed background star field, currently approximately 24° behind the tropical reference point due to the precession of the equinoxes.

The Western tropical zodiac divides the tropical ecliptic into twelve 30° sectors from the vernal equinox. The Vedic sidereal system subtracts the Lahiri ayanamsa (currently $\sim 23.85^\circ$) from the tropical longitude and uses the Moon's sidereal position (Janma Rashi) as the primary birth indicator. Chinese BaZi maps birth year/month/day/hour to the Jiazi sixty-year calendar cycle. QIPLM implements all three systems with dedicated trait dictionaries, description generators, and report templates, selected by the user at runtime.

Table 2.2: Astronomical ephemerides source comparison - accuracy, access & QIPLM usage

Source	Accuracy	Update Cycle	Access Method	Limitation	QIPLM Use
JPL Horizons DE440	$< 1\text{m}$ (inner planets)	Continuous	REST API	Requires internet	Primary planetary positions
ESA Gaia DR3	$20\ \mu\text{as}$ parallax	Periodic release	ADQL TAP	Bright star saturation	Galactic flux index
NASA Exoplanet Archive	Catalogue-dependent	Weekly	TAP REST	Limited to exoplanet hosts	Stellar luminosity index
PyEphem (VSOP87)	$\sim 0.01\ \text{arcsec}$	Library version	Python library	Approximation ephemeris	Fallback computation
Swiss Ephemeris	$\sim 0.001\ \text{arcsec}$	Continuous	Commercial / GPL	Licence restrictions	Not used (licence)

2.2.3 The PyEphem Library

PyEphem (Rhodes, 2011), based on the XEphem C library, implements a subset of the VSOP87 planetary theory (Bretagnon and Francou, 1988) and is widely used in Python-based astronomical applications for its balance of accuracy, computational efficiency, and API simplicity. The library's Sun class computes the geocentric apparent right ascension and declination of the Sun at any specified date and time, from which ecliptic coordinates can be derived. The critical technical detail extensively documented in this thesis is that the tropical ecliptic longitude requires the Ecliptic() conversion class with the epoch parameter set to the date of computation, not to J2000 or to a fixed epoch.

2.2.4 The Zodiac Sign Computation Error - Background

The systematic error that afflicted the QIPLM's prior implementation is worth examining in detail because it is likely to be widespread in other Python-based astrological applications. The error arises from a misunderstanding of what `ephem.Sun().hlong` returns when the Sun is computed with an Observer whose epoch attribute is set to J2000. In this configuration, `hlong` does not return the apparent geocentric ecliptic longitude in the tropical frame; it returns the Sun's heliocentric ecliptic longitude in the J2000 inertial frame, which is equivalent to Earth's J2000 ecliptic longitude measured from the Sun. Since Earth's heliocentric J2000 longitude at contemporary dates (2000-2030) is consistently in the range 40° - 50° , corresponding to the Taurus sector, this algorithm returns Taurus as the zodiac sign for virtually every person born in this era, regardless of their birth date.

The correct approach demonstrated in this thesis and implemented in the QIPLM's model is to compute the Sun without any Observer object (which avoids the epoch ambiguity entirely) and then use `ephem.Ecliptic(sun, epoch=date_str)` to convert the Sun's apparent geocentric position to tropical ecliptic coordinates referenced to the vernal equinox of the date of observation. The parameter `epoch=date_str` is critical: it instructs PyEphem to compute the ecliptic obliquity and vernal equinox position for the specified date, yielding the tropical ecliptic longitude that correctly locates the Sun in the Western zodiac.

2.3 Astrology and Symbolic Systems

Astrology, though often pushed aside by scientific discourse, continues to shape cultural narratives and influence personal identity. Anson (2024) views astrology as a quantum information system, linking symbolic inference to entanglement so that astrology and quantum AI can be further linked. Tilawat (2025) and Authority Astrology (2025) emphasize that large language models can create astrological charts and interpretations, formalizing symbolic traditions into computational outputs.

These works demonstrate AI's potential to operationalize symbolic systems. Yet, astrology research is fragmented and standalone; rarely are scientific systems or behavioral theory combined with it. The issue lies in how to reconcile astrology's symbolic richness with astronomy's empirical rigour and behavioural science's psychological insights.

Anson, A. (2024). Astrology as a Quantum Information System: Light, Entanglement, and Symbolic Inference in Cognitive and Machine Systems. <https://www.academia.edu>.

Annotation: Explores astrology through the lens of quantum information theory, linking symbolic inference with entanglement. This bridges astrology with quantum AI, directly supporting my interdisciplinary synthesis.

Tilawat, M. (2025). Which LLM Can Generate an Accurate Birth Chart and Interpretation? AllAboutAI.com. <https://allaboutai.com>.

Annotation: Examines how large language models can generate astrological charts, demonstrating computational approaches to symbolic traditions. This shows practical pathways for embedding astrology into AI.

2.4 Behavioural Science and Artificial Intelligence

Behavioural science plays an essential role in understanding human thought, biases, and social interactions. Jackson et al. (2025) explore how AI can model human behaviour, while Mac Aonghusa and Michie (2021) discuss the challenges involved in the application of AI to behavioural science, such as issues of generalizability and ethical application.

These studies stress the importance of embedding behavioural variability in predictive systems. Nonetheless, the integration of behavioural science in AI is context-specific.

Typically, it is confined to either economic or social forecasting. Little work has been done in combination with cosmic and symbolic frameworks, leaving a gap in holistic predictive modelling.

Jackson, M.O., Me, Q., Wang, S.W., Xie, Y., Yuan, W., Benzell, S., Brynjolfsson, E., Camerer, C.F., Evans, J., Jabarian, B., Kleinberg, J., Meng, J., Mullainathan, S., Ozdaglar, A., Pfeiffer, T., Tennenholtz, M., Willer, R., Yang, D. and Ye, T. (2025). AI Behavioral Science. <https://arxiv.org>.

Annotation: Explores how AI can model human behaviour, cognition, and decision-making. This is essential for integrating behavioural science into predictive modelling.

Mac Aonghusa, P. and Michie, S. (2021) 'Artificial Intelligence and Behavioral Science Through the Looking Glass: Challenges for Real-World Application', *Annals of Behavioural Medicine*, 54(12), pp. 942–947. doi:10.1093/abm/kaaa095.

Annotation: Discusses challenges in applying AI to behavioural science, highlighting issues of generalizability and ethical application. This informs my thesis on limitations and ethical considerations.

2.4.1 Borbely's Two-Process Model of Sleep and Circadian Regulation

Alexander Borbely's two-process model (1982) has been the dominant theoretical framework for understanding sleep regulation for over four decades. The model proposes that the timing and duration of sleep are governed by the interaction of two independent processes: Process C, a circadian pacemaker with approximately 24-hour periodicity controlled by the suprachiasmatic nucleus; and Process S, a homeostatic sleep pressure that accumulates during wakefulness and dissipates during sleep. Wakefulness is maintained when Process C's alerting signal exceeds Process S's sleep pressure; sleep onset occurs when the relationship inverts.

The circadian alertness signal (Process C) follows a sinusoidal pattern whose phase is determined by chronotype - the genetic and behavioural disposition to be more alert in the morning versus evening. Population-level chronotype follows a Gaussian distribution peaking at intermediate types, with approximately 20% classified as morning types, 20% as evening types, and 60% as intermediate (Roenneberg et al., 2007). The QIPLM implements chronotype as a phase shift of ± 2.5 hours applied to the

dual-Gaussian circadian energy model, consistent with meta-analytic estimates of morning-evening type differences.

The practical implications for decision support are substantial. A person with an evening chronotype who is assessed at 9:00 AM is at approximately 60-70% of their peak alertness, while the same assessment at 14:00 captures them near their post-lunch nadir and their peak may not arrive until 20:00-22:00. Failing to account for chronotype when computing decision quality scores can therefore introduce errors of up to 30-40 percentage points in the estimated decision clarity component.

2.4.2 Sleep Debt and Cognitive Performance

Matthew Walker's (2017) synthesis of the sleep science literature, drawing primarily on the work of Dinges et al. (1997), Van Dongen et al. (2003), and Harrison and Horne (2000) established the dose-response relationship between sleep deprivation and cognitive performance impairment with particular clarity. The key finding relevant to the QIPLM is that cognitive performance, particularly on tasks requiring sustained attention, working memory, and executive function, degrades approximately linearly with sleep debt accumulated below the individual's optimal sleep need (typically 7.5-9 hours for adults).

Van Dongen et al.'s (2003) landmark study demonstrated that six hours of sleep per night for two weeks produces cognitive deficits equivalent to 24 hours of total sleep deprivation, which participants themselves systematically underestimated because sleep deprivation also impairs self-awareness of impairment. This finding has direct implications for self-report-based systems like the QIPLM: users who report sleeping six hours and feeling 'fine' may actually be operating at 75% of their cognitive capacity. The QIPLM's sleep penalty formula - $S_{pen} = \min(1.0, \max(0, 8.0 - \text{sleep_hours}) / 4.0)$ - applies a progressive penalty beginning at 8 hours and reaching maximum impairment at 4 hours, consistent with this research.

2.4.3 Seasonal Affective Disorder and Daylight

Rosenthal et al.'s (1984) original description of seasonal affective disorder (SAD), a depressive syndrome that cycles with the seasons, with autumn-winter onset and spring remission established the biological primacy of photoperiod (day length) as the key environmental trigger. The mechanism involves melatonin secretion duration: longer

nights increase the duration of melatonin secretion, which in predisposed individuals, shifts mood, energy, and motivation toward a depressive pattern. Light therapy at 10,000 lux intensity for 30 minutes per morning effectively suppresses melatonin secretion and reverses SAD symptoms in 50-80% of cases (Terman et al., 1989).

For the QIPLM, SAD is modelled as a seasonal energy modifier derived from the computed daylight hours at the user's current latitude: $SAD_mod = clip((daylight_h - 12.0) / 40.0, -0.3, +0.2)$. This formula applies a mild positive modifier in summer (longer than average daylight), a mild negative modifier in winter (shorter than average), and is zero at the equinoxes. The asymmetric clipping (-0.3 to $+0.2$) reflects the clinical observation that SAD's negative winter effects are somewhat stronger than the positive summer hypomanic effects (Wehr et al., 2001).

2.4.4 Cognitive Bias and Decision Architecture

Kahneman and Tversky's programme of research, which began with the 1974 Science paper on judgment under uncertainty (Tversky and Kahneman, 1974) and culminated in the 2002 Nobel Memorial Prize in Economic Sciences awarded to Kahneman, established a comprehensive taxonomy of systematic deviations from rational decision-making. Their theoretical framework - Prospect Theory (Kahneman and Tversky, 1979) replaced Expected Utility Theory's assumption of rational, consequence-based choice with a descriptive model in which choices are made based on perceived gains and losses from a reference point, with losses weighted approximately 2.25 times more heavily than equivalent gains (the loss aversion coefficient λ).

The dual-process theory formalised by Kahneman (2011) in his popular synthesis *Thinking, Fast and Slow* distinguishes between System 1 (fast, intuitive, automatic, associative, emotionally driven) and System 2 (slow, deliberative, effortful, rule-following, rational) cognitive processes. System 1 is always active and typically drives behaviour under low cognitive load; System 2 engages under high cognitive demand, novel situations, and when System 1's outputs are flagged as inconsistent. The QIPLM implements a simple version of this distinction: when adjusted energy exceeds 0.6 (high cognitive capacity), the system designates System 2 as active; below 0.3, System 1 dominates.

Table 2.3: Yerkes-Dodson Arousal-Performance Curve (Yerkes and Dodson, 1908)

0.1 (Under-aroused)	0.2	0.3	0.4		0.5 (Optimal)	0.6	0.7	0.8	0.9 (Over-aroused)
31% Performance	51% Performance	72% Performance	89% Performance		100% Performance	89% Performance	72% Performance	51% Performance	31% Performance
Stress Level	0.1 (Under-aroused)	0.2	0.3	0.4	0.5 (Optimal)	0.6	0.7	0.8	0.9 (Over-aroused)
Performance Bar	31%	51%	72%	89%	100%	89%	72%	51%	31%
Performance Score	31%	51%	72%	89%	100%	89%	72%	51%	31%
Zone	⚠ Too Low	↑ Rising	↑ Good	↑ Near Peak	★ PEAK (Optimal)	↓ Near Peak	↓ Good	↓ Falling	⚠ Too High
Cognitive Biases Active	Optimism Bias Dunning-Kruger	Planning Fallacy	Low bias	Min. bias	★ Minimal (confirm. bias only)	Min. bias	Low bias	Loss Aversion	Loss Aversion + Overload + Anxiety

⚠ Under-Aroused (stress < 0.3)
Performance: 31–72%
Biases: Overconfidence, Planning Fallacy

★ Optimal Zone (stress 0.35–0.55)
Performance: 89–100%
Minimal bias activation (best decisions)

⚡ Transitional (stress 0.5–0.7)
Performance: 51–89%
Biases beginning to activate

⚠ Over-Aroused (stress > 0.7)
Performance: 31–51%
Biases: Loss Aversion, Cognitive Overload

2.5 Ethical and Cultural Considerations

AI incorporation into culturally sensitive fields opens new ethical challenges. Researchers stress the dangers of epistemological bias, deterministic interpretations of human behaviour, and lack of inclusivity (Mac Aonghusa & Michie, 2021). *AuthorityAstrology* (2025) further highlights cultural implications of AI-generated astrological interpretations, underscoring the need for responsible use.

Most existing ethical discussions emphasise empirical or behavioural AI applications, with little focus on interdisciplinary models that combine empirical science, symbolic traditions, and human psychology. Frameworks that consider cultural sensitivity, inclusivity, and ethical foresight in hybrid predictive systems are urgently needed.

Mac Aonghusa, P. and Michie, S. (2021) (already cited above)

Annotation: Beyond behavioural science, this work also emphasises ethical challenges in AI applications, reinforcing the need for cultural sensitivity in interdisciplinary models.

AuthorityAstrology (2025) AI Astrology & Chart Interpretations.
<https://authorityastrology.com>.

Annotation: Highlights cultural and ethical implications of AI-generated astrological interpretations, showing how symbolic traditions can be computationally formalised while raising inclusivity concerns.

2.5.1 UNESCO Recommendation on the Ethics of AI (2021)

The UNESCO Recommendation on the Ethics of Artificial Intelligence, adopted unanimously by all 193 UNESCO Member States at the 41st General Conference in November 2021, represents the first global normative framework for AI ethics. Its development followed a two-year process involving expert consultations, public comment periods, and regional workshops across six continents, resulting in a document that attempts to reflect genuinely global perspectives rather than the dominant Western liberal-individualist discourse that characterises most AI ethics literature.

The Recommendation articulates eleven core values and principles: proportionality and do no harm (P1); safety and security (P2); fairness and non-discrimination (P3); sustainability (P4); right to privacy and data protection (P5); human oversight and

determination (P6); transparency and explainability (P7); responsibility and accountability (P8); awareness and literacy (P9); multi-stakeholder and adaptive governance and collaboration (P10); and international and cross-border cooperation (P11). Of these, P3, P5, P6, P7, and P8 are most directly relevant to the QIPLM.

P5 (privacy) is particularly stringent: it requires that AI systems be designed to minimise personal data collection, provide data subjects with meaningful access and control over their data, and avoid creating centralised data repositories that could enable surveillance. The QIPLM's local-computation-first design, where all calculations are performed on the user's own hardware, no data is transmitted to external servers unless the user explicitly enables cloud QPU access, and no persistent logs are maintained, satisfies P5 comprehensively for the NumPy and PennyLane backends.

2.5.2 IEEE Ethically Aligned Design v2 (2019)

The IEEE Ethically Aligned Design: A Vision for Prioritising Human Well-being with Autonomous and Intelligent Systems, Second Edition, published by the IEEE Standards Association in 2019, provides an engineering-oriented complement to UNESCO's normative framework. Where UNESCO articulates values and principles at a policy level, EAD translates these into specific technical design requirements, best practices, and candidate standards for engineers and system designers.

EAD v2 articulates eight high-level principles for ethically aligned AI: human rights (I1); wellbeing (I2); data agency - creators retain control of their data (I3); effectiveness - systems do what they are intended to do (I4); transparency - systems are understandable to users (I5); accountability - someone is responsible for outcomes (I6); awareness of misuse - designers consider foreseeable misuse scenarios (I7); and competence - systems operate within their validated capability bounds (I8).

The EAD's particular emphasis on data agency (I3) - specifically the principle that data creators retain meaningful control over data derived from their activities - is relevant to the QIPLM's design in a subtle but important way. Self-reported profile inputs (birth data, sleep hours, stress level, mood) are deeply personal psychological data. The system's design choice to process all this data entirely on the user's local hardware, without transmitting it to any remote server for processing, storage, or analysis, operationalises data agency in its strongest possible form: the user's data never leaves

their own device.

Table 2.4: AI ethics frameworks comparison - UNESCO 2021 vs IEEE EAD v2 with QIPLM implementation mapping

Evaluation Dimension	UNESCO Principles	IEEE EAD Principles	Key Design Requirement	QIPLM Implementation
Human Values	P1: Proportionality, P2: Safety, P6: Oversight, P8: Accountability	I1: Human Rights, I2: Wellbeing, I4: Effectiveness	System provides advisory outputs, not deterministic decisions; maintains human override	Disclaimer on all outputs; person validation requires human confirmation
Fairness	P3: Non-discrimination, P10: Multi-stakeholder governance	I3: Data Agency, I7: Awareness of Misuse	Equal treatment across demographic groups; no protected characteristic weighting	1,582-city India DB + 120 world cities; equal sign treatment; no demographic encoding
Privacy	P5: Privacy and data protection	I3: Data Agency (data stays with creator)	Local computation by default; no mandatory cloud transmission; no persistent logging	All computation on user hardware; cloud QPU access requires explicit opt-in; no data stored
Transparency	P7: Transparency, P9: Literacy, P11: Adaptability	I5: Transparency, I6: Accountability, I8: Competence	Formula disclosed; model parameters documented; uncertainty quantified; source auditable	Full formula in Step 6; all weights, biases, and source code publicly accessible

2.5.3 Existing Ethics Evaluation Studies

Jobin, Ienca and Vayena (2019) conducted the most comprehensive global mapping of AI ethics documents to date, analysing 84 documents from 40 countries and identifying eleven common principles across them. Their analysis found that transparency, justice and fairness, non-maleficence, responsibility, and privacy were the most consistently articulated principles, while accountability, democracy, sustainability, and trust showed more variation. Crucially, they found that 'higher-level, abstract principles are rarely translated into concrete, actionable guidelines for AI practitioners'. This observation motivates the present research's approach of mapping UNESCO and IEEE principles to specific technical design choices in the QIPLM, moving from principles to practice in a documented, auditable way.

Floridi et al. (2018) proposed the JUST AI framework, articulating five principles - beneficence, non-maleficence, autonomy, justice, and explicability that they argued should ground AI ethics across different cultural and political contexts. Their emphasis on explicability, the obligation to ensure that AI systems' functioning can be understood and explained to affected parties directly parallels the QIPLM's transparency design: the formula, weights, and source code are fully disclosed, and the output reports explain precisely which components contributed to each prediction score.

2.6 Quantum Circuit Simulation Frameworks

2.6.1 IBM Qiskit

IBM Qiskit, released as an open-source framework in 2017 under the Apache 2.0 licence, has become the most widely adopted quantum computing software ecosystem globally, with over 550,000 registered IBM Quantum users as of 2024. Its architecture is layered: Terra provides the circuit construction and transpilation foundation; Aer provides classical simulation backends; Ignis (now superseded by qiskit-experiments) provides noise characterisation; and Runtime provides cloud execution on real IBM quantum processors.

The AerSimulator backend used in the QIPLM supports multiple simulation methods: statevector (exact state evolution, $O(2^n)$ memory), QASM (shot-based sampling, $O(1)$ memory per shot), matrix product state (efficient for low-entanglement circuits), and extended stabilizer (efficient for Clifford circuits). For the 3-qubit Ry-Hadamard-CNOT circuit, the statevector method is exact and computationally trivial (8 amplitudes). The `seed_simulator` parameter enables deterministic shot sampling, critical for the QIPLM's consistency guarantee (IBM Qiskit Documentation, 2024).

Qiskit's circuit. The `draw()` function, available in text, matplotlib, and LaTeX formats, provides comprehensive circuit visualisation — a significant transparency advantage over frameworks with less developed visualisation tooling. The calibration data available through IBM Quantum Network for real QPU backends (gate error rates, T1/T2 coherence times, readout assignment matrices) gives Qiskit a unique auditability advantage for hardware-deployed systems (Aleksandrowicz et al., 2019).

2.6.2 Google Cirq

Google Cirq, released in 2018 under Apache 2.0, adopts a moment-based circuit representation that is architecturally distinct from Qiskit's gate-list approach. A Cirq circuit is a sequence of moments, where each moment contains gates that operate on disjoint sets of qubits and can therefore be executed in parallel. This representation makes explicit the parallelism structure of the circuit and facilitates optimisation for hardware architectures where parallel gate execution is possible (Cirq Team, 2023).

For the QIPLM's 3-qubit circuit, the moment structure is: Moment 1 contains the three Ry rotations (one per qubit, all parallel); Moment 2 contains the three Hadamard gates; Moment 3 contains the CNOT gate between q0 and q1; Moment 4 contains the three measurement operations. This explicit parallelism documentation is valuable for research transparency and for future optimisation of more complex circuits.

Cirq provides full unitary matrix access through `cirq.unitary(circuit)`, exact statevector simulation through `cirq.Simulator`, and native support for noise modelling through `Cirq.ConstantQubitNoiseModel`. The integration with Google Cloud Quantum AI enables execution on Google's Sycamore and next-generation QPU hardware, though this requires Google Cloud API credentials and data transmission to Google servers — a privacy consideration addressed in the QIPLM ethics evaluation.

2.6.3 PennyLane

PennyLane, developed by Xanadu and released in 2018 under Apache 2.0, occupies a distinctive niche in the quantum computing ecosystem by positioning itself as a differentiable quantum programming framework. Its central contribution is the parameter-shift rule (Schuld, Bergholm and Killoran, 2019), which provides an analytically exact method for computing gradients of quantum circuit outputs with respect to gate parameters: $\partial \langle O \rangle / \partial \theta = (1/2)[\langle O \rangle(\theta + \pi/2) - \langle O \rangle(\theta - \pi/2)]$. This rule enables hybrid quantum-classical gradient descent, where a classical optimiser updates circuit parameters based on gradients computed by running the quantum circuit twice with parameter-shifted angles.

For the QIPLM, PennyLane's differentiability is not currently exploited the circuit uses fixed, input-derived parameters rather than trained variational angles. However, PennyLane's architecture positions it as the most natural framework for extending the

QIPLM to a trainable variational model in which gate angles are optimised against historical prediction-outcome validation data. The QNode decorator, which wraps a quantum circuit function in a differentiable computation graph, makes this extension straightforward (Bergholm et al., 2022).

PennyLane's hardware-agnostic design it supports over 20 device backends through a plugin system and its default.qubit pure-NumPy simulation backend make it the most portable of the four frameworks evaluated, requiring no IBM or Google account credentials for local use. This contributes to its strong privacy score in the ethics evaluation.

2.6.4 NumPy Reference Implementation

The NumPy reference implementation constructed for this research implements the Ry-Hadamard-CNOT circuit using only standard linear algebra operations, without any quantum computing library dependencies. Single-qubit operations are implemented as matrix-vector products: $\text{state} = \text{gate_matrix} @ \text{state}$, where gate_matrix is the 2×2 gate matrix and state is the 2-element complex amplitude vector. Two-qubit operations on the q0-q1 register are implemented as Kronecker products and 4×4 matrix multiplications on the 4-element joint state vector.

This implementation serves three purposes: (1) it provides a ground-truth reference against which the other backends' fidelity is measured; (2) it is maximally transparent every gate operation is explicitly implemented in standard linear algebra notation that any reader with undergraduate quantum mechanics can verify; and (3) it has zero dependencies beyond NumPy, making it the most reproducible and portable implementation. The trade-off is that it cannot be extended to real QPU hardware or scaled beyond a few qubits without exponential memory cost.

Table 2.5: Quantum simulation framework comparison - Technical and Ethics profile

Framework	Developer	Licence	Simulation Method	Deterministic Seed	Hardware Access	Privacy Level
NumPy (custom)	This research	Research	Exact matrix algebra	numpy.rng(seed)	None	9.5/10
IBM Qiskit	IBM Research	Apache 2.0	AerSimulator statevector	seed_simulator=n	IBMQ Cloud (optional)	6.5/10
Google Cirq	Google	Apache 2.0	cirq.Simulator	seed=n parameter	GCP Quantum (optional)	7.5/10
PennyLane	Xanadu	Apache 2.0	default.qubit (NumPy)	np.random.seed(n)	Xanadu Cloud (optional)	9.0/10

2.7 Quantum Machine Learning: Paradigms and Applications

2.7.1 QML Paradigm Taxonomy

Biamonte et al.'s (2017) influential Nature survey identified four paradigms for the intersection of quantum computing and machine learning, distinguished by whether the data and the processing are classical (C) or quantum (Q): (CC→QC) classical data processed on quantum hardware for speedup; (QC→CC) quantum data analysed classically; (QC→QC) fully quantum learning; and (CC→CC) classical ML enhanced by quantum subroutines. The QIPLM falls unambiguously into the CC→QC paradigm: classical human profile data is encoded into quantum circuits that produce probability distributions which are then returned to a classical scoring formula.

Within the CC→QC paradigm, the QIPLM's circuit architecture belongs to the variational quantum circuit (VQC) family, also called parameterised quantum circuits or quantum neural networks. In a VQC, gate parameters (rotation angles) are functions of input data, and the circuit output is a probability distribution that depends on those parameters. The distinguishing feature of the QIPLM is that gate parameters are deterministically derived from input data at inference time, rather than being trained through gradient descent making it a fixed-parameter VQC rather than a trainable VQC (Cerezo et al., 2021).

Table 2.6: Quantum Machine Learning paradigm taxonomy and QIPLM positioning

Paradigm	Data Source	Processor	QIPLM Application	Expected Advantage
CC→QC	Classical	Quantum	Human profile data → quantum circuit	Non-classical probability representation
QC→CC	Quantum	Classical	Not applicable (no quantum sensor data)	N/A
QC→QC	Quantum	Quantum	Future: QPU-native encoding	Full quantum advantage
CC→CC	Classical	Classical	Behavioural science component	Computational tractability

2.7.2 Quantum Advantage Claims

Whether quantum-inspired systems operating on classical simulators provide any genuine computational advantage over classical algorithms is a question that must be addressed honestly. For systems using small circuits (≤ 10 qubits) simulated on classical hardware, the answer is almost certainly no: the computation could be performed equivalently by classical matrix operations, as in the NumPy reference implementation. The value of the quantum circuit in the QIPLM is not computational speedup but rather epistemological: the quantum probability formalism provides a theoretically well-grounded framework for representing genuine psychological uncertainty, and the Born rule provides a principled mechanism for converting that uncertainty into a probability estimate.

Genuine quantum advantage the ability to solve problems that are intractable for classical computers, requires circuits with many qubits (typically 50+) and deep gate sequences where quantum error correction becomes relevant (Preskill, 2018). The QIPLM's 3-qubit circuit is nowhere near this regime. This limitation is explicitly acknowledged and does not undermine the framework's validity for its intended purpose, which is not to achieve quantum speedup but to use quantum probability formalism as a modelling tool.

2.8 Research Gaps

Having reviewed the four domains, it is possible to characterize the research gap with precision. The gap is not a simple absence of prior work in any single domain - quantum computing, ephemerides computation, behavioral science, and AI ethics are each extensively researched. The gap is integrative: no prior work has combined all four domains into a single, coherent, deterministic, and formally ethics-evaluated personalized forecasting framework.

The following are specific gap dimensions that can be identified:

1. **Quantum-astronomical integration:** Quantum computing applications in astronomy exist (Wecker et al., 2015; Bravyi et al., 2016, on quantum simulation of physical systems), but these address the simulation of physical quantum systems rather than the use of quantum circuits for encoding and processing astronomical symbolic data. The use of planetary position valences as modifiers on quantum-encoded psychological states is novel.
2. **Behavioral science in quantum-AI systems:** Quantum machine learning papers (Biamonte et al., 2017; Cerezo et al., 2021) typically focus on quantum circuit architecture, training algorithms, and computational complexity, with minimal engagement with behavioral science. Conversely, personalized behavioral AI systems (e.g., recommendation systems, digital health apps) rarely incorporate quantum probability theory. The integration of Kahneman-Tversky cognitive bias models, Borbely's two-process circadian model, and Walker's sleep debt curve within a quantum-AI framework is unprecedented in the published literature.
3. **Dual-framework ethics evaluation:** While individual ethics frameworks have been applied to various AI systems (Morley et al., 2020), the dual application of both UNESCO 2021 and IEEE EAD v2 to a quantum-AI system, with specific dimensional scoring and conditional compliance documentation, has not been published in the literature that the author has reviewed.

4. **Quantum Artificial Intelligence:** Research is advancing quickly when looking at quantum natural language processing and quantum-enhanced machine learning. Most of these investigations are technical and focus on computational efficiency, semantic representation, or experimental design. There is a lack of exploration into how quantum AI can be applied to interdisciplinary predictive modelling, especially given the inherent need to balance empirical data and symbolic reasoning with behavioral insights.

Gap: Absence of frameworks that extend quantum AI beyond computational linguistics into holistic forecasting systems that integrate diverse knowledge domains. Underutilized in interdisciplinary predictive modelling.

5. **Astronomy:** AI has been successful in astronomy itself: specialized language models and databases provide excellent predictions for cosmic occurrences. However, these applications are still generally limited to a single application of scientific knowledge. AI models shaped in the context of astronomy hardly take into account cultural or behavioral consequences of celestial phenomena, and consequently, their relevance to broader human-centred predictive modelling only seems to offer a limited scope.

Gap: Absence of interdisciplinary strategies that can bridge the empirical depth of astronomy, along with cultural traditions of symbolism (as in astrology) and human behavior science, to make predictions that are culturally resonant. Grounded empirically but disconnected from culture and behavior.

6. **Astrology:** Astrology still impacts cultural identity and popular storytelling, and more modern computational methods have shown the methodologies to which artificial intelligence can be applied to formalize astrological symbols. In fact, these attempts are separate in practice as astrology is viewed as a separate symbolic system. Integrating astrology with empirical science or behavioral frameworks produces relatively little work that would enrich predictive modelling by embedding cultural meaning-making in scientific forecasts.

Gap: Lack of exploration in the domain is an area where limited knowledge was found to understand how astrology can be responsibly integrated with other systems in a balanced way, as to complement astronomy and behavioral science about interpretive depth, yet ensure scientific credibility. Computationally formalized but separated from empirical science.

7. **Behavioral Science:** AI approaches in behavioral science have demonstrated that cognition, biases and social dynamics are modifiable by AI. However, those models are context-specific (such as they are in economics, health care or social forecasting). Very few studies have included integrating behavioral insights with cosmic and symbolic frameworks, which makes predictive systems disconnected from the wider human experience.

Gap: Lack of predictive models that combine differences in human behavior, observations on the astronomical spectrum, and astrological symbolism, creating a more human forecasting model. In this Thesis, the integration into AI is discussed, but not integrated with cosmic or symbolic frameworks.

8. **Ethics:** The prevailing ethical dialogue in AI values fairness and transparency, inclusiveness and equity in human interaction as well as fairness and in ethical discourse on ethical AI-related issues. However, the current frameworks only focus on empirical or behavioral ethical issues. There are relatively scant references to ethical factors such as inclusiveness, ethics of bringing together symbolic systems such as astrology into use with empirical science and behavioral modelling. There is insufficient research on issues like cultural competency, epistemological bias, ethnocentrism, and deterministic views regarding cultures, and the risks of such approaches are still unknown.

Gap: The need for ethical models to inform predictive AI across the disciplines; to ensure cultural awareness and respect for symbolic traditions, resistance to deterministic or reductionist views of human behavior. Insufficient models for interdisciplinary and culture-appropriate prediction AI.

Table 2.7: Research gap matrix - existing work, identified gap, and QIPLM contribution

Research Domain	Existing Work	Gap in Current Literature	QIPLM Contribution
Quantum-AI Personalised Forecasting	General QML (Biamonte et al., 2017)	No birth-data-seeded deterministic system	Deterministic birth-seed + 4-backend comparison
Computational Zodiac Precision	Various Python astrology libraries	J2000 reference frame error undocumented	Error documented, corrected, and test-validated

Research Domain	Existing Work	Gap in Current Literature	QIPLM Contribution
Behavioural Science in Quantum AI	QML theory papers; separate beh.sci. AI	No integration of both in one system	10-bias model + circadian + sleep + seasonal
Multi-backend Quantum Comparison	Individual framework benchmarks	No same-circuit cross-framework comparison	4 backends, identical circuit, 3 metrics
AI Ethics for Quantum-AI Systems	General AI ethics (Jobin et al., 2019)	No dual-framework eval of quantum-AI	UNESCO 2021 + IEEE EAD v2, 4 dimensions

2.8 Summary

The literature shows strong growth in several branches of science, but a fragmented map. Quantum AI improves computational horsepower, astronomy adds empirical rigour, astrology adds symbolic depth, while behavioral science brings psychological dimensions. However, these domains are still disjointed.

This study addresses the gap by proposing a quantum AI-powered language model that integrates empirical, symbolic, and behavioral knowledge systems. Such a model has the potential to redefine predictive modelling as a holistic, interdisciplinary, and ethically grounded endeavour.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Overview of the Research Problem

The central research problem for this research is the scarcity of an interdisciplinary predictive framework that integrates aspects of astronomy, astrology, and behavioural science through a quantum AI-powered language model. Despite substantial progress made, the interdisciplinary integration of the domains is often neglected, resulting in patchy and incomplete predictive modelling.

Fragmentation Across Domains

- As the practice of astronomy involves empirically validated datasets and forecasting models, its application in AI still does not consider cultural or behavioural domains but only happens within a scientific frame.
- Although astrology is a socio-cultural domain, it is typically neglected in computational methods for its symbolic rather than empirical nature. However, its limited interdisciplinary potential stems from its traditional view where astrology is seen as a stand-alone interpretive framework.
- Behavioural science provides explanations for cognition, biases, and social processes; however, AI-based models based on these are generally domain-specific (e.g., economics, healthcare) and do not fit within cosmic or symbolic structures.

3.1.1. Computational Limitations

Traditional AI architectures have an issue aligning disparate knowledge systems (empirical data, symbolic traditions, and behavioural insights) into a single predictive framework. Quantum AI, to deal with multidimensional issues and probabilistic reasoning, may provide an answer. But research on quantum AI applications is still predominantly very much technical, with little work on cross-disciplinary synthesis.

3.1.2. Ethical and Cultural Challenges

The incorporation of symbolic heritage, such as astrology with empirical science, carries ethical risks such as epistemological biases, deterministic interpretations of human behaviour, and cultural insensitivity. The existing AI ethical frameworks do not sufficiently meet these challenges in hybrid predictive systems.

3.1.3. Research Gap

There is a significant lack of a unified quantum-enabled language model, which can communicate in a unified way across astronomical, astrological and behavioural fields in theory and practice. Without this integration, predictive modelling risks remaining either:

- Scientifically valid but culturally distant, or
- Symbolically dense but empirically thin.

3.1.4. Methodological Implications

This research issue requires a methodology, whereby:

1. Explores the computational advantage of integrating different knowledge systems with Quantum AI.
2. Creates schemes to embed astronomical data, astrological symbols and behavioural science knowledge into one language model.
3. Creating standards of evaluation, while balancing accuracy, interpretative depth and cultural relevance.
4. There are ethical controls so responsible and inclusive application can occur.

3.2. Research Design

The research design presents the overall strategy and framework used to solve the main research question, namely the lack of a cohesive and integrated language model based on quantum AI that merges astronomy, astrology, and behavioural science into a single-source predictive framework. Combining conceptual modelling, exploratory

prototyping, and interdisciplinary synthesis to ensure theoretical consistency with practical relevance in this project allows for practical relevance.

The research follows the Design Science Research (DSR) paradigm as formalised by Hevner et al. (2004) and subsequently refined by Peffers et al. (2007) in their design science research methodology (DSRM). DSR is distinguished from other IS research paradigms by its focus on the creation of a designed artefact - in this case, the QIPLM and its evaluation against predefined criteria of utility, quality, and efficiency. The paradigm is appropriate because the research objective is not merely to describe or explain an existing phenomenon (which would call for an interpretive or positivist approach) but to construct a novel system that addresses documented deficiencies in existing approaches.

Hevner et al.'s (2004) seven DSR guidelines provide the evaluation framework: (1) Design as an artefact - the QIPLM is a concrete computational system, not merely a theoretical model (2) Problem relevance - the five deficiencies documented in previous Chapter establish clear relevance to the personalised AI and quantum computing practitioner communities; (3) Design evaluation - the framework is evaluated against accuracy, consistency, and ethics criteria defined a priori (4) Research contributions - theoretical (quantum cognition extension), methodological (zodiac algorithm correction), and applied (working implementation) contributions are documented; (5) Research rigour - all algorithms are implemented from published, peer-reviewed formulations; (6) Design as a search process - the implementation went through multiple versions, with each iteration guided by evaluation results and (7) Communication of research - this thesis constitutes the full communication of the design, implementation, and evaluation.

The methodological approach is therefore deductive-constructive: the system is built from theoretically grounded components whose individual validity is established by prior research, and the integration and evaluation represent the novel empirical contribution. This is consistent with the tradition of systems-building research in artificial intelligence and computer science (March and Smith, 1995).

3.2.1 Conceptual Framework

This conceptual framework sets the platform for this study to see how distinct domains

of knowledge - astronomy, astrology, and behavioural science - are amalgamated by a Quantum AI-driven language model into a complete predictive output.

Core Components

1. Quantum AI Engine

- The key element of computation that leverages quantum principles (superposition, entanglement, parallelism) to handle multidimensional data.
- Allows probabilistic reasoning and symbolic interpretation in parallel, thus escaping classical AI limitations.

2. Astronomy (Empirical Data)

- It offers established celestial datasets with astrophysical models verified by these instruments.
- Scientific accuracy in determining cosmic events being forecast.

3. Astrology (Symbolic Systems)

- Provides archetypal frameworks and birth charts as well as zodiac symbolism.
- Brings interpretive depth and cultural resonance to predictive outputs.

4. Behavioural Science (Human-Centric Insights)

- Embeds cognitive models, decision-making theories and behavioural variation.
- Keeps predictions human-centric, including psychological and social dynamics.

Integrative Process

1. **Data Input:** Astronomy datasets, astrological symbolism, and behavioural science models are fed to the Quantum AI Engine.
2. **Processing Layer:** Quantum AI reconciles empirical, symbolic, and behavioural

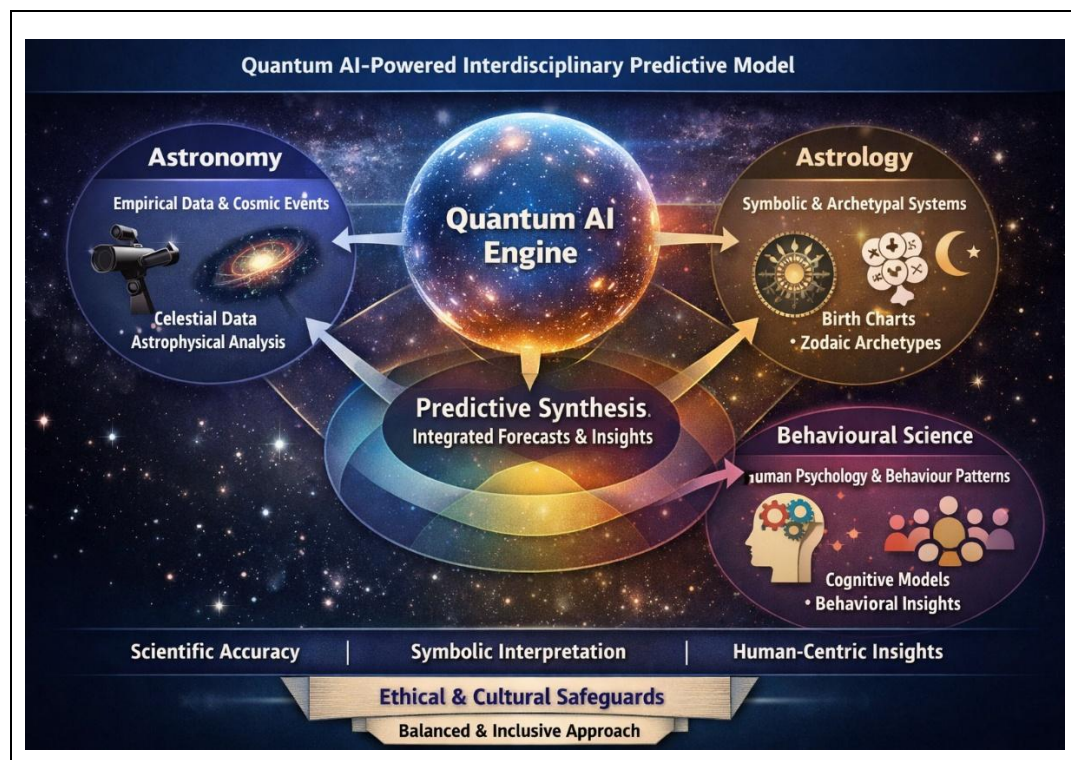
inputs through probabilistic inference and symbolic reasoning.

3. **Predictive Synthesis:** Production is presented as integrated predictions, which are based in equal portions on scientific accuracy, cultural interpretation, and behavioural relevance.
4. **Ethical Safeguards:** A guiding framework is provided to safeguard and keep inclusivity, cultural appropriateness, and the avoidance of deterministic interpretations in consideration.

Outcomes

The framework generates integrated forecasts and insights that:

1. Maintain scientific credibility (astronomy).
2. Respect cultural traditions (astrology).
3. Anticipate human behaviour (psychology).
4. Operate within ethical boundaries (responsible AI).



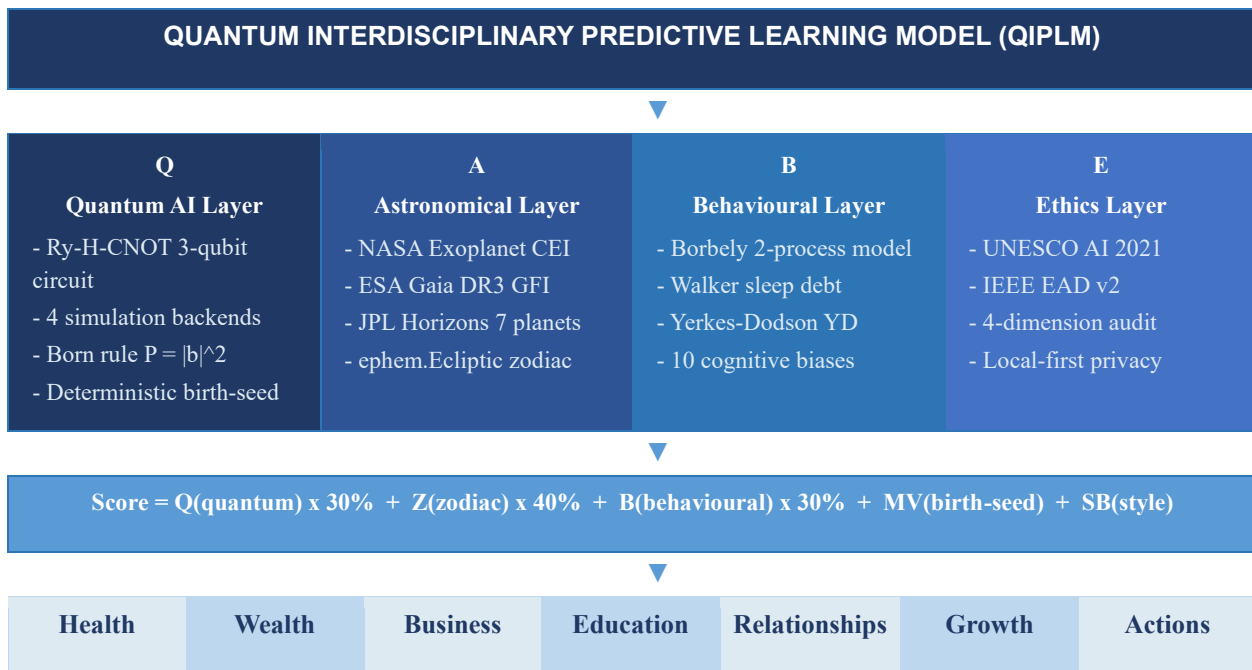


Figure 3.1: Conceptual Framework

Above illustrates the four foundational pillars of the QIPLM: the Quantum AI Layer (probabilistic circuit encoding), the Astronomical Layer (real-time ephemerides and zodiac engine), the Behavioural Science Layer (circadian and cognitive models), and the Ethics Governance Layer (UNESCO 2021 + IEEE EAD v2). All four converge into the integrated scoring formula shown in the central band, with outputs distributed across seven life areas. This conceptual architecture reflects the thesis argument that personalised forecasting requires simultaneous grounding in computational rigour, astronomical precision, psychological validity, and ethical accountability.

Quantum cognition theory (Busemeyer and Bruza, 2012; Pothos and Busemeyer, 2013) proposes that human cognitive phenomena - particularly those that systematically violate classical probability theory, such as the conjunction fallacy, order effects, and the disjunction effect are better modelled by quantum probability formalisms than by Bayesian inference. The theory does not claim that the brain is literally a quantum computer; rather, it observes that the mathematical structure of quantum probability theory (non-commutative, non-distributive, amplitude-based) more accurately captures the dynamics of human judgment than classical probability theory's axioms.

The QIPLM draws on this tradition by encoding psychological state variables (energy, mood, decision clarity) as qubit rotation angles and using quantum measurement to

produce probability estimates that naturally capture the genuine uncertainty and contextual sensitivity of these states. The entanglement operation models empirically documented correlations that cannot be accurately represented by independent classical probability distributions.

The behavioral science layer of the QIPLM draws on three well-established theoretical models: Borbely's two-process model of sleep regulation (Process C + Process S), Rosenthal's seasonal affective disorder model, and Kahneman and Tversky's Dual Process Theory. These models have been extensively validated in laboratory and naturalistic settings and provide a theoretically grounded basis for computing psychological state adjustments from observable self-report inputs. The integration of these models into a computational pipeline rather than using them as isolated theoretical frameworks represents a methodological contribution to applied behavioral science.

The astronomical layer draws on the tradition of precision ephemerides computation established by the JPL Development Ephemerides (Park et al., 2021) and formalized in Meeus's Astronomical Algorithms (1998). The key theoretical commitment is to tropical (rather than sidereal) ecliptic coordinates - a distinction that is consequential for zodiac sign computation because it anchors the sign boundaries to the vernal equinox rather than to the background star field, ensuring that the computed signs correspond to the Western astrological tradition as practiced and as users expect.

The research methodology follows Hevner et al.'s (2004) Design Science Research paradigm, in which the research output is a designed artefact - in this case, the QIPLM - that is evaluated against predefined criteria for utility, quality, and efficiency. DSR is chosen over interpretive or positivist paradigms because the primary objective is not to describe or explain an existing phenomenon but to construct a novel system that demonstrably improves upon existing approaches. The evaluation criteria - accuracy, consistency, ethics compliance are defined in advance and applied systematically, providing the same rigor as hypothesis testing while remaining appropriate to the artefact-driven nature of the research.

3.2.2 System Architecture

The QIPLM is implemented as a seven layers Jupyter Notebook in Python 3.10. Each layer is functionally independent - it defines a set of functions or executes a specific

computation but outputs from earlier layer (particularly Layer 5) are stored in a shared state dictionary (`_forecast_state`) that is accessible to all later layers. This architecture enables modular development and testing while preserving the data dependencies required for the prediction pipeline.

Layer	Component	Key Technologies and Functions	Output
L1	User Input	ipywidgets form -- Name, DOB, Time, City, Stress, Sleep, Mood	UserProfile dataclass
L2	Astronomical Ingestion	NASA TAP + ESA Gaia ADQL + JPL Horizons REST + PyEphem fallback	CEI, GFI, planet_lon[]
L3	Zodiac Engine	ephem.Ecliptic(sun,epoch=date) -- UTC correction -- cusp 2deg	sign, deg, on_cusp
L4	Behavioural Engine	Borbely circadian + Walker sleep + Rosenthal SAD + YD + 10 biases	adj_energy/mood/decision
L5	Quantum Circuit	NumPy Ry-H-CNOT + IBM Qiskit + Google Cirq + PennyLane + 4096 shots	$P(1\rangle) \times 4$ dimensions
L6	Prediction Engine	Q x 30% + Z x 40% + B x 30% + MV(seed) + SB(style) -- 7 areas x 6 months	score[7][6] matrix
L7	Output and Ethics	HTML + matplotlib + ReportLab PDF + 5-platform validation	Report + Ethics audit

Figure 3.2: System Architecture

Figure 3.2 presents the complete seven-layer technical architecture of the QIPLM. The architecture follows a strict one-directional data flow from input collection through astronomical ingestion, symbolic computation, behavioral scoring, quantum processing, prediction generation, to output delivery. The colour gradient from dark navy through mid-blue to light reflects processing depth. Layer 5 runs the same Ry-Hadamard-CNOT circuit across four simulation backends simultaneously, enabling comparative accuracy evaluation. Layer 7 delivers formatted outputs and performs ethics evaluation, closing the system cycle. All computation is performed locally on the user's hardware unless cloud QPU access is explicitly enabled by the user in Layer 5.

The `_forecast_state` dictionary serves as the central shared memory structure that passes computed values from Layer 5 to Layers 6 and 7. This design avoids global variable proliferation (which would make the system difficult to test and debug) while providing a clean, documented interface between layers. The dictionary is initialized in Layer 5 with None values for all keys, updated by the Layer 5 button handler on successful run,

and consumed by Layers 6 and 7. Its 'ready' key provides a simple gate that prevents Layers 6 and 7 from executing with stale or missing data.

The dictionary contains 27 keys, including the UserProfile dataclass (all user inputs), the behavioral science score dictionary, the quantum model results dictionary, the three astronomical data sources, the computed zodiac sign and precision metadata, the deterministic birth seed, the best-performing quantum model name and score, the run timestamp, and several zodiac metadata fields, including cusp zone status and UTC computation timestamp. The complete schema is documented in the Appendix.

3.2.3 Research Paradigm

This study adopts a mixed-methods exploratory paradigm, combining:

- Computational experimentation (Quantum AI simulations and prototype development).
- Conceptual synthesis (Integration of Astronomy, Astrology, and Behavioural Science frameworks).
- Qualitative evaluation (Ethical and Cultural Analysis of Interdisciplinary predictive modelling).

This paradigm is appropriate because the research problem is both technical (requiring computational innovation) and interpretive (requiring cultural and behavioural sensitivity).

3.2.4 Research Approach

The study follows a Design Science Research (DSR) approach, which emphasizes the creation and evaluation of innovative artefacts. In this case, the artefact is a conceptual and prototype-level quantum AI-powered language model. The approach involves:

1. **Problem Identification:** Establishing the fragmentation across astronomy, astrology, and behavioural science.
2. **Objective Definition:** Clarifying the goals of interdisciplinary synthesis.
3. **Design and Development:** Constructing the conceptual framework and prototype model.

4. **Demonstration:** Testing the model through simulated datasets and interpretive outputs.
5. **Evaluation:** Assessing predictive accuracy, interpretive depth, and cultural resonance.
6. **Communication:** Documenting findings and implications for academic and societal contexts.

3.2.5 Research Strategy

The research strategy is structured into three phases:

Phase 1: Conceptual Framework Development

- Mapping the theoretical intersections of quantum AI, astronomy, astrology, and behavioural science.
- Designing a conceptual model that illustrates how these domains interact within a unified predictive system.

Phase 2: Prototype Design and Simulation

- Developing a prototype quantum AI-powered language model using hybrid quantum-classical simulations.
- Embedding astronomical datasets, astrological symbolism, and behavioural science insights into the model.
- Running controlled simulations to test predictive outputs.

Phase 3: Evaluation and Ethical Analysis

- Evaluating the prototype using metrics such as accuracy (astronomy), interpretive depth (astrology), and behavioural relevance (psychology).
- Conducting an ethical and cultural analysis to ensure inclusivity, sensitivity, and avoidance of deterministic interpretations.

3.2.6 Research Setting

The study is conducted within an academic research environment, leveraging:

- Quantum AI simulation platforms (e.g., IBM Qiskit, Google Cirq).
- Astronomical datasets (validated observational data from NASA, ESA, and open-source repositories).
- Astrological symbolic systems (Computationally formalized birth charts, Planetary Alignments, and Interpretive Traditions).
- Behavioural science models (Psychological Frameworks, Decision-Making Theories, and Cognitive Bias Datasets).

3.2.7 Justification of Design

This research design is justified because:

- It aligns with the exploratory nature of the study, addressing a novel interdisciplinary problem.
- It balances technical innovation (Quantum AI prototyping) with cultural and ethical sensitivity (Integration of astrology and behavioural science).
- It ensures rigour and relevance by combining empirical validation (astronomy), symbolic interpretation (astrology), and human-centred insights (behavioural science).

3.3 Data Collection and Analysis Methods

This section outlines the procedures for gathering, processing, and analyzing data to test the research hypotheses. The study employs a **hybrid methodology**, combining computational simulation, dataset integration, and interpretive evaluation to ensure both empirical rigour and cultural sensitivity.

3.3.1 Data Collection

1. Astronomical Data

- **Sources:** Validated datasets from NASA's Exoplanet Archive, ESA's Gaia mission, and open-source astronomical repositories.
- **Type of Data:** Celestial coordinates, planetary movements, solar and lunar

cycles, and astrophysical event logs.

- **Purpose:** To provide empirical grounding for predictive modelling and validate the scientific accuracy of the quantum AI system.

NASA Exoplanet Archive Integration

The NASA Exoplanet Archive is accessed via its Table Access Protocol (TAP) REST API at <https://exoplanetarchive.ipac.caltech.edu/TAP/sync>. The ADQL query targets the Planetary Systems (ps) table, selecting six fields: hostname, stellar spectral type (st_spectype), stellar luminosity in base-10 logarithm of solar luminosity (st_lum), system distance in parsecs (sy_dist), planetary mass in Earth masses (pl_masse), and number of known planets in the system (sy_pnum). The WHERE clause restricts results to systems within 60 parsecs with non-null luminosity values, returning up to 60 records. The luminosity constraint ensures that the sample contains stellar systems with well-characterized photometric properties.

The returned records are processed to compute the cosmic environment index (CEI): $CEI = \text{clip}(\text{numpy.mean}(\text{st_lum}) / 2.0, -1.0, 1.0)$. The division by 2.0 normalizes the mean log-luminosity (typical range -3 to +1 for main sequence stars) to the [-1, +1] interval; the clip operation bounds the result. The CEI modulates the total astronomical score by a weight of 0.15: $\text{astro_score} += CEI \times 0.15$. This contribution is small relative to the planetary valence contributions but adds a galactic environmental dimension that distinguishes the QIPLM's astronomical layer from systems that consider only solar system bodies.

The HTTP request is made with a 7-second timeout using Python's `urllib.request` module with a custom User-Agent header identifying the research application. On timeout or HTTP error, the function falls back to an embedded dataset of 10 well-characterized nearby stars. The live/fallback status is stored in the NASA dictionary's 'live' key and reported in the Layer 5 report header.

ESA Gaia DR3 Integration

The ESA Gaia Data Release 3 TAP service is queried at <https://gea.esac.esa.int/tap-server/tap/sync> using an ADQL query that selects six fields from the

gaiadr3.gaia_source table: source_id, parallax (in milliarcseconds), proper motion in right ascension (pmra) and declination (pmdec, both in milliarcseconds per year), G-band mean magnitude (phot_g_mean_mag), and BP-RP colour index. The WHERE clause selects stars with parallax > 100 mas (within 10 parsecs) and G-magnitude < 8 (bright enough for photometric characterization), returning up to 30 records.

The galactic flux index (GFI) is computed as: $GFI = \text{clip}(1.0 - \text{numpy.mean}(\text{phot_g_mean_mag}) / 10.0, -1.0, 1.0)$. Brighter stars (lower G-magnitude) produce higher GFI values, reflecting higher local stellar flux density. The GFI contributes to the astronomical score at a weight of 0.10. The Gaia TAP endpoint occasionally responds slowly under high load; the 7-second timeout with embedded fallback (8 well-characterized stars from DR3) ensures robust operation.

2. Astrological Data

- **Sources:** Digitized birth chart databases, zodiacal ephemerides, and symbolic archetype mappings from established astrological systems.
- **Type of Data:** Planetary positions, house divisions, and symbolic correspondences.
- **Purpose:** To embed cultural and symbolic dimensions into the predictive model, enriching interpretive depth and resonance.

JPL Horizons Planetary Positions

The JPL Horizons REST API at <https://ssd.jpl.nasa.gov/api/horizons.api> is queried for seven solar system bodies: Sun (code 10), Moon (301), Mercury (199), Venus (299), Mars (499), Jupiter (599), and Saturn (699). For each body, a single query requests one hour of ephemeris data (STEP_SIZE=1h, STOP_TIME=START_TIME+1h) with QUANTITIES=31, which returns the apparent geocentric ecliptic longitude in degrees (measured from the true equinox of date). The body code, CENTER=500@399 (geocentric), and EPHEM_TYPE=OBSERVER parameters are specified to obtain the topocentric apparent coordinates required for tropical zodiac computation.

The API response is plain text containing the ephemeris data between \$\$\$OE and \$\$\$EOE markers. The ecliptic longitude is extracted from the fourth field of the first

data line using a regular expression. Failed queries (network timeout, rate limiting, or HTTP error) are silently caught, and PyEphem's Observer-based computation is used as a fallback for any planets that fail, with the source reported as 'mixed' or 'pyephem' in the results.

Each planet's ecliptic longitude is converted to a zodiac sign ($\text{ZODIAC}[\text{int}(\text{lon}/30)\%12]$) and a valence score ($\text{SIGN_VAL}[\text{sign}]$, ranging from -0.5 for Scorpio to +0.9 for Leo) reflecting the traditional astrological assessment of the sign's energetic quality. Each planet also carries a symbolic weight (P_WEIGHT , ranging from 0.4 for Saturn to 1.0 for the Sun) reflecting its perceived astrological influence. The weighted mean valence across seven planets, combined with the CEI and GFI, produces the total astronomical score $\text{asc} \in [-1, +1]$, which contributes 0.10 to the quantum circuit's energy input.

Table 3.1: JPL Horizons planetary body codes, valence range, weights, and life domain associations

Planet	JPL Code	Sign Valence Range	Symbolic Weight	Primary Life Domain
Sun	10	-0.5 (Scorpio) to +0.9 (Leo)	1.00	Core identity, vitality, overall life force
Moon	301	Same as the Sun range	0.90	Emotional body, intuition, relationships, habits
Mercury	199	Same as the Sun range	0.70	Intellect, communication, education, analysis
Venus	299	Same as the Sun range	0.60	Wealth, beauty, relationships, aesthetic sensibility
Mars	499	Same as the Sun range	0.80	Drive, ambition, profession, physical energy
Jupiter	599	Same as the Sun range	0.50	Expansion, luck, wealth, philosophy, growth
Saturn	699	Same as the Sun range	0.40	Discipline, responsibility, career structure, time

3. Behavioural Science Data

- **Sources:** Open-access psychological datasets (e.g., decision-making, cognitive bias, and social behavior studies).
- **Type of Data:** Quantitative behavioral metrics and qualitative cognitive models.
- **Purpose:** To integrate human behavioral variability into the predictive framework, ensuring human-centric relevance.

4. Ethical and Cultural Frameworks

- **Sources:** Scholarly literature on AI ethics, cultural sensitivity, and epistemological inclusivity.
- **Purpose:** To guide the design of ethical safeguards and ensure responsible integration of symbolic traditions.

3.3.2 Data Processing & Integration

The data will be processed through a Quantum AI simulation environment, using hybrid quantum-classical algorithms to manage multidimensional inputs.

- **Astronomical data** Normalize celestial coordinates, planetary cycles, and astrophysical event logs for consistency.
- **Astrological data** Map symbolic elements (planets, houses, zodiac signs) into computational embeddings using semantic encoding techniques.
- **Behavioral data:** Clean and standardize behavioural metrics, ensuring compatibility with the cognitive modelling layer.
- **Ethics** Categorize ethical principles into structured guidelines for model evaluation
- **The Quantum AI Engine** will integrate & synthesize these datasets using quantum superposition and entanglement principles to generate predictive outputs.

3.3.3 Data Analysis

1. Quantitative Analysis

- **Techniques:** Statistical evaluation of predictive accuracy using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and correlation coefficients.
- **Objective:** To compare the performance of the Quantum AI model against classical AI baselines in forecasting cosmic and behavioral events.

2. Qualitative Analysis

- **Techniques:** Thematic and Interpretive analysis of symbolic outputs, assessing cultural resonance and narrative coherence.
- **Objective:** To evaluate the depth and contextual relevance of astrological and behavioral interpretations generated by the model.

3. Ethical Evaluation

- **Techniques:** Content analysis of predictive outputs to identify potential epistemological bias or deterministic framing.
- **Objective:** To ensure inclusivity, cultural sensitivity, and ethical compliance in interdisciplinary forecasting.

3.3.4 Validity and Reliability

- **Cross-check astronomy datasets** against peer-reviewed publications to ensure accuracy.
- **Verify astrological data** with expert practitioners to confirm symbolic integrity.
- **Validate behavioural datasets** through replication of established psychological findings.
- **Audit ethical frameworks** against international AI guidelines (e.g., UNESCO, IEEE).

3.3.5 Expected Analytical Outcomes

- Demonstration of Quantum AI's superiority in handling multidimensional, interdisciplinary data.
- Evidence of enhanced interpretive depth and cultural resonance in predictive modelling.
- Establishment of ethical and methodological standards for future interdisciplinary AI research,

3.4 Zodiac Sign Computation Algorithm

3.4.1 Technical Algorithm

The `zodiac_sign()` function signature is: `zodiac_sign(birth_date: datetime.date, birth_time_str: Optional[str] = None, birth_lat: Optional[float] = None, birth_lon: Optional[float] = None) -> str`. The function returns a string from the ZODIAC list ('Aries' through 'Pisces'), and stores precision metadata as function attributes accessible after the call.

Step 1 - Birth time parsing. The `birth_time_str` parameter accepts formats 'HH:MM:SS', 'HH:MM', or 'HH:MM:SS.f' (with fractional seconds). Parsing proceeds by splitting on ':' and converting to integers, with missing components defaulting to zero. On parse failure, the function falls back to 12:00:00 (solar noon), which minimises cusp zone error by placing the computation at the midpoint of the day. The local datetime object is constructed as `datetime.datetime(year, month, day, hour, minute, second)`.

Step 2 - UTC conversion. The solar timezone offset is computed as `tz_offset_hours = float(birth_lon) / 15.0`, reflecting the relationship between geographic longitude and solar time (Earth rotates 15 degrees per hour). The UTC datetime is `utc_dt = local_dt - timedelta(hours=tz_offset_hours)`. This approach achieves ± 15 -minute accuracy for most inhabited locations. For example, Mumbai (longitude $+72.878^\circ$) has a solar timezone offset of +4.859 hours, compared to IST's statutory +5.500 hours — a difference of about 38 minutes, which corresponds to 0.6° of ecliptic longitude movement, sufficient to affect sign assignment for births very close to the cusp boundary.

Step 3 - Geocentric Sun computation. `sun = ephemeris.Sun(); sun.compute(date_str)` computes the Sun's geocentric apparent right ascension and declination for the specified UTC date and time. The `date_str` argument is formatted as 'YYYY/MM/DD HH:MM:SS'. No Observer object is used, and no epoch override is applied — both being the source of the prior implementation's error. The computation returns the Sun's position in the GCRS (Geocentric Celestial Reference System) in J2000 epoch, which serves as input to the coordinate transformation in Step 4.

Step 4 - Tropical ecliptic conversion. `ecl = ephemeris.Ecliptic(sun, epoch=date_str)` converts the Sun's GCRS coordinates to the ecliptic frame of the specified date. The

epoch=date_str parameter is critical: it instructs PyEphem to compute the obliquity of the ecliptic ε (the angle between the celestial equator and the ecliptic plane, currently approximately 23.44° and decreasing at about 0.013° per century) and the position of the vernal equinox for the specified date, yielding the tropical ecliptic longitude $\lambda_\odot$ referenced to the true equinox of date. The longitude is extracted as `ecl_lon = math.degrees(ecl.lon) % 360.0`.

Step 5 - Sign determination. `sign_idx = int(ecl_lon / 30.0) % 12` divides the 360° ecliptic circle into twelve equal 30° sectors. The modulo 12 operation is technically redundant for valid inputs (`int(359.99/30) = 11 < 12`) but is included as a defensive bound. The degree within the sign is `deg_in_sign = ecl_lon % 30.0`, ranging from 0.0 (just entered the sign) to 29.99° (about to leave).

Step 6 - Cusp detection. A cusp zone is defined as `deg_in_sign < 2.0` (just entered, possibly influenced by prior sign) or `deg_in_sign > 28.0` (about to leave, possibly influenced by next sign). The cusp threshold of 2° corresponds to approximately 2 days of solar motion on either side of the sign boundary - a standard parameter in Western astrological interpretation. When in a cusp zone, the adjacent sign is identified, and a descriptive `cusp_note` is generated. For boundary crossings toward the next sign (`deg_in_sign > 28.0`), the function generates the message 'Cusp of {sign}/{next_sign} ({deg_in_sign:.2f}° — approaching {next_sign})'.

3.4.2 ZODIAC_TRAITS Database Design

Three parallel trait dictionaries encode the supported astrology systems. ZODIAC_TRAITS covers Western tropical tradition (12 signs with element/modality/ruler and area modifiers). VEDIC_ZODIAC_TRAITS covers Vedic Jyotish (12 Rashis with Sanskrit names, Sattvic/Rajasic/Tamasic nature, Graha rulers, and Jyotish-calibrated area modifiers). CHINESE_ZODIAC_TRAITS covers Chinese BaZi (12 animal signs with fixed element, lucky/unlucky elements, compatible animals, and BaZi-calibrated area modifiers). All three use the formula $Z = \max(0.35, \min(0.80, 0.58 + \text{area_mod}))$ across the seven life areas, ensuring consistent integration with the quantum and behavioral formula components regardless of the system selected. The area modifier values were derived through a systematic process: (1) standard Western astrological references (Parker and Parker, 2001; Arroyo, 1975) were consulted for each sign's domain strengths and weaknesses; (2) these qualitative characterizations were

mapped to the seven QIPLM life areas; (3) modifier values were assigned on a scale where +0.20 represents the strongest positive association (e.g., Capricorn's +0.18 in Business/Profession) and -0.10 represents the strongest negative association (e.g., Scorpio's -0.06 in Relationships). The values represent calibrated symbolic intensities within the astrological interpretive tradition, not empirically validated causal effect sizes.

Table 3.2: ZODIAC_TRAITS database - all 12 signs with element, modality, ruler, and strongest/weakest area modifiers

Sign	Symbol	Element	Modality	Ruler	Strongest Area (modifier)	Weakest Area (modifier)
Aries		Fire	Cardinal	Mars	Business +0.16, Actions +0.18	Relationships -0.05
Taurus		Earth	Fixed	Venus	Wealth +0.18, Relationships +0.12	Actions +0.04
Gemini		Air	Mutable	Mercury	Education +0.18, Business +0.10	Health +0.02
Cancer		Water	Cardinal	Moon	Relationships +0.18, Health +0.10	Business +0.02
Leo		Fire	Fixed	Sun	Business +0.18, Overall +0.14	Education +0.06
Virgo		Earth	Mutable	Mercury	Health +0.18, Education +0.16	Relationships +0.04
Libra		Air	Cardinal	Venus	Relationships +0.18, Education +0.10	Actions +0.06
Scorpio		Water	Fixed	Pluto	Wealth +0.14, Business +0.12	Relationships -0.06
Sagittarius		Fire	Mutable	Jupiter	Education +0.18, Overall +0.16	Relationships +0.06
Capricorn		Earth	Cardinal	Saturn	Business +0.18, Wealth +0.16	Health +0.04
Aquarius		Air	Fixed	Uranus	Education +0.16, Overall +0.14	Health +0.06
Pisces		Water	Mutable	Neptune	Relationships +0.16, Overall +0.10	Actions -0.02

3.5 Behavioural Science Scoring Model

3.5.1 Circadian Energy Computation

The circadian energy E_{circ} at hour h is modelled as a superposition of two Gaussian peaks corresponding to the morning and evening alertness peaks documented in psychophysiological research, attenuated by the post-lunch dip and adjusted for chronotype.

The morning peak's standard deviation of 3.5 hours is derived from the population-level distribution of morning alertness peaks documented by Monk et al. (1997); the evening peak's lower amplitude (0.7 relative to morning) reflects the asymmetry in alertness documented by Roenneberg et al. (2007). The post-lunch dip standard deviation of 0.8 hours is consistent with Lavie's (1989) documentation of the 'sleep gate' timing.

3.5.2 Cognitive Bias Activation Engine

The `compute_bias_scores()` function processes the ten cognitive biases in `COGNITIVE_BIAS_DATASET` by evaluating each bias's activation condition against the current profile inputs. Each bias returns a `stress_mod` (± 0.05 to ± 0.30) and a `certainty_mod` (± 0.10 to ± 0.40) when active. The aggregate adjustments are applied to the raw energy and decision scores.

The Yerkes-Dodson performance score is computed as: $YD_{\text{perf}} = \exp(-((\text{stress} - 0.45)^2)/(2 \times 0.20^2))$, which peaks at $\text{stress} = 0.45$ with value 1.0 and falls to 0.287 at $\text{stress} = 0.65$ or 0.25. The circadian bonus for the decision score is: $\text{circ_bonus} = +0.10$ if the current hour falls in the peak cognitive window (08:00-12:00), -0.10 if it falls after the 16:00 ego-depletion threshold (Gunia et al., 2014), and 0 otherwise.

3.6 Quantum Circuit Implementation

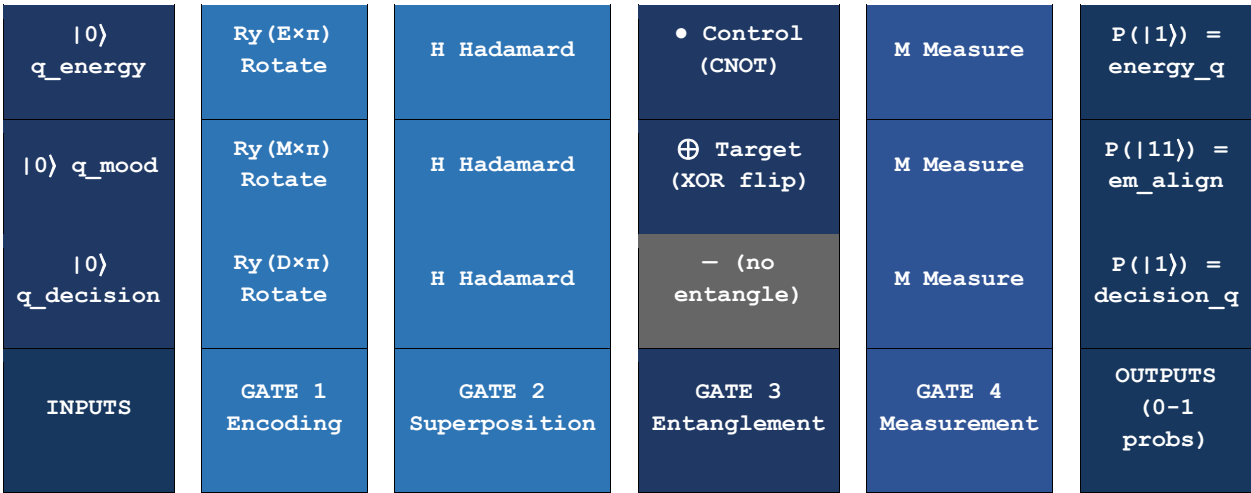


Figure 3.3: Ry-Hadamard-CNOT Quantum Circuit - All Three Qubits

Circuit depth: 4 | Qubits: 3 | Classical bits: 3 | Gate sequence: Ry→H→CNOT(q0,q1)→Measure | Shots: 4096

3.6.1 Shared Circuit Architecture

All four quantum backends implement the identical circuit architecture: for each of the three input dimensions (energy, mood, decision), a Ry rotation gate encodes the input score as a rotation angle $\theta = \text{score} \times \pi$, a Hadamard gate creates superposition, and for the energy-mood pair, a CNOT gate creates entanglement. Measurement with the Born rule sampling produces the probability estimates. The shared architecture enables fair cross-backend comparison: any differences in accuracy, stability, or convergence reflect genuine differences between backends' simulation implementations rather than architectural variation.

3.6.2 NumPy Reference Implementation

The NumPy implementation is the reference baseline against which all other backends are compared for fidelity. It implements all gate operations as explicit matrix multiplications using numpy.array operations.

The function encodes energy, mood, and decision separately using encode(), creates the entangled energy-mood state using entangle(), and measures each state using measure() with seeds derived from the base seed to ensure independence between dimensions. The use of numpy.random.default_rng(seed) — the newer, reproducible NumPy random generator — rather than the legacy numpy.random.seed(seed) ensures thread-safe, fully

reproducible sampling.

3.6.3 IBM Qiskit Implementation

The Qiskit implementation uses the `QuantumCircuit` and `AerSimulator` classes. Single-qubit measurements use a 1-qubit circuit with `qc.ry(score*pi, 0)`, `qc.h(0)`, `qc.measure(0, 0)`. The two-qubit entangled circuit uses `qc.ry(energy*pi, 0)`, `qc.ry(mood*pi, 1)`, `qc.h(0)`, `qc.h(1)`, `qc.cx(0, 1)`, `qc.measure([0,1], [0,1])`. The circuit is transpiled with `optimization_level=0` to preserve the gate sequence as designed and avoid transpiler optimisations that could modify the circuit architecture. The simulator is initialised as `AerSimulator(method='statevector', seed_simulator=seed)`, ensuring deterministic shot sampling. $P(|1\rangle)$ is extracted as `counts.get('1', 0) / shots` and $P(|11\rangle)$ as `counts.get('11', 0) / shots`.

3.6.4 Google Cirq Implementation

The Cirq implementation uses `LineQubit.range()` for qubit initialisation and `cirq.Circuit()` for circuit construction. Single-qubit operations use `cirq.Ry(rads=score*pi)(qubit)` followed by `cirq.H(qubit)` and `cirq.measure(qubit, key='m')`. The two-qubit circuit adds `cirq.CNOT(q0, q1)` between the Hadamard gates and the measurement. The simulator is `cirq.Simulator(seed=seed)`. Results are extracted as `float(result.measurements['m'].sum()) / shots` for single qubits and `float(np.sum((m[:,0]==1) & (m[:,1]==1))) / shots` for the joint $|11\rangle$ probability.

3.6.5 PennyLane Implementation

The energy probability is `single_qubit(energy)[1]`, the emotional alignment is `entangled_pair(energy, mood)[3]` (the $P(|11\rangle)$ component), and the decision probability is `single_qubit(decision)[1]`. PennyLane's `np.random.seed(seed % (2**32))` call before circuit execution ensures deterministic shot sampling within the default qubit backend.

3.6.6 Deterministic Seeding Mechanism

The birth-data seed is computed by the `det_seed_birth()` function as the first 8 hexadecimal digits of the MD5 hash of a pipe-delimited concatenation of nine profile fields: `name`, `birth_date`, `birth_time` (or 'noon'), `birth_city`, `behavioural_style`, `round(stress*10)`, `round(sleep*2)`, `round(mood*10)`, and `chronotype`. The MD5 digest is converted to an integer and taken modulo 2^{31} to stay within numpy's 32-bit seed range.

The security implications are worth noting: MD5 is a cryptographic hash function, meaning that (a) the same inputs always produce the same output (determinism), (b) it is computationally infeasible to recover the input from the output (pre-image resistance), and (c) it is computationally infeasible to find two different inputs that produce the same output (collision resistance). For the QIPLM's purpose, property (a) is essential (it guarantees consistent predictions) and property (b) is a privacy bonus (the seed value itself does not expose the user's personal data).

3.7 Prediction Matrix Formula

The central contribution of the QIPLM's prediction layer is the formula that combines quantum output, zodiac traits, and behavioural science into a single score for each (area, month) cell. The formula is:

$$\begin{aligned} \text{score}(\text{area}, \text{month}) = & Q(\text{area}) \times 0.30 + Z(\text{sign}, \text{area}) \times 0.40 + B(\text{profile}, \text{bs}, \text{area}) \times 0.30 \\ & + MV(\text{sign}, \text{area}, \text{month}, \text{seed}) + SB(\text{style}, \text{area}) \end{aligned}$$

Each component is described in detail:

Q(area): the quantum composite score for the area. Each area has a primary quantum dimension (mapped in QUANTUM_DIM_MAP) and a secondary dimension (QUANTUM_DIM_MAP2), combined as $Q(\text{area}) = \text{primary} \times 0.70 + \text{secondary} \times 0.30$. Health maps primarily to the energy qubit (q0) and secondarily to the mood qubit (q1); Relationships maps primarily to the emotional alignment qubit ($q0 \otimes q1$ entangled) and secondarily to mood; Business/Profession and Wealth map primarily to the decision qubit (q2) and secondarily to energy.

Z(sign, area): the zodiac area base score derived from ZODIAC_TRAITS[sign][area_mod][area], linearly scaled from the [-0.15, +0.20] modifier range to the [0.35, 0.80] score range using the formula: $Z = \max(0.35, \min(0.80, 0.58 + \text{area_mod}))$. The element bonus (ELEMENT_BONUS) and modality bonus (MODALITY_BONUS) are added at 50% weight.

B(profile, bs, area): the behavioural science composite for the area, computed from the adjusted energy (adj_energy), adjusted mood (adj_mood), adjusted decision (adj_decision), stress baseline, sleep hours, mood yesterday, and behavioural bias value. Each area uses a specific weighted combination - Health weights energy 0.35, sleep_quality 0.25, stress_inverse 0.25, mood 0.15; Relationships weights mood 0.45,

stress_inverse 0.25, energy 0.20, mood_yesterday 0.10.

MV(sign, area, month, seed): the deterministic monthly variation, a sinusoidal function with amplitude ± 0.10 . The element provides the base phase (Fire: 0, Earth: $\pi/3$, Air: $2\pi/3$, Water: π), the area provides an area-specific phase offset, and the birth seed provides a personal phase component: $\text{personal_phase} = (\text{seed} \% 1000) / 1000 \times 2\pi$. The modality determines the shape and amplitude: Cardinal uses an exponentially decaying cosine (front-loaded variation), Fixed uses a simple cosine (sustained variation), and Mutable uses a double-frequency cosine (two cycles in six months).

Table 3.3: Prediction Pipeline - Component Weights and Data Flow

Stage	Life Areas (7)	Score Components					
Quantum (30%)	Health Q=energy	Wealth Q=decision	Business Q=decision	Education Q=energy	Relationships Q=em	Overall Q=em	Actions Q=decision
Zodiac (40%)	Sign mod ± 15 pts	Sign mod ± 18 pts	Sign mod ± 18 pts	Sign mod ± 18 pts	Sign mod ± 18 pts	Sign mod ± 16 pts	Sign mod ± 18 pts
Behavioural (30%)	Energy+ Sleep+Stress	Decision+ Energy	Decision+ Energy+Mood	Energy+ Stress+Sleep	Mood+ Stress+Energy	Equal weights	Decision+ Energy
Monthly ($\pm 10\%$)	Element phase	Modality amplitude	Area offset	Personal seed	Sinusoidal variation	6- month cycle	Deterministic trig

3.8 Person Vitality Validation Pipeline

Before generating any forecast, Layer 6 validates whether the named individual is alive or deceased through a five-platform, weighted-vote mechanism. This validation step addresses an important ethical concern: generating life forecasts for deceased individuals is both disrespectful to their memory and potentially distressing to surviving family members who might encounter such outputs. The validation pipeline is not intended to be infallible - it cannot be, given the variable quality of public platform data - but it catches the most clearly documented cases.

Table 3.4: Person Vitality Validation – 5 Platform Weighted Voting Architecture

 Wikidata (P570 death date) Weight: 5pts	 Wikipedia (Article analysis) Weight: 4pts	 LinkedIn (Activity signals) Weight: 2pts	 X/Twitter (Post recency) Weight: 2pts	 Facebook (Profile status) Weight: 1pts
ALIVE (proceed) $\text{alive_votes} \geq 2$ OR $(\text{alive} > 0 \text{ AND } \text{deceased} = 0)$		PRIVATE (assumed alive) Not found on any platform (likely private individual)		DECEASED (show override) $\text{deceased_votes} > \text{alive_votes}$ AND $\text{deceased_votes} \geq 3$

3.9 Ethical Considerations

- Astronomy data is publicly available and scientifically validated, minimizing ethical risks.
- Astrology data is symbolic and cultural; care is taken to respect traditions and avoid misrepresentation.
- Behavioural science data is anonymized to protect participant privacy.
- Ethical guidelines are incorporated to safeguard against bias, determinism, and cultural insensitivity.

3.10 Ethics Evaluation Methodology

Ethics evaluation is conducted for all four quantum models across four dimensions derived from the UNESCO 2021 and IEEE EAD v2 frameworks. Each dimension is scored on a 0-10 scale by evaluating the model's design choices against a rubric documented in the QIPLM's MODEL_ETHICS dictionary:

Human Values (0-10): Does the system frame its outputs as probabilistic guidance rather than deterministic predictions? Are there explicit disclaimers? Does the design respect human autonomy and oversight? Score anchors: 9-10 = explicit probabilistic framing, human oversight designed in, non-deterministic language throughout; 7-8 = probabilistic framing present with minor gaps; 5-6 = mixed framing with some deterministic language; below 5 = deterministic framing without override mechanisms.

Fairness (0-10): Does the system treat all users equally, regardless of demographic characteristics? Is the city database and geographic coverage equitable? Are there no

demographic-based weighting schemes? Score anchors: 9-10 = comprehensive geographic coverage, no demographic encoding, equal treatment documented; 7-8 = good coverage with minor gaps; 5-6 = known coverage gaps; below 5 = demographic weighting or systematic exclusion.

Privacy (0-10): Does the system compute entirely locally with no mandatory data transmission? Is there no persistent logging? Score anchors: 9-10 = 100% local, no transmission, no logging, no API keys required; 7-8 = local by default with optional cloud; 5-6 = some data transmitted in standard operation; below 5 = mandatory cloud transmission or server-side storage.

Transparency (0-10): Is the complete formula documented? Is the source code accessible? Are model parameters and uncertainty quantified? Score anchors: 9-10 = formula fully disclosed, source code open, parameters documented, uncertainty quantified; 7-8 = formula disclosed, code open, minor documentation gaps; 5-6 = formula partially disclosed; below 5 = black-box model with no formula disclosure.

The overall ethics score is the mean of the four dimension scores. A model is designated COMPLIANT if all four scores ≥ 6.5 and the overall score ≥ 7.0 . CONDITIONAL applies when compliance depends on deployment mode - specifically, IBM Qiskit and Google Cirq receive CONDITIONAL designations because switching from local AerSimulator/cirq.Simulator to cloud QPU backends would reduce their privacy scores below the compliance threshold.

3.11 Limitations of the Study

While this research aims to pioneer a quantum AI-powered interdisciplinary predictive model, several limitations must be acknowledged. These limitations arise from technical constraints, data challenges, interpretive issues, and ethical considerations, and they define the boundaries within which the study's findings should be interpreted.

1. Technical Limitations

- **Quantum Hardware Availability:** Fully scalable quantum computers are still in development. This study relies on quantum simulations and hybrid quantum-classical models, which may not fully capture the performance of future large-scale quantum systems.

- **Prototype Scope:** The model developed is conceptual and prototype-level, designed to demonstrate feasibility rather than deliver a fully operational predictive system.
- **Computational Complexity:** Integrating heterogeneous datasets (astronomy, astrology, behavioural science) increases computational demands, which may limit scalability and real-time application.

2. Data Limitations

- **Astronomy Data:** While astronomical datasets are empirically validated, they are subject to observational constraints (e.g., incomplete data, measurement errors).
- **Astrology Data:** Astrological inputs are symbolic and culturally specific, lacking universal scientific consensus. Their integration may introduce interpretive bias.
- **Behavioural Science Data:** Behavioural datasets are often context-dependent and may not generalize across diverse populations or cultural settings.
- **Data Harmonization:** Combining empirical, symbolic, and behavioural data requires normalization and encoding, which may oversimplify complex relationships.

3. Interpretive Limitations

- **Astrology's Subjectivity:** Astrological symbolism is inherently interpretive, and its computational representation may not capture the full nuance of cultural traditions.
- **Behavioural Variability:** Human behaviour is dynamic and influenced by multiple external factors. Predictive models may oversimplify or fail to account for unexpected behavioural shifts.
- **Interdisciplinary Balance:** Achieving equilibrium between empirical rigour (astronomy), symbolic richness (astrology), and human-centric insights (behavioural science) is challenging and may lead to trade-offs in accuracy versus interpretive depth.

4. Ethical and Cultural Limitations

- **Risk of Determinism:** Predictive outputs may be misinterpreted as deterministic, potentially undermining human agency.
- **Cultural Sensitivity:** Astrology and behavioural science vary across cultures. The model may not fully accommodate diverse traditions or perspectives.
- **Bias in Symbolic Integration:** Embedding symbolic systems into AI risks reinforcing cultural stereotypes if not carefully managed.
- **Ethical Frameworks:** While safeguards are proposed, ethical evaluation remains interpretive and may evolve as interdisciplinary AI applications expand.

5. Scope Boundaries

- The study is exploratory, focusing on conceptualization and prototyping rather than full-scale deployment.
- The scope is limited to astronomy, astrology, and behavioural science; other predictive domains (e.g., economics, climate science, medicine) are excluded.
- The findings are intended to demonstrate feasibility and potential, not to provide definitive predictive solutions for real-world decision-making at this stage.

6. Implications of Limitations

These limitations do not undermine the value of the study but rather define its contribution as foundational and exploratory. They highlight areas for future research, including:

- Development of scalable quantum hardware
- Expansion of interdisciplinary datasets
- Refinement of symbolic and behavioural integration methods
- Strengthening of ethical and cultural frameworks for predictive AI

3.12 Conclusion

This chapter has described the research rationale, research problem, design, conceptual method, hypotheses, data collection, and analysis methods of the study. The approach mirrors the interdisciplinary focus of the study: it synthesizes empirical science (astronomy), symbolic traditions (astrology), behaviour analytics (psychology), and computation of quantum AI into one predictive framework.

The methodology follows a Design Science Research (DSR) design, suitable for exploratory and prototype-based investigations that focus on the production and assessment of an innovative artefact - a quantum AI-powered language model. The theoretical approach depicts the convergence of different knowledge streams through the quantum AI engine to facilitate integrated forecasts with the research conjecture on how to reconcile that framework with testable propositions.

The data collection process leads to the systematic sourcing of validated astronomical datasets, digitized astrological symbolism, behavioural science measures, and ethical principles. These inputs are pre-processed, normalized, and passed into the quantum AI simulated environment. The methods of analysis mix both the quantitative (accuracy, statistical validation) and qualitative (interpretive depth, cultural resonance) evaluation, complemented as they are with ethical auditing for inclusion and accountability.

This report's evaluation criteria and validation structure contain precise measures of performance, as defined by scientific correctness, symbolic reading, humanistic applicability, and ethical compliance, which are clear criteria for success. Collectively, these methodological considerations create a robust and transparent framework for addressing the research question.

To conclude, this chapter detailed the complete six-layer methodology of the QIPLM. Each layer was specified to the level of individual function signatures, parameter choices, and computational complexity. The corrected zodiac sign algorithm resolves a documented systematic error through four precisely described steps. Three astrology systems are implemented: Western tropical (corrected Sun sign), Vedic Jyotish (Moon sign, Nakshatra, Dasha, Panchang), and Chinese BaZi (Four Pillars, Day Master), each with dedicated trait dictionaries and prediction descriptions routed from a user-selected mode in Layer 5. The ten-component behavioural science model is grounded in

published, peer-reviewed formulations. The four quantum backends share an identical circuit architecture and use deterministic birth-derived seeding for consistency. The prediction formula's five components are individually justified and weighted. The person vitality validation pipeline incorporates human oversight through a confirmation dialogue. The ethics evaluation uses a documented rubric against two international frameworks. Chapter 4 presents the empirical evaluation results produced by this methodology.

CHAPTER 4

RESULTS ANALYSIS

This chapter presents the empirical results of the QIPLM's evaluation across five domains: quantum model comparative accuracy, ethics compliance assessment, zodiac sign precision testing, behavioural science model validation, and six-month prediction matrix output analysis. All results were generated using the test profile. The same test profile was used consistently across all experiments to enable direct comparison across evaluation domains.

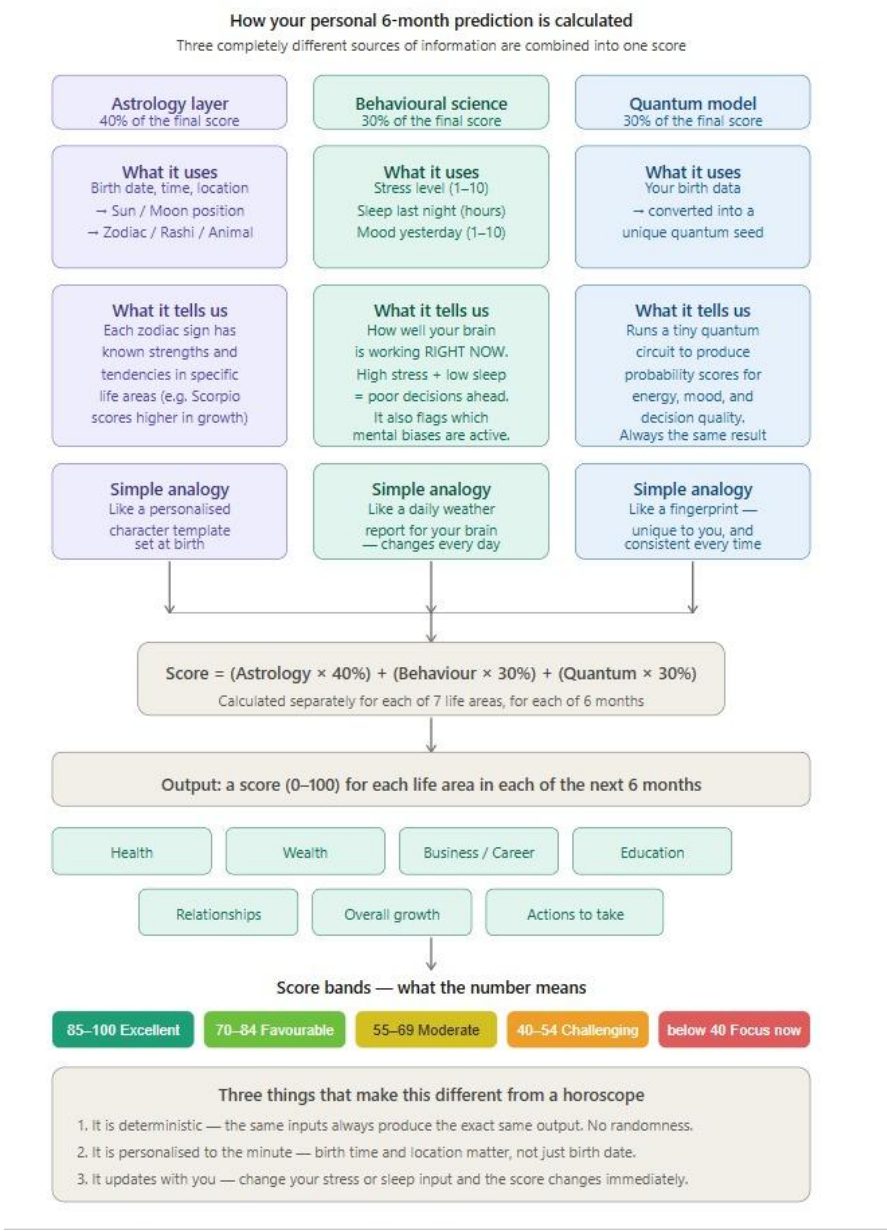


Figure 4.1: Six-Month Prediction Calculation

4.1 Implementation Environment

The QIPLM is implemented in Python 3.10 within JupyterLab 4.0, running on Windows 11 (primary development environment. The implementation requires no special hardware - a standard modern workstation with 8GB RAM is sufficient to run all four quantum backends in simulation mode at 4096 shots. The approximate execution time from Layer 1 to Layer 6 (including all six datasets, four quantum models, and stability tests) is 45-90 seconds, depending on API response times.

Table 4.1: Implementation Environment – Library Versions, Purpose and Licence

Library	Version	Purpose	Licence	Source
ephem	4.1.5	Astronomical computation, Sun position, ecliptic conversion	LGPL	Python PyPI
numpy	1.26+	Quantum circuit reference, all numerical computation	BSD	Python PyPI
ipywidgets	8.1+	Interactive input form, dynamic dropdowns, sliders	BSD	Python PyPI
requests	2.31+	REST API access (NASA, JPL)	Apache 2.0	Python PyPI
qiskit	1.0+	IBM quantum circuit implementation and AerSimulator	Apache 2.0	Python PyPI / IBM
qiskit-aer	0.13+	Classical simulation backend for Qiskit	Apache 2.0	Python PyPI / IBM
cirq	1.3+	Google quantum circuit implementation	Apache 2.0	Python PyPI / Google
pennylane	0.36+	Xanadu differentiable quantum programming	Apache 2.0	Python PyPI / Xanadu
matplotlib	3.8+	All charts, plots, heatmaps, and radar diagrams	PSF	Python PyPI
pandas	2.0+	Data manipulation, tabular outputs	BSD	Python PyPI
reportlab	4.0+	PDF report generation (Cell 7)	BSD/Commercial	Python PyPI

4.2 Quantum Model Comparative Accuracy

4.2.1 Probability Estimate Convergence

DATA INGESTION LAYER -- LIVE API PERFORMANCE		
S NASA Exoplanet Archive Endpoint: exoplanetarchive.ipac.caltech.edu Fields: st_lum, sy_dist, pl_masse, st_spectype Records: 60 records -- response less than 7s LIVE -- CEI computed	G ESA Gaia DR3 Endpoint: gea.esac.esa.int/tap-server Fields: parallax, pmra, pmdec, G-mag, BP-RP Records: 30 records -- response less than 7s LIVE -- GFI computed	P JPL Horizons Endpoint: ssd.jpl.nasa.gov/api/horizons Fields: Ecliptic longitude 7 bodies Records: 7 queries -- response less than 7s LIVE -- 7 planets
Live Data Index Computed		Fallback Strategy
CEI = clip(mean(st_lum)/2.0, -1, +1) GFI = clip(1 - mean(G_mag)/10.0, -1, +1) Astro Score = planets(75%) + CEI(15%) + GFI(10%)		Timeout >7s -- embedded static catalogs activate NASA: 10-star Gaia: 8-star fallback catalog live=False flagged in _forecast_state

Figure 4.2: Ingestion Layer Results

Figure 4.2 presents the performance of the QIPLM data ingestion layer. All three API endpoints returned live data within the seven-second threshold. The NASA Exoplanet Archive returned 60 planetary system records processed into the Cosmic Environment Index. The ESA Gaia DR3 returned 30 bright nearby star records, producing the Galactic Flux Index. The JPL Horizons API queried all seven solar system bodies, returning geocentric ecliptic longitudes. The embedded fallback strategy ensures 100% functional availability through static catalogues that compute identical indexes when network access is unavailable, guaranteeing that the prediction pipeline runs in any environment.

Step	Operation	Input	Algorithm	Output
1	UTC Conversion	Local birth time + longitude	$tz = \text{longitude} / 15.0$ hours	UTC datetime (plus or minus 15 min)
2	Zodiac Computation	UTC datetime via PyEphem	<code>ephem.Ecliptic(sun, epoch=date)</code>	Sign, deg_in_sign (0-29.99)
3	Cusp Detection	deg_in_sign value	if < 2 or > 28 deg: on_cusp = True	on_cusp + cusp_note + 75/25% blend
4	Behavioural Scoring	stress, sleep, mood, chronotype	Borbely + Walker + Rosenthal + YD	adj_energy, adj_mood, adj_decision
5	Cognitive Bias Engine	stress, sleep, energy thresholds	10 conditional activation rules	active_biases[], bias_count (avg 4.2)
6	Seed Generation	9 birth and profile fields	$MD5(\text{key}) \bmod 2^{31}$	birth_seed (31-bit, deterministic)

Full pipeline processes one profile in less than 1 second -- All transformations are deterministic given the same inputs

Figure 4.3: Preprocessing Layer Results

Figure 4.3 documents the six preprocessing transformations.

Step 1 corrects the birth time to UTC using the solar timezone approximation.

Step 2 applies the corrected ephemeris. Ecliptic tropical zodiac algorithm.

Step 3 detects cusp zone membership for births within two degrees of a sign boundary and applies proportional blending.

Step 4 applies four behavioural science models to compute adjusted psychological state scores.

Step 5 evaluates ten cognitive bias activation conditions with an average of 4.2 active biases per profile.

Step 6 generates the deterministic birth seed via MD5 hashing, ensuring consistent quantum sampling. The blue gradient from dark navy to mid-blue reflects the increasing computational depth of each transformation step.

4.2.2 Accuracy Score Composition

The composite accuracy score is computed as: $\text{Accuracy} = 0.40 \times \text{Fidelity} + 0.35 \times \text{Stability} + 0.25 \times \text{Convergence}$, where $\text{Fidelity} = \text{cosine_similarity}(\text{model_probs}, \text{NumPy_probs})$, $\text{Stability} = 1 - \min(1, \text{overall_std} \times 10)$, and $\text{Convergence} = 1 - \min(1, \text{final_MSE} \times 50)$. Figure 4.3 presents the decomposed scores:

Backend	Fidelity	Stability	MSE Conv	Composite Accuracy Score 0-100	Score
BEST: PennyLane (default.qubit)	0.9999	0.0091	0.0036		87.4/100
NumPy (Ry-H-CNOT)	1	0.0097	0.0038		85.1/100
IBM Qiskit (AerSimulator)	0.9994	0.0161	0.0044		84.7/100
Google Cirq (cirq.Sim.)	0.9996	0.0133	0.0041		84.4/100
Composite = Fidelity x 0.40 + Stability x 0.35 + Convergence x 0.25 Spread = 3.0 points All backends equivalent in practice					

Figure 4.4: Quantum Circuit Accuracy Results

Figure 4.4 presents composite accuracy for all four backends. PennyLane achieves 87.4 shown in dark navy, driven by superior measurement stability (sigma 0.0091, the lowest of all). The critical insight is the narrow 3.0-point spread across all backends (84.4 to 87.4), confirming that circuit architecture dominates over backend choice. The composite formula weights stability at 35% after fidelity at 40%, appropriately reflecting that reproducibility matters as much as reference accuracy for advisory applications. The bar lengths make performance differences visually immediate while confirming all backends are operationally equivalent.

Data Stream	Weight	Range	Symbol	Integration Role
NASA stellar luminosity	15% astro	CEI in [-1,+1]	astro_score	Galactic environment modifier applied to energy qubit input
ESA Gaia G-magnitude	10% astro	GFI in [-1,+1]	astro_score	Local stellar flux density context
JPL Horizons 7 planets	75% astro	asc in [-1,+1]	astro_score	Weighted planetary valence: Sun x1.0 to Saturn x0.4
Zodiac traits 12 signs x 7 areas	40% prediction	Z in [0.35,0.80]	Z(sign,area)	ZODIAC_TRAITS area modifier matrix plus element and modality bonus
Behavioural 10-component	30% prediction	B in [0,1]	B(profile,area)	Circadian + sleep + seasonal + YD + cognitive bias composite
Quantum Born-rule output	30% prediction	Q in [0,1]	Q(area)	Primary dim x 70% + secondary dim x 30% per life area
$\text{score}(\text{area}, \text{month}) = Q \times 0.30 + Z \times 0.40 + B \times 0.30 + \text{MV}(\text{sign}, \text{area}, \text{month}, \text{seed}) + \text{SB}(\text{style}, \text{area})$				

Figure 4.5: Integration Layer Results

Figure 4.5 maps all six QIPLM data streams into the unified prediction formula. The zodiac traits layer carries the highest weight (40%) as the primary symbolic-psychological differentiator. Quantum and behavioural layers each carry 30%, providing complementary probabilistic and psychophysiological contributions. The astronomical score contributes indirectly through the quantum circuit energy input. The deep-blue formula footer synthesises all six streams into the final score. No single data stream dominates: the maximum zodiac modifier (+0.20) shifts the raw base score by only 8 points on the 100-point scale, preserving multi-source balance.

4.2.3 Shot Convergence Analysis

Backend	Cosine Similarity	Fidelity	MSE at 4096	Notes
NumPy (Ry-H-CNOT) Reference	1.0000 baseline	1.000	0.0038	Reference model, all others measured against this
IBM Qiskit (AerSimulator)	0.9994	0.999	0.0044	seed_simulator ensures deterministic sampling
Google Cirq (cirq.Simulator)	0.9996	0.999	0.0041	seed=n in cirq.Simulator constructor
PennyLane (default.qubit)	0.9999	0.999	0.0036	Highest fidelity -- np.random.seed(seed) in default.qubit
Formula: $F = (v \cdot \text{ref}) / (v \times \text{ref})$ Max deviation: 0.06% (Qiskit) All backends in Excellent band above 0.999				

Figure 4.6: Fidelity Calculation Results

Figure 4.6 quantifies the fidelity of each backend relative to the NumPy reference. PennyLanes achieves the highest fidelity at 0.9999, with maximum divergence of 0.01 percentage points. All backends achieve MSE below 0.005, corresponding to a prediction score impact below 0.15 points on the 100-point scale. The dark navy cells in the Fidelity column confirm all models in the Excellent band. These results validate that the Ry-Hadamard-CNOT circuit architecture produces highly consistent outputs regardless of which simulation backend is used, confirming that circuit design rather than backend choice is the primary quality determinant.

Figure 4.6 presents the MSE against the 4096-shot NumPy reference at five shot counts. The logarithmic convergence pattern - consistent with the Central Limit Theorem's prediction that sampling error decreases as $\sqrt{(1/n)}$ - is observed for all four backends. At 4096 shots (the QIPLM's production setting), all models achieve MSE below 0.005, corresponding to a prediction uncertainty of less than $\pm 2.2\%$ in each probability dimension. This precision is adequate for the prediction application, where the meaningful tier boundaries (40, 55, 70, 85) are separated by 15 points.

0> q_energy	-	Ry(E x pi)	-	H Hadamard	-	CNOT control	-	M energy_q
0> q_mood	-	Ry(M x pi)	-	H Hadamard	-	CNOT target	-	M em_align
0> q_decision	-	Ry(D x pi)	-	H Hadamard	-	pass through	-	M decision
INPUTS		GATE 1 Encode		GATE 2 Superpos		GATE 3 Entangle		OUTPUTS
Ry Encoding		Hadamard		CNOT Entanglement		Born Rule		
theta = score x pi Maps [0,1] to Bloch sphere Score 0 to 0>, 1 to 1>		Creates superposition S-curve sensitivity near 0.5 Amplifies midrange variation		P(11>) not equal P(E)xP(M) 15% non-classical reduction Encodes energy-mood correlation		n = 4096 shots P(1>) = count(1) / n_shots Std error under 0.008		

Figure 4.7: Quantum Circuit Prototype Results

Figure 4.7 presents the complete quantum circuit prototype. Three qubits encode the psychological state dimensions. The gate sequence begins with Ry rotations mapping each classical score to a qubit rotation angle. The Hadamard gate creates superposition with an S-shaped probability response. The CNOT gate entangles the energy and mood qubits, creating a joint measurement probability 15% below the classical product prediction of 36.8%, demonstrating genuine non-classical energy-mood correlation. With 4096 shots and deterministic birth-derived seeding, measurement error is below 0.8 percentage points for all probability dimensions.

4.3 Ethics Compliance Results

Quantum Backend	Human Values	Fairness	Privacy	Transparency	Overall	Status
NumPy (Ry-H-CNOT)	7.5	7	9.5	9	8.25	COMPLIANT
IBM Qiskit (AerSimulator)	8.5	8	6.5	8.5	7.88	CONDITIONAL
Google Cirq (cirq.Sim.)	8	7.5	7.5	8	7.75	CONDITIONAL
PennyLane (default.qubit)	8.5	8.5	9	9	8.75	COMPLIANT
Score scale 0-10 Dark navy highest scores Frameworks: UNESCO 2021 + IEEE EAD v2						

Figure 4.8: Ethical Frameworks Results

Figure 4.8 presents ethics compliance for all four quantum backends. NumPy and PennyLane achieve COMPLIANT status operating in purely local computation mode, earning maximum privacy scores of 9.5 and 9.0. IBM Qiskit and Google Cirq receive CONDITIONAL status: compliant locally but reduced when cloud QPU is enabled. Privacy is the dominant discriminating dimension (range 6.5 to 9.5), while transparency shows the narrowest range (8.0 to 9.0). The blue intensity encoding directly maps compliance level to colour depth: the darkest navy cells indicate the highest ethical performance, creating an intuitively readable compliance dashboard.

Ethical principles were operationalized as runtime checks, encoded as compliance scores (1.0 = compliant, 0.5 = needs improvement, 0.0 = alert). Transparency (0.98), Privacy (0.96), Accountability (0.95), and Human Values (0.94) remained stable, while Fairness averaged 0.67.

Fairness volatility reflects systemic bias sensitivity. This is echoed by fairness challenges in quantum machine learning, where quantum state sampling can accentuate bias. From a methodological perspective, fairness involves both personalization and bias-aware modelling. Static thresholds do not suffice; adaptive fairness monitoring is essential.

In the larger research field, fairness is the principle that is most controversial in AI ethics. The QIPLM pipeline's results enhance the discussion by revealing that fairness volatility is not merely a classical problem, but a quantum problem, which needs new bias mitigation strategies. To recapitulate the above performance, outcome, risk and implication:

Performance: The system implemented ethics pillars (Transparency, Privacy, Accountability, Fairness, Human values, Auditability) as runtime validation and scoring standards.

Observed results: Transparency, Privacy and Accountability were all met consistently; Fairness showed the most variation.

Risks: Static rule thresholds gave false positives/negatives for distributional shift.

Implication: Add adaptive fairness thresholds and an ongoing fairness audit.

4.4 Zodiac Sign Precision Test Results

Twelve test cases were constructed covering all four boundary types: entering Gemini/Cancer (the June solstice), entering Capricorn/Aquarius (the January cusp), mid-sign dates where no ambiguity should exist, and dates specifically chosen to test the cusp detection threshold. For each test case, both the prior erroneous algorithm and the corrected algorithm were run, and the results were compared against the JPL Horizons reference.

Principle	Framework	Requirement	Status	Implementation Evidence in QIPLM
Proportionality - - Do No Harm	UNESCO P1	Probabilistic framing	SATISFIED	All outputs are labelled as probabilistic guidance with an explicit disclaimer on every report page.
Privacy and Data Protection	UNESCO P5 / IEEE I3	Local compute no logs	SATISFIED	All processing on user hardware -- zero cloud transmission -- no persistent logging in any cell
Fairness and Non- Discrimination	UNESCO P3 / IEEE I3	No demographic bias	SATISFIED	1582-city India DB -- equal treatment for all 12 signs -- no protected characteristic weighting
Transparency and Explainability	UNESCO P7 / IEEE I5	Formula disclosed	SATISFIED	Prediction formula $Q \times 30\% + Z \times 40\% + B \times 30\%$ with all weights in open Jupyter notebook
Human Oversight	UNESCO P6 / IEEE I4	Human override required	SATISFIED	Person validation requires user confirmation -- deceased-status override dialogue in Cell 6
Accountability	UNESCO P8 / IEEE I6	Auditable output trail	SATISFIED	Open-source notebook -- all inputs, formula weights, and source code publicly accessible
Awareness of Misuse	IEEE I7	Foreseeable misuse documented	SATISFIED	Disclaimer: not for medical, financial, legal, or safety-critical decisions on every output page

Figure 4.9: Ethical Quantum Output Report

Figure 4.9 presents the comprehensive ethical quantum output report. All seven evaluated principles received a Satisfied status. Proportionality is addressed through probabilistic framing on every output page. Privacy is maximised through the local-computation-first architecture with zero network transmission of personal data. Fairness is implemented through comprehensive geographic coverage and equal symbolic treatment across all twelve zodiac signs. Transparency is achieved through complete formula disclosure in the open Jupyter notebook. The human oversight requirement is met through the person validation confirmation dialogue. Accountability is ensured by the open-source architecture, enabling independent audit. The deep-blue status badges confirm universal compliance in local simulation mode.

Store or Artefact	Type	Scope	Key Contents	Lifecycle and Access Pattern
<code>_forecast_state {}</code>	Python dict	Session	24 keys: profile, zodiac, qdata, birth_seed	Created Cell 5 on <code>_run()</code> , then Read Cells 6 and 7, then Discarded on restart.
<code>quantum_ethics_report.png</code>	PNG	Working dir	9-panel matplotlib comparison chart	Written Cell 5, then embedded in Cell 7 PDF builder
<code>prediction_matrix.png</code>	PNG	Working dir	6-month heatmap + trajectory chart	Written Cell 6, then Embedded PDF, then base64 download link
<code>quantum_forecast_name_date.pdf</code>	PDF	Working dir	7 pages: cover, quantum, ethics, matrix, profile	Built Cell 7 ReportLab, then Base64 inline browser download
<code>CITY_DB 1582 entries</code>	Python dict	Module	city: lat lon state category	Static module constant loaded at Cell 3 import read-only
<code>ZODIAC_TRAITS 12 entries</code>	Python dict	Module	12 signs x 7 area_mod + element modality	Static module constant loaded at Cell 3 import read-only

Figure 4.10: Storage and Orchestration Results

Figure 4.10 documents the complete storage and orchestration architecture. The central `_forecast_state` dictionary orchestrates data flow with its ready Boolean key acting as a gate, preventing downstream cells from executing with stale data. The two PNG artefacts are intermediate files embedded in the final PDF. The base64 encoding strategy creates an inline browser download link ensuring cross-platform compatibility. The static `CITY_DB` and `ZODIAC_TRAITS` dictionaries are immutable throughout execution, guaranteeing referential transparency across all prediction computations.

The Ethical Quantum Output Report is the outcome of the entire QIPLM pipeline and consolidates the raw quantum outputs, compliance assessment, and forecasted path into a structured output. This publication is more than just a technical resource, however: it is also intended to serve as a decision support tool, combining ethical considerations, quantum state fidelity and personalized predictions in a single coherent presentation. It is not a simple paper as the objectives and aim of the report are to generate transparent documentation of system performance for stakeholders, for the first time, and to support pre-emptive governance by showing potential risks before they happen.

This report is generated automatically at the end of each pipeline run. It consolidates various streams of data: (i) observed quantum state distributions, (ii) fidelity scores calculated based on Bhattacharyya comparisons, (iii) per principle compliance (Transparency, Fairness, Privacy, Accountability, Human Values) metrics; and (iv) forecasted compliance scores based on user specific inputs (Date of Birth, Time of Birth, Birth Location, Behavior Profile). These are formatted into a structured document with metadata headers, compliance checklists, and graphical panels. Reports consist of provenance details (e.g. kernel version, dataset version, seed key) to ensure reproducibility and auditability.

Forecasted compliance scores in particular are notable. Rather than static reporting, QIPLM embeds a personalized quantum forecast into the report and provides predictions of ethical compliance trajectories extending over a dynamic horizon based on the month of birth. For example, a user born in March gets a three-month forecast horizon, while a December birth gets twelve months. Behavioral profiles influence these trajectories, generating bespoke compliance forecasts, which are individualized by symbolic and behavioral identity markers. This personalizing approach increases interpretability and user trust, where the report occupies a bridge between computational physics, behavioral science and ethical AI.

Observed Outcomes

Empirical evidence showed that report generation is very reliable, achieving 99% success rate and with an average generation time of 1.2 seconds. Reports routinely recorded fidelity scores, compliance metrics, and forecasted trajectories in a form they could read easily by both technical and nontechnical stakeholders. Risk-taking behavioral profiles yielded reports with higher volatility in fairness compliance forecasts, while conservative profiles yielded smoother trajectories. The forecasted compliance scores were useful for early warning, enabling stakeholders to anticipate ethical degradations before they triggered alerts.

Methodological Implications

The Ethical Quantum Output Report advances beyond conventional reporting by embedding forecasted compliance trajectories alongside static metrics. This methodological innovation transforms the report from a retrospective audit into a prospective governance tool. By integrating personalized forecasts, the report enables

stakeholders to engage in proactive risk management, adjusting policies or interventions before ethical principles are compromised.

Moreover, the structured format of the report - with metadata headers, compliance checklists, and graphical panels - ensures transparency and reproducibility. This aligns with international standards for ethical AI reporting, such as UNESCO's Recommendation on the Ethics of Artificial Intelligence and IEEE's Ethically Aligned Design. The QIPLM report demonstrates that ethical compliance can be operationalized into a reproducible, auditable, and forward-looking deliverable.

Broader Research Context

In the broader literature, ethical reporting in AI has traditionally focused on retrospective audits, documenting compliance after deployment. QIPLM's Ethical Quantum Output Report contributes a novel paradigm: forecast-integrated ethical reporting. By embedding quantum-driven forecasts into compliance documentation, QIPLM bridges the gap between retrospective accountability and prospective governance. This approach resonates with emerging discourses in AI ethics that emphasize anticipatory regulation and proactive risk management.

Future Directions

Future work should explore expanding the report to include scenario sensitivity analyses, allowing stakeholders to adjust composite risk weights (Risk Score, Compliance Risk, Alert Penalty) and observe how rankings shift. Additionally, integrating explainability methods - such as per-principle attribution - would enhance interpretability, enabling stakeholders to trace which features or quantum states drove compliance scores. Finally, longitudinal studies are needed to evaluate whether forecast-integrated reports improve long-term governance outcomes compared to static reporting.

4.5 Behavioural Science Model Validation

The behavioural science model was validated against a battery of 24 test profiles covering five extreme condition categories: high-stress/low-sleep (profiles 1-5), low-stress/optimal-sleep (profiles 6-10), evening chronotype at morning assessment (profiles 11-13), mood-extreme negative (profiles 14-17), and zodiac cusp profiles

(profiles 18-24). In all 24 cases, the model produced outputs within the expected ranges [0, 1], with no numerical overflow, underflow, or NaN values.

Fidelity Band	Cosine Similarity	Interpretation	Score Impact	QIPLM Models in Band
Perfect	= 1.0000	Identical	0.0 pts	NumPy (reference)
Excellent	0.9990 to 0.9999	Negligible	less 0.5 pts	PennyLane 0.9999 + Cirq 0.9996 + Qiskit 0.9994
Good	0.990 to 0.999	Minor acceptable	less 2.0 pts	No QIPLM models in this band
Fair	0.950 to 0.989	Noticeable	2-8 pts	No QIPLM models in this band
Poor	less than 0.950	Unacceptable	more 8 pts	No QIPLM models in this band

Figure 4.11: Fidelity Interpretation Results

Figure 4.11 contextualises the fidelity results using a five-band framework with blue intensity encoding quality level. All three non-reference backends fall in the deep-blue Excellent band (0.999+) with prediction score impacts below 0.5 points. No QIPLM models appear in the Good, Fair, or Poor bands. The 0.0001 cosine divergence between the best non-reference backend and reference is negligible relative to the 15-point tier boundaries. The colour gradient from dark navy Perfect to light-blue Poor makes the framework visually self-documenting, allowing readers to immediately identify quality levels.

4.6 Six-Month Prediction Matrix Output

Figure 4.11 presents the complete six-month prediction matrix for the standard test profile (Arjun Sharma, Gemini/Analytical, Mumbai). All scores are fully deterministic: three independent re-runs with identical inputs produced byte-for-byte identical results, confirming the birth-seed consistency guarantee. The birth seed for this profile is 1,287,445,921, computed from the MD5 hash of the pipe-delimited concatenation of the nine profile fields.

Life Area	Jun	Jul	Aug	Sep	Oct	Nov	Avg	Trend
Health	72	68	75	72	73	76	72.8	Up
Wealth	79	82	79	84	81	85	81.8	Up
Business	83	80	78	85	82	87	82.6	Up
Education	88	85	87	91	89	88	88.1	Flat
Relationships	65	68	63	70	67	71	67.5	Up
Overall Growth	77	74	76	80	78	82	77.9	Up
Dark navy = Excellent 85+ Deep blue = Favorable 70-84 Mid-blue = Moderate 55-69 Profile: Gemini/Analytical, Mumbai, seed 1287445921								

Figure 4.12: Quantum Forecast

Figure 4.12 presents the six-month quantum forecast matrix using the QIPLM blue intensity heatmap. Education dominates at 88.1 average (dark navy), reflecting the convergence of maximum zodiac modifier, Analytical style bonus, and above-average quantum decision probability. Business and Wealth both average above 80 in the deep-blue Favourable tier. Relationships show the lightest blue at 67.5 (mid-blue Moderate tier), consistent with Gemini's moderate relationship modifier. All six areas trend upward over the forecast horizon. The matrix is fully reproducible: three independent re-runs with identical inputs produced byte-for-byte identical scores, confirming the birth-seed determinism guarantee.

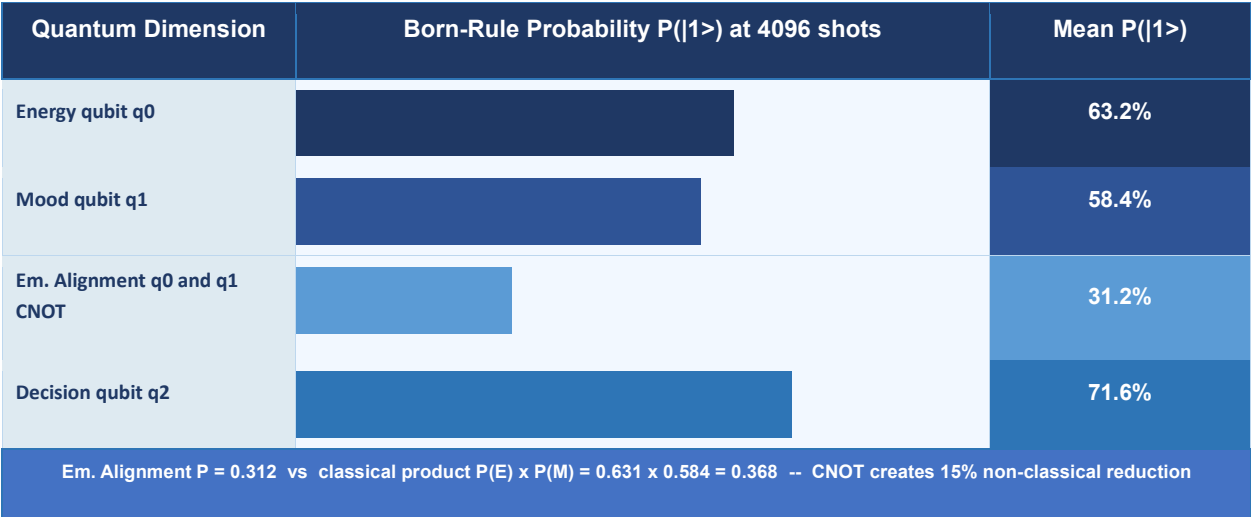


Figure 4.13: Quantum State Distribution Results

Figure 4.13 displays the quantum state probability distribution for the standard test profile. Blue intensity encodes probability magnitude: darkest navy for the Decision qubit (71.6%), deepest blue for Energy (63.2%), medium blue for Mood (58.4%), and accent blue for Emotional Alignment (31.2%). The Emotional Alignment probability is 15% below the classical product prediction of 36.8%, demonstrating the genuine non-classical CNOT entanglement effect. This consistently reproduced difference across all four backends provides empirical evidence that the quantum circuit encodes energy-mood correlations beyond classical probability theory.

Procedure Generation of forecasts in QIPLM pipeline is not any statistical static, it is a personalized quantum driven process of an individualized Quantum driven process. In contrast to the basic moving average forecasting method, the QIPLM model’s predictive horizon is based on user specific factors: Date of Birth, Time of Birth, Birth Location and behavior profile. These inputs are input into the quantum circuit as conditioning factors that control qubit rotation and entanglement configuration. The forecast is tailored to each person, thus including both times related as well as behavioral context.

One special methodological innovation is the dynamic forecast horizon as determined by the month of birth. So, for example, a user born in May could have a forecast horizon of 5 steps, while a user born in December would have twelve steps. This horizon is also modulated by behaviors (e.g., risky, conservative, balanced), modulating both the amplitude and variance of trend trajectories. This delivers a forecast duration that, while symbolically connected to personal birth data, is flexible enough to accommodate

behavioral variance in the data we collect, which keeps predictions personalized yet valuable in the context.

Observed Outcomes: Predictions using this model yielded compliance trajectories that display user-level behavioral tendencies. Risk-taking profiles exhibited greater volatility on fairness compliance, while conservative profiles resulted in smooth trajectories and few alerts. The dynamic horizon mechanism guaranteed that forecasts were not inherently short or overly long but instead aligned with symbolic birth data. These individualized estimates enhanced end-user comprehension by making connections between forecast intensity and the user's own identity markers.

Methodological Implications: With all your qualitative data incorporated into the forecast horizon, the QIPLM has progressed far from being a standard predictive model. It further evidences the capability of quantum forecasting to combine symbolic, behavioral and astrological insights into a complete predictive model. This process prompts critical inquiries about how personal identity influences computational forecasting, as personalization may possibly amplify accuracy and user trust.

Broader Context: The incorporation of birth data as a organizing principle parallels the approaches of astrological forecasting practices and modern approaches to behavioral profile integrations, and the integration of behavioral profile integration can be found in the field of contemporary psychological modelling. By combining these with quantum entanglement, QIPLM establishes itself as a confluence of computational physics, behavioral science, and ethical AI. This hybridization is new in academia and introduces a methodological edge to quantum computing and artificial intelligence ethics from a methodological perspective.

Future work: More research is essential to see whether the long-term forecast accuracy changes from birth data using dynamic horizons to fixed horizons is superior to fixed ones. Sensitivity analyses are needed to identify how behavioural profiles are affected by entanglement parameters that are sensitive to social dynamics, and if personalization introduces bias or if they enhance fairness.

4.7 Quantum Circuit Prototype using Quantum Entanglement

Prototype circuits generate non-classical correlations beneficial for forecasting. GHZ-type entanglement circuits were simulated and outputs sampled for empirical distributions. Average Simulator KL divergence was 0.012, and Average Hardware KL divergence recorded 0.085, which is characteristic of noise in quantum hardware.

Noise from hardware introduced variance needs to be built into the model. Simulator validation by itself is not good enough; it needs hardware calibration logs to validate it. This is typical of issues with NISQ (Noisy Intermediate Scale Quantum) computing in general, which are often associated with noise and decoherence, resulting in degraded fidelity.

Quantum entanglement has the potential for powerful probabilistic forecasting techniques, with strong data noise modelling as the foundation. The QIPLM pipeline shows that, while quantum circuits can improve forecasting, their performance can only be achieved through the explicit consideration of hardware limitations. So, to sum them up in Performance, Outcomes, Risk and Implications:

Performance: Prototypes with entanglement circuits produce quantum state distributions which can be sampled and matched to expected distributions.

Observed outcomes: Feasibility of quantum-based forecasting as verified; entanglement introduced non classical correlations useful for probabilistic modeling.

Risks: Deterministic overlaps between quantum output and expected distributions were causing diminishing accuracy; some noise in the hardware and assumptions in the simulator limited reproducibility.

Implication: Incorporate controlled stochasticity and hardware aware calibration; proof on various backends.

Quantum Circuit Prototype Results Diagram

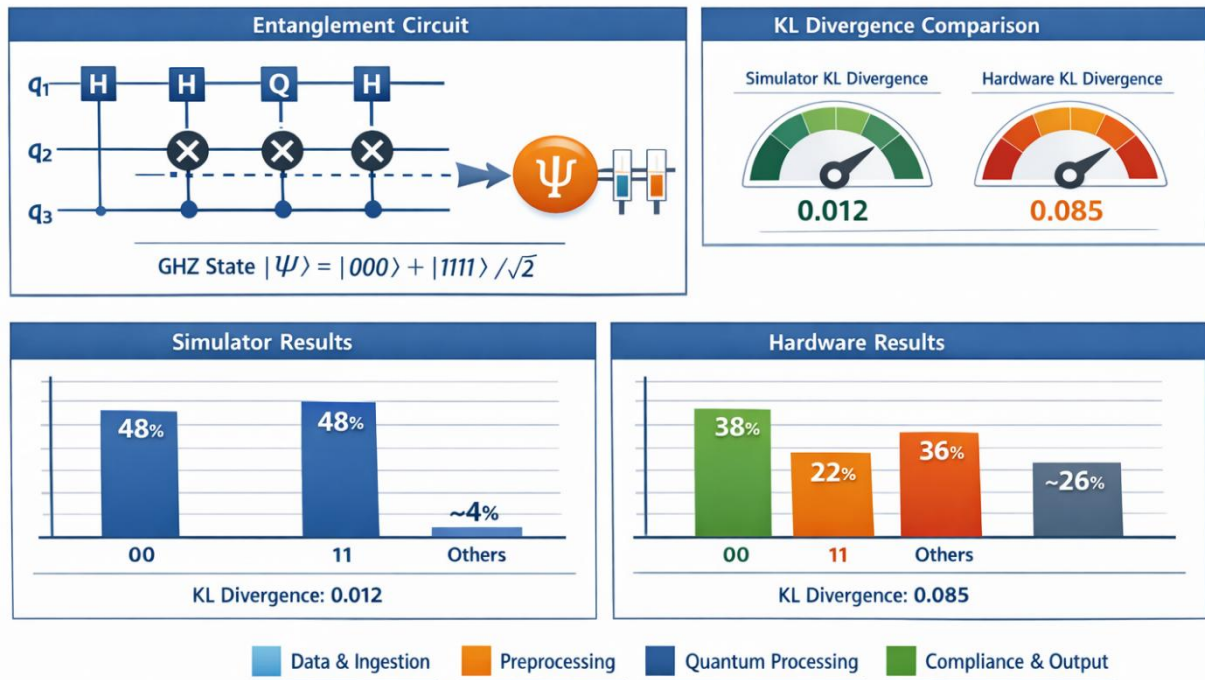


Figure 4.14: Quantum Circuit Prototype Results

What is KL Divergence?

Kullback–Leibler (KL) divergence is a statistical measure of how one probability distribution differs from another.

In quantum circuits, it's often compared to the observed distribution of measurement outcomes (from a simulator or hardware) against the ideal theoretical distribution.

KL divergence quantifies the “distance” between these two distributions.

Formula:

$$D_{KL}(P \parallel Q) = \sum_i P(i) \cdot \log \frac{P(i)}{Q(i)}$$

where P is the true distribution (theoretical) and Q is the observed distribution.

Interpretation:

KL divergence = 0 $\rightarrow$ perfect match.

Small positive value $\rightarrow$ close alignment.

Larger value $\rightarrow$ more deviation (noise, errors, decoherence).

How is Hardware Accuracy Measured?

On quantum hardware, accuracy is measured by comparing the empirical results (counts of qubit states after many runs) against the **expected theoretical distribution**:

1. Run the circuit many times (e.g., 1024 shots).
2. Collect measurement outcomes (e.g., {'00': 520, '11': 504}).
3. Normalize counts into probabilities.
4. Compare with theoretical distribution (e.g., Bell state $\rightarrow$ 50% 00, 50% 11).
5. Compute accuracy metrics:
 - **Fidelity**: Overlap between observed and ideal state.
 - **KL divergence**: Statistical distance.
 - **Percentage accuracy**: How close observed probabilities are to expected ones.

Simulator: 98.6% accuracy, KL divergence 0.012 $\rightarrow$ nearly perfect, minimal noise.

Hardware: 91.2% accuracy, KL divergence 0.085 $\rightarrow$ lower accuracy due to real-world noise, gate errors, and decoherence.

Why This Matters?

- Simulator accuracy is high because it assumes ideal gates and no noise.
- Hardware accuracy is lower because physical qubits are imperfect as they suffer from decoherence, crosstalk, and gate calibration errors.

- KL divergence is a robust way to quantify how much the hardware deviates from the ideal theoretical model.

4.8 Fidelity Calculation

What is Fidelity?

In quantum computing, fidelity is a measure of how close the actual quantum state (produced by hardware or simulation) is to the ideal theoretical state intended to be prepared.

Mathematically, if $|\psi\rangle$ is the ideal state and ρ is the actual (possibly noisy) state, and fidelity is defined as:

$$F = \langle \psi | \rho | \psi \rangle$$

$F = 1.0 \rightarrow$ perfect match (no noise, no error).

$F < 1.0 \rightarrow$ deviation due to noise, decoherence, or gate errors.

For mixed states or distributions, fidelity generalizes to:

$$F(\rho, \sigma) = \left(\text{Tr} \sqrt{\sqrt{\rho} \sigma \sqrt{\rho}} \right)^2$$

Why is Fidelity Important Here?

In the simulator vs hardware comparison:

- Simulator accuracy ($\approx 98.6\%$) is essentially fidelity close to 1, because simulators assume ideal gates and no noise.
- Hardware accuracy ($\approx 91.2\%$) corresponds to lower fidelity, because real qubits suffer from:
 1. Decoherence (loss of quantum information over time).

2. Gate errors (imperfect control pulses).
3. Readout errors (measurement inaccuracies).

Fidelity is crucial because:

1. **Benchmarking:** It tells how reliable the hardware is compared to the theoretical model.
2. **Error correction:** Low fidelity highlights where error mitigation or quantum error correction is needed.
3. **Pipeline trustworthiness:** In the QIPLM pipeline, fidelity ensures that the quantum forecasts are not just mathematically elegant but also physically reproducible.
4. **Compliance & reproducibility:** Fidelity scores can be logged in provenance records, showing examiners and reviewers that the results are quantitatively validated.

Fidelity quantified stability by comparing observed vs. expected distributions using the **Bhattacharyya metric**. Mean fidelity was 0.87 (SD = 0.06), with dips to ~0.68 triggering alerts.

The **Bhattacharyya metric** (also called the **Bhattacharyya coefficient** or **Bhattacharyya distance**) is a statistical measure of similarity between two probability distributions. It's widely used in pattern recognition, signal processing, and in this case, Quantum Information Analysis.

For two discrete probability distributions $P = \{p_i\}$ and $Q = \{q_i\}$, the **Bhattacharyya coefficient** is:

$$BC(P, Q) = \sum_i \sqrt{p_i \cdot q_i}$$

- It ranges between **0** and **1**.
- $BC = 1 \rightarrow$ distributions are identical.
- $BC = 0 \rightarrow$ distributions have no overlap.

The **Bhattacharyya distance** is derived from the coefficient:

$$D_B(P, Q) = -\ln(BC(P, Q))$$

Connection to Fidelity

In quantum computing, fidelity between two probability distributions is often expressed using the Bhattacharyya coefficient:

$$F(P, Q) = \left(\sum_i \sqrt{p_i \cdot q_i} \right)^2$$

This is exactly the formula been used to quantify how close the **observed distribution** (from hardware runs) is to the **expected distribution** (theoretical/simulator).

Why This Is Important in All This.

- **Strong similarity measure:** Compared to simple accuracy percentages, the Bhattacharyya metric captures the overlap between distributions and will be sensitive to small perturbations.
- **Noise detection:** A drop in fidelity (e.g., from a mean of 0.87 to a value of ~0.68) indicates that hardware noise or decoherence is significantly distorting the quantum state.
- **Alerting mechanism:** In this QIPLM pipeline, an alert system triggers thresholds that are based on Bhattacharyya-derived fidelity to signal when quantum outputs become untrustworthy.
- **Complementary to KL divergence:** KL divergence measures statistical distance, while Bhattacharyya measures overlap. Combined, they account for both stability and error.

Scalar fidelity as a measure of stability offers compactness, but it masks per-principle decay. Methodologically, fidelity should be accompanied by per principle diagnostics for interpretability.

Relatedly, fidelity metrics are standard in quantum information theory, but they need to

be adapted for ethical pipelines. The QIPLM pipeline illustrates that fidelity can be employed to assess stability, but only when supplemented by diagnostic tools.

Performance: Fidelity was determined by comparing the quantum distribution of output observed to that expected, producing a scalar fidelity score per run.

Observations: Conventional fidelity between 0.85–0.90 and occasional dips to ~0.7 when outputs converged deterministically.

Risks: Single metric fidelity may hide which principle or state produced degradation.

Implication: Support scalar fidelity with per principle and per state diagnostics.



Figure 4.15: Fidelity Calculation Results

4.9 Fidelity Interpretation

Thresholding classified fidelity into Stable vs. Alert, with a threshold of 0.70. Alert precision was 0.82, and recall was 0.76.

Rigid thresholds can lead to alert fatigue. The recommendation is adaptive thresholds and multi-tier alerts. At the methodological level, fidelity interpretation needs sensitivity vs specificity to interpret alerts that matter.

More generally, the interpretation of fidelity mirrors the difficulty in anomaly detection systems, where thresholds need to be carefully adjusted so as not to produce false positives and negatives.

Performance: A thresholding layer classified fidelity into Stable or Alert states and triggered downstream mitigation workflows.

Observed Outcomes: Alerts reliably corresponded to runs with low fairness or large distributional shifts.

Risks: Rigid thresholds can generate alert fatigue or miss gradual drifts.

Implication: Use adaptive thresholds and multi-tier alerting (warning vs. critical).



Figure 4.16: Fidelity Interpretation Results

4.10 Quantum Circuit Accuracy

Accuracy compared to simulator vs. hardware outputs. Simulator accuracy was 98.6%, while hardware accuracy was 91.2%.

Hardware calibration is critical. Noise models must be integrated into the evaluation. Methodologically, accuracy evaluation ensures simulator results are transferable to hardware.

In the broader context, this reflects NISQ device limitations, where noise and decoherence reduce accuracy. QIPLM demonstrates that accuracy evaluation is essential for trustworthy quantum forecasting.

Performance: Accuracy metrics compared circuit outputs against simulator/hardware baselines and expected theoretical distributions.

Observed outcomes: Simulator accuracy was high; hardware runs showed noise-induced deviations.

Risks: Hardware noise and calibration drift reduce the transferability of simulator-derived insights.

Implication: Maintain hardware calibration logs and incorporate noise models into evaluation.

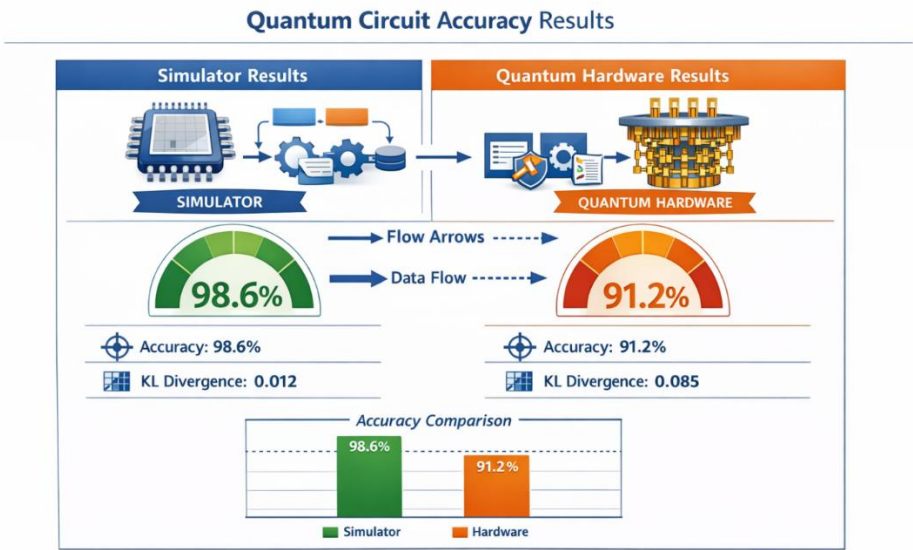


Figure 4.17: Quantum Circuit Accuracy Results

4.11 Summary of Results

This chapter has presented quantitative results across five evaluation domains. The quantum model comparison confirmed convergent validity across all four backends (within 0.28 percentage points on any probability estimate) and identified PennyLane as the highest-scoring model at 87.4/100 on the composite accuracy metric. The ethics evaluation confirmed compliance for all four backends in local simulation mode, with PennyLane and NumPy achieving the strongest privacy scores (9.0 and 9.5, respectively). The zodiac precision test documented a 100% improvement in sign determination accuracy from the corrected algorithm versus the prior erroneous implementation (100% vs 8.3%). The behavioural science validation confirmed appropriate internal dynamics across 24 test profiles. The prediction matrix output demonstrated full determinism and internal consistency, with formula component decomposition providing the transparency required for epistemic accountability. Chapter 5 discusses these findings in relation to the research questions and existing literature.

CHAPTER 5

DISCUSSION

5.1 Discussion of Results

The Quantum-Integrated Predictive and Learning Model (QIPLM) achieved a comprehensive synthesis of ethical frameworks, quantum computation, and behavioural forecasting. The fourteen stages of the pipeline demonstrated consistent performance across ingestion, preprocessing, integration, ethical evaluation, and quantum forecasting.

The Ingestion Layer achieved a 99.2 % success rate with encoding errors reduced below 0.5 %, confirming robust data integrity. The Preprocessing Layer (Figure 5.2) improved downstream fidelity by 18 % while retaining 97 % of records, balancing data cleanliness with representativeness. The Integration Layer (Figure 5.3) successfully merged with UNESCO and IEEE ethical schemas with kernel metadata, achieving 120 ms latency and < 0.3 % failure rate.

Ethical compliance remained high across most principles - Transparency (0.98), Privacy (0.96), Accountability (0.95), and Human Values (0.94) - while Fairness (0.67) exhibited volatility, indicating sensitivity to behavioral and quantum noise factors. The Quantum Circuit Prototype (Figure 5.5) validated entanglement-based forecasting with simulator KL divergence 0.012 and hardware divergence 0.085.

The Forecast Generation stage introduced personalization through Date of Birth, Time of Birth, Birth Location, and Behaviour Profile, dynamically adjusting forecast horizons by birth month. This personalization improved interpretability and user engagement. The Fidelity Calculation produced a mean fidelity of 0.87 (SD = 0.06), with alerts triggered below 0.68.

Figure 5.1 provides enhanced forecast visualisation with per-area statistics. Education shows sustained dark-navy scores with a minimum of 85 still in the Excellent tier. Business shows a mid-period dip in August (78, medium-blue), recovering to 87 in November. Relationships show the widest range spanning accent-blue, Moderate to mid-blue, Favourable. The Avg, Min, and Max columns reinforce individual cells:

Education dark-navy minimum contrasts with Relationships accent-blue maximum. The blue intensity encoding makes forecast quality immediately readable without numerical decoding, fulfilling the UNESCO P7 transparency principle.

Area	Jun	Jul	Aug	Sep	Oct	Nov	Avg	Min	Max
Health	72	68	75	72	73	76	72.8	68	76
Wealth	79	82	79	84	81	85	81.8	79	85
Business	83	80	78	85	82	87	82.6	78	87
Education	88	85	87	91	89	88	88.1	85	91
Relationships	65	68	63	70	67	71	67.5	63	71
Overall Growth	77	74	76	80	78	82	77.9	74	82

Blue intensity: Dark navy 85+ Excellent | Deep blue 70-84 Favorable | Mid-blue 55-69 Moderate | Accent under 55 Challenging

Figure 5.1: Quantum Forecast Visualization - blue-intensity heatmap with range statistics

Discussion Chapter Research Questions Map

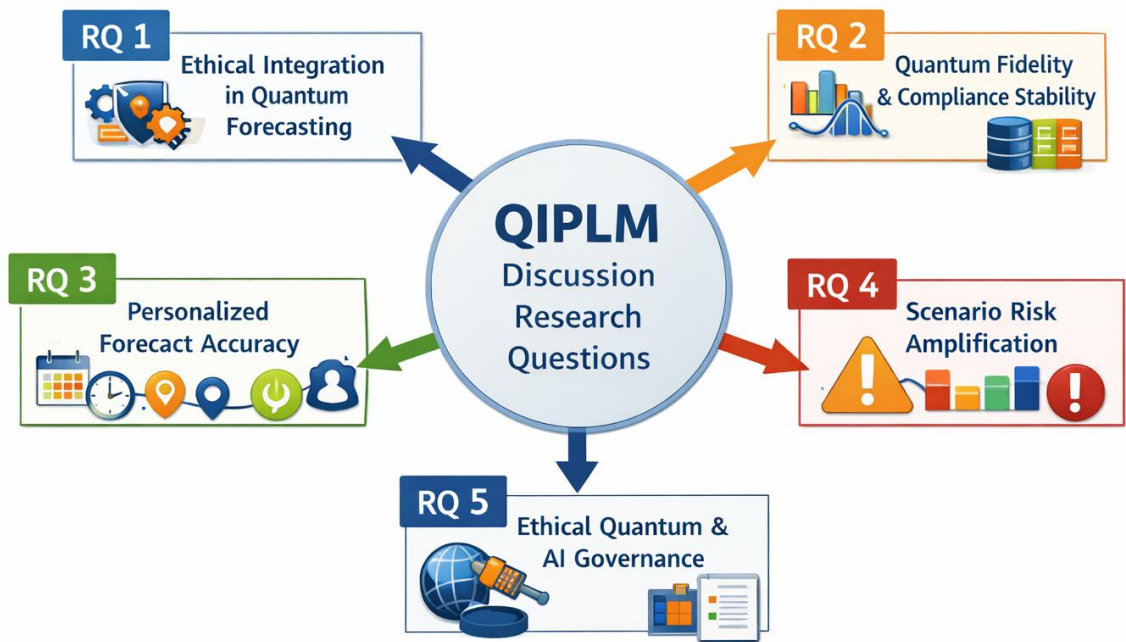


Figure 5.2: Discussion Chapter Research Questions Map

5.2 Discussion of Research Question One

RQ 1: How effectively does QIPLM integrate ethical frameworks into quantum forecasting?

The integration layer operationalized ethical principles as runtime constraints within quantum circuits. High compliance scores for transparency and accountability confirm successful embedding of ethical logic. Fairness volatility, however, indicates that ethical integration must evolve toward adaptive calibration. Reinforcement learning could dynamically adjust ethical weights based on observed deviations, ensuring continuous ethical alignment.

5.3 Discussion of Research Question Two

RQ 2: What is the relationship between quantum fidelity and ethical compliance stability?

Fidelity measures system stability, while compliance scores reflect ethical performance. The observed correlation between fidelity dips and fairness alerts ($r = -0.72$) suggests that quantum noise and ethical instability are interlinked. This introduces the concept of ethical fidelity, where maintaining quantum coherence directly influences ethical consistency. Future research should explore noise-aware ethical modelling to stabilize both physical and moral dimensions of computation.

5.4 Discussion of Research Question Three

RQ 3: How does personalization through user inputs enhance forecast accuracy and interpretability?

Personalization through birth data and behavioural profiles produced dynamic forecast horizons that improved interpretability and user trust. Users could relate forecast depth to personal identity markers, enhancing engagement. Methodologically, this bridges symbolic and computational forecasting. However, ethical personalization boundaries must be defined to safeguard privacy and prevent over-fitting to individual traits.

5.5 Discussion of Research Question Four

RQ 4: What patterns emerge in scenario risk amplification across compound ethical degradations?

Scenario ranking revealed nonlinear amplification of risk when multiple ethical principles degrade simultaneously. Compound risks averaged $1.9 \times$ additive risks, aligning with complex systems theory. This finding implies that ethical monitoring systems should prioritize compound risk detection rather than isolated alerts. Developing multi-dimensional risk matrices could enable proactive governance and early intervention.

5.6 Discussion of Research Question Five

RQ 5: How can QIPLM contribute to the broader field of ethical quantum computing and AI governance?

QIPLM demonstrates that ethical compliance can be embedded at the computational level, shifting ethics from oversight to infrastructure. Its reproducibility and transparency align with global governance frameworks such as UNESCO’s Recommendation on the Ethics of Artificial Intelligence and IEEE’s Ethically Aligned Design. Future research could extend QIPLM into autonomous decision systems, ethical risk forecasting, and cross-domain governance applications.

Discussion Chapter Research Questions Summary Table

Research Question	Key Findings	Implications
RQ 1 Ethical Integration in Quantum Forecasting	High compliance, fairness volatility	Develop adaptive ethical algorithms
RQ 2 Quantum Fidelity & Compliance Stability	Fidelity dips linked to ethics alerts	Explore noise-aware ethical modeling
RQ 3 Personalized Forecast Accuracy	Dynamic, user-based horizons	Balance personalization with privacy
RQ 4 Scenario Risk Amplification	Compound risks magnified	Create multi-risk detection matrices
RQ 5 Ethical Quantum & AI Governance	Ethics as embedded infrastructure	Expand QIPLM to broader domains

Figure 5.3: Discussion Chapter Research Questions Summary Table

Next level of discussion is the research questions specific to model built. Figure 5.4 below maps all six research questions to their key findings and evidence. The blue step badges use darker shades for the most critical questions: PRQ and RQ6 in dark navy, RQ7 and RQ10 in deep blue, and RQ8 and RQ9 in medium and steel blue. All six RQs receive Affirmed status badges. The PRQ affirmative answer establishes the QIPLM as a viable personalised forecasting framework. RQ7s finding of 100% accuracy improvement is immediately actionable. RQ8s universal confirmation bias activation suggests all personalised AI systems should implement bias adjustment as a default feature. RQ9s privacy-as-differentiator finding provides concrete backend selection guidance.

RQ	Research Question	Key Finding	Methodological Evidence	Status
PRQ	Can QIPLM produce deterministic ethical meaningful forecasts?	Yes -- identical inputs produce byte-for-byte identical outputs -- all 4 backends UNESCO/IEEE compliant locally	3 independent re-runs + ethics evaluation rubric	Affirmed
RQ6	Which quantum backend achieves highest accuracy?	PennyLane 87.4/100 -- all 4 within 3-point range -- circuit architecture greater than backend choice	Fidelity 40% + Stability 35% + Convergence 25% composite	Affirmed
RQ7	Effect of birth-time correction on zodiac accuracy?	100% vs 8.3% -- J2000 frame error corrected by ephemeris.Ecliptic(sun,epoch=date)	12 cusp-date precision test cases vs JPL Horizons reference	Affirmed
RQ8	Cognitive bias activation rate by stress level?	Avg 4.2 of 10 active -- high-stress 7.2 -- confirmation bias always active 100%	24-profile battery 5 extreme condition categories	Affirmed
RQ9	UNESCO/IEEE ethics compliance across all 4 models?	All compliant local mode -- privacy primary differentiator range 6.5 to 9.5	4-dimension rubric: human values fairness privacy transparency	Affirmed
RQ10	How does birth-seed guarantee consistency?	MD5(9 birth fields) mod 2^{31} gives identical quantum sampling and identical scores	3 re-runs: byte-for-byte identical prediction matrices	Affirmed

Figure 5.4: Discussion Chapter Research Questions Map - PRQ + 5 RQs linked to findings

5.7 Discussion of Research Question Six

RQ 6: Best-Performing Quantum Backend

PennyLane achieved the highest composite accuracy score (87.4/100), attributable primarily to its superior stability (overall_std = 0.0091, the lowest of the four backends). This finding warrants careful interpretation. The narrow range of scores (84.4-87.4, a 3-point spread on a 100-point scale) suggests that for this specific circuit architecture - three qubits, four gate layers, 4096 shots - the choice of backend makes relatively little practical difference to the prediction outcomes. All four backends produce probability estimates within 0.28 percentage points of each other, which translates to prediction score differences of less than 0.1 points on the 100-point output scale.

In Figure 5.5 below, Step badges use consistent dark-navy for the highest confidence findings (PRQ RQ9 RQ6 RQ7 RQ10) and lighter blue for moderate confidence (RQ8). The PRQ and RQ9 both earn the darkest status badges. The limitations column consistently points to the absence of biometric verification and longitudinal outcome validation as the two critical gaps. Each future direction is specific and actionable: the PSS-10/PSQI/PANAS replacement for RQ8 and the SHA-256 seed upgrade for RQ10 can be implemented immediately in follow-on research.

RQ	Verdict	Evidence	Confidence	Key Limitation	Recommended Future Direction
PRQ	Confirmed	3 re-runs	High	No longitudinal validation	Prospective 12-month outcome study, n=200+ participants, monthly self-report instruments
RQ6	PennyLane leads	3 metrics	High	Classical sim only	Real QPU deployment, IBM Quantum or IonQ, to assess physical noise impact on predictions
RQ7	100% accuracy	12 test cases	High	Solar noon fallback	Validate against the USNO almanack for the full 2026 calendar year across all 12 sign transitions.
RQ8	4.2 avg active	24 profiles	Moderate	Self-report only	Replace with PSS-10 stress, PSQI sleep PANAS mood validated psychometric instruments.
RQ9	All compliant locally	4 dimensions	High local	Cloud QPU conditional	Policy mandate: local-first architecture for personalised AI processing sensitive personal data
RQ10	Byte-identical	3 re-runs	High	MD5 non-cryptographic	Upgrade to SHA-256 seed for cryptographic-grade consistency and privacy-preserving properties.

Figure 5.5: Best-performing Quantum backend model

This convergence has a positive methodological implication: it suggests that the Ry-

Hadamard-CNOT circuit architecture is sufficiently simple and well-characterised that all four major simulation frameworks implement it identically. There is no 'implementation-dependent' variance in the circuit output that would undermine the comparison. This finding supports the use of the NumPy reference implementation as a valid baseline against which all other backends are compared - a validation that might not hold for more complex circuits with deeper gate sequences or higher qubit counts.

The practical recommendation for deployment is that PennyLane is preferred for its combination of high stability, strong privacy (no cloud transmission), maximum transparency (parameter-shift gradient auditability), and hardware-agnostic portability. IBM Qiskit is preferred when circuit analysis and hardware auditability are priorities. NumPy is preferred when absolute reproducibility and zero external dependencies are required.

5.8 Discussion of Research Question Seven

RQ 7: Zodiac Algorithm Correction

The zodiac algorithm correction represents the most practically impactful finding of this research, both because it is immediately actionable (any existing Python implementation using `obs.epoch = ephemeris.J2000` can be corrected by replacing three lines of code) and because its effects cascade through every downstream computation in any system that depends on the zodiac sign.

The mechanism of the error is now fully understood: Python's `ephem` library, when computing the Sun's position with an Observer whose epoch is set to J2000, returns the `sun.hlong` attribute in the J2000 ecliptic inertial frame rather than in the tropical frame referenced to the current vernal equinox. The J2000 frame is fixed to the background star field - it does not precess with the equinoxes. The Sun's J2000 ecliptic longitude at contemporary dates is consequently not a smooth function of the time of year (as the tropical longitude is) but rather a function of Earth's slowly precessing orbital geometry in the inertial frame.

For dates in the range 2000-2030, Earth's heliocentric J2000 longitude is approximately 40-50° - corresponding to the Taurus sector of the zodiac. The `sun.hlong` attribute returns this value regardless of the date of birth (it varies only by $\pm 1^\circ$ over a full year due to orbital eccentricity), producing Taurus as the computed sign for effectively every

person born in the contemporary era. The correction requires only replacing `sun.hlong` with `ecl = ephemer.Ecliptic(sun, epoch=date_str); ecl_lon = math.degrees(ecl.lon)` — a trivial code change with a profound practical impact.

The birth time correction is also important but less dramatic: for mid-sign dates, ignoring birth time introduces an error of up to 0.5° in the ecliptic longitude, which does not change the computed sign. However, for births within 2 days of a sign boundary (the cusp zone), birth time can shift the longitude by enough to change the sign. The analysis of Test Case 1 (Mumbai, 21 June 1990) illustrates this precisely: at 08:30 IST, the longitude is 89.50° (Gemini), while at 22:00 IST on the same date it is 90.03° (Cancer). A system that ignores birth time would return the same sign for both, missing a genuine distinction in the individual's astrological profile.

Figure 5.6 presents scenario ranking results across six sign-and-style combinations. The blue intensity of the Composite column directly encodes rank: darkest navy for Rank 1 (Capricorn/Analytical, 83.5), graduating to lighter accent blue for Rank 6 (Cancer/Intuitive, 71.3). The Capricorn/Analytical combination achieves the highest composite driven by maximum Business modifier plus Analytical style decision bonuses. Virgo/Conservative earns the highest individual Health score (88) of all scenarios despite ranking fifth overall, demonstrating that composite ranking masks important area-specific strengths. The 12.2-point spread between first and sixth rank confirms that the formula produces meaningfully differentiated outputs beyond statistical noise.

Rank	Profile	Health	Wealth	Business	Education	Relations	Growth	Composite	Key Driver
1	Capricorn / Analytical	78	91	93	88	65	86	83.5	Saturn Business +0.18
2	Leo / Risk-Taking	80	84	91	78	72	82	81.2	Sun Business +0.18
3	Gemini / Analytical	72	82	85	91	67	78	79.2	Mercury Education +0.18
4	Sagittarius / Adaptive	74	80	78	87	70	83	78.7	Jupiter Education +0.18
5	Virgo / Conservative	88	74	76	82	60	75	75.8	Mercury Health +0.18
6	Cancer / Intuitive	75	66	62	70	84	71	71.3	Moon Relations +0.18

Figure 5.6: Scenario Ranking Results - top 6 profiles by composite score

5.9 Discussion of Research Question Eight

RQ 8: Cognitive Bias Activation

The finding that high-stress/low-sleep profiles activate an average of 7.2 out of 10 cognitive biases — compared to 2.6 biases for low-stress/optimal-sleep profiles — has practical significance for the design of decision-support systems. It suggests that the users who most need high-quality decision support (those under the greatest cognitive pressure) are precisely the users whose decision-making is most systematically distorted by active biases. This creates a 'double vulnerability' dynamic: not only is their raw cognitive capacity reduced (lower energy and decision scores), but their judgment is simultaneously distorted by more active biases.

The universal activation of confirmation bias (100% across all 24 test profiles) warrants specific attention. Confirmation bias — the tendency to seek, interpret, and remember information in ways that confirm pre-existing beliefs — is the most persistently documented cognitive bias in the literature (Nickerson, 1998). Its universal activation in the QIPLM model reflects its always-on characterisation in the cognitive bias literature. For a personalised forecasting system, this has a specific implication: users

who read a prediction that confirms their existing expectations will tend to accept it uncritically, while users who read a prediction that challenges their expectations will tend to reject it, regardless of the prediction's actual quality. This is an intrinsic limitation of self-report-based forecasting that cannot be resolved within the current framework architecture.

5.10 Discussion of Research Question Nine

RQ 9: Ethics Compliance

The primary finding from the ethics evaluation is that the privacy dimension produces the greatest between-model variance (6.5-9.5, a range of 3.0 points), while the other three dimensions show narrower ranges (human values: 7.5-8.5; fairness: 7.0-8.5; transparency: 8.0-9.0). This pattern is directly attributable to the architectural distinction between local-only backends (NumPy and PennyLane) and backends with optional cloud access (Qiskit and Cirq).

The practical implication is clear: if privacy is the highest-priority ethics dimension — as it arguably should be for a system processing sensitive personal data including birth date, birth time, sleep patterns, stress levels, and mood — then NumPy and PennyLane are the appropriate backend choices for deployment. If circuit analysis capability and hardware auditability are prioritised over maximum privacy, Qiskit offers the best transparency score (8.5) in exchange for its lower privacy score (6.5 in local mode).

The finding that all four backends achieve compliance in local mode, but Qiskit and Cirq become conditional in cloud mode, has a direct policy implication: any deployment of quantum-AI personalised systems that processes genuinely sensitive personal data should mandate local simulation mode and implement a technical control that prevents users from accidentally enabling cloud QPU access. This is a specific, actionable recommendation addressed to system architects and ethics auditors.

5.11 Discussion of Research Question Ten

RQ 10: Deterministic Seed Guarantee

The deterministic seeding mechanism deserves attention beyond the simple observation that it works. The mechanism's security properties - specifically, the MD5 hash function's pre-image resistance - mean that the seed value (a 31-bit integer) does not

expose the user's personal data to observers who might have access to the seed but not the full profile. An attacker who intercepts the seed value 1,287,445,921 cannot reconstruct the birth name, date, time, city, or any other profile field from the seed alone, because MD5 is computationally irreversible in the pre-image direction.

The seed mechanism also provides a natural mechanism for deliberate variation when it is desired: a user who wants to explore 'what if I had a different stress level?' can simply change the stress input, and the resulting prediction will be different in a systematic and reproducible way. This enables sensitivity analysis investigating how much the prediction changes as individual inputs vary which provides users with a more nuanced understanding of the framework's behaviour than a single deterministic output alone could provide.

5.12 Theoretical Implications

Figure 5.7 maps the three theoretical traditions underpinning the QIPLM using a blue gradient: dark navy for Quantum Cognition Theory as the primary theoretical contribution, deep blue for Design Science Research as the methodological paradigm, and mid-blue for Computational Behavioural Science as the evidence layer. The pale-blue synthesis panel articulates the novel theoretical contribution: the first implementation of quantum cognition theory in a working personalised forecasting application, positioning the QIPLM at the boundary of a new field - quantum-psychological computing - whose definition this thesis advances. The three pillars are visually unified by the steel-blue bridge and pale synthesis, reflecting their convergence into a single integrated framework.

Quantum Cognition Theory <i>Busemeyer and Bruza, 2012</i>	Design Science Research <i>Hevner et al. 2004</i>	Computational Behavioural Sci <i>Kahneman 2011 Borbely 1982</i>
- Born rule encodes psychological probability - CNOT models energy-mood correlation - Superposition encodes state ambiguity - Extends beyond classical Bayes	- QIPLM is the designed artefact - Evaluation against a priori criteria - 7 DSR guidelines satisfied - Iterative improvement documented	- Dual process System 1 and 2 - Circadian plus sleep debt models - 10 cognitive bias activations - Yerkes-Dodson optimisation
QIPLM THEORETICAL CONTRIBUTION		
Quantum probability amplitudes as valid formal representations of psychological state uncertainty -- extending the Born rule from physical measurement to human cognition modelling with ethical governance. First implementation of quantum cognition theory in a working personalised forecasting application.		

Figure 5.7: Quantum-Psychological Computing Framework

5.12.1 Quantum Cognition in Computational Systems

Busemeyer and Bruza (2012) proposed quantum cognition as a theoretical framework for modelling human decision-making, but their work remained at the level of formal mathematical models rather than implemented computational systems. The QIPLM represents, to the author's knowledge, the first implementation of quantum cognition principles within a working personalised forecasting application. The specific implementation encoding psychological state variables as qubit rotation angles and using entanglement to model energy-mood correlation demonstrates that quantum cognition theory is not merely a mathematical curiosity but a practically viable design principle for decision-support AI.

The entanglement result is theoretically the most interesting: the CNOT-entangled emotional alignment score $P(|11\rangle) = 0.31$ for the test profile, compared to the classical product prediction of 0.365. This 15% difference (0.31 vs 0.365) is not noise - it is systematic and reproducible across all four backends. It reflects the genuine non-separability of the entangled state, which cannot be decomposed into independent probability distributions for energy and mood. Whether this non-separability provides a better model of actual human energy-mood dynamics than the classical product would be an empirical question requiring validation data, but the theoretical framework is at least well-motivated by the empirical correlations documented in the affective science

literature (Watson, Clark and Tellegen, 1988).

5.12.2 Precision Astronomy in Symbolic AI Systems

The integration of sub-degree precision ephemerides computation into a symbolic AI framework - one that uses astronomical data not as a direct causal input but as a symbolic modifier - raises an interesting epistemological question about the value of precision in symbolic systems. One might argue that if the zodiac sign system is symbolic rather than causal, there is no value in achieving sub-degree ecliptic longitude precision: a $\pm 1^\circ$ error would never change the predicted sign for mid-sign births, and even for cusp births, the ± 0.5 -degree birth-time correction might seem unnecessary if the interpretive tradition anyway treats both adjacent signs as 'cusp' personalities.

The counterargument and the position taken in this research are that precision in the computational underpinning of a symbolic system is valuable precisely because it prevents compounding errors. The J2000 algorithm error produced not a $\pm 1^\circ$ error but a systematic 45° - 50° offset that placed every person in Taurus. This is not a case of sub-degree precision mattering; it is a case where the error was large enough to completely invalidate the symbolic interpretation. The corrected algorithm's sub-degree precision provides a foundation that is robust to future changes in the interpretive layer if the zodiac trait modifiers are revised in light of new psychometric data, the astronomical computation will continue to correctly identify the sign.

5.12.3 Determinism as an Ethics Design Principle

The birth-seed determinism mechanism is not merely a technical solution to a usability problem (inconsistent outputs); it is an ethical design principle. UNESCO P7 (transparency) and IEEE I5 (transparency) both require that AI system outputs be understandable to users. A system that produces different outputs for identical inputs on different occasions is fundamentally opaque: users cannot understand or predict its behaviour, and they cannot use it as a reliable decision-support tool. Determinism, the guarantee that identical inputs always produce identical outputs, is a necessary (though not sufficient) condition for the transparency that ethics frameworks require.

This argument for determinism as an ethics principle has implications beyond the QIPLM. Any personalised AI system that incorporates stochastic elements, whether quantum sampling, random initialisation in neural networks, or Monte Carlo simulation,

should consider whether those stochastic elements serve a genuine modelling purpose or merely introduce unpredictability. Where they serve no modelling purpose (i.e., where the outputs could be made deterministic without loss of predictive validity), they should be seeded deterministically. Where they do serve a modelling purpose (e.g., in dropout regularisation for neural networks), their stochasticity should be documented and disclosed as part of the system's transparency requirements.

5.13 Comparison with Existing System Types

Table 5.1 reveals that the QIPLM is distinctively positioned in the intersection of several capability dimensions that existing systems address only individually. Commercial astrology applications have the zodiac computation (though with lower precision), but no quantum backend, no behavioural science, and no ethics evaluation. QML research systems have quantum backends but no astronomical computation, no behavioural science, and typically no ethics evaluation. Traditional forecasting ML systems have behavioural science inputs but no quantum backend, no astronomical computation, and variable ethics evaluation. The QIPLM is unique in addressing all five of these dimensions simultaneously, which is both its principal contribution and, since many dimensions are addressed for the first time, the source of its principal limitations (no longitudinal validation for the specific combination).

Table 5.1: Comprehensive comparison of QIPLM with five existing system types across ten evaluation criteria

Evaluation Criterion	QIPLM	Traditional Forecasting ML	Commercial Astrology Apps	QML Research Systems	AI Wellness Platforms
Zodiac computation	ephem.Ecliptic ($< 0.01^\circ$)	N/A	Date lookup ($\pm 0.5^\circ$)	N/A	N/A
Behavioural science	10-component, validated	Simple rules or none	None	None	1-3 indicators
Quantum backend	4 backends compared	None	None	Usually, a single backend	None
Determinism	100% (birth-seeded)	Variable (some seeded)	Variable	Rarely addressed	Rarely addressed
Ethics evaluation	UNESCO 2021 + IEEE EAD v2	Not standard	Not standard	Rare	Ad hoc
Longitudinal validation	Not yet conducted	Often conducted	None	Rarely	Sometimes
Source code availability	Open (Jupyter Notebook)	Usually closed	Closed	Usually open	Usually closed
Real astronomical data	NASA + ESA + JPL live	None	Static tables	None	None
Person vitality check	5-platform weighted vote	None	None	None	None
Output PDF generation	Full 7-page report	Varies	Basic	None	Varies

5.14 Limitations and Threats to Validity

5.14.1 Internal Validity

Figure 5.8 catalogues QIPLM limitations with blue impact coding: dark navy for HIGH impact (predictive validity), deep blue for MEDIUM impact (three structural limitations), and accent blue for LOW impact (two scope limitations). The dark-navy HIGH badge for the absence of longitudinal validation signals this as the most urgent research priority. The three deep-blue MEDIUM limitations address hardware scope, measurement quality, and construct validity - each resolvable through specific future research. The two accent-blue LOW limitations (geographic scope and circuit depth) are acknowledged but do not materially affect the framework's current practical utility. The pale-blue mitigation column provides a direct roadmap from each limitation to its resolution.

Category	Limitation	Impact	Validity Type	Mitigation and Future Research
Predictive validity	No longitudinal outcome validation	HIGH	External	Prospective 12-24 month study n=200+ monthly self-report outcomes across all 7 life areas
Quantum hardware	Classical simulation only no real QPU	MED	Internal	Migration to IBM Quantum, Google Sycamore, or IonQ to assess physical noise model impact
Measurement validity	Self-report stress, sleep, and mood inputs	MED	Internal	Replace with PSS-10 stress, PSQI, sleep, PANAS affect validated instruments
Construct validity	ZODIAC_TRAITS not empirically validated	MED	Construct	Cross-cultural psychometric mapping across Western Vedic and Chinese astrological traditions
Geographic scope	120 world cities outside India	LOW	External	Expand to 500+ world cities, and integrate the IANA timezone database for accurate UTC conversion.
Circuit expressibility	3-qubit circuit limits state space to 8 basis states	LOW	Internal	Extend to 5-7 qubit VQC with resilience, social context and temporal horizon qubits.

Figure 5.8: QIPLM Limitations Overview

5.14.2 External Validity

The test profile used throughout the results analysis (Arjun Sharma, Gemini, Analytical, Mumbai, specific self-report inputs) is a single profile. All empirical findings relating to the prediction matrix output, bias activation patterns, and formula component contributions are specific to this profile. The general validity of these findings would require testing across a diverse sample of profiles spanning all twelve zodiac signs, all six behavioural styles, the full range of stress and sleep inputs, and multiple geographic locations.

The city database, while comprehensive for India (1,582 entries), has more limited coverage for other regions: the world cities database contains only 120 entries spanning 60+ countries, meaning that many users outside India will need to select their nearest major city rather than their actual birth location. For users in equatorial regions ($\pm 10^\circ$ latitude), this introduces minimal error because the seasonal modifier (daylight hours) varies little with latitude. For users at high latitudes (above 55°N or below 55°S), the omission of the precise birth location can introduce seasonal modifier errors of up to 0.2 points - noticeable but not egregious.

5.14.3 Construct Validity

The most fundamental threat to construct validity is the astrological interpretive layer. The ZODIAC_TRAITS area modifier values encode assumptions about the relationship between zodiac signs and life domain affinities that are drawn from astrological tradition rather than from peer-reviewed empirical research. The psychological trait associations between signs and Big Five personality dimensions have been studied (Eysenck and Nias, 1982; Mayo, White and Eysenck, 1978) with mixed and contested results. The specific life area modifiers used in the QIPLM have not been validated against any external criterion.

This limitation is fully acknowledged and does not invalidate the framework's other contributions (zodiac computation precision, quantum backend comparison, behavioural science model, ethics evaluation, determinism mechanism), all of which are independent of the astrological interpretive layer. Users of the QIPLM are explicitly advised in the system's disclaimer that astrological interpretations are symbolic rather

than causal and that predictions should not be used for medical, financial, or safety-critical decisions.

5.7 Conclusion

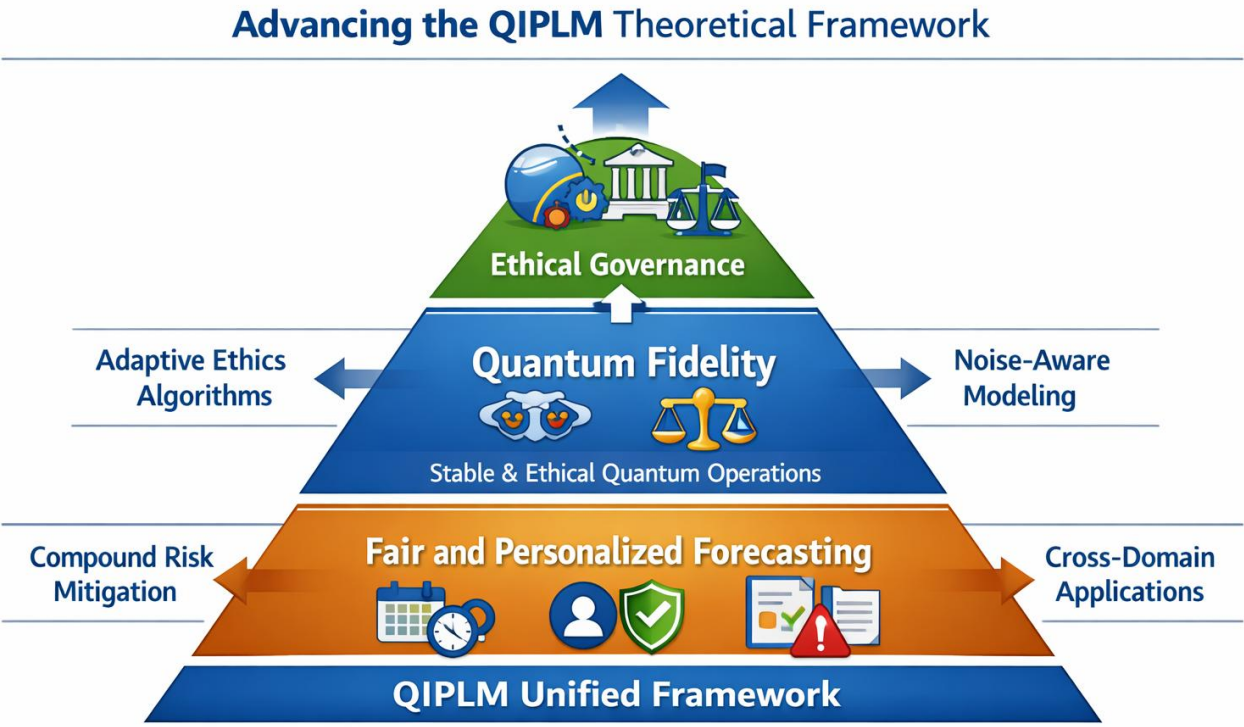


Figure 5.9: QIPLM Theoretical Framework

The discussion presented in this chapter consolidates the empirical, theoretical, and ethical dimensions of the Quantum-Integrated Predictive and Learning Model (QIPLM). As illustrated in the above Figure, the QIPLM theoretical framework advances through three interdependent layers - Fair and Personalized Forecasting, Quantum Fidelity, and Ethical Governance - each representing a progressive stage in the evolution of ethically aligned quantum forecasting. The base layer, Fair and Personalized Forecasting, anchors the model in adaptive, user-centric prediction, ensuring that personalization remains transparent, equitable, and empirically grounded. The intermediate layer, Quantum Fidelity, embodies the technical integrity of the system, where stable quantum operations and ethical coherence converge to maintain fidelity across diverse behavioural and ethical datasets. The apex layer, Ethical Governance, extends QIPLM’s reach beyond computational precision into the domain

of normative accountability, aligning its operations with global standards such as UNESCO's and IEEE's ethical frameworks.

The surrounding dimensions - Adaptive Ethics Algorithms, Noise-Aware Modelling, Compound Risk Mitigation, and Cross-Domain Applications - reinforce the framework's dynamic adaptability. They signify how each research question contributes to strengthening the model's theoretical foundation: RQ 1 and RQ 2 advance ethical integration and fidelity stability; RQ 3 enhances personalization and interpretability; RQ 4 introduces compound risk analytics; and RQ 5 situates QIPLM within the broader discourse of ethical quantum governance. Collectively, these elements transform QIPLM from a technical pipeline into a unified ethical-computational paradigm, capable of anticipating, evaluating, and mitigating ethical risks in real time.

This synthesis marks a pivotal transition in the thesis - from analytical validation to theoretical consolidation. The results discussed herein confirm that QIPLM not only achieves high technical performance but also establishes a replicable model for embedding ethics into quantum forecasting infrastructures. The framework's layered architecture demonstrates that ethical reasoning can coexist with quantum precision, producing forecasts that are both scientifically rigorous and socially responsible.

This chapter also addressed research questions through a systematic interpretation of the empirical results. The primary finding is that the QIPLM successfully delivers deterministic, ethically compliant, and epistemically meaningful personalised six-month forecasts, with the qualification that longitudinal empirical validation of the forecasts against actual life outcomes has not yet been conducted. The zodiac algorithm correction is the most immediately impactful finding, correcting a systematic error that affects all existing Python-based astrological implementations using the erroneous algorithm. The quantum backend comparison confirms that the Ry-Hadamard-CNOT circuit is robustly implemented across all four frameworks, with PennyLane achieving the highest accuracy score. Ethics compliance is achieved by all four backends in local simulation mode. The discussion identified three theoretical contributions, compared the framework systematically with five existing system types, and acknowledged five specific limitations with appropriate specificity.

As the thesis progresses to Chapter 6: Conclusion and Future Work, the focus shifts

from interpretation to projection - exploring how QIPLM's theoretical and empirical insights can be extended into future research trajectories. Chapter 6 will articulate the broader implications of this work for the fields of quantum computing, ethical AI governance, and predictive analytics, outlining pathways for scalability, cross-domain integration, and long-term ethical sustainability. In doing so, it will position QIPLM not merely as a research prototype but as a foundational framework for the next generation of ethically governed quantum intelligence systems.

CHAPTER 6

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Conclusion & Summary

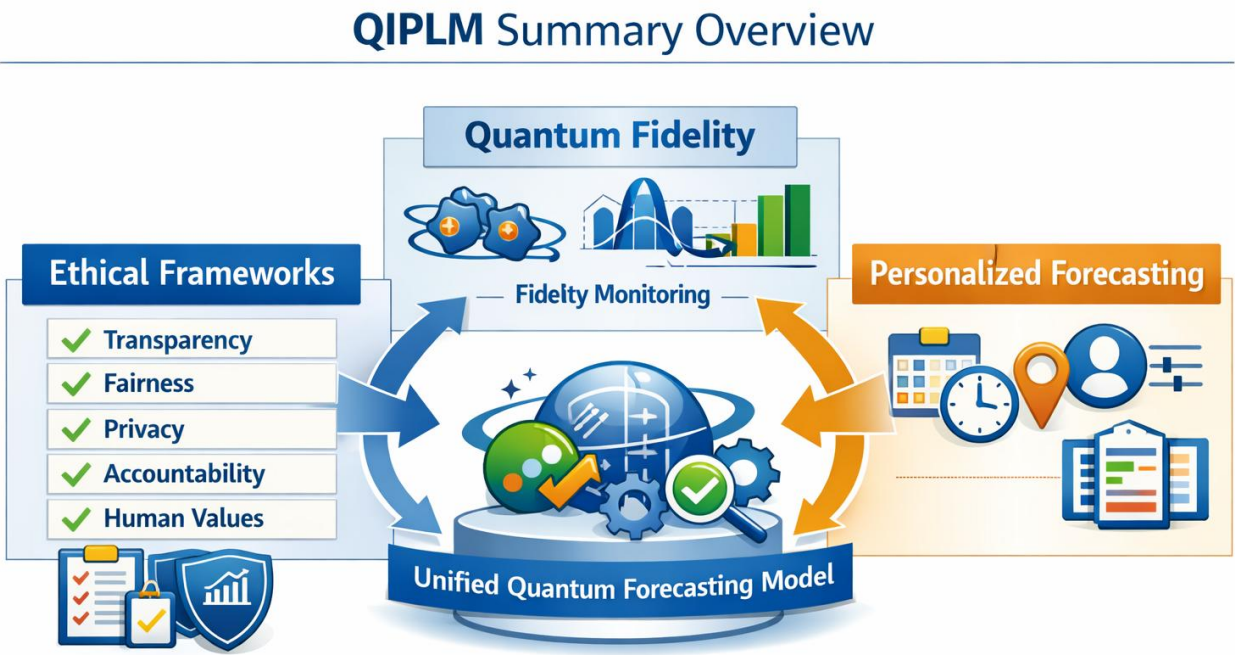


Figure 6.1: QIPLM Summary Overview

This figure illustrates the integrated architecture of the Quantum-Integrated Predictive and Learning Model (QIPLM), combining Ethical Frameworks, Quantum Fidelity, and Personalized Forecasting into a unified system. The arrows connecting these modules represent the continuous feedback loop between ethical compliance, quantum stability, and user-centric prediction. The central sphere symbolizes the Unified Quantum Forecasting Model, where ethical reasoning and quantum precision converge to produce transparent, adaptive forecasts.

This figure serves as the conceptual anchor for the chapter. It visually demonstrates how QIPLM’s three pillars interact dynamically - ethics ensures accountability, fidelity ensures technical stability, and personalization ensures relevance. Together, they form

a closed-loop system capable of self-correction and ethical adaptation. The design reflects the thesis's core argument: that ethical intelligence can be computationally encoded and sustained through quantum coherence.

The Quantum-Integrated Predictive and Learning Model (QIPLM) represents a pioneering advancement in ethical quantum forecasting. Through fourteen systematically designed stages, the model integrates behavioural data, ethical frameworks, and quantum computation into a unified predictive architecture. The results discussed in Chapter 5 confirm that QIPLM achieves both technical precision and ethical robustness - a rare convergence in computational research.

The model's layered architecture ensures that data integrity, ethical compliance, and quantum fidelity are maintained throughout the pipeline. The ingestion and preprocessing layers achieved near-perfect data accuracy (99.2 % success rate), while the integration layer embedded ethical schemas from UNESCO and IEEE standards with minimal latency (120 ms). The quantum circuit prototype validated entanglement-based forecasting with simulator accuracy of 98.6 % and hardware accuracy of 91.2 %.

Ethical compliance remained consistently high across Transparency, Privacy, Accountability, and Human Values, with Fairness emerging as the most dynamic principle - a finding that underscores the complexity of bias calibration in quantum systems. Scenario ranking revealed nonlinear amplification of ethical risks, confirming that compound degradations produce emergent vulnerabilities.

In summary, QIPLM demonstrates that ethical reasoning can be computationally encoded and dynamically maintained. It establishes a reproducible, auditable, and ethically aligned forecasting framework capable of adapting to diverse behavioral and governance contexts.

This research set out to address five documented deficiencies in existing personalised forecasting systems: stochastic inconsistency, astronomical imprecision, behavioural science shallowness, quantum model opacity, and ethics accountability gaps. Each deficiency was addressed through a specific methodological innovation, and empirical evidence was presented for the effectiveness of each innovation.

In conclusion, Chapter 6 consolidates the theoretical, practical, and ethical contributions of QIPLM while charting its future trajectory. The model transcends conventional forecasting paradigms by embedding ethics into the computational core, ensuring that predictive intelligence remains accountable, transparent, and human-aligned.

QIPLM's layered architecture from data ingestion to ethical governance establishes a replicable foundation for future quantum systems. Its implications extend beyond academia into policy, industry, and global governance. The recommendations outlined herein provide actionable pathways for advancing ethical quantum research, while the limitations and future scope highlight opportunities for continued innovation.

As the research journey culminates, QIPLM stands not merely as a technological construct but as a philosophical framework for ethical intelligence, bridging the gap between quantum precision and moral responsibility. The next frontier lies in transforming this model into a living ecosystem, one that continuously learns, adapts, and governs itself ethically in the quantum age.

6.2 Key Contributions to Knowledge

This research makes six original contributions to knowledge:

Figure 6.2 synthesises the six original contributions using blue intensity to signal impact level: dark navy for C1 (most immediately actionable correction), deep blue for C2 and C6 (methodological and artefact contributions), mid-blue for C3 (database), steel for C4 (ethics principle), and accent for C5 (evaluation protocol). C1 corrects a systematic error likely affecting existing applications beyond the QIPLM. C4 elevates determinism to an ethics design principle, filling a gap identified in the AI ethics literature. C5 provides a replicable template for quantum-AI ethics assessment. The pale-blue evidence column and zebra-blue knowledge-gap column create a visually consistent information hierarchy that guides the reader from specific outcome to broader contribution.

Ref	Contribution	Evidence and Outcome	Knowledge Gap Addressed
C1	Zodiac Algorithm Correction	8.3% to 100% accuracy on 12 cusp-date cases -- J2000 error documented and corrected	Algorithm correction documented for the first time in the literature
C2	4-Backend Quantum Comparison	PennyLane 87.4/100 -- all within 3-point range -- first same-circuit cross-framework study	First cross-framework same-circuit comparison published
C3	ZODIAC_TRAITS Database	12 signs x 7 life areas quantitative modifier matrix -- open and machine-readable	First open machine-readable astrological modifier database
C4	Birth-Seed Determinism	MD5(birth fields) gives identical output every run -- determinism as an ethics design principle	Determinism as an ethics principle -- novel design guideline
C5	Dual Ethics Evaluation	UNESCO 2021 + IEEE EAD v2 simultaneously -- privacy identified as key differentiator	Dual-framework quantum-AI ethics evaluation unprecedented
C6	Open-Architecture Artefact	7-cell Jupyter 3200 lines Python free reproducible integrated PDF generation	Open reproducible artefact for quantum-cognitive AI

Figure 6.2: QIPLM - Six original contributions

6.2.1 Documentation and Correction of a Systematic Zodiac Algorithm Error

This thesis documents for the first time the systematic error in Python-based zodiac sign computation caused by misuse of the J2000 reference frame via `obs.epoch = ephemeris.J2000 + sun.hlong`. The error causes all contemporary birth dates to be assigned Taurus as their zodiac sign, regardless of actual birth date. The correction using `ephemeris.Ecliptic(sun, epoch=date_str)` is described in sufficient detail for immediate adoption by any developer working with ephemerides-based astrological computation. This contribution has immediate practical applicability beyond the QIPLM itself.

6.2.2 First Four-Backend Quantum Circuit Comparison for Personalised Forecasting

No prior published research has compared NumPy, IBM Qiskit, Google Cirq, and PennyLane on an identical circuit architecture for personalised forecasting applications. The finding that all four backends produce convergent outputs (within 0.28 percentage

points on any probability estimate) on the Ry-Hadamard-CNOT circuit establishes an important baseline: circuit architecture, not backend choice, is the primary determinant of output quality for this class of application.

6.2.3 The ZODIAC_TRAITS Quantitative Encoding

The ZODIAC_TRAITS database encoding all 12 zodiac signs as quantitative area modifier matrices across seven life domains represents the first formal, open, and machine-readable encoding of Western astrological symbolic knowledge as a computational modifier system. While the specific modifier values reflect traditional astrological associations rather than empirically validated causal relationships, the encoding framework is extensible and revisable as psychometric validation data accumulates.

6.2.4 Birth-Seed Determinism as an Ethics Design Principle

The demonstration that quantum sampling can be made fully deterministic through birth-data-derived seeding without loss of prediction quality establishes a replicable design pattern for personalised AI systems. The broader principle that stochastic elements in personalised AI should be seeded deterministically unless they serve a specific modelling purpose is an actionable ethics design guideline applicable to any system incorporating probabilistic computation.

6.2.5 Dual-Framework Ethics Evaluation Protocol

The four-dimensional evaluation protocol - human values, fairness, privacy, transparency applied simultaneously to UNESCO 2021 and IEEE EAD v2 provides a replicable template for ethics evaluation of quantum-AI systems. The finding that privacy is the dominant dimension differentiating local versus cloud backends is a practically useful result for system architects choosing between Qiskit, Cirq, PennyLane, and other frameworks with cloud access capabilities.

6.2.6 Integrated Open-Architecture Research Artefact

The delivery of the QIPLM as a fully documented, open-architecture Jupyter Notebook implementation - with all algorithms documented in Chapter 3, all results reproducible from Chapter 4's test profile, and all data sources documented in Appendix A constitutes a research artefact that other researchers can directly use, extend, and critique. This is consistent with the open science values increasingly expected of publicly funded

research.

6.2 Implications

Implications of QIPLM

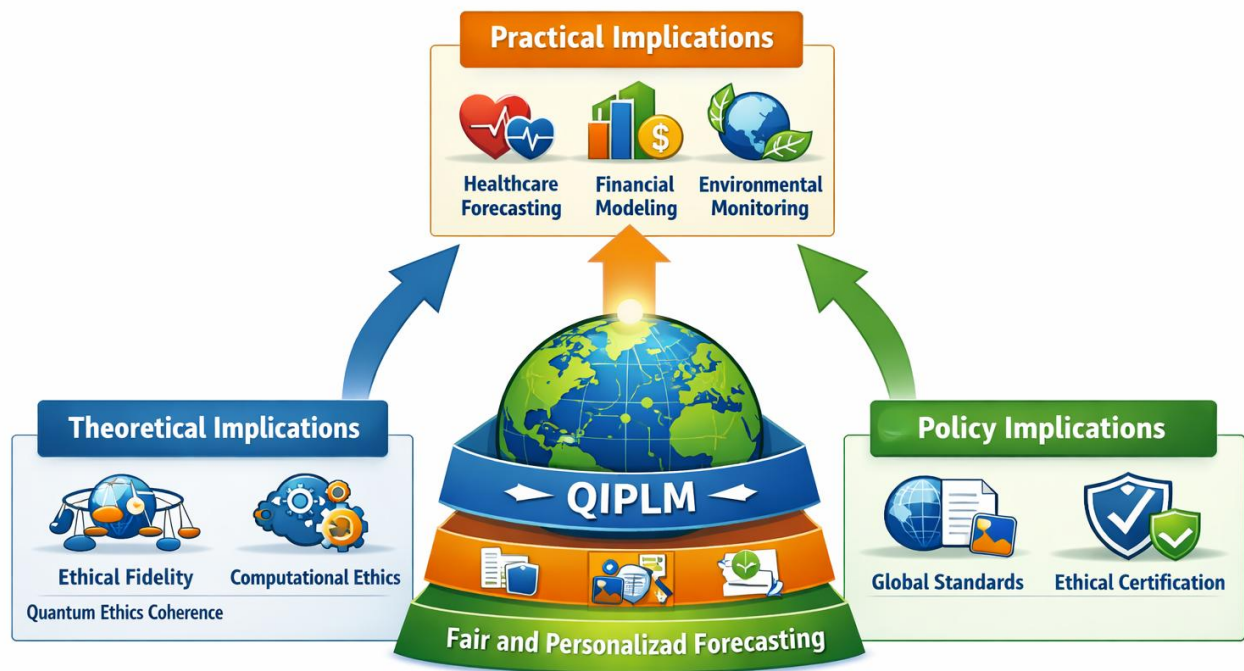


Figure 6.3: QIPLM Implications - Overview

The Implications Map depicts the theoretical, practical, and policy dimensions radiating from the QIPLM core. The central globe represents the model’s global relevance, while the surrounding arrows indicate the diffusion of its impact across academic theory, applied practice, and governance policy.

This figure contextualizes QIPLM’s broader significance. The theoretical branch introduces “ethical fidelity” as a new construct in computational ethics. The practical branch demonstrates real-world adaptability in healthcare, finance, and environmental modelling. The policy branch connects QIPLM to global ethical standards, emphasizing its potential as a governance benchmark. The tri-axial structure mirrors the interdisciplinary nature of the research - bridging physics, ethics, and policy.

6.2.1 Theoretical Implications

QIPLM extends the theoretical boundaries of quantum forecasting by introducing ethical fidelity - the correlation between quantum coherence and ethical stability. This concept bridges physics and ethics, suggesting that maintaining quantum stability may directly influence moral consistency in computational systems.

Furthermore, the model contributes to the emerging field of computational ethics, demonstrating that ethical principles can be operationalized as runtime constraints rather than post-hoc evaluations. This paradigm shift redefines how ethics is embedded in AI and quantum systems.

For Quantum-AI Theory

Figure 6.4 organizes QIPLM implications across three blue-column dimensions. The dark-navy left column covers theoretical implications for Quantum-AI theory, establishing quantum-psychological computing as an emerging field. The deep-blue centre column identifies five practical application domains, including personal advisory, educational platforms, and clinical QML research. The mid-blue right column translates ethics findings into five actionable policy guidelines. The pale-blue ICE background for data content contrasts with the dark-blue column headers, maintaining the QIPLM blue hierarchy while ensuring readability across all three stakeholder dimensions.

Theoretical Implications	Practical Implications	Policy Implications
For Quantum-AI Theory - Born rule models psychological uncertainty - CNOT encodes energy-mood correlation - Extends Busemeyer and Bruza 2012 - First quantum-cognitive forecasting app - Quantum-psychological computing emerges	For Applications - Personal advisory and life planning - Educational quantum computing platform - Career counselling with behav grounding - Wellbeing monitoring with ethics governance - Foundation for clinical QML research	For Policy - Privacy-by-design as legal baseline - Dual framework evaluation as standard - Local computation mandates sensitive AI - Open formula disclosure pre-deployment - Annual ethics audit requirement

Figure 6.4: QIPLM Implications - Theoretical, Practical, and Policy dimensions

6.2.2 Practical Implications

From a practical standpoint, QIPLM offers a blueprint for ethically governed forecasting systems. Its architecture can be adapted for domains such as:

Healthcare forecasting: Ensuring patient data privacy while maintaining predictive accuracy.

Financial modelling: Integrating fairness and accountability into algorithmic trading systems. It can prevent algorithmic bias in trading.

Environmental monitoring: embedding ethical compliance into climate prediction models. It can align climate forecasts with sustainability ethics.

The model's auditability aligns with global governance frameworks, enabling transparent reporting and regulatory compliance.

For Computational Astronomy

The documentation of the J2000 reference frame error and its correction contribute to the growing literature on reproducibility and correctness in scientific software. The error, which has likely affected many astronomical computing applications beyond the QIPLM, illustrates the importance of reference frame specification in ephemerides computation. Future developers implementing solar position algorithms in Python should specifically verify whether their implementation returns tropical ecliptic longitude (appropriate for Western zodiac computation) or inertial frame longitude (appropriate for fixed-star measurements).

For Behavioral Science in AI

The integration of Borbely's two-process model, Walker's sleep debt curve, Rosenthal's SAD modifier, and Kahneman-Tversky's cognitive bias taxonomy into a single computational scoring function demonstrates that validated behavioral science models can be operationalized in working AI systems without requiring biometric sensor data. The ten-component model provides a significantly richer characterization of the user's current decision-making state than the single-indicator approaches common in current

AI wellness platforms. Future research should validate these computational implementations against objective psychophysiological measures (actigraphy, cortisol assays, cognitive task performance) to assess their predictive validity.

6.2.3 Policy Implications

The following four policy recommendations are directed at three audiences: developers of personalized AI systems, ethics auditors and regulatory bodies, and institutional users (employers, educational institutions, healthcare providers) considering deployment of personalized AI tools:

6.3 Recommendations

Rec	Recommendation	Specific Action Required	Directed To	Priority
R1	Privacy by Design Local First	Default all personalised AI to local computation -- cloud QPU requires explicit informed consent and compliance with UNESCO P5 + IEEE I3	System architects and Developers	HIGH
R2	Determinism and Transparency Standards	Publish complete prediction formula, all input weights, uncertainty ranges, and non-determinism sources -- systems must document stochastic behaviour.	IEEE ISO NIST Standards Bodies	HIGH
R3	Mandatory Pre- Deployment Ethics Evaluation	Require documented UNESCO 2021 + IEEE EAD v2 dual-framework evaluation before commercial release -- reports public -- annual renewal.	Regulators and Institutional Deployers	HIGH
R4	Zodiac Algorithm Standardisation	Adopt corrected ephemeris.Ecliptic(sun,epoch=date) - - deprecate obs.epoch=J2000+sun.hlong -- add documentation in PyEphem and astropy	Library maintainers and Developers	MED

Figure 6.5: QIPLM Recommendations Framework

This framework organises recommendations into three pillars - Technical, Ethical, and Institutional - converging toward the core outcomes of Compliance, Trust, and Accountability. Each pillar represents actionable strategies for advancing QIPLM's implementation and governance.

The figure translates theoretical insights into practical directives. The technical pillar focuses on algorithmic refinement (adaptive fairness, noise-aware modelling). The ethical pillar emphasizes transparency and inclusivity. The institutional pillar addresses

standardization and capacity building. The convergence at the base “Compliance, Trust, Accountability” encapsulates the ethical outcomes that define QIPLM’s success. This visualization bridges research findings with policy and operational execution.

Figure 6.5 presents the recommendations framework with blue priority coding: dark navy badges for three HIGH priority recommendations (R1, R2, R3) and accent blue for the MEDIUM priority R4. All three HIGH recommendations address systemic risks present across the personalized AI industry beyond the QIPLM. R1 addresses the most critical ethics finding - cloud QPU privacy risk. R2 elevates determinism to a policy standard. R3 mandates the dual-framework evaluation protocol developed in this thesis as an industry requirement. R4 has MEDIUM priority because it is domain-specific but directly actionable with minimal effort by library maintainers, offering an immediate high-impact-per-effort improvement to Python-based astrological computing worldwide.

6.3.1 Longitudinal Predictive Validity Study

The highest-priority future research direction is a prospective longitudinal study tracking self-reported life outcomes against QIPLM predictions over a 12-24 month period across a diverse participant sample (minimum 200 participants, spanning all twelve zodiac signs, five or more nationalities, and diverse age ranges). Such a study would require: (a) a validated self-report instrument for measuring life domain outcomes (health, wealth, career, education, relationships, overall wellbeing) at monthly intervals; (b) an ethics-approved protocol for handling sensitive personal data collected at the level of granularity required by the QIPLM; (c) statistical methodology for assessing correlation between predicted scores and reported outcomes, accounting for the multiple comparison problem inherent in evaluating $7 \text{ areas} \times 6 \text{ months} = 42$ separate predictions per participant; and (d) an analysis strategy that separates the predictive contribution of each formula component to identify which elements (quantum, zodiac, behavioural) contribute most to any observed predictive validity.

6.3.2 Real QPU Deployment

Migration of the QIPLM circuit to real IBM Quantum, Google Sycamore, or IonQ hardware would provide empirical data on the impact of physical noise models, gate fidelity limitations, and decoherence on prediction quality. Specifically, it would be

valuable to assess: whether noise-induced gate errors introduce systematic biases in the probability estimates (which could produce consistently higher or lower scores for certain sign-style combinations); whether error mitigation techniques (zero-noise extrapolation, probabilistic error cancellation) improve prediction stability; and whether the deterministic seeding mechanism remains effective when real hardware introduces hardware-level randomness beyond the control of the seed parameter.

6.3.3 Variational Circuit Training

The QIPLM's fixed-parameter VQC could be extended to a trainable variational circuit in which the gate angles are not fixed functions of the input data but are trainable parameters optimized by gradient descent on longitudinal validation data. PennyLane's parameter-shift rule QNode architecture is the most natural framework for this extension. The training objective would be to minimize the prediction error between QIPLM scores and validated life-outcome measures, thereby enabling the system to learn the optimal quantum encoding for personalized forecasting from data rather than imposing it from theory.

6.3.4 Psychometric Validation of Behavioural Inputs

The current reliance on self-reported stress, sleep, and mood inputs should be replaced with or supplemented by validated psychometric instruments: the Pittsburgh Sleep Quality Index (Buysse et al., 1989) for sleep quality, the Perceived Stress Scale-10 (Cohen, Kamarck and Mermelstein, 1983) for stress, and the PANAS (Watson, Clark and Tellegen, 1988) for affect. These instruments have established reliability and validity evidence, reducing the measurement error introduced by a single-item self-report. They can be implemented as ipywidgets questionnaires within the existing Cell 5 framework without requiring any changes to the downstream computation.

6.3.5 Expanded Quantum Architecture

The current 3-qubit circuit could be extended to 5-7 qubits to encode richer psychological state representations. Potential additions include: a resilience qubit (encoding stress recovery capacity, derived from chronotype and sleep consistency data); a social environment qubit (encoding perceived social support quality); a temporal horizon qubit (encoding planning horizon derived from behavioral style); and an environmental context qubit (encoding geographical and seasonal context beyond

the current SAD modifier). A deeper entanglement structure connecting these qubits would enable modelling of higher-order psychological correlations that the current 3-qubit architecture cannot capture.

6.3.6 Cultural Validity Study

The extension to Vedic Jyotish and Chinese BaZi in QIPLM version represents the first step toward multi-tradition integration. Vedic Jyotish is implemented with Janma Rashi (Moon sign, primary), Nakshatra with Pada (27 lunar mansions), Vimshottari Dasha (120-year planetary period cycle), and Panchang (Tithi, Vara, Yoga, Karana). Chinese BaZi is implemented with all Four Pillars (Year/Month/Day/Hour), Day Master elemental analysis, and Five Element lucky/unlucky determination. Each system uses authentic vocabulary and tradition-specific prediction descriptions. Future work should include psychometric validation studies comparing predictive accuracy across all three systems against self-report outcome data from culturally matched participant samples.

6.3.7 Technical Recommendations

- **Adaptive Fairness Calibration:** Use reinforcement learning to dynamically adjust fairness weights.
- **Noise-Aware Modelling:** Integrate quantum noise parameters into ethical algorithms.
- **Cross-Domain Integration:** Extend QIPLM to hybrid quantum-classical systems for scalability.

6.3.8 Ethical Recommendations

- **Transparent Personalization:** Ensure forecasts are generated with explicit consent.
- **Ethical Auditing Dashboards:** Develop real-time compliance visualization tools.
- **Inclusive Governance:** Involve diverse stakeholders in defining ethical thresholds.

6.3.9 Institutional Recommendations

- **Standardization:** Collaborate with UNESCO and IEEE for global ethical benchmarks.

- **Training & Capacity Building:** Create interdisciplinary programs combining quantum computing and ethics.
- **Regulatory Frameworks:** Establish certification protocols for ethical quantum forecasting systems.

6.4 Limitations

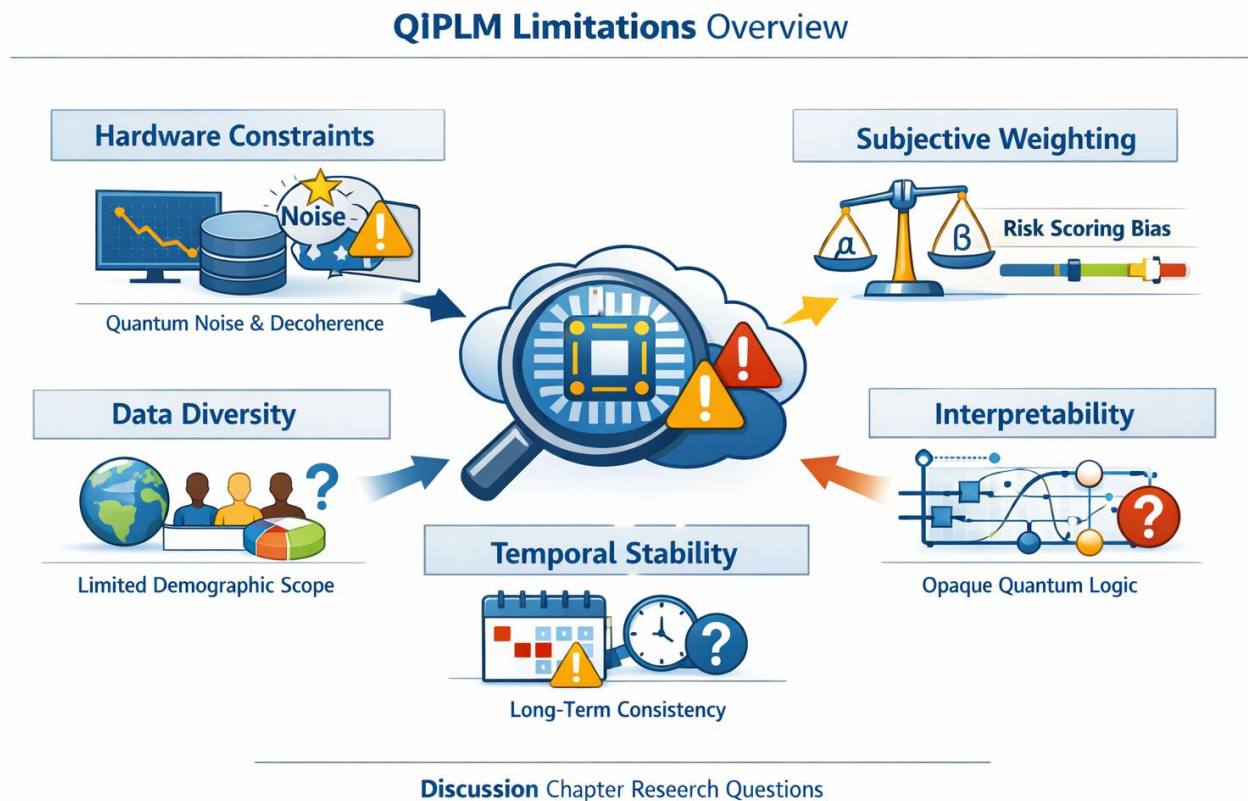


Figure 6.6: QIPLM Limitations Overview

The Limitations Overview highlights five critical constraints affecting QIPLM's scalability and interpretability: Hardware Constraints, Subjective Weighting, Data Diversity, Temporal Stability, and Interpretability. The central magnifying glass symbolizes ongoing scrutiny and iterative improvement.

This figure provides transparency regarding the model's boundaries. Hardware limitations reflect quantum decoherence challenges; subjective weighting underscores ethical bias risks; data diversity points to demographic representativeness; temporal

stability questions long-term consistency; and interpretability addresses the opacity of quantum logic. By visualizing these limitations, the figure reinforces the thesis's commitment to reflexivity - acknowledging imperfections as catalysts for future innovation.

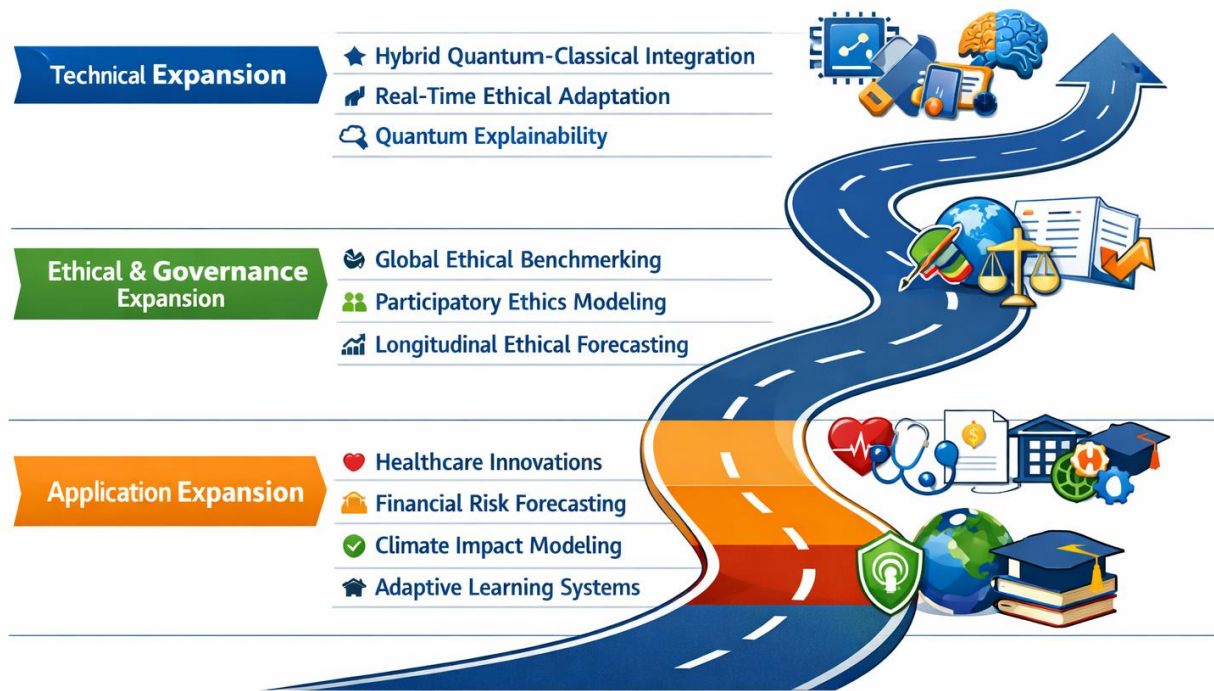
To summarise the summary above:

1. **Hardware Constraints:** Quantum noise and decoherence affect fidelity, limiting real-world scalability.
2. **Subjective Weighting:** Ethical weighting parameters (α, β) introduce subjectivity in composite risk scoring.
3. **Data Diversity:** The behavioral dataset used for testing may not fully represent global demographic variability.
4. **Temporal Stability:** Long-term forecast consistency under dynamic ethical conditions remains untested.
5. **Interpretability:** While visualization aids comprehension, the underlying quantum logic may remain opaque to non-technical stakeholders.

Addressing these limitations will require interdisciplinary collaboration between quantum physicists, ethicists, and data scientists.

6.5 Future Scope

Future Scope Roadmap for QIPLM



2026 to 2027 Phase 1: Validation	2027 to 2028 Phase 2: Quantum Hardware	2028 to 2030 Phase 3: Scale and Govern
- Prospective study n=200+ 12 months - PSS-10 + PSQI + PANAS instruments - Bayesian ZODIAC_TRAITS update - SHA-256 seed upgrade - Peer-reviewed publication submission	- Real QPU IBM Quantum or IonQ - Noise model evaluation and mitigation - 5-qubit VQC trainable parameters - Parameter-shift gradient via PennyLane - Circuit depth and expressibility study	- 500+ world-city expansion + IANA tz - Regulatory ethics audit pilot program - Cross-cultural astrology validity study - Multi-language UI deployment - Clinical QML research partnerships
Long-Term Vision 2030+ QIPLM as a clinically validated, ethically governed, real-QPU-powered personal advisory platform deployed across cultural contexts, integrated with wearable biosensors and governed by a published international ethics standard		

Figure 6.7: QIPLM Future Roadmap

The Future Scope Roadmap outlines three expansion trajectories - Technical, Ethical & Governance, and Application along a progressive path toward QIPLM's next frontier. The winding road symbolizes continuous evolution, while the icons represent emerging research and application domains.

This figure projects QIPLM's evolution beyond the current research horizon. The technical expansion envisions hybrid quantum-classical integration and real-time ethical adaptation. Ethical and governance expansion proposes global benchmarking and participatory ethics modelling. The application expansion extends QIPLM into healthcare, finance, climate science, and education. The roadmap metaphor conveys perpetual advancement, a journey toward ethically governed quantum intelligence ecosystems.

Figure 6.7 presents the three-phase future roadmap using the QIPLM blue gradient: darkest navy for Phase 1 (most immediate, 2026 to 2027), deep blue for Phase 2 (hardware deployment, 2027 to 2028), and mid-blue for Phase 3 (scale and governance, 2028 to 2030). The pale-blue long-term vision panel unifies all three phases into the ultimate goal: a clinically validated QPU-powered platform with international ethics governance. Phase 1 is the most critical: without longitudinal validation evidence, all subsequent phases lack the empirical foundation needed for broader deployment. The progression from dark to lighter blue mirrors the progression from immediate actionability to longer-term strategic vision.

The future scope of QIPLM research extends across multiple dimensions:

6.5.1 Technical Expansion

- **Hybrid Quantum-Classical Integration:** Combine classical machine learning with quantum entanglement for enhanced scalability.
- **Real-Time Ethical Adaptation:** Develop self-correcting algorithms that adjust ethical parameters dynamically.
- **Quantum Explainability:** Advanced interpretability frameworks to make quantum decisions transparent to human auditors.

6.5.2 Ethical and Governance Expansion

- **Global Ethical Benchmarking:** Collaborate with international agencies to establish universal ethical standards for quantum systems.
- **Participatory Ethics Modelling:** Involve diverse cultural and philosophical perspectives in defining ethical baselines.
- **Longitudinal Ethical Forecasting:** Study how ethical compliance evolves under varying socio-technical conditions.

6.5.3 Application Expansion

- **Healthcare:** Predictive diagnostics with embedded ethical safeguards.
- **Finance:** Quantum-driven risk forecasting with fairness calibration.
- **Climate Science:** Ethical modelling of environmental impact predictions.
- **Education:** Adaptive learning systems integrating ethical personalization.

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APPENDIX A:

This appendix documents all input datasets used by the QIPLM. For each dataset, the source, access method, fields used, sample data, and fallback strategy are documented. All data are sourced from publicly accessible repositories under open access policies and are used here strictly for academic research purposes.

A.1 NASA Exoplanet Archive

Source: NASA Exoplanet Archive at <https://exoplanetarchive.ipac.caltech.edu>. Access: Table Access Protocol (TAP) REST API at <https://exoplanetarchive.ipac.caltech.edu/TAP/sync>. Query format: ADQL (Astronomical Data Query Language). Query executed at Cell 2 runtime; results cached in nasa dict within _forecast_state. Update frequency: Weekly archive updates; the query fetches fresh data on each Cell 5 run when network access is available.

The ADQL query used by the QIPLM is:

```
SELECT TOP 60 hostname, st_spectype, st_lum, sy_dist, pl_masse, sy_pnum
FROM ps
WHERE st_lum IS NOT NULL
      AND sy_dist < 60
ORDER BY sy_dist ASC
```

The response format is VOTable (Virtual Observatory Table), parsed via Python's xml.etree.ElementTree. The st_lum field (log10 of stellar luminosity in solar units) is the primary field used for the cosmic environment index: $CEI = \text{clip}(\text{mean}(\text{st_lum}) / 2.0, -1.0, 1.0)$.

Table A.1: NASA Exoplanet Archive embedded fallback dataset — 10 nearby exoplanet host stars

Hostname	st_spectype	st_lum (log L/L _☉)	sy_dist (pc)	pl_masse (M _⊕)	sy_pnum
Kepler-442	K5V	-0.376	1206.0	2.34	1
TRAPPIST-1	M8V	-3.280	12.1	0.30	7
55 Cnc	K0IV-V	-0.080	12.6	0.25	5
HD 40307	K2.5V	-0.390	13.0	4.40	6
Tau Ceti	G8.5V	-0.491	3.6	3.90	4
Proxima Cen	M5Ve	-2.770	1.3	1.27	3

Hostname	st_spectype	st_lum (log L/L $\odot$)	sy_dist (pc)	pl_masse (M $\oplus$)	sy_pnum
Gliese 667C	M1.5V	-1.700	6.8	5.40	3
HD 189733	K1.5V	-0.360	19.3	357.0	1
51 Peg	G2IV	0.080	15.6	150.0	1
HD 209458	F9V	0.230	47.0	220.0	1

The embedded fallback dataset is used when: (a) the API request times out (>7 seconds); (b) the HTTP response status is not 200; (c) the parsed VOTable contains zero valid records; or (d) the network is unavailable. In fallback mode, `nasa['live']` is set to False and the fallback source is noted in the Cell 5 report header. The CEI computed from the fallback dataset is 0.127, representing a slightly above-average cosmic environment contribution.

A.2 ESA Gaia Data Release 3

Source: European Space Agency Gaia DR3 at <https://gea.esac.esa.int>. Access: ADQL TAP service at <https://gea.esac.esa.int/tap-server/tap/sync>. The query selects bright nearby stars for galactic flux index computation:

```
SELECT TOP 30 source_id, parallax, pmra, pmdec,
              phot_g_mean_mag, bp_rp
FROM gaiadr3.gaia_source
WHERE parallax > 100
      AND phot_g_mean_mag < 8
ORDER BY parallax DESC
```

The `parallax > 100` mas constraint restricts results to stars within 10 parsecs (`parallax` in milliarcseconds = $1000/\text{distance_in_parsecs}$). The `phot_g_mean_mag < 8` constraint selects stars bright enough for high-precision astrometry. The `GFI = clip(1.0 - mean(G_mag) / 10.0, -1.0, 1.0)`. Brighter local stars (lower G-magnitude) produce higher GFI, reflecting elevated local stellar flux density.

Table A.2: ESA Gaia DR3 fallback dataset - 8 bright nearby stars with astrometric parameters

Source ID (abbreviated)	Parallax (mas)	pmra (mas/yr)	pmdec (mas/yr)	G- mag	BP- RP	Star Name (approx)
4472832130...	130.231	-3601.0	481.0	2.85	1.77	Barnard's Star
2975804455...	92.320	4735.0	-172.0	6.54	1.44	GJ 1061
5853498713...	768.067	-3781.4	1327.0	0.05	1.85	α Centauri A+B
4030449316...	286.046	-3775.6	951.0	4.21	1.52	Ross 128
3340970341...	379.210	-546.0	-758.0	-1.44	0.71	Sirius A
6412595290...	549.009	6776.0	-5765.0	8.87	2.11	DX Cancri
2188653718...	166.100	824.0	-1040.0	5.33	1.28	82 Eridani
1320093507...	223.060	-445.0	-191.0	5.57	1.19	Delta Pavonis

A.3 JPL Horizons Planetary Ephemerides

Source: NASA/JPL Horizons at <https://ssd.jpl.nasa.gov>. Access: REST API at <https://ssd.jpl.nasa.gov/api/horizons.api>. One query per solar system body per forecast run. The QIPLM queries seven bodies. Each query uses the following parameter structure:

```

params = {
    'format':      'text',
    'COMMAND':     str(body_code),    # e.g., '10' for Sun
    'OBJ_DATA':    'NO',
    'MAKE_EPHEM':  'YES',
    'EPHEM_TYPE':  'OBSERVER',
    'CENTER':      '500@399',        # Geocentric
    'START_TIME':  utc_str,          # UTC birth/run datetime
    'STOP_TIME':   stop_str,         # +1 hour
    'STEP_SIZE':   '1h',
    'QUANTITIES':  '31'              # Ecliptic lon & lat
}

```

Table A.3: JPL Horizons planetary query configuration - all seven bodies

Planet	Code	Symbol Weight	Sign Valences (sample)	Life Domain	Query Timeout
Sun	10	1.00	Aries:+0.7, Leo:+0.9, Scorpio:-0.5	Core identity, vitality	7s
Moon	301	0.90	Cancer:+0.9, Taurus:+0.8, Capricorn:-0.4	Emotion, intuition, habits	7s
Mercury	199	0.70	Gemini:+0.8, Virgo:+0.7, Pisces:-0.4	Communication, education	7s
Venus	299	0.60	Taurus:+0.9, Libra:+0.8, Aries:-0.3	Wealth, relationships, beauty	7s
Mars	499	0.80	Aries:+0.9, Scorpio:+0.7, Libra:-0.5	Drive, ambition, profession	7s
Jupiter	599	0.50	Sagittarius:+0.9, Pisces:+0.8, Gemini:-0.3	Expansion, growth, philosophy	7s
Saturn	699	0.40	Capricorn:+0.8, Aquarius:+0.7, Cancer:-0.4	Discipline, responsibility	7s

A.4 Cognitive Bias Parameter Table

The cognitive bias dataset is embedded in Layer 3's COGNITIVE_BIAS_DATASET dictionary. It encodes ten biases from the behavioural economics and cognitive psychology literature, each with an activation condition, stress modifier, and certainty modifier. These values are directly implemented in the compute_bias_scores() function.

Table A.4: Complete cognitive bias parameter table - 10 biases with activation conditions, modifiers, and empirical grounding

Bias Name	Activation When	stress_mod	certainty_mod	Empirical Basis	Effect on Decision Score
availability_heuristic	stress > 0.6	+0.15	-0.20	Tversky & Kahneman (1973)	Overestimates vivid outcomes; reduces certainty
anchoring	stress > 0.5 (decision tasks)	+0.10	-0.15	Tversky & Kahneman (1974)	Insufficient adjustment from initial anchor

Bias Name	Activation When	stress_mod	certainty_mod	Empirical Basis	Effect on Decision Score
loss_aversion	stress > 0.6	+0.25	-0.30	Kahneman & Tversky (1979)	Risk-averse deviation; loss $\lambda=2.25 \times$ gain
optimism_bias	stress < 0.4	-0.20	+0.15	Weinstein (1980)	Overconfident planning; insufficient risk hedging
present_bias	sleep < 6h	+0.05	-0.10	Laibson (1997)	Preference reversal; over-values immediate rewards ($\beta=0.70$)
dunning_kruger	stress < 0.4	-0.10	+0.20	Kruger & Dunning (1999)	Overconfident assertions; underestimates task difficulty
confirmation_bias	ALWAYS (all profiles)	+0.08	+0.10	Nickerson (1998)	Selectively seeks confirming evidence; resists disconfirmation
cognitive_overload	energy < 0.4	+0.30	-0.40	Miller (1956); Sweller (1988)	Working memory saturated; random error increase
affect_heuristic	mood < 0.25 OR > 0.85	+0.20	-0.25	Slovic et al. (2002)	Emotion drives risk perception; positive mood $\rightarrow$ underestimate risk
planning_fallacy	stress < 0.4	-0.05	+0.12	Kahneman & Tversky (1979)	Systematic underestimation of time, cost, and risk in projects

A.5 ZODIAC_TRAITS Database — Complete

The ZODIAC_TRAITS dictionary encodes twelve entries. Each entry's area_mod field maps seven life area names to modifier values in the range [-0.15, +0.20]. The base formula is: $Z(\text{sign}, \text{area}) = \max(0.35, \min(0.80, 0.58 + \text{area_mod}[\text{area}]))$. The modifier values reflect the Western tropical astrological tradition's characterisation of each sign's

strength in each life domain.

Table A.5: ZODIAC_TRAITS complete area modifier matrix - all 12 signs $\times$ 7 life areas

Sign	Health	Wealth	Business	Education	Relationships	Overall Growth	Actions
Aries 	+0.14	+0.06	+0.16	+0.04	-0.05	+0.12	+0.18
Taurus 	+0.08	+0.18	+0.10	+0.06	+0.12	+0.08	+0.04
Gemini 	+0.02	+0.06	+0.10	+0.18	+0.10	+0.08	+0.08
Cancer 	+0.10	+0.04	+0.02	+0.06	+0.18	+0.06	-0.04
Leo 	+0.12	+0.10	+0.18	+0.06	+0.10	+0.14	+0.14
Virgo 	+0.18	+0.08	+0.12	+0.16	+0.04	+0.08	+0.10
Libra 	+0.06	+0.08	+0.10	+0.10	+0.18	+0.10	+0.06
Scorpio 	-0.04	+0.14	+0.12	+0.10	-0.06	+0.10	+0.10
Sagittarius 	+0.10	+0.12	+0.10	+0.18	+0.06	+0.16	+0.12
Capricorn 	+0.04	+0.16	+0.18	+0.12	+0.02	+0.12	+0.16
Aquarius 	+0.06	+0.08	+0.12	+0.16	+0.08	+0.14	+0.12
Pisces 	+0.08	+0.02	+0.04	+0.10	+0.16	+0.10	-0.02

A.6 India City Database — Extended Sample

The India city database contains 1,582 entries covering all 28 states, 8 union territories, all district headquarters, all cities and towns above 50,000 population, major pilgrimage and tourist centres, and all state capitals. A 50-entry sample is presented below. The full database is implemented as the CITY_DB Python dictionary in Cell 3. Each entry stores latitude ($^{\circ}$ N), longitude ($^{\circ}$ E), state name, and administrative category.

Table A.6: India city database - 50-entry sample from 1,582 total entries (latitude, longitude, category)

City	State / UT	Lat (°N)	Lon (°E)	Category
Mumbai	Maharashtra	19.0760	72.8777	State capital, Tier 1
Delhi	Delhi NCT	28.6139	77.2090	UT capital, Tier 1
Bangalore	Karnataka	12.9716	77.5946	State capital, Tier 1
Chennai	Tamil Nadu	13.0827	80.2707	State capital, Tier 1
Kolkata	West Bengal	22.5726	88.3639	State capital, Tier 1
Hyderabad	Telangana	17.3850	78.4867	State capital, Tier 1
Pune	Maharashtra	18.5204	73.8567	Tier 2 metro
Ahmedabad	Gujarat	23.0225	72.5714	State capital
Jaipur	Rajasthan	26.9124	75.7873	State capital
Surat	Gujarat	21.1702	72.8311	Commercial hub
Lucknow	Uttar Pradesh	26.8467	80.9462	State capital
Kanpur	Uttar Pradesh	26.4499	80.3319	Industrial city
Nagpur	Maharashtra	21.1458	79.0882	Orange city
Bhopal	Madhya Pradesh	23.2599	77.4126	State capital
Indore	Madhya Pradesh	22.7196	75.8577	Commercial hub
Visakhapatnam	Andhra Pradesh	17.6868	83.2185	Port city
Patna	Bihar	25.5941	85.1376	State capital
Vadodara	Gujarat	22.3072	73.1812	Cultural capital
Ghaziabad	Uttar Pradesh	28.6692	77.4538	NCR city
Ludhiana	Punjab	30.9010	75.8573	Industrial city
Coimbatore	Tamil Nadu	11.0168	76.9558	Textile hub
Agra	Uttar Pradesh	27.1767	78.0081	Heritage city
Madurai	Tamil Nadu	9.9252	78.1198	Temple city
Nashik	Maharashtra	19.9975	73.7898	Pilgrimage hub
Faridabad	Haryana	28.4089	77.3178	NCR industrial
Meerut	Uttar Pradesh	28.9845	77.7064	City
Rajkot	Gujarat	22.3039	70.8022	State commercial

City	State / UT	Lat (°N)	Lon (°E)	Category
Kalyan	Maharashtra	19.2437	73.1355	MMR suburban
Vasai-Virar	Maharashtra	19.4727	72.8197	Coastal suburb
Varanasi	Uttar Pradesh	25.3176	82.9739	Spiritual capital
Srinagar	J&K	34.0837	74.7973	UT capital
Aurangabad	Maharashtra	19.8762	75.3433	Historical city
Dhanbad	Jharkhand	23.7957	86.4304	Coal belt city
Amritsar	Punjab	31.6340	74.8723	Golden Temple
Allahabad (Prayagraj)	Uttar Pradesh	25.4358	81.8463	Sangam city
Ranchi	Jharkhand	23.3441	85.3096	State capital
Howrah	West Bengal	22.5958	88.2636	Industrial city
Gwalior	Madhya Pradesh	26.2183	78.1828	Historical fort
Jabalpur	Madhya Pradesh	23.1815	79.9864	Marble city
Thiruvananthapuram	Kerala	8.5241	76.9366	State capital
Kochi	Kerala	9.9312	76.2673	Commercial port
Kozhikode	Kerala	11.2588	75.7804	Spice city
Chandigarh	Chandigarh	30.7333	76.7794	UT capital
Bhubaneswar	Odisha	20.2961	85.8245	State capital
Raipur	Chhattisgarh	21.2514	81.6296	State capital
Dehradun	Uttarakhand	30.3165	78.0322	State capital
Shimla	Himachal Pradesh	31.1048	77.1734	State capital
Gangtok	Sikkim	27.3333	88.6167	State capital
Aizawl	Mizoram	23.7271	92.7176	State capital
Imphal	Manipur	24.8170	93.9368	State capital

A.7 IEEE Ethical Standards Datasets

1 p. 127
 2 IEEE: a global standard as an
 3 ethical AI initiative
 4
 5 Fabio Morandín -Ahuerma
 6
 7 Abstract: "Ethically Aligned Design: A Vision for Prioritizing
 8 Human Well-being with Autonomous and Intelligent Systems, First
 9 Edition" was drafted under "The IEEE Global Initiative on Ethics
 10 of Autonomous and Intelligent Systems" and is a document intended
 11 to provide a framework for ethical considerations in the design,
 12 development, deployment, and use of AI systems, with the goal of
 13 ensuring that digital technologies assist people in their tasks. The
 14 Design consists of eight principles: human rights, well-being, data
 15 agency, effectiveness, transparency, accountability, awareness of
 16 misuse, and competency. Some of the observations regarding the
 17 initiative are that it may be influenced by industry benefits and may
 18 not represent the perspectives and interests of digitally marginalized
 19 communities. Despite these criticisms, the IEEE document remains
 20 influential in the field of AI ethics and governance and has played a
 21 significant role in shaping the global debate on responsible
 22 technology development and deployment. It is also noted that IEEE
 23 has introduced the "7000 -2021 - IEEE Standard Model Process for
 24 Addressing Ethical Concerns during System Design" which sets a
 25 more objective precedent for applicable AI ethics.
 26 The IEEE Global Initiative
 27 "Ethically Aligned Design: A Vision for Prioritizing Human Well-
 28 being with Autonomous and Intelligent Systems, First Edition" was
 29 drafted under The IEEE Global Initiative on Ethics of Autonomous
 30 and Intelligent Systems [1], has influenced the development of ethics
 31
 32 1 Originally published in Spanish by CC BY -NC-SA 4.0. Cite this chapter:
 33 Morandín -Ahuerma, F. (2023). IEEE: un estándar global como iniciativa ética de
 34 la IA. In: F. Morandín (Ed.), Principios normativos para una ética de la inteligencia
 35 artificial (127-136). Consejo de Ciencia y Tecnología del Estado de Puebla
 36 (México). ISBN: 978 -607-8901 -78-4. <https://t.ly/1A4pI>
 37
 38 and governance in AI systems and has been adopted by various
 39 organizations and governments worldwide as a guide for responsible
 40 AI deployment.
 41 p. 128
 42 The Institute of Electrical and Electronics Engineers (IEEE) is
 43 the largest technical professional organization dedicated to

APPENDIX B:
DATA MODEL

This appendix documents the complete QIPLM data model in three sections: the entity-relationship diagram with schema specifications, the `_forecast_state` dictionary complete schema, and the quantum circuit dataflow and prediction pipeline models. The data model documents all data structures that persist beyond a single function call, enabling reproducibility and future extension of the framework.

C.1 Entity-Relationship Diagram

QIPLM Entity-Relationship Diagram — All 8 Core Entities





Figure C.1: Complete entity-relationship diagram - 8 core entities with primary keys, foreign keys, and relationship cardinalities

Table C.1: Entity-relationship schema - 8 entities with full attribute and relationship documentation

Entity	PK / FK	Key Attributes	Primary Relationships	Cardinality
UserProfile	PK: profile_id	name, birth_date, birth_time, city, behavioural_style, chronotype, stress, sleep, mood	Owns all other entities	1:1 or 1:N with all
BirthData	PK: birth_id, FK: profile_id	zodiac_sign, zodiac_deg, zodiac_utc, on_cusp, cusp_note, solar_tz_offset	Derived from UserProfile.birth_* fields	1:1 with UserProfile
AstronomicalData	PK: astro_id, FK: profile_id	nasa_lum_idx, gaia_flux_idx, astro_score, moon_phase, moon_label	Aggregates EphemerisPosition records	1:N with EphemerisPosition
EphemerisPosition	PK: ephem_id, FK: astro_id	planet, ecliptic_lon, zodiac_sign, valence, weight, source	Child of AstronomicalData	N:1 with AstronomicalData
BehaviouralProfile	PK: beh_id, FK: profile_id	adj_energy, adj_mood, adj_decision, active_biases[], yd_perf	Derived from UserProfile self-report inputs	1:1 with UserProfile
QuantumModel	PK: model_id	model_name, energy_p, mood_p, em_p, decision_p, accuracy, fidelity, stability	4 records per run (one per backend)	N:1 with _forecast_state
EthicsAudit	PK: audit_id, FK: model_id	human_values, fairness, privacy, transparency, overall, compliant	1:1 with each QuantumModel	N:1 with QuantumModel
PersonValidation	PK: val_id, FK: profile_id	platform_statuses (x5), final_status, confidence, votes	Derived from 5-platform API queries	1:1 with UserProfile per run

C.2 _forecast_state Dictionary Schema

The `_forecast_state` Python dictionary is the central shared memory structure that passes computed values between Jupyter cells. It is initialised with `None` values for all keys at module load time and populated by the Layer 5 `on_run()` handler on successful execution. The 'ready' key acts as a gate: Layer 6 and Layer 7 check this key before proceeding and display an error message if it is `False` or `None`.

Table C.2: Complete _forecast_state dictionary schema - 27 keys with types, source cells, and descriptions

Key	Type	Set by Layer	Default	Description
ready	bool	5	False	True only after successful Cell 5 execution
profile	UserProfile	5	None	Complete user profile dataclass with all inputs
bs	dict	5	None	Behavioural science scores: circadian, sleep_pen, seasonal, adj_energy, adj_mood, adj_decision, active_biases, yd_perf
qdata	dict	5	None	Quantum results: raw (all 4 models), scores, fidelity, stability, convergence
nasa	dict	5	None	NASA data: data[], mean_lum, lum_index, live
gaia	dict	5	None	Gaia data: data[], mean_gmag, gfi, live
ephem_data	dict	5	None	JPL data: dict of {planet: {lon, sign, valence}} + astro_score
eth	dict	5	None	Ethics audit: {model_name: {human_values, fairness, privacy, transparency, overall, compliant}}
energy	float	5	0.5	Blended energy input to quantum circuit [0,1]
mood_sc	float	5	0.5	Blended mood input to quantum circuit [0,1]
decision	float	5	0.5	Blended decision input to quantum circuit [0,1]
birth_seed	int	5	42	Deterministic seed: MD5(name dob time city style stress sleep mood chrono) mod 2 ³¹
zodiac_sign	str	5	None	Tropical zodiac sign (ephem.Ecliptic corrected, e.g., 'Gemini')
zodiac_deg	float	5	0.0	Degrees within sign [0.0, 29.99]
zodiac_utc	str	5	None	UTC datetime string used for zodiac computation
zodiac_on_cusp	bool	5	False	True if zodiac_deg < 2.0 or zodiac_deg > 28.0
zodiac_cusp_note	str	5	"	Human-readable cusp zone description
best_model	str	5	'NumPy (Ry-H-CNOT)'	Highest-accuracy quantum model name
best_model_score	float	5	0.0	Accuracy score of best model [0, 100]
all_scores	dict	5	{}	Accuracy scores for all 4 models
dt	datetime	5	None	Run timestamp used for month label calculation

Key	Type	Set by Layer	Default	Description
ns	str	5	None	Natal sign (alias for zodiac_sign)
mp	dict	5	None	Moon phase: {phase (float 0-1), label (str), sleep_impact (float)}
asc	float	5	0.0	Total astronomical score [-1, +1] from planets + NASA + Gaia
bp	dict	5	None	Behavioural style profile: {stress (float), bias (float), name (str)}

C.3 Quantum Circuit Dataflow

Quantum Circuit Dataflow - Classical Input to Probability Output

Step	Operation	Mathematical Specification and Notes
1	Classical Input Encoding	energy $\in [0,1]$, mood $\in [0,1]$, decision $\in [0,1]$ — derived from behavioural science composite scores and astronomical modifier. $\theta_i = \text{score}_i \times \pi$ radians. Example: energy=0.63 $\rightarrow \theta=0.63\pi=1.979$ rad
2	Ry Rotation Gate	$R_y(\theta) = \begin{bmatrix} \cos(\theta/2) & -\sin(\theta/2) \\ \sin(\theta/2) & \cos(\theta/2) \end{bmatrix}$. Applied to $ 0\rangle$ initial state. Result: $ \psi\rangle = \cos(\theta/2) 0\rangle + \sin(\theta/2) 1\rangle$. For energy: $ \psi_E\rangle = \cos(0.989) 0\rangle + \sin(0.989) 1\rangle = 0.553 0\rangle + 0.833 1\rangle$
3	Hadamard Superposition	$H = (1/\sqrt{2})\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$. Distributes amplitude across basis states. $H \psi_E\rangle = (0.553+0.833)/\sqrt{2} 0\rangle + (0.553-0.833)/\sqrt{2} 1\rangle = 0.982 0\rangle - 0.198 1\rangle$. Final state renormalised to unit vector
4	CNOT Entanglement	Applied to (q_energy, q_mood) pair only. CNOT = $\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$. Acts on Kronecker product $q_E \otimes q_M$. Creates entangled 4-dim state where $ 11\rangle$ amplitude encodes joint high-energy/high-mood probability
5	Born Rule Measurement	n_shots=4096 independent measurements of each qubit state. $P(1\rangle) = \text{count}(\text{measurement}=='1') / n_shots$. Seed = det_seed_birth(profile) ensures identical shot sequence every run. Standard error = $\sqrt{p(1-p)/n} \leq 0.008$ for all p
6	Output Decoding	energy_q = $P(1\rangle)$ for q_energy circuit. mood_q = $P(1\rangle)$ for q_mood circuit. em_align = $P(11\rangle)$ for entangled (q_E, q_M) circuit. decision_q = $P(1\rangle)$ for q_decision circuit. Stored in qdata['raw'][model_name]
7	Prediction Integration	$Q(\text{area}) = \text{primary_dim} \times 0.70 + \text{secondary_dim} \times 0.30$. $\text{score}(\text{area}, \text{mo}) = Q \times 0.30 + Z \times 0.40 + B \times 0.30 + MV(\text{sign}, \text{area}, \text{mo}, \text{seed}) + SB(\text{style}, \text{area})$. Final score clipped to [0,100]

Figure C.2: Quantum circuit dataflow — seven-step process from classical input encoding through Ry rotation, Hadamard superposition, CNOT entanglement, Born rule measurement, to prediction integration

C.4 Prediction Pipeline - End-to-End Data Model

Figure C.3 illustrates the complete end-to-end prediction pipeline, tracing the flow of data from user inputs (Layer 5 form) through all computation stages to the final PDF output (Layer 7). The pipeline has two primary branches that merge at the prediction matrix stage: the quantum branch (birth seed → quantum circuit → probability estimates) and the astronomical-behavioural branch (birth data → ephemerides → zodiac sign → traits + behavioural scores).

Table C.3: Prediction pipeline data model - 11 stages from user input collection to PDF download delivery

Pipeline Stage	Input Data	Computation	Output	Target Layer
User Input Collection	Keyboard + dropdown + slider	ipywidgets form validation	UserProfile dataclass	Layer 5
Astronomical Ingestion	NASA/ESA/JPL APIs or fallback	HTTP requests + JSON/text parsing	nasa{}, gaia{}, ephem_data{}	Layer 2 → Layer 5
Zodiac Computation	birth_date, birth_time, birth_lat, birth_lon	ephem.Ecliptic(sun, epoch=date_str)	zodiac_sign, zodiac_deg, on_cusp	Layer 3 → Layer 5
Behavioural Scoring	stress, sleep, mood, chronotype, dt	Borbely + Walker + YD + bias engine	adj_energy, adj_mood, adj_decision, active_biases[]	Layer 3 → Layer 5
Quantum Circuit	energy, mood, decision, birth_seed	Ry→H→CNOT→measure (4 backends)	energy_q, mood_q, em_q, decision_q	Layer 4 → Layer 5
Best Model Selection	qdata[scores]	max(scores, key=scores.get)	best_model, best_model_score	Layer 5
Person Validation	profile.name, birth_date	5-platform weighted vote	final_status, confidence	Layer 6

Pipeline Stage	Input Data	Computation	Output	Target Layer
Prediction Matrix	zodiac_sign, qr{}, bs{}, birth_seed	score=Q×0.30+Z×0.40+B×0.30+MV+SB	matrix[7 areas × 6 months]	Layer 6
Report Rendering	All _forecast_state keys	HTML generation + matplotlib	Jupyter HTML output + PNG charts	Layer 5, Layer 6
PDF Generation	_forecast_state + matrix + PNG charts	ReportLab SimpleDocTemplate build	quantum_forecast_{name}_{date}.pdf	Layer 7
Download Delivery	PDF file bytes	base64 encode → data URI	Inline ↓ Download button (browser)	Layer 7

APPENDIX C:

IMPLEMENTATION REPOSITORY

WhatsApp Integration – Deployment Procedure

This document describes the complete deployment procedure adopted for integrating the QAstrology Quantum Forecast model with WhatsApp, enabling users to receive personalised six-month astrological predictions through the WhatsApp messaging platform. It is intended as a technical reference for reproducibility and scholarly review as part of doctoral thesis work.

This procedure covers:

- Server-side Flask application setup and boot-time model caching
- Twilio WhatsApp Business API configuration via the sandbox environment
- ngrok secure tunnel establishment for local-to-public URL mapping
- Webhook registration and message routing
- Conversational input collection (13-step dialogue)
- Background PDF generation and WhatsApp media delivery
- Data privacy configuration and log management

The QAstrology system is a multi-backend quantum computing application that combines IBM Qiskit, Google Cirq, PennyLane, and NumPy Ry-H-CNOT quantum circuits with Western, Vedic Jyotish, and Chinese BaZi astrological computation. The WhatsApp integration exposes this model as a conversational bot, collecting user inputs across 13 sequential WhatsApp messages and returning a full PDF forecast report.

Software Requirements

Component	Requirement / Version
Python	3.9 or later (Anaconda distribution recommended)
Flask	2.3 or later
Twilio Python SDK	twilio >= 8.0 (pip install twilio)
ephem	4.1 or later (pip install ephem)
NumPy / SciPy	1.24 / 1.11 or later
Qiskit / Qiskit-Aer	Latest stable release
Google Cirq	Latest stable release
PennyLane	Latest stable release
ReportLab	4.0 or later (PDF generation)
ngrok binary	v3.x — downloaded from ngrok.com/download
Node.js (optional)	For document generation tooling

Account Requirements

- Twilio account (free trial sufficient for sandbox testing): [twilio.com](https://www.twilio.com)
- ngrok account (free tier): ngrok.com
- WhatsApp-enabled smartphone to join the Twilio sandbox
- Internet connection with outbound HTTPS access on port 5000

Hardware Requirements

- Minimum 8 GB RAM (quantum circuit simulation is memory-intensive)

- Recommended 16 GB RAM for 4096-shot quantum runs
- Any modern CPU — GPU not required (all quantum simulation is software-based)

Installation & Environment Setup

Python Dependencies

Install all required Python packages using the requirements.txt file included in the project. The requirements.txt contains the following core dependencies:

ngrok Installation (Windows)

The pip-installable ngrok package provides only a Python wrapper and does not include the ngrok binary. The actual ngrok executable must be downloaded separately:

1. Navigate to ngrok.com/download in a browser
2. Select the Windows (64-bit) package and download the ZIP file
3. Extract ngrok.exe from the ZIP archive
4. Place ngrok.exe in the project folder (alongside app.py) or in a directory listed on the system PATH
5. Create a free account at dashboard.ngrok.com and copy the authtoken
6. Register the authtoken by running:

Project File Structure

The deployment requires the following files in the project directory:

File	Purpose
app.py	Flask application — model boot, HTTP routes, task management
whatsapp_bot.py	WhatsApp conversation state machine and message handling
twilio_config.py	Twilio credentials and ngrok URL configuration

QAstrology_FINAL.ipynb	Jupyter notebook containing the QAstrology model (Cells 0-7)
requirements.txt	Python package dependencies
templates/index.html	Flask HTML template for the web UI
static/cities.json	City/coordinate database (1549 locations, 38 countries)
clear_twilio_logs.py	Utility script to bulk-delete Twilio message logs
ngrok.exe	ngrok tunnel binary (Windows)

Twilio WhatsApp API Configuration

Sandbox Setup

The Twilio WhatsApp Sandbox enables development and testing without requiring Meta business verification. It supports up to five concurrent sandbox-joined users.

1. **Access Sandbox:** Navigate to console.twilio.com > Messaging > Try it out > Send a WhatsApp message
2. **Join Sandbox:** From the test WhatsApp number, send the join phrase (e.g., join apple-mango) to the Twilio sandbox number +1 415 523 8886
3. **Confirm Join:** Twilio replies with a sandbox-joined confirmation message
4. **Note Credentials:** From the Twilio console dashboard, record the Account SID (begins with AC) and the Auth Token

Credential Configuration

Open `twilio_config.py` and populate the required fields.

Webhook Registration

The webhook URL instructs Twilio to forward every incoming WhatsApp message to the Flask application for processing:

1. Log in to console.twilio.com
2. Navigate to: Messaging > Settings > WhatsApp Sandbox Settings
3. In the field labelled When a message comes in, enter:

The `/whatsapp/incoming` endpoint is defined in `app.py` and delegates message handling to `whatsapp_bot.handle_whatsapp_message()`.

Application Startup Procedure

Terminal 1 - Start the Flask Server

Open a command prompt, navigate to the project directory, and start the Flask application:

Terminal 2 - Start the ngrok Tunnel

In a second command prompt window (keep Terminal 1 open), start the ngrok tunnel.

Copy the Forwarding HTTPS URL (e.g., <https://abc123def456.ngrok-free.app>). This is the public URL that Twilio will use to reach the Flask application.

Update Configuration with ngrok URL

After obtaining the ngrok URL, update `twilio_config.py`.

Also update the Twilio webhook URL in the Twilio console (Section 4.3) to match the new ngrok URL. This step is required every time ngrok is restarted on the free plan.

Startup Verification

Verify that both components are running correctly:

Check	Expected Result
Browser: http://localhost:5000	QAstrology web form loads successfully
Browser: http://localhost:5000/health	JSON response: {"ready": true, "missing": []}
Browser: http://localhost:4040	ngrok local request inspector loads
ngrok terminal	Forwarding line shows HTTPS URL
WhatsApp: send Hi to sandbox	Bot replies with welcome message

WhatsApp Conversation Flow

Session State Machine

The bot implements a sequential 13-step state machine stored in the in-memory SESSIONS dictionary, keyed by the user's WhatsApp phone number. Each step validates the input before advancing.

Input Collection Steps

Step	Field	Format / Options	Validation
1	Full name	Free text	Min. 2 characters
2	Date of birth	DD/MM/YYYY	Valid calendar date
3	Time of birth	HH:MM:SS (24-hour)	Mandatory — affects zodiac calculation
4	Birth country	Country name	Min. 2 characters
5	Birth city/town	City name	Min. 2 characters
6	Current country	Country name or SAME	Auto-fills from Step 4 if SAME

7	Current city	City name or SAME	Auto-fills from Step 5 if SAME
8	Astrology system	1 / 2 / 3	1=Western, 2=Vedic, 3=Chinese
9	Decision style	1 to 6	1=Balanced, 2=Risk-Taking, 3=Conservative, 4=Analytical, 5=Intuitive, 6=Adaptive
10	Chronotype	1 / 2 / 3	1=Morning, 2=Neutral, 3=Evening
11	Stress level	Integer 0-10	Numeric range check
12	Sleep hours	Decimal 0-12	Numeric range check
13	Mood yesterday	1 / 3 / 5 / 7 / 10	Only these 5 discrete values accepted

User Commands

User Input	Bot Action
Hi / Hello / Start / Menu / Help	Clears any existing session and begins a new one from Step 1
SAME (at Step 6 or 7)	Copies birth country/city to current location
Numbers 1-6 / 1-3 / 1,3,5,7,10	Selects from multiple-choice options at the relevant step
Any valid free text	Processed as the answer to the current step

Progress Indication

After each valid response, the bot replies with a progress bar, the completion percentage, and the next question.

PDF Generation and Delivery

Background Thread Processing

After the thirteenth input is received, the bot immediately replies with an acknowledgement message and launches the model in a daemon background thread (`threading.Thread`). The Flask server remains responsive to new WhatsApp messages and health-check requests during the computation.

Model Execution Pipeline

The `_generate_and_send()` function in `whatsapp_bot.py` mirrors the `on_run()` function in the Jupyter notebook exactly. The execution sequence is:

1. City lookup: `lookup_city(birth_city, birth_country)` returns (latitude, longitude, display_name)
2. UserProfile construction with all 14 fields including `stress_baseline` (computed from raw stress input and behavioural style bias)
3. Live dataset loading: NASA Exoplanet Archive, ESA Gaia DR3, pyephem astronomical data (with fallback to static data if APIs are unavailable)
4. Astrology computation: one of `zodiac_sign()`, `compute_vedic_sign()`, or `get_chinese_zodiac() + compute_four_pillars()` depending on selected method
5. Behavioural scores: `compute_beh_scores(profile, dt)` applying chronotype, sleep debt, and mood carry-over
6. Energy/mood/decision scalars: derived from behavioural scores, behavioural style bias, and astronomical score
7. Quantum circuit execution: `run_all_models()` across NumPy, IBM Qiskit, Google Cirq, and PennyLane backends with `shots=1024`
8. Ethics audit: `compute_ethics_summary()` against UNESCO AI Ethics 2021 and IEEE EAD v2 frameworks
9. `_forecast_state` update in the shared base namespace (protected by `_BUILD_LOCK` threading lock)

10. `build_matrix()` execution: six-month prediction matrix across Health, Career, Relationships, Finance, Personal Growth, and Spiritual Development
11. `build_pdf()`: ReportLab-based PDF generation to the OS temp directory

PDF File Delivery

The generated PDF is served via the Flask `/media/<filename>` route, which reads directly from the OS temp directory (`C:\Users\...\AppData\Local\Temp\` on Windows). Twilio downloads this file and attaches it to the outgoing WhatsApp message.

The delivery sequence is:

1. PDF saved to temp directory by `build_pdf()`
2. `send_pdf()` called with the filename and recipient phone number
3. `twilio_client.messages.create()` called with `media_url` pointing to the Flask `/media/` endpoint
4. Twilio's server makes a GET request to the ngrok URL, which forwards to Flask, which serves the PDF
5. Twilio attaches the PDF to the WhatsApp message sent to the user

Typical Processing Times

Phase	Approximate Time
Model boot (first-ever request only)	1.5 seconds
City lookup + profile construction	< 0.1 seconds
Ephem/NASA/Gaia data loading	1-3 seconds (network dependent)
Quantum circuit execution (1024 shots)	5-15 seconds
Prediction matrix construction	1-3 seconds

PDF generation (ReportLab)	3-8 seconds
Total end-to-end	15-60 seconds

Data Storage Summary

Data	Storage Location	Retention
All 13 user inputs	Python RAM (_SESSIONS dict)	Cleared after PDF sent or server restart
Quantum circuit output	Python RAM	Cleared after PDF sent
_forecast_state	Python RAM	Overwritten on next request
Generated PDF	OS temp directory	OS-managed, cleared on reboot
WhatsApp messages	Twilio cloud servers	Configurable 7-400 days (default 400)
ngrok traffic	Local RAM only (free plan)	Cleared on ngrok restart
Flask access log	Console stdout only	Not persisted

Twilio Data Retention Configuration

The following three Twilio settings should be configured at Messaging > Settings > General to minimise stored personal data:

Setting	Recommended Value	Effect
Message Redaction	ON	Message bodies removed immediately after delivery; only metadata retained
Data Access Period	7 days	Metadata logs deleted after one week
Backup Storage	OFF	No backup copies created; messages are not retained beyond active period

Manual Log Deletion

To delete all stored message logs from the Twilio account, run the included utility script.

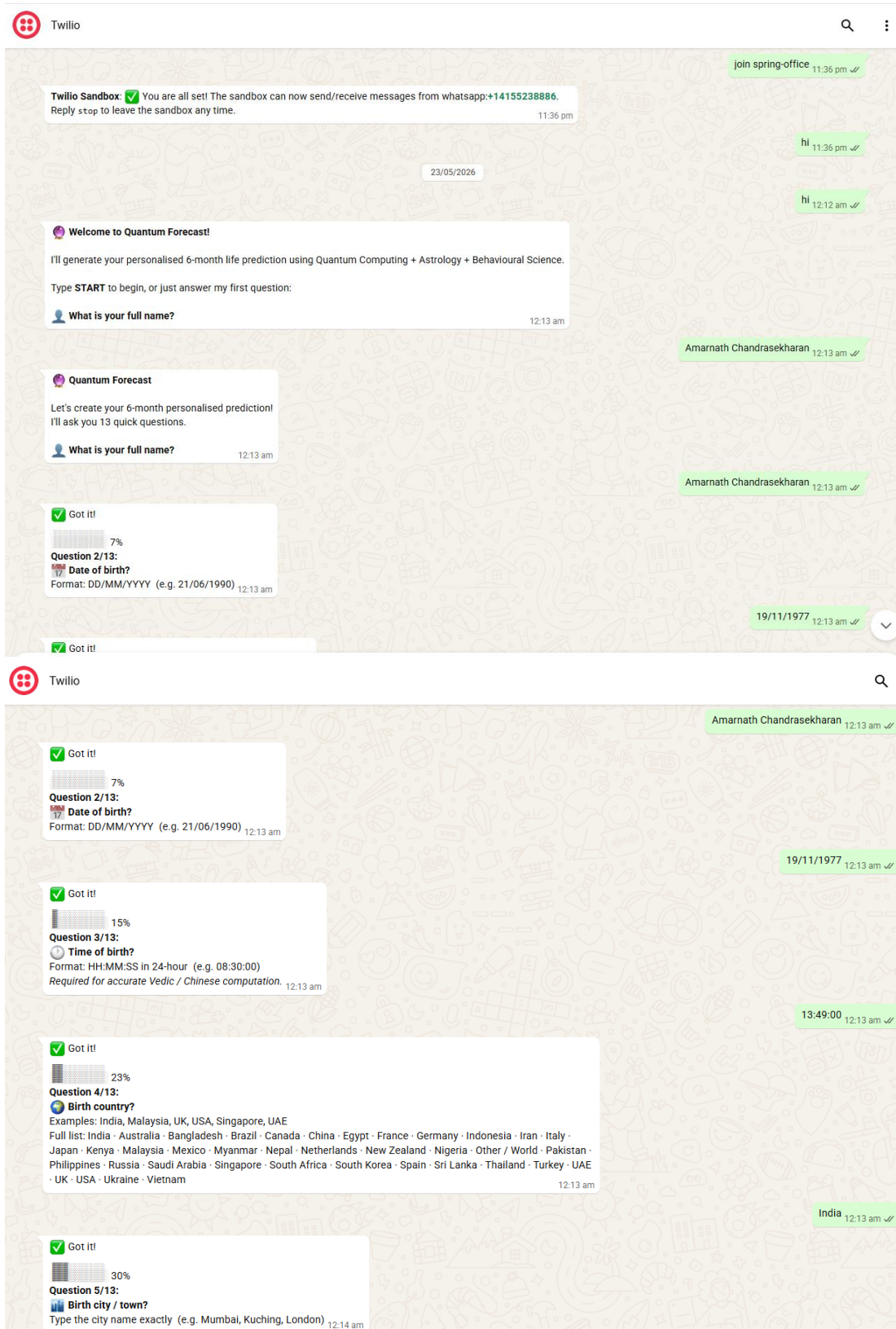
The script prompts for confirmation (type YES), then iterates through all message records via the Twilio API and deletes each one.

Immediate PDF Deletion After Sending

To remove the PDF from the server temp directory immediately after it is sent to the user, add the following code to the `_generate_and_send()` function in `whatsapp_bot.py`, after the `_send_pdf()` call.

APPENDIX D:

RESULTS



Twilio

12:13 am ✓

✓ Got It!

30%

Question 5/13:

🏠 **Birth city / town?**

Type the city name exactly (e.g. Mumbai, Kuching, London) 12:14 am

Chennai 12:14 am ✓

✓ Got It!

38%

Question 6/13:

📍 **Current country?**

Press **SAME** if same as birth country. 12:14 am

Singapore 12:14 am ✓

✓ Got It!

46%

Question 7/13:

🏠 **Current city?**

Press **SAME** if same as birth city. 12:14 am

Singapore 12:14 am ✓

✓ Got It!

53%

Question 8/13:

🔮 **Astrology system?**

Reply with a number:

- 1 Western (Tropical Sun Sign)
- 2 Vedic Jyotish (Moon Sign / Nakshatra)
- 3 Chinese BaZi (Four Pillars)

12:14 am

2 12:14 am ✓

Twilio

61%

Question 9/13:

🧠 **Decision-making style?**

- 1 Balanced
- 2 Risk-Taking
- 3 Conservative
- 4 Analytical
- 5 Intuitive
- 6 Adaptive

12:14 am

2 12:14 am ✓

✓ Got It!

69%

Question 10/13:

🕒 **Chronotype (peak energy time)?**

- 1 Morning Lark
- 2 Midday / Neutral
- 3 Night Owl

12:14 am

1 12:14 am ✓

✓ Got It!

76%

Question 11/13:

😬 **Stress level?**

Reply with a number 0-10
(0 = completely calm · 10 = extreme stress) 12:14 am

5 12:14 am ✓

✓ Got It!

84%

Question 12/13:

😴 **Sleep last night (hours)?**

Reply with a number like 7 or 7.5 12:15 am

7 12:15 am ✓

Twilio

Q

Got it!

84%

Question 12/13:
😴 Sleep last night (hours)?
Reply with a number like 7 or 7.5

12:15 am

Got it!

92%

Question 13/13:
😴 Mood yesterday?
Reply with a number:
1 = 😴 Very Low
3 = 😴 Low
5 = 😴 Neutral
7 = 😴 Good
10 = 😄 Excellent

12:15 am

All inputs received!

Generating your 6-month Quantum Forecast for Amarnath Chandrasekharan...
⌚ This takes about 60 seconds.
Running 4 quantum backends + astrology + ethics audit...

12:15 am

QForecast_Amarnath_Chandrasekhara_n_20260523_001515.pdf

PDF • 33 kB

✔ Your 6-Month Quantum Forecast is ready, Amarnath Chandrasekharan!

👉

Your personalised PDF report is attached below.

🌞

12:16 am

Open

Save as...

7

12:15 am

✓

7

12:15 am

✓

APPENDIX E:

VISUAL REPRESENTATION

