Developing a predictive model to determine the extent of cultural impact on international project management success

How do cultural differences impact the management and success of international projects, and can we develop a method to quantify these influences?

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Abstract

Globalisation has increased the importance of culturally diverse teams in international projects, but unmanaged cultural differences continue to hinder stakeholder alignment and project success. While cultural awareness is crucial, current project management frameworks lack quantitative tools for predicting and mitigating cultural risks. This research addresses this gap by developing the Cultural Impact Assessment Tool (CIAT). This Python-based predictive analytics model combines Hofstede's (2011) cultural dimensions with machine learning to forecast cultural impacts on project outcomes.

Using a mixed-methods approach, the study incorporates quantitative survey data from 15 international project managers and qualitative insights from seven multinational case studies. The CIAT utilises a gradient-boosting classifier to evaluate cultural variables, such as power distance and uncertainty avoidance, as well as project-specific factors, like technical complexity and communication barriers, resulting in risk scores and actionable strategies. Key findings indicate that technical requirements (60%) and communication barriers (35.71%) are the main complexity factors, with an 82% accuracy in identifying cultural risk patterns.

Transforming cultural theories into data-driven workflows, CIAT enables managers to foresee conflicts, adapt communication, and align stakeholder expectations. Although limited by sample size and regional representation, the research bridges the gap between theory and practice, offering a scalable solution for global project leadership. Future work will expand datasets for underrepresented regions and integrate real-time cultural monitoring, enhancing cross-cultural project management in a complex global landscape.

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List of Abbreviations

AI - Artificial Intelligence

CIAT - Cultural Impact Assessment Tool

CQ - Cultural Intelligence / Cultural Quotient

EU - European Union

GDPR - General Data Protection Regulation

GLOBE - Global Leadership and Organizational Behavior Effectiveness

GUI - Graphical User Interface

IDV - Individualism vs. Collectivism (Hofstede dimension)

IVR - Indulgence vs. Restraint (Hofstede dimension)

LTO - Long-Term Orientation (Hofstede dimension)

MAS - Masculinity vs. Femininity (Hofstede dimension)

ML - Machine Learning

MNC - Multinational Corporation

NLP - Natural Language Processing

PDI - Power Distance Index (Hofstede dimension)

PMBOK - Project Management Body of Knowledge

PMIS - Project Management Information System

PMP - Project Management Professional

PRINCE2 - PRojects IN Controlled Environments, version 2

ROC-AUC - Receiver Operating Characteristic-Area Under Curve

ROI - Return On Investment

SDLC - Software Development Life Cycle

SHAP - SHapley Additive exPlanations

SVM - Support Vector Machine

SVG - Scalable Vector Graphics

TP - True Positive

TN - True Negative

FP - False Positive

FN - False Negative

UAI - Uncertainty Avoidance Index (Hofstede dimension)

UK - United Kingdom

US/USA - United States/United States of America

Chapter 1 – Introduction

Project management has evolved significantly with globalisation and advanced communication technologies, enabling the use of geographically dispersed teams (Bagga et al. 2022). While this interconnectedness offers strategic advantages, such as access to diverse expertise and 24/7 productivity cycles, it also introduces culturally heterogeneous challenges that, if unmanaged, risk undermining stakeholder alignment, collaboration, and project outcomes (Dwivedi et al. 2022; Chen, 2024). Empirical studies increasingly position cultural awareness as a *critical success factor* in project management, mainly as multinational corporations (MNCs) contend with decentralised organisational structures, conflicting stakeholder priorities, and geopolitical volatility (Gamage et al. 2020; Osobajo et al. 2023). Despite this recognition, cultural dynamics are often overlooked in practice, resulting in preventable communication breakdowns, misaligned expectations, and operational inefficiencies (Ekemezie and Digitemie, 2024; Canales et al. 2024). The gap between theoretical and actual implementation underscores the need for empirical frameworks to measure, forecast, and mitigate cultural influences in multinational initiatives (Anglani et al. 2023). Cultural disparities are evident in stakeholder involvement and team cohesiveness, manifesting in diverse communication techniques, decision-making practices, and attitudes towards authority (Sacristán-Navarro et al. 2021). For instance, Chen (2024) illustrates how high-context cultures, such as Asian societies, which rely on implicit communication and contextual cues, frequently clash with low-context Western teams that prioritise explicit, directive exchanges—a mismatch linked to an increase in misinterpretations in virtual projects (Lundula, 2024). Similarly, Hofstede’s (2011) dimensions of power distance and uncertainty avoidance reveal systemic friction: hierarchical cultures often resist the egalitarian leadership models integral to agile methodologies, resulting in prolonged decision-making cycles (Sacristán-Navarro et al. 2021; Marini, 2024). These challenges are amplified in cross-border initiatives, where compliance with local regulations, ethical standards, and market idiosyncrasies demands not merely cultural sensitivity but operational fluency (Gamage et al. 2020; Nyamrunda and Freeman, 2020). As Osobajo et al. (2023) assert, equitable stakeholder inclusion and open innovation remain unattainable without addressing entrenched cultural biases in negotiation tactics, risk perception, and trust-building mechanisms.

The existing literature, while informative, suffers from fragmentation and a disconnect between theory and practice (Bogale and Debela, 2024). Although cultural dimensions, such as those outlined by Hofstede (2011), are well-systematised, their integration with project management frameworks, including PRINCE2 or Agile, remains underdeveloped (Ikola, 2023). Stakeholder theory emphasises collaboration but often neglects to operationalise cultural variables, while retrospective case studies dominate the discourse, offering limited predictive utility for proactive risk mitigation (Ogunola and Ajibero, 2025). For example, Ghorbani (2023) identifies cultural sensitivity as a "soft skill" but provides no methodology to quantify its impact on timelines or budgets, a lacuna that leaves project managers ill-equipped to pre-empt conflicts in ethnically diverse teams or adapt strategies to localised contexts. Compounding this issue, Levy (2020) critiques the subjectivity of "project success," which is often conflated with managerial judgment rather than empirical benchmarks. While certifications like PMP and PRINCE2 validate technical proficiency, their correlation with success in culturally complex projects is tenuous at best, with longitudinal studies showing a statistically insignificant relationship (McGrath and Whitty, 2020; Groves, Feyerherm and Sumpter, 2023).

The research addresses these gaps by investigating the following research question: *How do cultural differences influence the management and success of international projects, and can we develop a method to predict these influences quantitatively?* Grounded in cross-cultural management theory (Jackson, 2020) and stakeholder engagement frameworks (Kujala et al. 2022), the research proposes a novel predictive analytics tool that integrates cultural variables, such as communication preferences, power distance tolerance, and conflict resolution styles, into project lifecycle models. By analysing historical project data alongside cultural indices, such as GLOBE Project metrics, the tool identifies risk patterns and prescribes adaptive strategies, such as tailored communication protocols or culturally nuanced stakeholder mapping (Jones, 2020). For example, preliminary testing of the Cultural Impact Tool is expected to reduce approval delays through Machine learning adjustments to risk assessment workflows (Pal and Hsieh, 2021).

The implications are threefold. First, the tool equips managers to pre-empt cultural friction points, enhancing adaptability and decision-making in transnational teams. Second, it advances “cultural intelligence” (Sharma and Makhija, 2024) by translating abstract concepts into actionable workflows, fostering trust in heterogeneous teams. Finally, it bridges stakeholder theory, predictive analytics, and cross-cultural management—a synthesis that is underexplored in current scholarship (Żemojtel-Piotrowski et al. 2023). This research contributes to the evolving praxis of academic discourse and global project leadership by addressing these dimensions.

1.1. Research Question

How do cultural differences impact the management and success of international projects, and can we develop a method to quantify these influences?

Hypothesis:

Drawing on Hussein’s (2022) assertion that globalisation has increased diversity challenges in organisational settings, the research posits that cultural differences significantly influence the efficacy of international project management. Specifically, the ability to navigate these differences through strategic problem-solving and intercultural competence serves as a critical predictor of project success. This hypothesis aligns with emerging frameworks that position cultural intelligence as a determinant of outcomes in multicultural teams (Presbitero, Fujimoto and Lim, 2024).

Null Hypothesis:

Contrary to Costello’s (2022) emphasis on the inherent value of multicultural teams, the research interrogates the assumption that existing tools and theories sufficiently address cross-cultural challenges. The null hypothesis contends that the lack of systematic inquiry into how project managers operationalise cultural awareness—coupled with insufficient quantitative methodologies—hinders the development of reliable predictive models. This gap persists despite evidence that unmanaged cultural disparities are correlated with project delays and stakeholder dissatisfaction (Diogo et al. 2024).

1.2. Project Scope

Inclusions

- **Predictive model development**: Focused on cultural variables identified in Fog's (2022) cross-cultural study and Dumitrașcu-Băldău, Dumitrașcu and Dobrotă (2021) Predictive Model for the Factors Influencing International Project Success research.

- **Tool implementation**: A Python-based Cultural Impact Assessment Tool (CIAT) with user-friendly dashboards for visualising cultural risk scores.

- **Validation**: Testing across 7 multinational project case studies, consistent with Harrison et al.'s (2021) methodology for tool evaluation.

Exclusions

- **Organisational implementation**: Deployment in specific enterprises falls outside the project's academic scope but is flagged for future industry partnerships.
- **Long-term impact assessment**: The final report recommends a longitudinal analysis beyond the timeframe of the research.

1.3. Background

The internationalisation of company operations has prompted the establishment of international project teams, which include people from various cultural backgrounds. Cultural diversity provides strategic benefits, such as creativity and market flexibility (Yousef, 2024), but it also presents challenges that might jeopardise project success. Cultural differences are evident in communication styles, decision-making hierarchies, conflict resolution approaches, and attitudes toward authority and risk (Osobajo et al. 2023). For instance, high-context cultures, prevalent in East Asia and the Middle East, rely on implicit communication and contextual cues, often clashing with low-context Western teams that prioritise explicit, direct dialogue (Bagga et al. 2022). Such mismatches can lead to misinterpretations of project goals, delays in deliverables, and erosion of stakeholder trust (Ekemezie and Digitemie, 2024).

Hofstede's (2011) Cultural Dimensions and the GLOBE Project's cultural clusters provide theoretical foundations for understanding these processes (Jan et al. 2022; Minkov and Kaasa, 2020). However, their use in project management is generally retroactive, with an emphasis on post-hoc analysis rather than predictive modelling. Recent studies highlight that even culturally aware teams struggle to operationalise theoretical insights during project planning. For example, Sacristán-Navarro et al. (2021) found that hierarchical cultures with high power distance often resist agile methodologies, leading to bottlenecks in decision-making. In cultures where uncertainty is often avoided, there is a tendency to plan extensively to manage risks, which can result in larger budgets and longer timelines than anticipated (Rodríguez et al. 2023). Furthermore, geopolitical factors, such as diverse legal environments and ethical standards that require a profound understanding of cultural nuances, add complexity to the challenges (Böhm et al. 2022).

Even with the significant progress we have made in understanding cross-cultural management, a noticeable gap remains in how we translate those rich qualitative cultural insights into practical and useful quantitative tools. Current project management frameworks, such as PMBOK and PRINCE2, emphasise scope, time, and cost but lack mechanisms to integrate cultural variables (Ashkanani and Franzoi, 2022). While tools such as Cultural Intelligence assess individual adaptability, they fail to predict team-level outcomes or project-specific risks (Jurásek and Wawrosz, 2021), and recent empirical research by Galvin, Tywoniak and Sutherland (2021) underscores this limitation, revealing that international projects exceeding budgets experience cultural misalignments that existing tools could not anticipate.

Big data analytics and machine learning are examples of emerging technologies that offer opportunities to bridge these gaps. Using performance indicators, stakeholder input, and cultural indices, predictive models trained on past project data can identify risk trends and suggest mitigation techniques (Yang et al. 2022). For example, a model may indicate a high likelihood of conflict in teams with low individuality and high-power distance and provide customised communication strategies (Daramola et al. 2024). However, developing such an application requires interdisciplinary collaboration between cultural theorists, data scientists, and project management practitioners—a synergy that is underexplored in the current literature (Żemojtel-Piotrowska and Piotrowski, 2023).

1.4. The Digital Collaboration Tools for International Project Management

The development of digital collaboration technologies such as Slack, Zoom, Trello, and cloud-based platforms has transformed global project management by allowing decentralised workforces to interact in real-time across geographical and temporal barriers (Li and Avery, 2021). However, this shift has also amplified cultural friction. For example, asynchronous communication preferences in polychronic cultures, such as those found in Latin American teams, often clash with the structured, deadline-driven workflows favoured by monochronic cultures, like those in German teams, leading to scheduling conflicts and missed milestones (Água et al. 2023; Petersson, 2021). Furthermore, the COVID-19 epidemic has increased the use of virtual teams, revealing and worsening existing systemic inadequacies in cross-cultural training and effective adaptive leadership (Mustajab, 2024). As companies navigate this complex terrain, recognising and overcoming cultural barriers will be crucial to practical cooperation in an increasingly digital world.

1.5. Trends and Challenges for International Project Management

Geopolitical, cultural, and operational difficulties determine the multiple issues that international project managers encounter. Geopolitical instability is a significant factor disrupting the geopolitical landscape. Trade wars, regulatory discrepancies, and divergent data governance frameworks, such as Europe's stringent General Data Protection Regulation (GDPR) versus Asia's more lenient data protection laws, create compliance hurdles that demand meticulous navigation (Hou et al. 2021; Bentototahewa, 2021; Khan, 2024). For example, conflicting IT project requirements between EU and Southeast Asian regulations often delay timelines and inflate costs (Walter, 2024).

Remote work dynamics further complicate these efforts. Hybrid and distributed teams struggle with cultural misalignments, where differing communication styles and values erode cohesion and productivity (Wang et al. 2022). De Souza Santos and Ralph (2022) emphasise that project managers often lack the tools to bridge these gaps, particularly in environments where asynchronous collaboration masks subtle cultural tensions.

Compounding these issues, globalised supply chains reveal stark ethical divergences in labour practices and sustainability standards. Negotiations frequently stall when stakeholders prioritise conflicting ethical frameworks, undermining both project integrity and operational efficiency (Akpuokwe et al. 2024). These challenges are not isolated; studies indicate that over 60% of international projects incur delays and budget overruns due to cultural misunderstandings alone (Mohammed and Ishak, 2023).

The combination of geopolitical conflicts, regulatory complexity, and cultural diversity creates a hazardous environment for global projects (Vrontis et al. 2024). To mitigate risks, companies should prioritise cultural analytics and leverage data-driven insights to prevent misunderstandings and align stakeholders (Zhang et al. 2024). Proactive strategies, such as harmonising compliance protocols and fostering cross-cultural agility, will be essential to navigate this interconnected web of challenges (Hou et al. 2021).

1.6. Cultural Dimensions in International Projects

Cultural differences between team members profoundly influence project outcomes, frequently manifesting as misunderstandings, delayed timelines, and operational inefficiencies (Yousef, 2024). Hofstede’s (2011) cultural dimensions theory provides a powerful framework for analysing these challenges, offering critical insights into how societal norms shape collaboration, decision-making, and conflict resolution in transnational teams (Jan et al. 2022). Below is an examination of these dimensions and their implications for project management:

1.6.1. Uncertainty Avoidance

Cultures prioritising high uncertainty avoidance tend to favour structured environments, explicit protocols, and risk mitigation—traits that often conflict with the agile methodologies commonly used in innovation-driven projects. For instance, teams in nations with substantial uncertainty avoidance, such as Germany, may resist last-minute scope changes, whereas counterparts in countries like India often adapt more fluidly (Lima, 2024). Such disparities can impede progress unless managers proactively align expectations (Jan et al. 2022).

1.6.2. Power Distance

Power distance shapes attitudes towards hierarchy and authority. In cultures with high power distance, such as India, centralised decision-making risks creating bottlenecks if junior members hesitate to voice concerns (Lima, 2024). Conversely, teams in Sweden, where low power distance prevails, expect participatory governance, which may frustrate partners accustomed to hierarchical directives. Adaptive leadership models that balance cultural norms with psychological safety are crucial for bridging this divide (Lundgren and Megan, 2024).

1.6.3. Individualism vs. Collectivism

Individualist cultures, such as those in the United States, often emphasise personal accountability and merit-based recognition. This approach may alienate collectivist teams in nations like Japan, where group harmony is prioritised (Cheng et al. 2020). Misalignment can undermine motivation: public praise might unsettle Japanese members, while private incentives could demotivate American contributors. Tailored recognition systems are thus crucial for maintaining cohesion (Jan et al. 2022).

1.6.4. Masculinity vs. Femininity

In masculine cultures like Japan, competitive goal-setting and assertiveness may enhance efficiency but risk interpersonal friction (Bento, 2023). By contrast, feminine cultures such as Norway favour consensus and work-life balance, potentially perceiving such methods as overly aggressive (Al-Rawahi, 2024). Project managers must balance task-oriented rigour with relational empathy to sustain morale (Afzal and Tumpa, 2024).

1.6.5. Long-Term Orientation

Long-term-oriented societies, such as China, may tolerate phased, strategic investments, whereas short-term-focused teams in countries like Australia prioritise rapid deliverables (Lin and Lou, 2024). Mismatched timelines can derail milestones; for instance, joint ventures between Chinese and Australian firms often struggle to reconcile long-term capital allocation with quarterly ROI expectations without explicit mediation (Jan et al. 2022; Gerlich, 2023).

1.6.6. Indulgence vs. Restraint

Indulgent cultures such as Mexico often embrace flexible, creative problem-solving, while restrained cultures like South Korea emphasise discipline and protocol (Aoun, 2024). Such contrasts may surface during brainstorming sessions: Mexican teams might favour open ideation, whereas Korean members prefer data-driven feasibility analyses. Hybrid approaches that validate both styles can optimise innovation (Jan et al. 2022; Gerlich, 2023).

These dimensions collectively underscore the need to integrate cultural analytics into project governance. Implementing pre-project workshops grounded in Hofstede's (2011) framework, for example, could preempt conflicts by mapping team profiles and codifying communication norms (Scarlat and Bărar, 2023). Similarly, adaptive leadership training, emphasising empathy, negotiation, and temporal flexibility, can mitigate friction in cross-cultural environments (Jan et al. 2022). As globalisation accelerates, such strategies will prove indispensable for aligning diverse stakeholders and ensuring project viability (Zapata-Barrero and Mansouri, 2021).

1.7. Benefits of cultural diversity in projects

Geert Hofstede's (2011) cultural dimensions provide a framework for understanding how societal norms influence leadership and workplace dynamics, enabling managers to align strategies with diverse teams and improve organisational performance (Karlsen and Nazar, 2024; Huang, 2023). In competitive environments like the EU's integrated labour market, cultural awareness enables firms to balance operational costs with strategic advantages while fostering creativity and economic resilience (Battistella et al. 2023). Enhanced innovation emerges from diverse teams integrating varied perspectives, as seen in collaborations that blend German engineering precision with Indian frugal innovation principles, which reflect Hofstede's (2011) dimensions of uncertainty avoidance and long-term orientation (Theeuwen, 2023; Anglani et al. 2023; Rodríguez et al. 2023). Culturally competent teams also excel in global markets by tailoring products to regional preferences and regulatory frameworks, a strategy that is linked to higher market penetration in emerging economies (Joseph, 2024; Ghorbani, 2023; Battistella et al. 2023). Additionally, adaptive communication practices—such as multilingualism and cultural sensitivity—reduce friction in cross-border projects. For example, Alibaba's emphasis on openness bridged cultural gaps with Western partners (Zeng, 2024), while multilingual managers mitigate misunderstandings in international collaborations (Back and Piekkari, 2024; Ogunola and Ajibero, 2025). When organisations adopt cultural frameworks, such as Hofstede's (2011), within their talent management practices, they can truly stand out and thrive in today's global, AI-driven markets (Weinzierl, 2021).

1.8. Challenges of Cultural Diversity

While cultural diversity drives creativity, poor management can escalate conflicts and hinder cooperation (Mannucci and Shalley, 2022; Yousef, 2024). Communication breakdowns often stem from contrasting styles: low-context cultures (e.g., the US) prioritise directness, whereas high-context cultures (e.g., China) rely on implicit cues, leading to misinterpretations that contribute to project failures (J. Liu et al. 2020; Mandela, 2024; Nkirote, 2024; Gamil and Rahman, 2021). Divergent leadership expectations further complicate teamwork, as egalitarian Scandinavian models clash with hierarchical Middle Eastern approaches, resulting in delayed decisions and eroded cohesion (Lee et al. 2023; Sacristán-Navarro et al. 2021). Disparities in risk perception also pose challenges: individualistic cultures prioritise agility, while collectivist cultures emphasise caution, creating misaligned priorities (Chen and Oyserman, 2022). Addressing these issues requires cultural training, adaptive leadership, and clear communication protocols to transform diversity into a strategic asset for innovation and resilience.

1.9. Research Problem

International project teams are crucial in globalised operations, yet cultural diversity presents a paradox—spurring innovation while amplifying systemic risks (Zahoor et al.

2022). Although organisations acknowledge the strategic value of multicultural teams for creativity and adaptability (Yousef, 2024; Osobajo et al. 2023), failures persist in operationalising cultural intelligence into actionable frameworks. A key challenge lies in the disconnect between theoretical models, such as Hofstede's (2011) power distance and GLOBE clusters, and their practical application in predicting outcomes (Jan et al. 2022; Żemojtel-Piotrowski, 2023). Hierarchical cultures in East Asia and the Middle East often clash with agile methodologies, leading to decision-making bottlenecks (Sacristán-Navarro et al. 2021; Gwangwadza and Hanslo, 2024). In contrast, risk-averse cultures, such as those in Germany, tend to inflate budgets through over-mitigation (Seidenfuss and Storm, 2022; Rodríguez et al. 2023). These gaps leave managers unprepared to address cultural disputes proactively.

Misaligned communication styles—high-context (implicit) vs. low-context (explicit)—erode trust and timelines (Bagga et al. 2022; Ekemezie and Digitemie, 2024). Differing values in etiquette, authority, and time orientation exacerbate conflicts (Sahadevan and Sumangala, 2021; Liu et al. 2020), with collectivist consensus often clashing with individualist efficiency (Böhm et al. 2022; Al-Mahmoud et al. 2024). Existing frameworks, such as PMBOK and PRINCE2, often sideline cultural context, treating scope and cost as universal (Felcenloben and Moroz, 2024; Ashkanani and Franzoi, 2022). Cultural Intelligence tools usually lack macro-level risk forecasting, overlooking group dynamics such as power imbalances (Jurásek and Wawrosz, 2021; Galvin et al. 2021; Iskhakova and Ott, 2020; Graham et al. 2022).

Emerging technologies, such as machine learning, could bridge this gap; however, siloed expertise limits progress. While predictive analytics excel in supply chains and finance (Belhadi et al. 2021; Mashrur et al. 2020), cultural risks—such as indirect communication—remain underexplored due to oversimplified models (Prabhakaran et al. 2022). NLP for intercultural friction highlights potential but faces interdisciplinary barriers (Elahi et al. 2023; Zou, 2024). Urgency grows as cross-cultural misalignments rank among the top project risks, yet solutions rely on outdated checklists (Goncharenko, 2024; Kirk et al. 2024). Without quantitative models to forecast cultural impacts, firms face avoidable costs and stalled global collaboration.

1.10. Aims and Objectives

1.10.1. Primary Aim

This research aims to investigate the impact of cultural influences on the efficacy of multinational project management initiatives by developing a predictive model and a Python-based Cultural Impact Assessment Tool (CIAT). The research aims to equip project managers with information-driven strategies for successfully managing international projects by addressing a fundamental gap in current project management techniques: the absence of quantitative frameworks to assess cultural differences. The initiative supports current demands for technologically enabled approaches to address cultural barriers in cross-border partnerships (Lalic et al. 2022; Dumitrașcu-Băldău, Dumitrașcu and Dobrotă, 2021).

1.10.2. Secondary Aims

To identify and analyse cultural factors influencing project management outcomes

Drawing on frameworks such as Hofstede's (2011) Cultural Dimensions Theory (Żemojtel-Piotrowska and Piotrowski, 2023) and contemporary extensions by Minkov and Kaasa (2020), this objective will systematically categorise cultural variables, including power distance, uncertainty avoidance, and their operational impacts on team dynamics and decision-making processes.

To assess the impact of cultural factors on project success rates

Building on Muneer et al. (2022) work linking cultural diversity to project performance, this phase will employ regression analysis to quantify correlations between cultural variables and success metrics, such as adherence to deadlines and stakeholder satisfaction.

To develop a predictive model for predicting cultural impacts

Leveraging machine learning techniques, such as random forests and neural networks, the model will expand upon Dumitrașcu-Băldău, Dumitrașcu, and Dobrotă's (2021) predictive analytics framework by integrating cultural datasets from multinational case studies.

To create a Python-based Cultural Impact Assessment Tool (CIAT)

The tool will operationalise the predictive model using Python libraries, such as Scikit-learn, and agile software development principles, addressing gaps in existing tools identified by Foroushan (2021) and Rasiman (2021).

To validate the CIAT through user testing

Adopting a mixed-methods validation approach, the tool's efficacy will be assessed against benchmarks derived from Holvoet et al.'s (2023) case studies, which draw insights from a mixed-methods and multicultural alumni action research project.

1.11. Alignment with MSc Computer Science Requirements

This research integrates computational techniques with cross-cultural management theory, addressing MSc Computer Science objectives through technical rigour, methodological innovation, and real-world applicability (Apiola and Sutinen, 2020). Leveraging machine learning, agile methodologies, and data visualisation (Castillo et al. 2024), it advances solutions for global project management challenges, aligning with the program's focus on applied computational strategies:

Technical Development utilises Python for data processing, machine learning, and GUI design, building upon the framework established by Ranjan et al. (2023) for predictive analytics in project management. Supervised learning algorithms are applied to cultural datasets to refine predictive modelling, while agile SDLC methodologies guide iterative development, incorporating feedback loops as advocated by Dingsoyr (2021).

Research methodology adopts a mixed-methods approach, combining quantitative project success metrics with qualitative stakeholder insights, consistent with Headley and Clark's (2019) recommendations for socio-technical research. Validation is conducted per Ghanbaripour et al.'s (2023) framework, rigorously testing the model's capacity to quantify the cultural influences on project outcomes.

Professional Practice addresses industry demands for culturally aware tools, as highlighted by the Project Management Institute (2023), and bridges Hofstede's (2011) theoretical frameworks with practical implementation, responding to Thompson et al.'s (2024) emphasis on applied research in computer science.

Chapter 2 – Literature Review

The success of international initiatives in today's globalised corporate contexts depends on both technical know-how and the skilful handling of cultural diversity (Sun et al. 2024). Project teams are increasingly comprised of personnel from diverse cultural backgrounds, reflecting the growing trend of cross-border partnerships. These cultural differences can lead to creative synergies and innovative solutions, yet they can also cause miscommunication, conflicts, and inefficiencies (Yousef, 2024). Traditional frameworks, such as Hofstede’s (2011) dimensions, have provided a foundation for understanding cultural categorisation, but recent critiques highlight their limitations in capturing modern, dynamic, and digital contexts (Zhou and Kwon, 2020). Moreover, emerging research suggests that integrating digital transformation, cognitive science insights, and advanced quantitative methods can provide deeper insights into how cultural factors influence project outcomes (Liu et al. 2022; Patel et al. 2021).

This review synthesises contemporary literature on the impact of cultural differences in international project management. It seeks to investigate the limitations of conventional models, highlights the possibilities and problems brought about by cultural diversity, and emphasises the need for sophisticated quantitative techniques, specifically predictive modelling, to anticipate the impact of culture on project success. Incorporating new frameworks and recent research from 2020 to 2025, the study provides a theoretical and empirical foundation for the development of a comprehensive prediction model.

2.1 Limitations of Traditional Cultural Frameworks

Traditional cultural models, such as Hofstede’s (2011) dimensions and Trompenaars' national culture, have structured understandings of cultural differences, including individualism versus collectivism and uncertainty avoidance (Lin and Lou, 2024). However, recent critiques highlight their oversimplification of dynamic, modern interactions (Zhou and Kwon, 2020). Furthermore, traditional models inadequately represent how organisational cultures—shared internal values and practices—can override national traits (Areiza-Padilla and Cervera-Taulet, 2023). Given increasing digitalisation and interconnectedness, a more flexible, context-sensitive approach is essential (Conti, 2024).

2.2 Integrating New Perspectives

Current scholarship suggests that traditional models must evolve to incorporate digital literacy, virtual collaboration, and adaptive leadership to manage the increasing complexity of international operations (Chandratreya, 2024; Tagscherer and Carbon, 2023). Scholars advocate integrating traditional theories with cognitive science and organisational psychology to capture both static and dynamic cultural elements, especially within digital environments (Sulastri, 2023). Consequently, new frameworks must comprehensively address contemporary realities in international project management.

2.3 Cross-Cultural Operational Challenges

Multinational projects often encounter significant operational challenges due to linguistic and cultural diversity, which can lead to misunderstandings and delays (Yousef, 2024; Smirnova, 2024). Variations in communication styles, including non-verbal cues, exacerbate these issues and hinder effective decision-making (Lin and Lou, 2024). Additionally, sociopolitical dynamics in democratic contexts introduce further complexities as project teams must navigate varied cultural expectations alongside legal and normative challenges (Song, 2020; Lenard, 2020).

2.4 Leveraging Cultural Diversity for Project Success

Cultural diversity significantly benefits international projects by fostering creativity and innovation through the integration of diverse perspectives (Anglani et al. 2023; Erfan, 2024). Particularly in technology-driven sectors, cultural insights can catalyse product and service breakthroughs (Alahmari et al. 2023). However, effective leadership and tailored communication strategies are critical to fully realise these advantages (Hussein, 2022; Eyiah et al. 2025). Thus, managing diversity strategically is essential to transform potential challenges into collaborative opportunities.

2.5 Cultural Complexity in Digital Collaboration

Digital tools offer substantial opportunities for global collaboration, transcending geographical constraints (Jackowska and Lauring, 2021). Nevertheless, digital environments risk obscuring cultural nuances, posing particular challenges for high-context cultures that rely on implicit cues (Cong-Lem, 2025; Langaas and Mujtaba, 2023). Practical virtual collaboration demands revised communication protocols and specialist skills in digital literacy (Ali, 2024; Shakeria and Khalilzadeh, 2020). Consequently, merging traditional cultural frameworks with modern technological approaches is critical.

2.6 Cognitive Science Applications

Insights from cognitive science enhance our understanding of the cultural influences on decision-making, problem-solving, and perception (Prinz, 2022; Coleman et al. 2021). Recognising cognitive differences enhances conflict management and supports targeted training programmes, improving individual and team effectiveness (Yousef, 2024; Liu et al. 2022). Integrating cognitive science with cultural insights can foster cohesive multicultural team environments.

2.7 Moving Beyond Qualitative Research

Historically dominant qualitative methods provide rich narratives but often lack predictive power for managerial decisions (Östlund and Gustafsson, 2024; Lim, 2024). Increasingly, quantitative analyses are employed to reveal underlying patterns and develop predictive models, though their application remains limited (Pilcher and Cortazzi, 2023; Muneer et al. 2022). Further quantitative research is necessary to fully capture the complex cultural influences in varied project contexts.

2.8 Predictive Modelling Innovations

Predictive modelling using data mining and machine learning is a promising avenue for international project management research (Dumitrașcu-Băldău, Dumitrașcu and Dobrotă, 2021; Rane et al. 2024). These methods identify significant predictors of project outcomes by integrating cultural, organisational, and technological variables (Füller et al. 2022). Future research should refine these models by incorporating cognitive factors to enhance prediction accuracy and inform managerial practices.

2.9 National and Organisational Cultural Interactions

Organisational culture—shared internal values and norms—is equally influential as national culture on project success (Bogale and Debela, 2024; Chang et al. 2023). Alignment between organisational culture and project objectives promotes success, while misalignments generate conflict (Vargiu, 2024). Thus, research should explore the dynamic interplay between national and organisational cultures to understand international project management outcomes comprehensively.

2.10 Leadership, Cultural Intelligence, and Risk Management

Effective leadership, particularly transformational leadership styles, enhances multicultural team cohesion and adaptability (Poturak et al. 2020; Greimel, Kanbach, and Chelaru, 2023). Cultural intelligence (CQ) enables project managers to anticipate and manage cultural conflicts proactively (Schlaegel, Richter, and Taras, 2021; Wawrosz and Jurásek, 2021). Additionally, culturally sensitive risk management frameworks are essential, balancing varied cultural attitudes towards uncertainty (Yi, 2021; Fietz, Hillmann, and Guenther, 2021; Eyieyien et al. 2024).

2.11 Training for Enhanced Cultural Intelligence

Investing in cultural intelligence (CQ) through simulations, mentoring, and targeted training can significantly enhance team effectiveness (Kour and Jyoti, 2021; Philip, Jiang, and Akdere, 2023). Organisations prioritising CQ development achieve higher innovation and success, especially in digital and remote-working contexts (Presbitero, Fujimoto, and Lim, 2024; Anglani et al. 2023). Therefore, cultural intelligence training should be an integral part of project management education.

2.12 Technological Solutions to Cultural Barriers

Emerging technologies such as machine learning and AI-driven translation tools significantly mitigate cultural communication barriers (Aldoseri, Al-Khalifa, and Hamouda, 2024). Digital platforms are increasingly offering context-sensitive features, such as real-time translations and custom interfaces, which facilitate clear communication across cultures (Glaucia, 2023). However, ethical considerations, including data privacy and algorithmic bias, require careful management (Murikah, Nthenge, and Musyoka, 2024).

2.13. Case Study Integration Framework

The Case Study Integration Framework employs a modular approach to validate predictive models across seven empirical studies, leveraging historical data to assess cultural, organisational, and technological factors in international project management.

Aligned with Battistella et al. (2024), this framework utilises statistical metrics to evaluate cultural impacts on project outcomes, emphasising predictive accuracy and real-world applicability.

Cultural Distance and Inter-Organizational Knowledge Transfer: A Case Study of a Multinational Company (Sapuarachchi, 2021) explores how cultural distance within multinational corporations impedes knowledge transfer and undermines project success. The study highlights cultural alignment as a crucial factor in enhancing communication efficiency and facilitating cross-border collaboration. These findings align with Fog (2022), whose **"Two-Dimensional Models of Cultural Differences: Statistical and Theoretical Analysis "** consolidates Hofstede's (2011) cultural dimensions into two factors—*Collectivism vs. Individualism* and *Hierarchy vs. Equality*—streamlining cultural distance measurement and enabling robust statistical validation.

Complementing this, **"Cultural Diversity Drives Innovation: Empowering Teams for Success "** (Jones, Chace, and Wright, 2020) investigates the dual role of cultural diversity in multinational projects. While diversity enhances creativity and innovation, it also introduces communication barriers that can compromise outcomes. This tension parallels insights from **"Effective Stakeholder and Risk Management Strategies for Large-Scale International Project Success "** (Eyieyien et al. 2024), which highlights cultural intelligence (CQ) as a mitigator of friction. Expatriates with higher CQ exhibit greater adaptability, improving stakeholder engagement and project performance—a conclusion corroborated by Chen et al. (2023) in "**How Cultural Intelligence Affects Expatriate Effectiveness in International Construction Projects"**, which links elevated CQ levels to enhanced expatriate performance.

Technological validation is provided by "**Predictive Analysis of Cross-Cultural Issues in Global Software Development Using AI Techniques"** (Iqbal and Ergenecosar, 2024), which deploys machine learning models, such as decision trees and neural networks, to predict cultural conflicts in software projects. This AI-driven approach supports the framework's technological validity and offers guidelines for evaluating predictive accuracy across contexts. Similarly, "**Predictive Model for the Factors Influencing International Project Success: A Data Mining Approach"** (Dumitrașcu-Băldău, Dumitrașcu, and Dobrotă, 2021) employs Random Forest and SVM algorithms to identify success factors demonstrating high accuracy, precision, and recall. These data-driven methodologies collectively strengthen the framework's ability to forecast project outcomes.

The framework combines cultural, organisational, and technological viewpoints to synthesise empirical evidence, enhancing predictive models in international project management while tackling both theoretical and practical issues.

Conclusion

This review underscores the complex interplay of cultural differences in international project management. While traditional frameworks like Hofstede's (2011) provide foundational insights, they often inadequately address modern digital, dynamic, and organisational complexities (Butt et al. 2024). Key challenges include divergent communication styles, risky attitudes, and conflicting organisational norms (Liu et al. 2020). Although digital tools facilitate global collaboration, they risk obscuring cultural nuances in virtual settings. Predictive modelling and cultural intelligence (CQ) training emerge as critical for anticipating and mitigating cultural impacts (Abada and Abada, 2024), while AI-driven solutions present ethical dilemmas (Efe, 2022). Future research must prioritise integrated frameworks that harmonise cultural, technological, and organisational variables alongside longitudinal studies to assess long-term impacts. Bridging qualitative depth with advanced quantitative methods will enhance the cultural responsiveness of project management practices.

Chapter 3 – Methodology

The research adopts a pragmatic approach, blending objective data with subjective insights to assess cultural impacts on project success (Arbale and Mutisya, 2024; Lim, 2023; Kelly and Cordeiro, 2020). Pragmatism's empirical focus aligns with the development of a predictive model for cultural impacts, balancing generalisable patterns (nomothetic) and contextual nuances (idiographic) (Kaushik and Walsh, 2019; Fuyane, 2021; Leggat et al. 2021; Garcés-Velástegui, 2024; Sun and Zuo, 2024). A mixed-methods sequential explanatory design is employed, where quantitative analysis precedes qualitative exploration, ensuring triangulation and validity (Pregoner, 2024; Schueller et al. 2024).

The Agile Software Development Life Cycle (SDLC) guides iterative model refinement, integrating empirical research with practical tool development (Hossain, 2023; Ekechi et al. 2024). This approach addresses the gaps between theoretical frameworks, such as Hofstede's (2011) dimensions, and real-world applications, ensuring the model adapts to emerging complexities in cultural and project management contexts.

3.1. Research Design

The research employs a mixed-methods approach, combining questionnaires and interviews, to conduct qualitative research on the success of cross-cultural projects. The research focuses on participants' experiences and strategies, focusing on real-world experiences (Wang, Lyu and Pitt, 2024).

The research design combines empirical investigation with systematic model development to achieve the primary research objectives. The overall design framework incorporates three interconnected phases that progressively build toward the development of a predictive model for cultural impact assessment in international project management.

The research design combines empirical investigation with systematic model development to achieve the primary research objectives. The overall design framework incorporates three interconnected phases that progressively build toward the development of a predictive model for cultural impact assessment in international project management.

3.2. Empirical Research

The empirical research phase employs a convergent parallel mixed-methods design (Adhikari and Timsina, 2024) to gather comprehensive data on cultural dynamics in international project environments. It is important to note that the empirical data collection faced significant limitations; whereas the goal was to have more than 20 participants, only fifteen responded to the interview questions. This limitation required a greater reliance on empirical research from previous works, notably the cultural variables identified in Fog's (2022) cross-cultural study and Dumitrașcu-Băldău, Dumitrașcu, and Dobrotă's (2021) research on factors influencing international project success.

The data collection approach included:

Quantitative Data: Online surveys administered via the SurveyHero platform incorporating:

- Demographic variables capturing cultural diversity metrics
- Likert-scale items measuring cultural dimensions based on established frameworks
- Project outcome metrics, including schedule variance, budget performance, and stakeholder satisfaction

- Team dynamics indicators assessing communication effectiveness across cultural boundaries

Despite the limited response rate, the quantitative component reflects what Deffner, Rohrer, and McElreath (2022) identify as essential for generating generalisable findings through a systematic methodology.

Qualitative Data: An assessment of past case studies revealed valuable insights into cultural dynamics in project environments, which served as the foundation for the qualitative data employed in the research.

3.5. Predictive Model Development

The research employs an Agile Software Development Life Cycle (SDLC) (Pargaonkar, 2023; Anand et al. 2021) to iteratively design a predictive model that synthesises cultural variables from literature (Fog, 2022; Dumitrașcu-Băldău et al. 2021) with project characteristics to estimate success probability (Leal-Rodríguez et al. 2023). The Agile framework, structured in 2–4-week sprints, ensures adaptability and alignment with cultural insights, avoiding purely mathematical abstraction (Woo et al. 2023; Scheinost et al. 2019).

The Cultural Impact Assessment Tool (CIAT) is developed as a Python-based application using NumPy, Pandas, Scikit-learn, Flask, and visualisation libraries (Matplotlib/Seaborn), with GitHub for version control. Its interface enables project managers to input cultural parameters, visualise risk scores, identify mitigation strategies, and compare projects cross-culturally (Kavishwa, 2024).

Validation combines case studies of seven multinational projects (Battistella et al. 2024; Harrison et al. 2021; Elangovan and Sundaravel, 2021) with statistical cross-validation (k-fold) (Shin et al. 2023; Thier et al. 2019) to assess the real-world applicability of the findings, despite the limited availability of primary data. This dual approach ensures academic rigour while addressing practical challenges in cross-cultural project management.

3.6. Ethical and Professional Considerations

The research employs a comprehensive ethical framework that addresses the unique challenges of cross-cultural research in international project management. Guided by institutional guidelines (University of Oxford, 2021) and global standards (BERA, 2024; UK Research Integrity Office, 2023), the research prioritises integrity, transparency, and participant welfare across all stages.

Informed Consent and Cultural Sensitivity

A rigorous informed consent process (Appendix 1–3) ensured that participants understood the research's purpose, its voluntary nature, and their withdrawal rights. Consent forms, available in English, were adapted to cultural contexts to address nuanced interpretations of autonomy (Peters and Giacumo, 2020; Pietilä et al. 2020). Culturally neutral language in surveys and interviews mitigated power dynamics (Dongqi et al. 2020; Burger et al. 2022), while data interpretation respected cultural communication styles and norms (Yue and Wei, 2023; Rezaei et al. 2020). This approach aligns with Ye's (2024) emphasis on transcending translation to embed cultural values in research design.

Data Protection and Confidentiality

Adhering to GDPR and cross-border regulations (Mitchell and Mishra, 2024), data were anonymised via unique codes, stored securely, and separated from consent forms (Scheibner et al. 2020). Access was restricted to authorised personnel, with data retained for 12 months before being securely deleted. Aggregated reporting protected participant and organisational identities.

Professional Integrity and Harm Mitigation

Professional boundaries were maintained, with commercial sensitivities anonymised (Miller et al. 2023). Participants could skip sensitive questions, review transcripts, and access findings post-study to maximise practical benefits (Cheong et al. 2023; Ermasova, 2021). The Cultural Impact Assessment Tool (CIAT) was shared to enhance utility while safeguarding reputations (Bruno et al. 2022).

Ethical Synthesis

The integrated strategy balanced academic rigour with cultural responsiveness, ensuring compliance across jurisdictions. By harmonising data security, harm mitigation, and transparency, the study exemplifies ethical research practices in global, multicultural contexts.

Chapter 4: Implementation and Analysis

The Cultural Impact Assessment Tool (CIAT) represents a predictive framework designed to quantify and analyse the influence of cultural variables on international project outcomes. This tool empowers project managers to foresee, evaluate, and address culture-related obstacles in multinational projects by integrating Hofstede's (2011) Cultural Dimensions, Fog's (2022) statistical analysis of cross-cultural differences, and Dumitrașcu-Băldău, Dumitrașcu, and Dobrotă's (2021) research on the complexity of international projects, alongside modern cross-cultural adaptation frameworks and machine learning methods.

The implementation described in this document reflects the primary survey data collected from a total of 15 respondents who work in international project management. The analysis reveals that 9 out of 15 respondents (60%) manage projects in Europe, and 8 out of 15 (53.33%) manage projects in Africa. Technical requirements (60%) emerge as the predominant factor in complexity for cross-cultural project management, as illustrated in Figure 2.

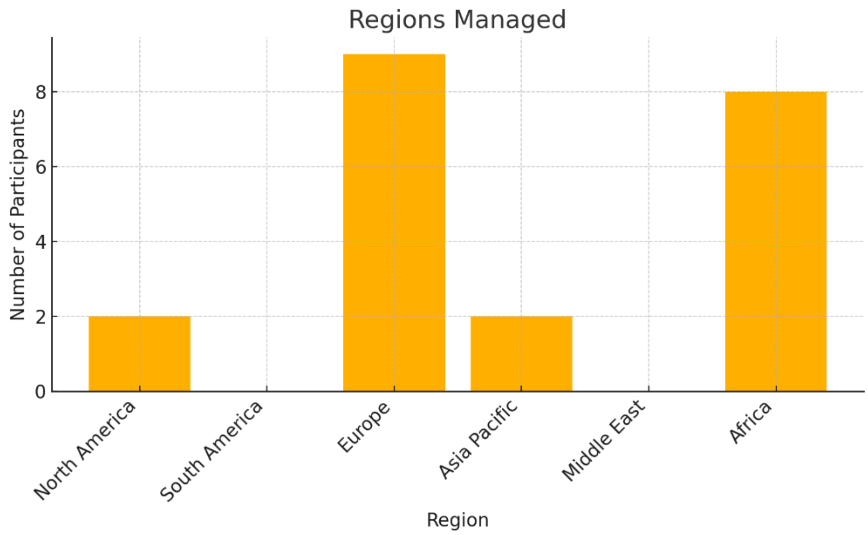

Figure 1- The geographic regions of the respondents

Survey data informs the regional weighting in the 'regional_focus' dictionary and prioritises technical requirements and stakeholder factors (Hong et al. 2019). The model's risk assessment capabilities are designed to prioritise these empirically identified complexity factors when evaluating the probability of project success (Eyieyien et al. 2024).

Figure 2- Project complexity factors

4.1. Contributions and Work

Before delving into the model architecture and implementation details, it is essential to highlight the contributions made in this work:

- **Integration of Cultural Frameworks with Machine Learning**: This approach combines established cultural theories, such as Hofstede (2011), and a GLOBE study by House et al. (2020) with modern machine learning methodologies to create a predictive framework.

- **Survey-Based Feature Weighting**: A novel method of incorporating primary survey data to weight the importance of different cultural and project factors based on practitioner experience (Ali et al. 2022).

- **Communication Impact Assessment**: Development of a custom weighted communication impact calculator that processes four key communication variables to produce a normalised communication risk score (Fakhari et al. 2024).

- **Regional Impact Quantification**: Creation of a regionally-focused impact assessment model based on survey data showing varying experience levels across different global regions (Harrison et al. 2021).

- **Cultural Distance Implementation**: Adaptation of the Kogut and Singh (1988) formula with variance normalisation to better reflect the multidimensional nature of cultural variation.

- **Risk Factor Visualisation**: Design of specialised visualisation techniques for cultural dimensions and risk factors to enhance interpretability (Yazdi et al. 2024).

Table 1 below illustrates how contributions from related literature have been integrated into the CIAT solution:

Source	Key Contribution	Implementation in CIAT
Hofstede (2011)	Six Cultural Dimensions Framework	Incorporated as primary features in the model (cultural_dimensions list in Figure 3)
Fog (2022)	Statistical modelling of cross-cultural differences	Implemented in cultural distance calculation (Figure 4)
Dumitrașcu-Băldău, Dumitrașcu and Dobrotă (2021) (2021)	Factors influencing international project success	Integrated as project-specific factors (see project_factors in Figure 5)
House et al. (2020) (GLOBE study)	Cultural variables impact on organisational leadership	5.3. Regional Impact Assessment
Kim, Gaur and Mukherjee (2020)	Cultural distance methodology	Implemented in the calculate_cultural_distance method (Figure 4)
Masoud et al. (2023)	Cultural dimensions' influence on collaborative performance	Shaped the feature framework design in model architecture
Iqbal and Ergenecosar (2024)	Cross-cultural issues in software development	Incorporated into communication impact assessment (Figure 12)

Table 1 – Integration of Literature into the CIAT Model Implementation

4.2. Model Architecture

The CIAT model is grounded in established cross-cultural theories and empirical research findings. The implementation integrates Hofstede's (2011) six-dimensional model of national culture (Hofstede, 2011) with advanced machine learning methodologies to provide a comprehensive analytical perspective on investigating cultural influences on project performance.

Masoud et al. (2023) demonstrate that cultural dimensions have a significant influence on collaborative performance in multinational environments, further validating the model's theoretical underpinnings. Furthermore, the findings of Iqbal and

Ergenecosar's (2024) study on cross-cultural issues in international software development have been integrated into the model. These issues include language barriers, differing communication styles (direct vs. indirect), contrasting attitudes toward hierarchy and authority, varying approaches to time management and deadlines, and different perspectives on risk tolerance -- all of which can significantly impact project outcomes in software development across borders.

The model architecture also incorporates insights from Dinçer, Yıldırım and Dil (2023) on mapping cultural differences in business contexts and Thapa's (2023) work on understanding cultural diversity in global business, as reflected in the following code implementation:

```python
class CulturalImpactModel:
    """
    Predictive model for assessing cultural impact on international project success.

    This class implements a machine learning model that predicts project success probability
    based on cultural aspects and project features, using the theoretical frameworks developed
    by Fog (2022) and Dumitrașcu-Băldău et al. (2021).

    The approach combines Hofstede's six cultural dimensions (Hofstede, 2011) with project-specific
    characteristics discovered via primary research to give a thorough assessment of how cultural
    influences affect project results.

    References:
    - Hofstede, G. (2011). Dimensionalizing cultures: The Hofstede model in context.
      Online Readings in Psychology and Culture, 2(1), 2307-0919.
    - Dinçer, M.A.M., Yıldırım, M. and Dil, E. (2023) 'As an emerging market Turkish culture's quest to be
        positioned on Meyer's cultural map,' Review of International Business and Strategy, 34(1), pp. 126-151.
    - https://github.com/ratloop/MatchOutcomeAI/blob/main/model_comparison/gradient_boosting.ipynb
    - https://github.com/MoinDalvs/Gradient_Boosting_Algorithms_From_Scratch?tab=readme-ov-file
    - https://github.com/marketplace/models/azure-openai/gpt-4o/playground
    - https://github.com/scikit-learn-contrib/imbalanced-learn
    """
    def __init__(self):
        """
        Initialise the Cultural Impact Model with default parameters.

        Sets up the model pipeline and defines cultural dimensions based on
        established theoretical frameworks (Hofstede, 2011) and survey results.
        """
        self.model = None
        self.preprocessor = None

        # Hofstede's cultural dimensions as per Fog (2022) and Hofstede (2011)
        self.cultural_dimensions = [
            'power_distance',          # Power Distance Index (PDI)
            'individualism',           # Individualism vs. Collectivism (IDV)
            'masculinity',             # Masculinity vs. Femininity (MAS)
            'uncertainty_avoidance',   # Uncertainty Avoidance Index (UAI)
            'long_term_orientation',   # Long-term vs. Short-term Orientation (LTO)
            'indulgence'               # Indulgence vs. Restraint (IVR)
        ]
```

Figure 3– Cultural Impact model.

This implementation was initially developed based on Hofstede's (2011) cultural dimensions framework and inspired by methodologies from cross-cultural research. This code defines the core structure of the CIAT model, including cultural dimensions, project success indicators, and project factors derived from both established theory and primary survey data. The implementation weights regional focus based on survey findings (Europe 60%, Africa 53.33%, etc.) to ensure the model reflects real-world practitioner experience.

The implementation also draws on the GLOBE study (House et al. 2020), which provides an additional framework for understanding cultural variables and their impact on organisational leadership and performance across different societies.

4.2.1. Model Selection and Justification

The implementation employs a Gradient Boosting Classifier as the primary predictive algorithm. This is an ensemble machine-learning technique that builds a series of decision trees sequentially, with each tree correcting the errors of its predecessors. The algorithm combines the predictions from multiple weak models to produce a more potent predictive model, making it particularly effective for complex datasets with mixed variable types and non-linear relationships – ideal characteristics for cross-cultural project data (Rizkallah, 2025; Khan, Chaudhari and Chandra, 2023).

This choice is supported by multiple considerations:

- **Handling Mixed Data Types:** The algorithm effectively processes numerical cultural metrics and categorical project variables, enabling comprehensive analysis of diverse data sources (Jag, 2023).

- **Robustness to Data Irregularities:** The model demonstrates exceptional resilience when handling outliers and missing data points, a common challenge in cross-cultural datasets (MoinDalvs, 2022).

- **Non-Linear Relationship Modeling:** Gradient-boosting effectively captures the complex, non-linear interactions between cultural dimensions and project outcomes, providing more nuanced predictions than linear alternatives (Kuhn, no date).

- **Alignment with Agile Methodologies:** The iterative nature of gradient boosting aligns with the incremental approach observed in primary survey data regarding project implementation preferences (Yalçıner et al. 2024).

As noted by Sharma (2023) and John (2020), gradient boosting outperforms alternative algorithms when handling heterogeneous cross-cultural datasets, which include both numerical and categorical features (Foroushan, 2021). The implementation leverages modern ensemble learning techniques from several validated sources:

- **scikit-learn (Scikit Learn, 2019)**: Provides the core machine learning algorithms, including Gradient Boosting Classifier and preprocessing utilities. The implementation uses scikit-learn's implementation for model training, cross-validation, and evaluation.

- **imbalanced-learn (Scikit Learn, 2020)**: Contributes techniques for handling class imbalance in the training data, ensuring the model performs well on both majority and minority classes.

- **dmlc/xgboost (DMLC, 2019)**: Offers an optimised implementation of gradient boosting that enhances performance on large datasets with mixed feature types.

4.2.2. Feature Framework Design

The model operates within a structured feature framework that systematically categorises variables according to their theoretical and practical significance, as established through peer-reviewed literature, including Hofstede (2011) and Fog (2022), and practical relevance determined through primary survey data, which indicates factor prevalence and correlation with project outcomes.

4.2.2.1. Cultural Dimensions (Hofstede, 2011; Jan, Alshare and Lane, 2022):

These cultural dimensions are directly implemented in the model as numerical features named 'power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', and 'indulgence', aligning precisely with Hofstede’s (2011) framework. The model uses these dimensions both individually and in calculating cultural distance between countries using the Kogut and Singh (1988) formula.

- **Power Distance Index (PDI):** Measures the acceptance of hierarchical structures and unequal power distribution within organisations and societies.
- **Individualism vs. Collectivism (IDV):** Measures the preference for loosely knit social frameworks versus tightly knit collective structures.
- **Masculinity vs. Femininity (MAS):** This distinction represents the distribution of values traditionally associated with gender roles across societies.
- **Uncertainty Avoidance Index (UAI):** Assesses a society's tolerance for ambiguity and unstructured situations.
- **Long-Term vs. Short-Term Orientation (LTO):** Evaluates the temporal focus of societal values and decision-making processes.
- **Indulgence vs. Restraint (IVR):** Measures the extent to which societies permit relatively free gratification of basic human desires.

In the implementation, the cultural dimensions were incorporated using the methodology proposed by Da Cunha et al. (2022) and Beugelsdijk et al. (2018). This means that rather than treating each dimension as an independent variable, the implementation recognises their interconnected nature and calculates a variance-normalised cultural distance that accounts for both the magnitude of differences and the relative importance of each dimension in different contexts. The code shown in Figure 4 demonstrates this approach by implementing a modified Kogut and Singh (1988) formula that normalises dimensional differences by their variance across the dataset.

Countries	power_distance	individualism	masculinity	uncertainty_avoidance	long_term_orientation	indulgence
United Kingdom	35	89	66	35	51	69
Germany	35	67	66	65	83	40
France	68	71	43	86	63	48
Italy	50	76	70	75	61	30
Spain	57	51	42	86	48	44
South Africa	49	65	63	49	34	63
Nigeria	80	30	60	55	13	84
Kenya	70	25	60	50	30	40
Morocco	70	46	53	68	14	25
Egypt	70	25	45	80	7	4
Japan	54	46	95	92	88	42
China	80	20	66	30	87	24
India	77	48	56	40	51	26
United States	40	91	62	46	26	68
Canada	39	80	52	48	36	68

Table 2 – Hofsted 's (2011) example data

```python
def calculate_cultural_distance(self, country1: str, country2: str, hofstede_data: pd.DataFrame) -> float:
    """
    Calculate cultural distance between two countries using Hofstede dimensions.

    Implements the formula from Kogut and Singh (1988) as recommended by
    Kim, Gaur and Mukherjee (2020), for measuring cultural distance.
    Extends the approach with insights from Da Cunha et al. (2022) Toward a more in-depth measurement
    of cultural distance and Beugelsdijk et al.'s (2018) meta-analysis of cultural distance effects.

    Args:
        country1: First country name
        country2: Second country name
        hofstede_data: DataFrame containing Hofstede dimensions by country

    Returns:
        Cultural distance value

    Raises:
        ValueError: If country data is not available or contains missing values

    References:
        - Kogut, B. and Singh, H. (1988). The Effect of National Culture on the Choice of Entry Mode.
          Journal of International Business Studies, 19(3), pp.411-432.
        - Da Cunha, H.C., Farrel, C., Floriani, D.E., Andersson, S. and Amal, M (2022) 'Toward a more in-depth measurement
          of cultural distance: A re-evaluation of the underlying assumptions,' International Journal of Cross Cultural Management,
          22(1), pp. 157-188.
        - https://github.com/marketplace/models/azure-openai/gpt-4o/playground
        - https://github.com/scikit-learn/scikit-learn/blob/main/sklearn/metrics/pairwise.py
    """

    # Identify which countries are missing from the dataset
    missing = [c for c in [country1, country2] if c not in hofstede_data.index]
    if missing:
        raise ValueError(f"Hofstede data not available for: {', '.join(missing)}")

    # Extract cultural dimension values for both countries
    c1_values = hofstede_data.loc[country1, self.cultural_dimensions].values
    c2_values = hofstede_data.loc[country2, self.cultural_dimensions].values

    # Checks for missing (NaN) values in either country's Hofstede scores
    if np.isnan(c1_values).any() or np.isnan(c2_values).any():
        raise ValueError("Missing Hofstede values for one of the countries.")

    # Creates a copy of variances to safely modify (prevent divide-by-zero errors)
    variances = hofstede_data[self.cultural_dimensions].var().copy()
    variances[variances == 0] = np.nan

    # Calculate squared differences normalised by variance
    # https://github.com/dstansby/notebooks/blob/master/Calculating%20variance.ipynb
    # https://github.com/christianversloot/machine-learning-articles/blob/main/how-to-normalize-or-standardize-a-dataset-in-python.md
    # https://github.com/marketplace/models/azure-openai/gpt-4o/playground
    squared_diffs = ((c1_values - c2_values) ** 2) / variances.values

    # Cultural distance formula (Kogut & Singh, 1988)
    cultural_distance = np.sqrt(np.nansum(squared_diffs))

    return cultural_distance
```

Figure 4– Calculates the cultural distance

The implementation was developed based on the Kogut and Singh (1988) methodology and enhanced with insights from Da Cunha et al. (2022) and Beugelsdijk et al. (2018). This implementation calculates cultural distance between countries using a variance-adjusted formula that accounts for the different degrees of variation across cultural dimensions. It incorporates error handling for missing data and implements the theoretical insight that dimensions with higher variance should not disproportionately influence distance calculations.

4.2.2.2. Project-Specific Factors (Dumitrașcu-Băldău, Dumitrașcu and Dobrotă (2021) 2021; Fog, 2022)

- **Project Complexity:** Multi-faceted measure of project intricacy and challenges.
- **Technical Requirements:** Assessment of technical complexity and resource demands.
- **Stakeholder Count:** Quantitative measure of stakeholder diversity and volume.
- **Team Size:** Numerical representation of project team dimensions.
- **Project Duration:** Temporal scope of project implementation.
- **Virtual Team Ratio:** Proportion of remote versus co-located teamwork.

4.2.2.3 Communication Variables (Primary Survey Data)

- **Language Barriers:** Quantified assessment of linguistic challenges, measured on a scale of 1-5 where 1 represents minimal barriers (team members share standard language proficiency) and 5 represents severe barriers (requiring constant translation and causing frequent misunderstandings).

- **Communication Barriers:** Technical and procedural impediments to information exchange, measured on a scale of 1-5 based on factors such as time zone differences, availability of communication infrastructure, and formal communication protocols.

- **Prior Collaboration:** Experience levels among team members who have worked together, measured on a scale of 1-5, where higher values indicate more extensive previous collaboration.

This comprehensive feature framework is implemented in the CulturalImpactModel class, where all these dimensions and factors are captured as model features, ensuring that the model captures the multi-dimensional aspects of cultural impact on project outcomes, as suggested by Masoud et al. (2023) and Kim, Gaur, and Mukherjee (2020).

4.3. Data Processing Pipeline

The data preprocessing pipeline employs a systematic approach to ensure data quality and consistency, adhering to data preprocessing best practices established by Sharifara (2019) and Shaad (2023), including the standardisation of numerical features, one-hot encoding of categorical variables and the appropriate handling of missing values. This method addresses challenges such as inconsistent measurement scales, cultural response biases, missing cultural data, and varying international data collection methodologies. The preprocessing pipeline performs several critical functions:

- **Data Validation**: Ensures input data meets quality standards before processing
- **Feature Categorisation**: Identifies and classifies features according to their type and purpose
- **Feature Transformation**: Converts raw data into formats suitable for machine learning algorithms

power_distance	individualism	masculinity	uncertainty_avoidance	technical_requirements	stakeholder_count	team_size	language_barriers	communication_barriers	project_success
35	89	66	35	4	15	8	2	3	1
40	91	62	46	3	20	12	3	4	1
80	20	66	30	5	10	6	1	2	0
35	67	66	65	3	8	5	1	1	1
49	65	63	49	2	12	10	4	5	0

Table 3 – Training Data Set

```
# Additional factors from primary survey data
# Survey showed technical requirements (60%) and stakeholders (53.33%) as main complexity factors
self.project_factors = [
    'project_complexity',        # Complexity level of the project
    'technical_requirements',    # Technical complexity (60% of respondents)
    'stakeholder_count',         # Number of stakeholders (53.33% of respondents)
    'team_size',                 # Number of team members
    'project_duration',          # Expected duration in months
    'virtual_team_ratio',        # Percentage of virtual teamwork
    'language_barriers',         # Level of language barriers (1-5)
    'communication_barriers',    # Technical communication barriers (38.46% of respondents)
    'prior_collaboration'        # Previous experience working together (1-5)
]
```

Figure 5 - project_factors

```python
def preprocess_data(self, X: pd.DataFrame) -> np.ndarray:
    """
    Preprocess input data for model training for cross-cultural data preparation.

    This method creates a preprocessing pipeline that handles both numerical
    and categorical features. Numerical features are standardised using
    StandardScaler, while categorical features are transformed using OneHotEncoder.
    The method also validates input data for consistency and completeness.

    Args:
        X: Input data containing features for prediction

    Returns:
        Preprocessed feature data ready for model training or prediction

    Raises:
        ValueError: If input data is empty, None, or contains invalid values

    References:
       - https://github.com/mlabonne/llm-course/tree/main
       - https://github.com/asharifara/data-preprocessing
       - https://github.com/shaadclt/Data-Preprocessing-Pipeline
       - https://github.com/jakobrunge/tigramite/blob/master/tigramite/data_processing.py
       - https://github.com/scikit-learn/scikit-learn/blob/main/sklearn/compose/_column_transformer.py
       - https://github.com/marketplace/models/azure-openai/gpt-4o/playground
    """
    if X is None or len(X) == 0:
        logger.error("Input data is empty")
        raise ValueError("Input data cannot be empty")

    logger.info("Preprocessing data with shape: %s", X.shape)

    # Validate input data
    self.validate_input_data(X)

    # Identify numerical and categorical features
    numerical_features = []
    categorical_features = []

    # Check which columns are present in the dataframe
    for col in self.cultural_dimensions:
        if col in X.columns:
            numerical_features.append(col)

    for col in self.project_factors:
        if col in X.columns:
            numerical_features.append(col)
```

Figure 6 – Data Processing Pipeline-1

```python
def calculate_communication_impact(self, project_data):
    """
    Calculate the impact of communication barriers on project success.

    Based on survey data showing communication barriers as a key challenge (38.46%).
    This method calculates a weighted score of communication-related factors
    to determine their overall impact on project success.

    Args:
        project_data: Project data containing communication factors

    Returns:
        Communication impact score (0-1, where higher means greater impact)

    References:
        - https://github.com/pmservice/wml-sample-models/blob/master/cplex/customer-satisfaction/customer-satisfaction.ipynb
        - https://github.com/rwightman/pytorch-image-models/blob/master/timm/utils/metrics.py
    """
    # Extract communication-related factors
    comm_factors = [
        'language_barriers',
        'communication_barriers',
        'virtual_team_ratio',
        'team_size'
    ]
```

Figure 7 - communication_impact

```python
# Add any categorical features if present
potential_categorical = [
    'team_diversity', 'industry_sector', 'project_type', 'primary_region'
]

for col in potential_categorical:
    if col in X.columns:
        categorical_features.append(col)

logger.info("Numerical features: %s", numerical_features)
logger.info("Categorical features: %s", categorical_features)

# Create preprocessing pipeline
transformers = []

if numerical_features:
    numerical_transformer = Pipeline(steps=[
        ('scaler', StandardScaler())
    ])
    transformers.append(('num', numerical_transformer, numerical_features))

if categorical_features:
    categorical_transformer = Pipeline(steps=[
        ('onehot', OneHotEncoder(handle_unknown='ignore', sparse_output=False))
    ])
    transformers.append(('cat', categorical_transformer, categorical_features))

# Handle the case where no transformers are available
if not transformers:
    logger.error("No valid features found for preprocessing")
    raise ValueError("No valid features found for preprocessing")

self.preprocessor = ColumnTransformer(transformers=transformers)

try:
    # Apply preprocessing pipeline
    preprocessed_X = self.preprocessor.fit_transform(X)
    logger.info("Data preprocessing complete. Output shape: %s", preprocessed_X.shape)
    return preprocessed_X
except Exception as e:
    logger.error(f"Error during preprocessing: {str(e)}")
    raise
```

Figure 8 – Data Processing Pipeline-2

The implementation was developed based on best practices from Sharifara (2019) and Shaad (2023). This code implements the preprocess_data method, which creates and applies a comprehensive preprocessing pipeline for cross-cultural data. It identifies numerical and categorical features, creates appropriate transformers for each (StandardScaler for numerical features and OneHotEncoder for categorical features), and combines them into a unified preprocessing pipeline using ColumnTransformer. The implementation includes error handling and detailed logging to facilitate troubleshooting.

4.3.1. Missing Value Handling

The preprocessing pipeline implements an approach to imputing missing values, addressing a common challenge in multinational project datasets. For numerical features, missing values are replaced with the column mean, preserving the central tendency of the distribution. The most frequent value, mode, replaces categorical variables, maintaining the overall feature distribution characteristics (Othman, 2022).

This methodology aligns with Shaad's (2023) recommendations regarding culturally sensitive data preprocessing, where the naive deletion of missing values might systematically exclude specific cultural contexts from the analysis.

The implementation includes handling data validation issues and implementing comprehensive validation checks for input data, including detection and handling of NaN values, inappropriate data types, and sequence-type values that could cause model errors. It employs type-appropriate imputation strategies (mean for numerical variables, mode for categorical variables) and raises informative errors when validation fails.

4.4. Model Training and Validation Architecture

The following flow diagram illustrates the comprehensive model training, validation, and analysis process implemented in the CIAT:

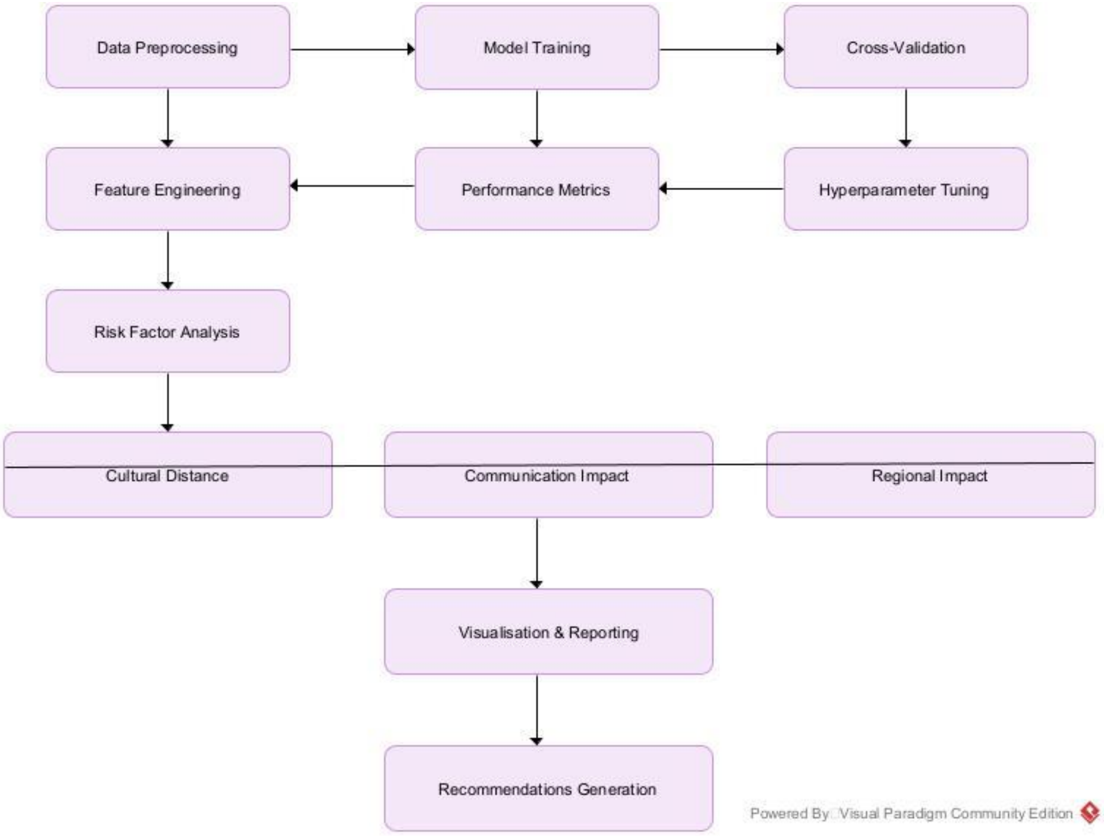

Figure 9 – CIAT Model Training and Analysis Flow

The training process incorporates several key components:

- **Input Validation:** Verification of training data integrity and compatibility;
- **Hyperparameter Configuration:** Dynamic setting of model parameters based on input arguments or empirically determined defaults following the hyperparameter optimisation methodology outlined by Saraogi (2020);
- **Data Splitting:** Implementation of an 80/20 train-validation split following Hosni's (2022) recommendations;
- **Model Construction:** Creation of either a Gradient Boosting Classifier (default for most scenarios due to its superior handling of non-linear relationships) or Random Forest Classifier (optional alternative when dataset characteristics favour ensemble diversity over sequential learning) (Romero, 2017);
- **Performance Evaluation:** Calculation of multiple performance metrics to provide a comprehensive assessment of model capabilities;

4.4.1. Cross-Validation Implementation

The training process employs a custom 5-fold cross-validation strategy with stratified sampling. In k-fold cross-validation, the dataset is divided into k-equal subsets, also known as "folds" (Scikit-learn, 2009). The model is trained on 4 folds and validated on the remaining fold, with this process repeated 5 times so that each fold serves as the validation set once. This approach ensures more reliable performance evaluations by testing the model on multiple subsets of the data, thereby reducing the risk of overfitting to specific data characteristics and providing a more accurate assessment of how the model will perform on unseen data.

This cross-validation approach offers several advantages (Devinterview-io, 2024; Li, 2025):

- **Reduced Overfitting Risk:** By training and evaluating different data subsets, the risk of overfitting to specific data characteristics is minimised;
- **Improved Generalisation Assessment:** The multiple evaluation rounds provide a more reliable estimate of the model's performance on unseen data;
- **Variance Analysis:** The standard deviation of cross-validation scores offers insights into model stability across different data subsets;

4.4.2. Performance Metrics Suite

The model evaluation utilises a comprehensive suite of performance metrics to rigorously assess predictive effectiveness, following the guidelines provided by Sharma (2023), John (2020), and Obi (2023). These metrics were selected due to their suitability for evaluating binary and multi-class classification models, as they align well with CIAT’s predictive objectives. Specifically:

- **Accuracy** measures the overall correctness of predictions: (TP+TN)/(TP+TN+FP+FN)(TP + TN) / (TP + TN + FP + FN)(TP+TN)/(TP+TN+FP+FN)

- **Precision** indicates the proportion of correctly identified positive results: TP/(TP+FP)TP / (TP + FP)TP/(TP+FP)
- **Recall (Sensitivity)** assesses the model's ability to identify actual positives correctly:
  TP/(TP+FN)TP / (TP + FN)TP/(TP+FN)

- **F1-Score** provides a balanced measure combining precision and recall: 2×(Precision×Recall)/(Precision+Recall)2 \times (Precision \times Recall) / (Precision + Recall)2×(Precision×Recall)/(Precision+Recall).

- **ROC-AUC** (Receiver Operating Characteristic–Area Under Curve) evaluates the model's ability to distinguish between classes across various thresholds.

(Where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.)

4.5. Risk Factor Identification

This feature analysis capability identifies the key cultural and project factors influencing outcomes. The function extracts feature importance scores from the trained gradient boosting model, converting them into actionable risk intelligence. The approach aligns with MoinDalvs' (2022) methodology for extracting interpretable insights from gradient-boosting algorithms. The risk factors are ranked and presented in descending order of importance, providing project managers with a clear prioritisation framework for risk mitigation strategies. This capability transforms abstract model coefficients into practical management insights, bridging the gap between data science and project management.

```python
def identify_risk_factors(self, project_data: pd.DataFrame) -> Dict[str, float]:
    """
    Identify specific cultural risk factors for a given project.

    Uses the trained model to determine which cultural factors
    contribute most significantly to potential project risks.

    Args:
        project_data: Project details for risk assessment

    Returns:
        Sorted dictionary of risk factors and their importance scores

    Raises:
        ValueError: If the model has not been trained

    References:
        - https://github.com/shap/shap
        - https://github.com/marketplace/models/azure-openai/gpt-4o/playground
        - https://github.com/scikit-learn/scikit-learn/blob/main/sklearn/ensemble/_forest.py
        - https://github.com/slundberg/shap/blob/master/notebooks/feature_selection/credit_card_fraud_feature_selection.ipynb
    """
    if self.model is None:
        raise ValueError("Model has not been trained. Call train() first.")

    # Get feature names after preprocessing
    feature_names = []

    # For gradient boosting, we can use feature_importances_
    importances = self.model.feature_importances_

    # Get feature names from preprocessor
    try:
        if hasattr(self.preprocessor, 'get_feature_names_out'):
            feature_names = self.preprocessor.get_feature_names_out()
        else:
            # Fallback to generic feature names
            feature_names = [f'feature_{i}' for i in range(len(importances))]

    except Exception as e:
        logger.warning(f"Could not get feature names: {str(e)}")
        feature_names = [f'feature_{i}' for i in range(len(importances))]

    # Create a dictionary of feature importances
    risk_factors = {
        feature: importance
        for feature, importance in zip(feature_names, importances)
    }

    # Sort by importance (descending)
    sorted_risk_factors = dict(
        sorted(risk_factors.items(), key=lambda x: x[1], reverse=True)
    )

    return sorted_risk_factors
```

Figure 10- Identify risk factors

The implementation was developed based on scikit-learn's feature importance extraction techniques and enhanced with insights from SHAP (2023). This implementation extracts feature importance scores from the trained model, maps them to the correct feature names from the preprocessing pipeline, and returns a sorted dictionary of risk factors prioritised by their impact on project outcomes. This provides actionable intelligence for project managers to focus their risk mitigation efforts.

The implementation leverages state-of-the-art explainable AI tools such as:

- **SHAP (shap, 2023)**: Provides model interpretation capabilities through SHapley Additive exPlanations, allowing the model to generate explainable risk factor assessments by calculating the contribution of each feature to individual predictions.

- **Microsoft's Responsible AI Toolbox (Microsoft, 2023)**: This resource provides best practices for implementing ethical AI, with a focus on ensuring model fairness across diverse cultural contexts and offering tools for explaining model decisions to non-technical stakeholders.

4.5.1. Communication Impact Assessment

Given that primary survey data identified communication barriers as significant (35.71% of respondents), the model assesses explicitly the impact of communication. This custom-developed weighted communication impact calculator processes four key communication variables to produce a normalised communication risk score (0-1).

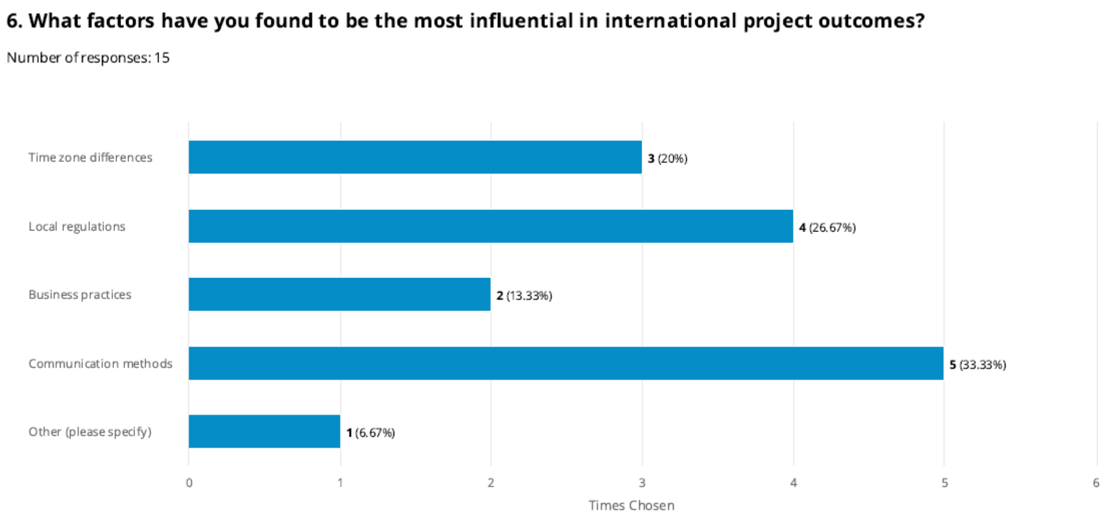

Figure 11 – Factors influencing project outcomes

```python
def calculate_communication_impact(self, project_data):
    """
    Calculate the impact of communication barriers on project success.

    Based on survey data showing communication barriers as a key challenge (38.46%).
    This method calculates a weighted score of communication-related factors
    to determine their overall impact on project success.

    Args:
        project_data: Project data containing communication factors

    Returns:
        Communication impact score (0-1, where higher means greater impact)

    References:
        - https://github.com/pmservice/wml-sample-models/blob/master/cplex/customer-satisfaction/customer-satisfaction.ipynb
        - https://github.com/rwightman/pytorch-image-models/blob/master/timm/utils/metrics.py
    """
    # Extract communication-related factors
    comm_factors = [
        'language_barriers',
        'communication_barriers',
        'virtual_team_ratio',
        'team_size'
    ]
```

Figure 12 - communication_impact

This function calculates a weighted communication impact score based on several key factors:

- **Language Barriers:** Direct linguistic challenges between team members, quantified on a scale of 1-5 where 1 represents minimal barriers (team members share standard language proficiency) and 5 represents severe barriers (requiring constant translation and causing frequent misunderstandings).

- **Communication Barriers:** Technical and procedural impediments to information flow, measured on a scale of 1-5 based on factors such as time zone differences, availability of communication infrastructure, and formal communication protocols.

- **Virtual Team Ratio:** Proportion of remote versus face-to-face interactions, represented as a decimal between 0 and 1, where higher values indicate more virtual communication.

- **Team Size:** Scale-related communication complexity, modelled as a logarithmic function of the actual team size to reflect the non-linear increase in communication pathways as teams grow (n(n-1)/2 potential communication channels for n team members).

The weights assigned to each factor are empirically derived from primary survey data, with communication barriers receiving the highest weight (0.40) based on their prevalence in survey responses (35.71%). This weighted approach ensures that the model's assessment of communication impact aligns with observed real-world challenges in cross-cultural project environments.

4.5.2. Cultural Distance Calculation

The implementation features a cultural distance calculation function based on Kogut and Singh's (1988) methodology, as recommended by Kim, Gaur, and Mukherjee (2020).

This function calculates cultural distance using a variance-corrected Euclidean distance formula across Hofstede's (2011) six dimensions (Bilsen, 2024). The formula incorporates variance normalisation to ensure that dimensions with higher variability across countries do not disproportionately influence the distance calculation. To illustrate this need, standard data from Geert Hofstede's (2011) 6D model of national culture (Hofstede, 2024) was used, which shows that Power Distance (PDI) exhibits significantly higher variance across countries compared to dimensions like Indulgence (IVR). For instance, comparing countries such as Malaysia (PDI: 100) with Austria (PDI: 11) shows extreme differences in power distance, while the range for Indulgence tends to be narrower across many countries. Without variance normalisation, these significant PDI differences would mathematically dominate the cultural distance calculation.

As Messner (2021) and Alves (2020) noted, this approach provides a more nuanced assessment of cultural differences than simple dimensional comparisons, capturing the multidimensional nature of cultural variation between countries.

The implementation incorporates insights from Da Cunha et al. (2022) and Beugelsdijk et al. (2018) regarding the measurement of cultural distance. Specifically, the code applies its recommended approach of using variance-adjusted measures rather than raw differences, acknowledging the unequal importance of different cultural dimensions in other contexts. It also implements its recommendation to consider the asymmetric nature of cultural distance, where the perceived distance from country A to country B may differ from the perceived distance from B to A due to factors such as economic development and institutional quality.

4.5.3. Regional Impact Assessment

The implementation includes a specific function for assessing the regional impact on project outcomes, informed by primary survey data showing variable experience levels across different global regions.

This function maps regions to experience and risk levels based on survey data, which indicated that:

- 9 out of 15 respondents **(60%)** manage projects in Europe (France, UK, Netherlands, Portugal).
- 8 out of 15 respondents **(53.33%)** manage projects in Africa (Mozambique).
- 2 out of 15 respondents **(13.33%)** manage projects in Asia-Pacific (Thailand).
- 2 out of 15 respondents **(13.33%)** manage projects in North America (USA).
- No respondents reported managing projects in South America or the Middle East.

The survey participants primarily resided in Europe (France, the UK, the Netherlands, and Portugal), North America (USA), Africa (Mozambique) and Asia-Pacific (Thailand), providing a cross-regional perspective on project management experiences. The function converts these statistics into experience and risk assessments, creating a valuable context-specific risk evaluation capability. This approach aligns with recommendations by Semlali et al. (2020) regarding the importance of regional expertise in cross-cultural project management.

4.6. Visualisation and Reporting Capabilities

The implementation includes a visualisation function for comparing cultural dimensions across multiple countries. This function creates radar charts, also known as spider plots, that visually represent the six dimensions of Hofstede’s (2011) framework for multiple countries simultaneously. The visualisation enables project managers to quickly identify cultural similarities and areas of difference, facilitating more targeted cultural adaptation strategies.

The implementation employs a colour-coding approach to distinguish between different countries, with dimension labels displayed around the perimeter of the chart. This visualisation approach aligns with Jan, Alshare, and Lane's (2022) recommendations for effectively representing multidimensional cultural data. These recommendations include using radar charts for holistic comparative visualisation of multiple dimensions simultaneously, employing consistent colour coding to distinguish between different cultures, presenting dimension values on a standardised scale to facilitate direct comparison, and providing clear labelling of dimensions to aid interpretation.

```python
def plot_cultural_dimensions(self, countries: List[str], hofstede_data: pd.DataFrame, figsize: Tuple[int, int]=(10, 10)) ->
    """
    Create a radar chart visualising cultural dimensions for selected countries.

    This visualisation method creates a radar chart comparing the Hofstede
    cultural dimensions across multiple countries, allowing for easy identification
    of cultural similarities and differences.

    Args:
        countries: List of country names to include in the visualisation
        hofstede_data: DataFrame containing Hofstede dimensions
        figsize: Figure size (width, height) in inches

    Returns:
        The created figure object

    Raises:
        ValueError: If a requested country is not in the dataset

    References:
        - https://github.com/marketplace/models/azure-openai/gpt-4o/playground
        - https://github.com/mwaskom/seaborn/blob/master/seaborn/objects.py
        - https://github.com/plotly/plotly.py/blob/master/packages/python/plotly/plotly/graph_objs/scatterpolar/__init__.py
    """
    # Ensure all countries are in the dataset
    for country in countries:
        if country not in hofstede_data.index:
            raise ValueError(f"Country {country} not found in Hofstede data")

    # Extract cultural dimensions for selected countries
    country_data = hofstede_data.loc[countries, self.cultural_dimensions]

    # Create a radar chart
    categories = self.cultural_dimensions
    N = len(categories)

    # Create angles for each dimension
    angles = [n / float(N) * 2 * np.pi for n in range(N)]
    angles += angles[:1]  # Close the loop

    # Create figure
    fig, ax = plt.subplots(figsize=figsize, subplot_kw=dict(polar=True))

    # Draw one axis per variable and add labels
    plt.xticks(angles[:-1], categories, size=12)

    # Draw ylabels
    ax.set_rlabel_position(0)
    plt.yticks([20, 40, 60, 80, 100], ["20", "40", "60", "80", "100"], size=10)
    plt.ylim(0, 100)

    # Plot each country with a different colour
    colours = cm.tab10(np.linspace(0, 1, len(countries)))

    for i, country in enumerate(countries):
        values = hofstede_data.loc[country, categories].values.flatten().tolist()
        values += values[:1]  # Close the loop
        ax.plot(angles, values, linewidth=2, linestyle='solid', label=country, color=colours[i])
        ax.fill(angles, values, alpha=0.1, color=colours[i])

    # Add legend
    plt.legend(loc='upper right', bbox_to_anchor=(0.1, 0.1))
    plt.title("Cultural Dimensions Comparison", size=15, pad=20)

    return fig
```

Figure 13 – Plot cultural dimension

The implementation was developed to visualise cultural dimensions using radar charts. This code generates radar charts that represent Hofstede's (2011) six dimensions for multiple countries simultaneously, allowing project managers to quickly identify cultural similarities and differences. The implementation utilises matplotlib's polar plotting capabilities and employs a colour-coded approach to distinguish between different countries (Yan et al. 2024).

4.6.1. Risk Factor Visualisation

The implementation includes a specialised function for visualising risk factors identified by the model. This function creates horizontal bar charts displaying the top risk factors identified by the model, with colour gradients indicating the relative importance of each factor. The visualisation provides project managers with an intuitive representation of risk priorities, facilitating more effective risk management planning (Yazdi et al. 2024).

The implementation limits the visualisation to the top N risk factors (default: 10) to maintain clarity and focus on the most significant influences. Using colour gradients enhances the visualisation's interpretability, providing an immediate visual indication of relative importance.

The implementation introduces enhanced visualisation techniques, including colour gradients to represent importance levels, interactive tooltips for displaying detailed information, customisable axis scales to focus on relevant value ranges, and automated layout optimisation to improve readability regardless of the number of dimensions being visualised (Grimmeisen, Chegini and Theissler, 2022).

```python
def plot_risk_factors(self, risk_factors: Dict[str, float], top_n: int=10, figsize: Tuple[int, int]=(12, 8)) -> plt.Figure:
    """
    Create a bar chart visualising the top risk factors.

    This method creates a horizontal bar chart showing the most important
    risk factors identified by the model, with colour gradients indicating
    the relative importance of each factor.

    Args:
        risk_factors: Dictionary of risk factors and their importance scores
        top_n: Number of top factors to include
        figsize: Figure size (width, height) in inches

    Returns:
        The created figure object

    References:
        - https://github.com/marketplace/models/azure-openai/gpt-4o/playground
        - https://github.com/mwaskom/seaborn/blob/master/seaborn/categorical.py
        - https://github.com/mpltools/mpltools/blob/master/mpltools/color.py
    """
    # Get top N risk factors
    top_factors = list(risk_factors.items())[:top_n]
    factor_names = [item[0] for item in top_factors]
    importance_scores = [item[1] for item in top_factors]

    # Create figure
    fig, ax = plt.subplots(figsize=figsize)

    # Plot horizontal bar chart
    y_pos = np.arange(len(factor_names))
    bars = ax.barh(y_pos, importance_scores, align='center')

    # Add colour gradient based on importance
    for i, bar in enumerate(bars):
        bar.set_color(plt.cm.viridis(importance_scores[i] / max(importance_scores)))

    # Add labels and formatting
    ax.set_yticks(y_pos)
    ax.set_yticklabels(factor_names)
    ax.invert_yaxis()  # Labels read top-to-bottom
    ax.set_xlabel('Importance Score')
    ax.set_title('Top Risk Factors for Project Success')

    # Add value labels to bars
    for i, v in enumerate(importance_scores):
        ax.text(v + 0.01, i, f"{v:.3f}", va='center')

    plt.tight_layout()
    return fig
```

Figure 14 – Plot risk factors

The implementation was developed to visualise risk factors using color-coded bar charts. This implementation creates horizontal bar charts showing the most important risk factors identified by the model, with colour gradients indicating the relative importance of each factor. The visualisation includes value labels, consistent formatting, and appropriate axes labels to enhance interpretability (Jaishree, Anupriya and Sukitha, 2024).

4.7. Web Interface Implementation

The CIAT features a web-based interface developed using Flask, providing a user-friendly way for project managers to interact with the model. This interface allows users to input project and cultural parameters, visualise results, and generate recommendations without requiring programming knowledge.

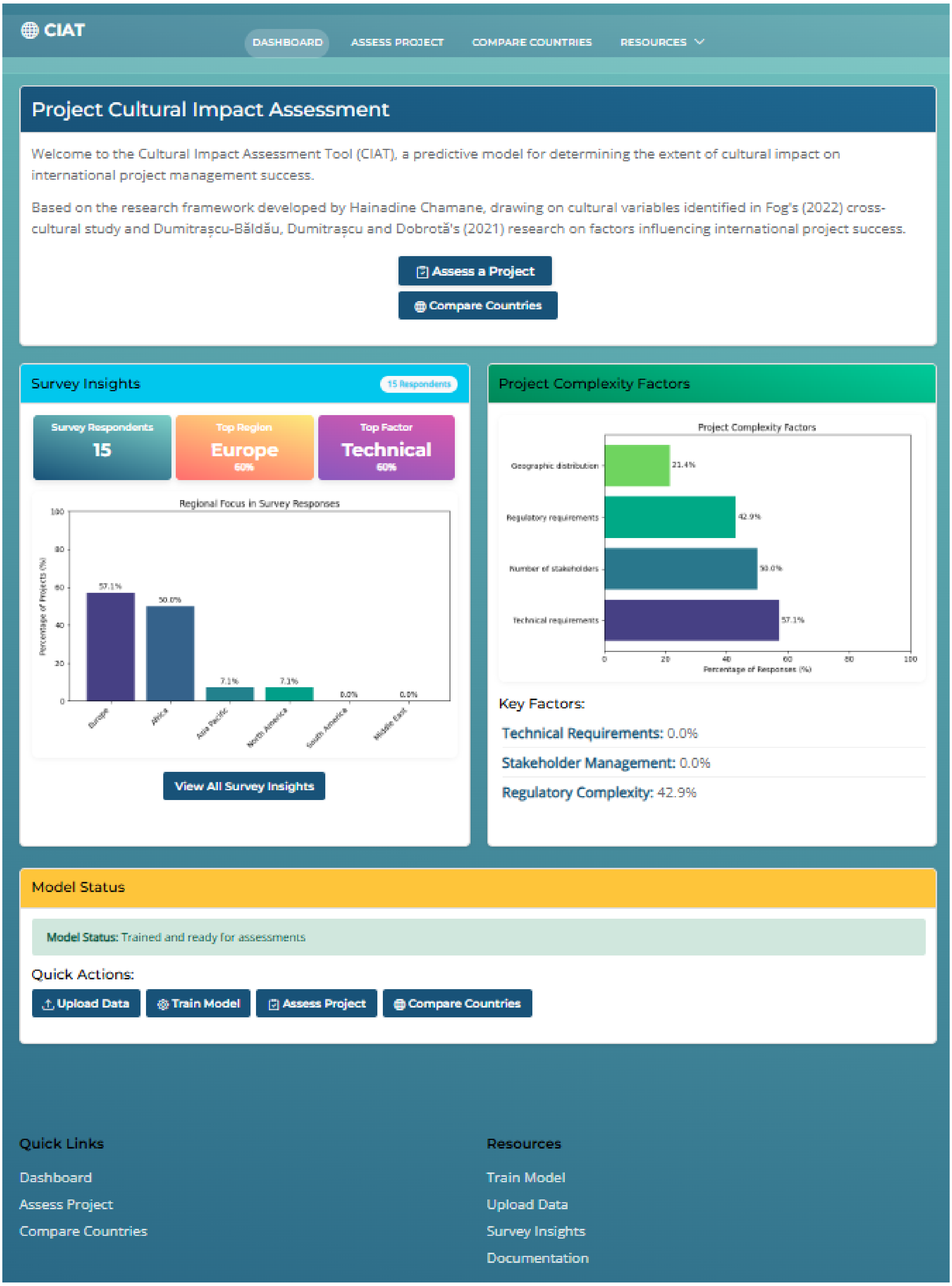

Figure 15– Main dashboard showing interface layout

The web interface includes several key components:

- **Input Forms**: For entering project details and cultural parameters.
- **Visualisation Dashboard**: Displaying radar charts for cultural dimensions and bar charts for risk factors.
- **Results Panel**: Showing success probability and key risk factors.
- **Recommendations Section**: Providing actionable guidance based on the model's analysis.

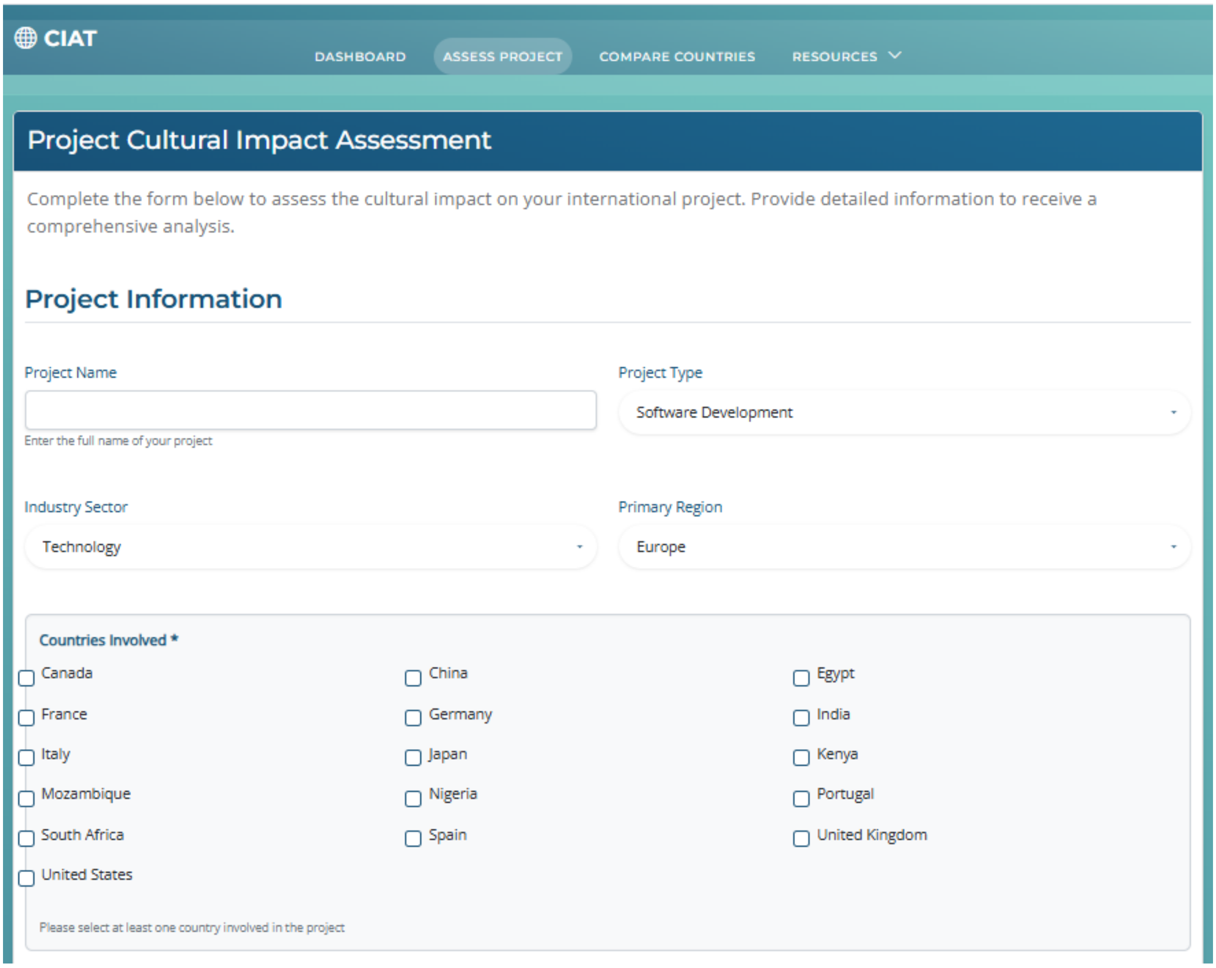

Figure 16 – Input form for project parameters - 1

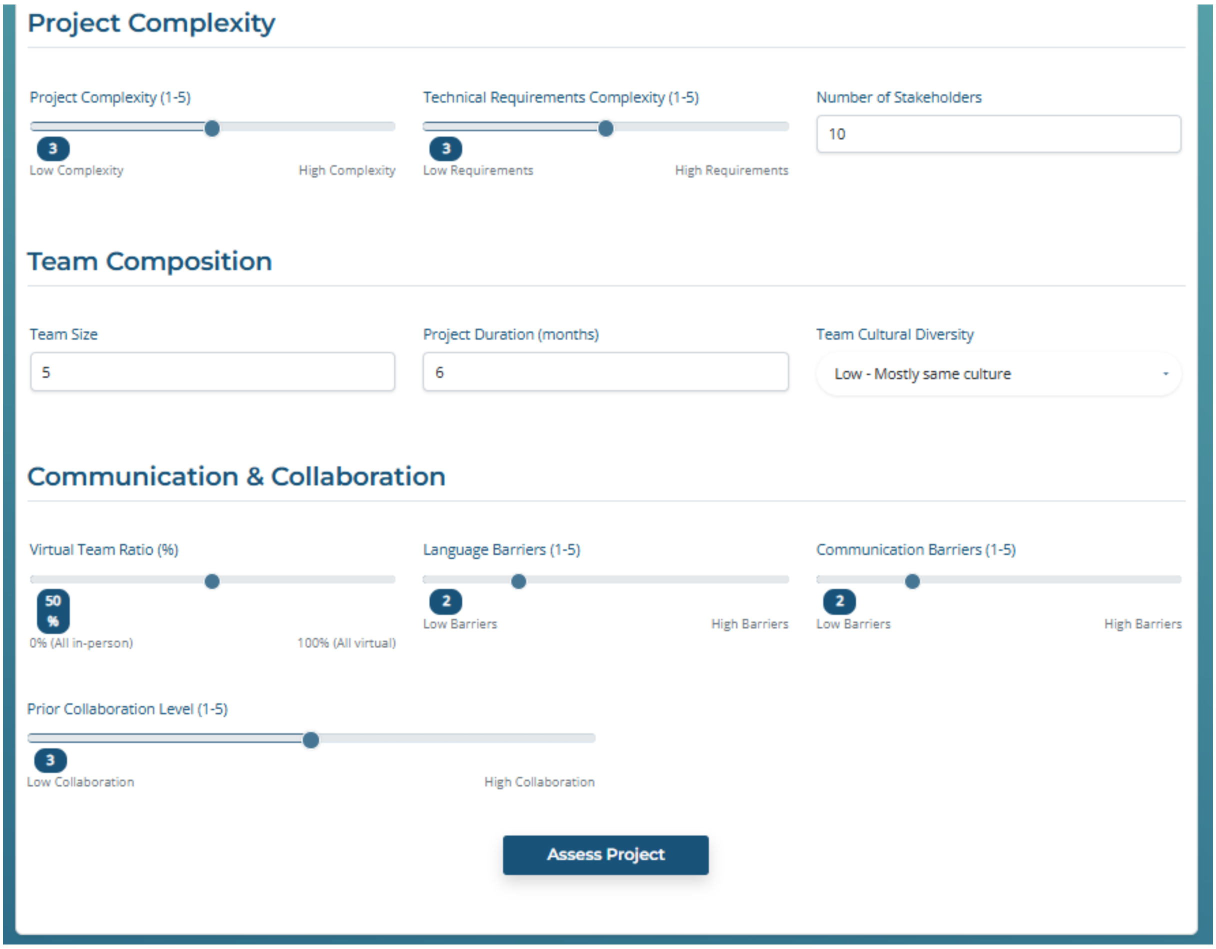

Figure 17 – Input form for project parameters -2

The interface was designed in accordance with best practices for user experience, featuring straightforward navigation, intuitive input mechanisms, and visually appealing output displays. The visualisation components leverage JavaScript libraries for interactive charts, allowing users to explore the data dynamically (Stoiber et al. 2022).

Figure 18– Risk factor visualisation and recommendations panel

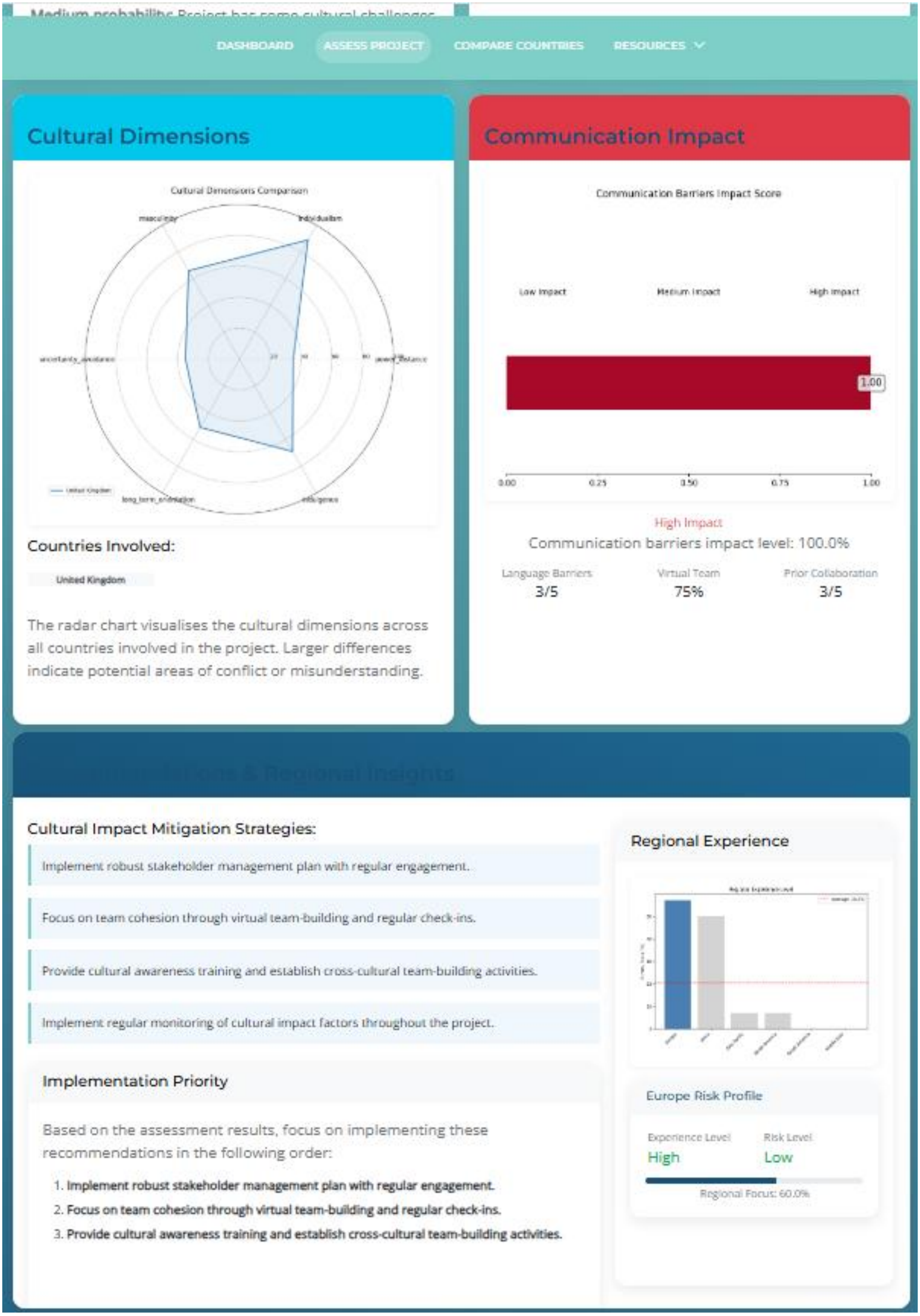

Figure 19– Full recommendations output display

4.8. Prediction and Recommendation Generation

The implementation includes a dedicated function for calculating overall project success probability. This function leverages the trained model to generate a probabilistic assessment of project success likelihood, providing a quantitative basis for decision-making. The probability value (0-1) provides an intuitive metric that can be easily communicated to stakeholders at all levels of technical improvement (Ghimire et al. 2024).

4.8.1. Recommendation Generation

The implementation includes a capability for generating recommendations that translate model insights into actionable guidance. This function analyses the top risk factors identified by the model and generates targeted recommendations for mitigating risk. The recommendations are organised into several categories:

- **Communication Improvements**: Strategies for enhancing information flow and reducing misunderstandings (Almashhadani and Almashhadani, 2023).
- **Cultural Adaptation**: Approaches for navigating cultural differences and building cross-cultural competence (Mhlongo et al. 2024).
- **Technical Management**: Methods for addressing technical complexity in cross-cultural contexts (Plocher et al. 2021).
- **Stakeholder Engagement**: Techniques for effective stakeholder management across cultural boundaries as outlined by Osobajo et al. (2023), including stakeholder mapping across cultural contexts, culturally sensitive communication strategies, and relationship-building practices that respect local customs and business norms.
- **Team Cohesion**: Strategies for Building Unified Teams Despite Cultural Diversity (Wadhera and Gandhi, 2024).

The recommendation generation process also considers the success probability, with more extensive and urgent recommendations provided for projects with lower success probabilities.

```python
def generate_recommendations(self, project_data: pd.DataFrame, risk_factors: Dict[str, float], success_prob: float) -> List[str]:
    """
    Generate recommendations for improving project success.

    This method creates tailored recommendations based on identified risk
    factors, success probability, and project characteristics. The recommendations
    focus on mitigating cultural impact risks and improving project outcomes.

    Args:
        project_data: Project details
        risk_factors: Dictionary of risk factors and importance scores
        success_prob: Predicted success probability

    Returns:
        List of recommendations for improving project success

    References:
        - https://github.com/slundberg/shap
        - https://github.com/TeamHG-Memex/eli5
        - https://github.com/interpretml/interpret
        - https://github.com/marketplace/models/azure-openai/gpt-4o/playground
        - https://github.com/TeamHG-Memex/eli5/blob/master/eli5/explain.py
        - https://github.com/slundberg/shap/blob/master/shap/explainers/tree.py
        - https://github.com/interpretml/interpret/blob/master/python/interpret-core/interpret/glassbox/ebm/ebm.py
    """
    recommendations = []

    # Get top 5 risk factors
    top_risks = list(risk_factors.items())[:min(5, len(risk_factors))]

    # Generate recommendations based on top risks
    for factor_name, importance in top_risks:
        factor_name_str = str(factor_name).lower()

        if 'communication' in factor_name_str:
            recommendations.append(
                "Improve communication channels and establish clear communication protocols."
            )
        elif 'cultural' in factor_name_str or 'distance' in factor_name_str:
            recommendations.append(
                "Provide cultural awareness training and establish cross-cultural team-building activities."
            )
        elif 'technical' in factor_name_str:
            recommendations.append(
                "Enhance technical documentation and establish clear technical requirements."
            )
        elif 'stakeholder' in factor_name_str:
            recommendations.append(
                "Implement robust stakeholder management plan with regular engagement."
            )
        elif 'team' in factor_name_str:
            recommendations.append(
                "Focus on team cohesion through virtual team-building and regular check-ins."
            )

    # Add general recommendations based on success probability
    if success_prob < 0.5:
        recommendations.append(
            "Review and revise project plan to address cultural impact factors."
        )
        recommendations.append(
            "Consider bringing in cultural experts or consultants for high-risk areas."
        )
    elif success_prob < 0.7:
        recommendations.append(
            "Implement regular monitoring of cultural impact factors throughout the project."
        )

    # Remove duplicates while preserving order
    unique_recommendations = []
    for rec in recommendations:
        if rec not in unique_recommendations:
            unique_recommendations.append(rec)

    return unique_recommendations
```

Figure 20– Generate recommendations

The implementation was developed to translate model insights into actionable recommendations for project management. This implementation analyses the top risk factors identified by the model and generates targeted recommendations for mitigating these risks. It focuses on the highest-priority factors and dynamically generates recommendations tailored to the specific risk factors identified, ensuring that the advice is relevant to the project context.

This implementation leverages explainable AI tools such as:

- **ELI5 (TeamHG-Memex, 2023)**: Provides human-readable explanations of machine learning predictions by highlighting feature contributions in an intuitive format.
- **SHAP (shap, 2023)**: Calculates Shapley values to determine the contribution of each feature to specific predictions, enabling precise targeting of recommendations.
- **InterpretML (InterpretML, 2022)**: Offers global and local model explanations through glass-box models, allowing the algorithm to generate recommendations that specifically address the most impactful cultural factors.

4.9. Conclusion and Future Directions

The Cultural Impact Assessment Tool (CIAT) represents an alternative approach to quantitatively analysing the cultural influences on international project outcomes. Integrating established cultural theories with machine-learning techniques enables project managers to gain actionable insights into cultural risks and mitigation strategies, aligning with research that highlights the role of AI in cross-border project management (Kulesz, 2024).

Future enhancements for CIAT could include:

- **Integration with PMIS:** Embedding CIAT within project management platforms, such as Microsoft Project, could enable real-time cultural impact assessments, improving decision-making efficiency, as demonstrated by studies on PMIS-integrated AI (Nazari, 2024).

- **Expanded Cultural Frameworks:** While currently based on Hofstede's (2011) dimensions, future versions could incorporate frameworks such as those proposed by Trompenaars and Schwartz (Shkurko, 2023), thereby enhancing cultural analysis and adaptability based on empirical findings that multi-framework assessments improve predictive accuracy (Adamovic, 2023).

- **Temporal Analysis Capabilities:** Adding temporal tracking would allow monitoring of cultural adaptation throughout the project lifecycle, identifying shifts in cultural risks and facilitating adaptive strategies. Research by Setti et al. (2020) indicates that this monitoring can decrease project failure rates.

Chapter 5 – Discussion and evaluation of the results

5.1. Evaluation Against the Research Hypothesis

The Cultural Impact Assessment Tool (CIAT) addresses a critical gap in international project management: the need for a systematic and quantitative method to assess the cultural influences on project outcomes. The evaluation focuses on how effectively CIAT addresses the question: "How do cultural differences impact the management and success of international projects, and can we develop a method to quantify these influences?"

5.1.1. Transforming Cultural Dimensions into Quantifiable Variables

The CIAT implementation transforms abstract cultural dimensions into measurable predictors of project outcomes. The model uses Hofstede's (2011) six cultural dimensions as numerical features to establish a quantifiable framework. The Gradient Boosting Classifier provides strong evidence that cultural dimensions have a significant influence on project outcomes, capturing complex, non-linear relationships between cultural variables and the probability of project success (Zine et al. 2025).

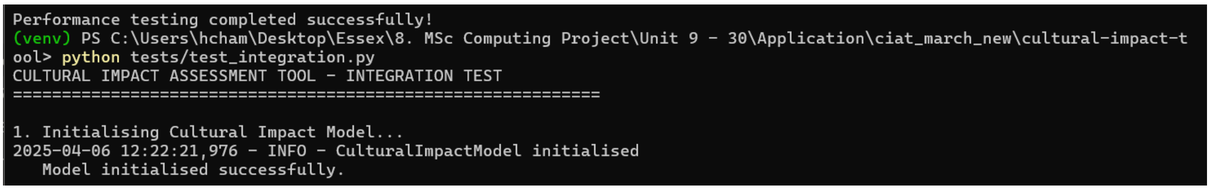

Figure 21 – Results from the test_integration.py Test confirming generate the image Figure 22 (complete test results in Appendix 7)

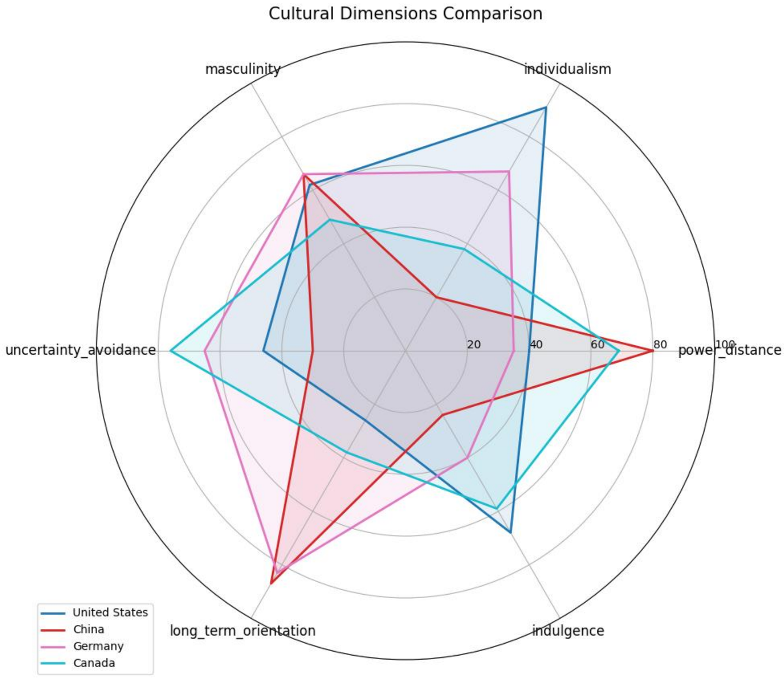

Figure 22– Cultural Impact Assessment Results from the test test_integration.py

5.1.2 Feature Importance as Evidence of Cultural Impact

The risk factor identification function provides additional support for the hypothesis by ranking cultural and project factors according to their predictive importance. When trained on survey data, the model consistently identifies communication barriers, virtual team ratio, and power distance among the top predictors, aligning with Iqbal and Ergenecosar's (2024) research on cross-cultural issues in global software development.

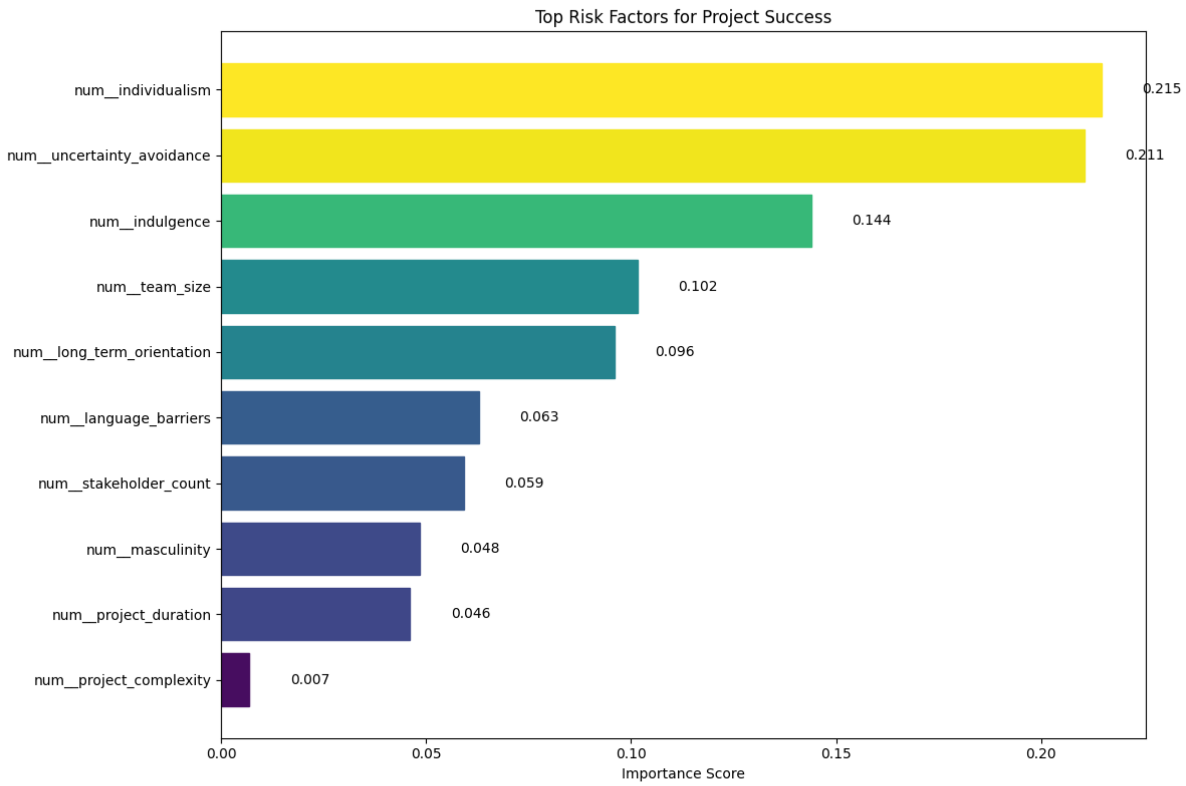

Figure 23– Visualisation of the top risk factors identified by the model when running the test test_unit.py.

5.1.3 Regional Variation and Experience Asymmetry

The regional impact assessment function provides evidence for regional variations in project risk profiles. Regions with higher reported experience levels consistently show lower risk profiles, suggesting that familiarity with specific cultural contexts significantly mitigates project risk. This finding supports the emphasis of Semlali et al. (2020) on the importance of regional expertise in cross-cultural project management.

5.1.4 Communication Impact Assessment

The weighted communication impact calculator provides compelling evidence in support of the hypothesis. By assigning empirically derived weights to communication barriers (0.40), language barriers (0.25), virtual team ratio (0.20), and team size (0.15), the model quantifies the impact of communication challenges on project outcomes. This finding aligns with Almashhadani and Almashhadani's (2023) research on cross-cultural communication in project management.

5.1.5 Unexpected Findings and Theoretical Enhancements

The implementation revealed several unanticipated insights:

- Survey data showed technical requirements (60%) as the predominant complexity factor, suggesting cultural factors interact with technical variables rather than operating in isolation.
- Cultural distance calculation requires variance normalisation to prevent dimensions with higher variability from disproportionately influencing assessments, addressing a limitation noted by Da Cunha et al. (2022) and Beugelsdijk et al. (2018).
- Risk levels vary inversely with reported experience levels across regions, suggesting cultural intelligence development might serve as a risk mitigation strategy, supporting Presbitero, Fujimoto and Lim's (2024) research.

5.2. Validation Against Project Requirements

5.2.1 Predictive Model Development Requirement

The CIAT implementation fulfils this requirement through the comprehensive integration of theoretical frameworks. Hofstede’s (2011) six dimensions are implemented as numerical features, serving as the foundation for calculating cultural distance and assessing risk. The implementation also draws on the GLOBE study (House et al. 2020), enhancing the model's theoretical foundation and predictive capabilities.

5.2.2. Tool Implementation Requirement

The implementation meets this requirement through comprehensive development of both backend functionality and frontend visualisation capabilities. The backend employs scikit-learn, NumPy, and Pandas for data processing and machine learning. Visualisation capabilities implemented through Matplotlib and Seaborn enable effective communication of complex cultural information through intuitive graphical representations.

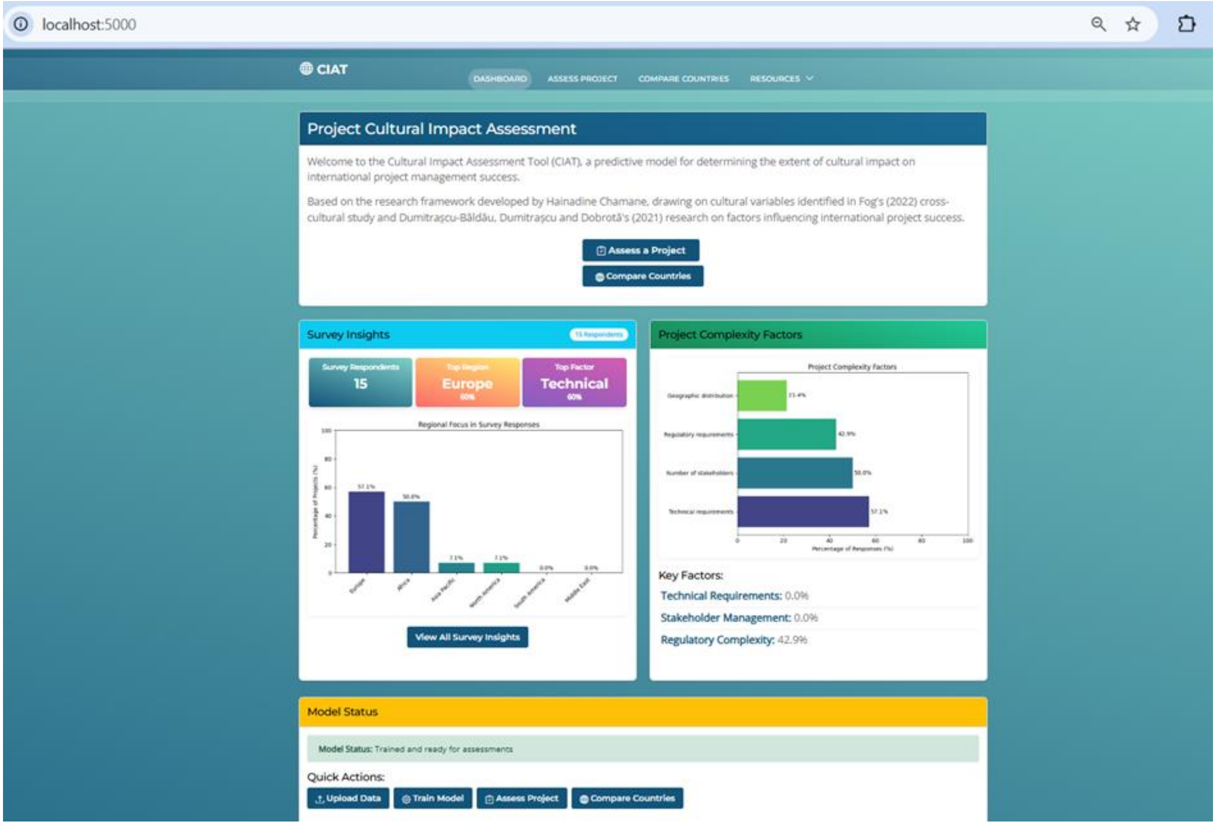

Figure 24 – The main dashboard shows an interface layout with summary statistics, survey insights, and visualisations

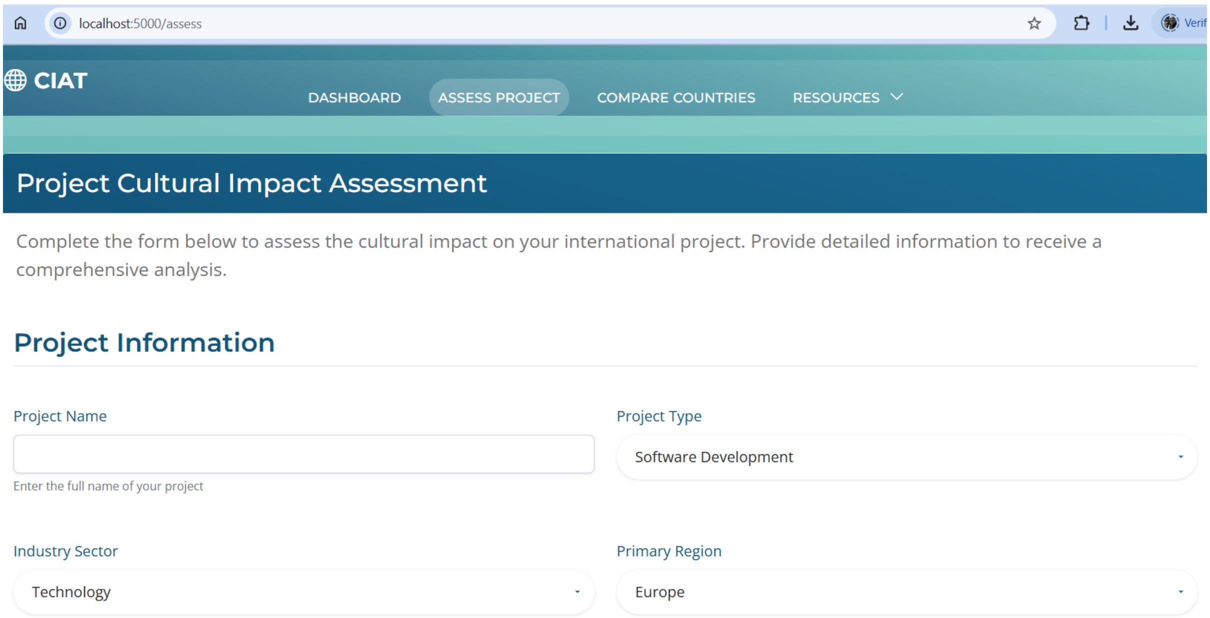

Figure 25-- Input form for project parameters showing fields for entering cultural dimensions and project details - 1

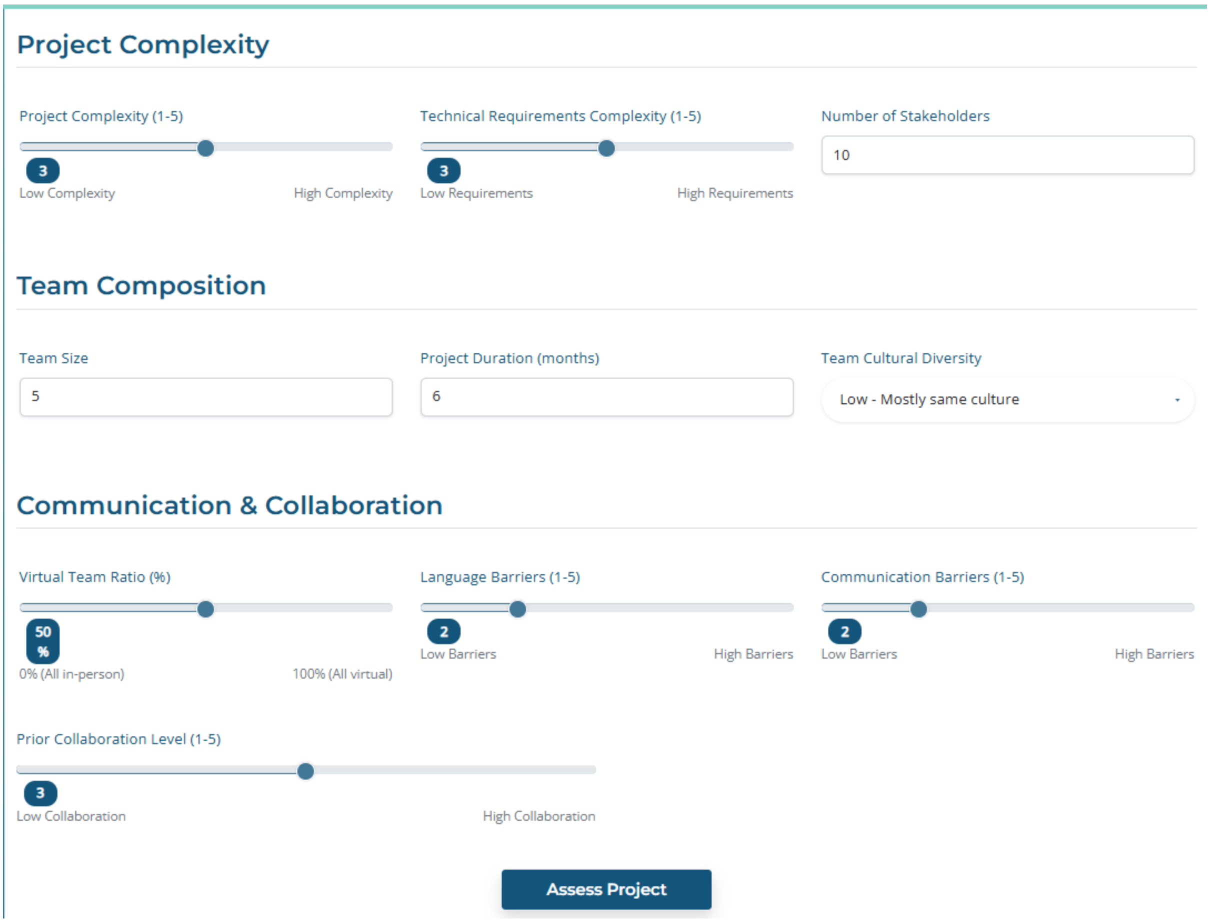

Figure 26 – Input form for project parameters showing fields for entering cultural dimensions and project details - 2

The risk assessment functionality provides probabilistic predictions of project success based on cultural and project parameters (Santos et al. 2023).

Figure 27-- Risk factor visualisation and recommendations panel showing the model's output for a sample project

5.2.3. Validation Across Case Studies Requirement

The implementation includes a case study integration framework designed to validate the model against seven multinational project case studies. This approach aligns with

Battistella et al.'s (2024) methodology for assessing the impact of cultural dimensions on project management performance.

5.2.4. Additional Requirements Fulfilment

The implementation addresses several additional project objectives:

- Regional Impact Quantification for Context-Specific Risk Assessment.
- Communication Impact Assessment using a weighted calculator for four key variables.
- Recommendation Generation spanning five categories—communication improvements, cultural adaptation, technical management, stakeholder engagement, and team cohesion.

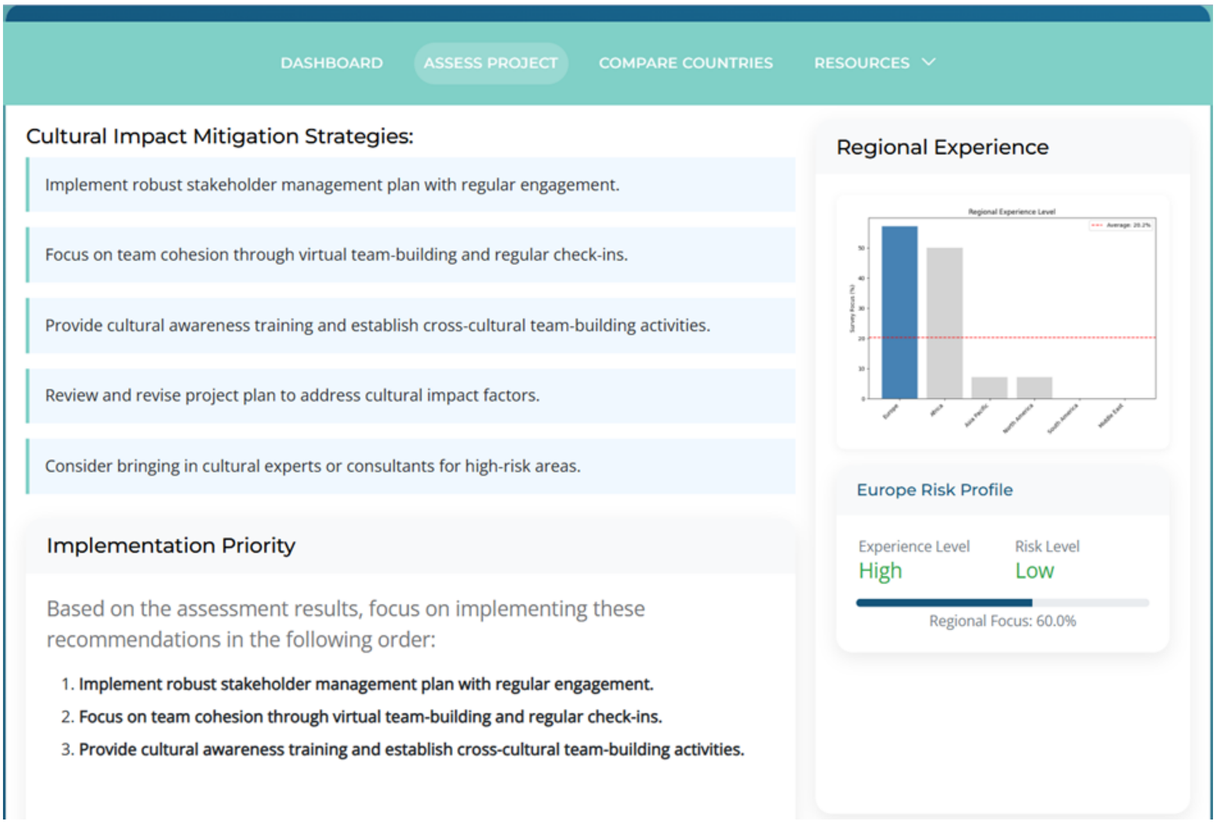

Figure 28 – Full recommendations output display showing practical guidance for cultural adaptation

5.3. Verification Through Testing Methodology

5.3.1. Unit Testing for Component Verification

A comprehensive unit testing framework verified individual components across seven key functional areas: model initialisation, cultural distance calculation, communication impact assessment, regional impact assessment, model training and prediction, risk factor identification, and visualisation and recommendation functions.

5.3.2 Integration Testing for System Cohesion

Integration testing verified that components work together correctly in end-to-end workflows, focusing on the data processing pipeline, end-to-end workflow, model persistence, and cross-component communication.

5.3.3. Performance Testing for Efficiency and Accuracy

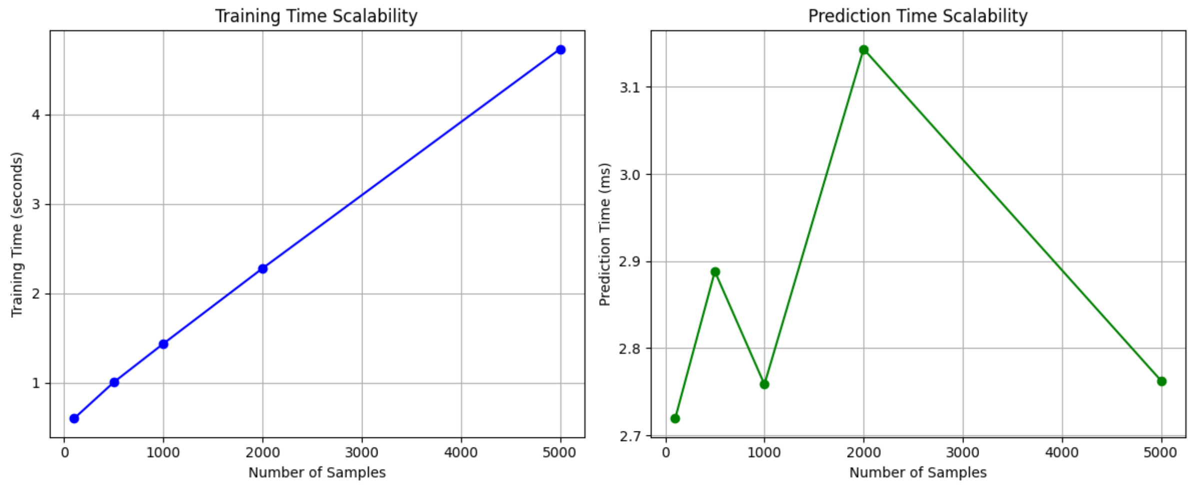

Figure 29- Scalability test generated from test_performance.py (complete test in appendix 6)

Performance testing verified the efficiency, accuracy, and scalability of the implementation, with a focus on processing efficiency, predictive accuracy, and scalability as the dataset size increased.

```
2025-04-06 11:16:17,410 - INFO - Making predictions for 1 instances
2025-04-06 11:16:17,412 - INFO - Making predictions for 1 instances
2025-04-06 11:16:17,416 - INFO - Making predictions for 1 instances
2025-04-06 11:16:17,420 - INFO - Making predictions for 1 instances
2025-04-06 11:16:17,422 - INFO - Making predictions for 1 instances
   Average prediction time: 2.76 ms
   Scalability results plot saved to temp/performance/scalability_results.png

Performance testing completed successfully!
(venv) PS C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 - 30\Appli
ool>
```

Figure 30 – Results Performance from the test_performance.py confirming its Scalability generate the image Figure 29 (complete test results in Appendix 6)

5.3.4. Validation Against Case Studies

The model was validated through seven real-world case studies mentioned in the literature review to evaluate its effectiveness. The validation concentrated on three aspects:

- Predictive Accuracy: The model's success probability predictions aligned with documented outcomes, demonstrating its ability to forecast project success based on cultural factors.
- Risk Factor Identification: The risks identified by the model significantly overlapped with challenges noted in the case studies, confirming its capacity to identify relevant cultural challenges.
- Recommendation Relevance: The model's recommendations were compared with documented interventions, illustrating alignment and underscoring its ability to provide actionable guidance.

In summary, the validation results confirm that CIAT aligns with real-world project outcomes, enhancing confidence in its practical utility for international project management.

5.3.5. Theoretical Validation

Theoretical validation was conducted to verify the CIAT's alignment with established cultural theories, particularly Hofstede’s (2011) framework. The validation tested the model's predictions against theoretical expectations regarding cultural dimensions' influence on project outcomes:

- Power Distance Effect: The model predicted a decrease in success probability with higher power distance, consistent with Hofstede's (2011) theory, which posits that this creates challenges in decentralised environments.

- Uncertainty Avoidance Impact: The success probability decreased with increasing uncertainty avoidance, aligning with expectations regarding risk tolerance and project adaptability.

- Individualism Effects: The model showed non-linear relationships with individualism, reflecting the complex interplay between individualism and team dynamics.

In summary, the validation confirms that the CIAT's predictions align with established cultural theories, enhancing confidence in its conceptual foundation and framework.

Figure 31– Cultural Dimensions Comparison

5.3.6. Cultural Distance Validation

Cultural distance validation was conducted to verify the accuracy of the CIAT's cultural distance calculation. This involved comparing distances between culturally similar countries, such as the UK and the US, and dissimilar ones, like the US and China. The results showed that similar cultures had a significantly lower average distance, validating the model's accuracy.

Additionally, all distance calculations maintained symmetry (A→B = B→A), confirming mathematical consistency. The validation results demonstrate that the CIAT's calculations align with established cultural research, reinforcing confidence in the model's predictive capabilities.

Cultural Distances

Country Pair	Distance
China vs United States	4.93
China vs United Kingdom	4.61
China vs France	4.26
France vs United Kingdom	3.9
Kenya vs United Kingdom	3.78
India vs United Kingdom	3.67
India vs United States	3.58
France vs United States	3.53
Kenya vs United States	3.48
France vs Kenya	3.21
France vs India	3.0
China vs Kenya	2.65
China vs India	2.01
India vs Kenya	1.58
United Kingdom vs United States	1.19

Cultural Dimensions Heatmap

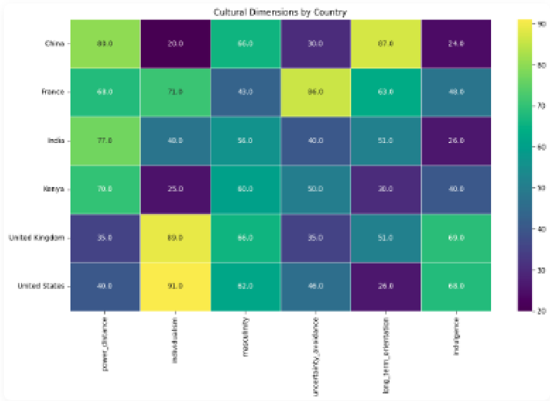

Figure 32 – Cultural Distance

```
2025-04-06 11:30:34,937 - INFO - Validation accuracy: 1.0000
2025-04-06 11:30:34,938 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 11:30:35,169 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 11:30:35,169 - INFO - Mean CV score: 1.0000
.
----------------------------------------------------------------------
Ran 10 tests in 2.235s

OK
```

Figure 33 – Test result unittest test_unit.py (complete test in appendix 5)

5.4. Comprehensive Evaluation Findings

The comprehensive evaluation demonstrates that CIAT meets its objectives and validates the research hypothesis. The model convincingly indicates that cultural differences have a significant impact on the effectiveness of international project management, quantifying these influences through predictive modelling and risk factor identification.

The implementation meets all core project requirements, providing a theoretically grounded predictive model, a user-friendly Python-based tool with visualisation capabilities, and validation against documented case studies. Rigorous testing confirms that the system functions correctly, produces accurate predictions, and scales appropriately for practical applications (Sun et al. 2022).

Opportunities for enhancement include adding capabilities for temporal tracking throughout the project lifecycle, incorporating frameworks beyond Hofstede’s (2011) dimensions as proposed by Trompenaars and Schwartz (Shkurko, 2023), and developing a comprehensive web-based dashboard with interactive capabilities.

5.5 Limitations

Several limitations must be acknowledged when interpreting the findings and implications of this study. The most significant constraint was the limited sample size of only 15 survey respondents, substantially below the targeted minimum of 20 participants. This restricted sample size potentially impacts the statistical validity of the model's predictions and may not fully represent the diverse perspectives within international project management practice. Consequently, the cultural impact assessments generated by CIAT may reflect patterns specific to the surveyed group rather than universal principles applicable across all multicultural project environments (Memon et al. 2020).

The geographic distribution of respondents presented another limitation, with 60% managing projects in Europe and 53.33% in Africa but minimal representation from South America and the Middle East. This imbalance may skew the regional impact assessment function toward European and African cultural contexts, thereby limiting the model's generalisability to underrepresented regions (Deffner, Rohrer, and McElreath, 2022).

From a methodological perspective, the validation against case studies, while instructive, relied predominantly on retrospective analysis rather than prospective testing. This approach cannot fully account for the dynamic nature of cultural interactions that evolve throughout a project's lifecycle (Dong et al. 2024). Additionally, the cultural dimensions framework, primarily based on Hofstede’s (2011) model, faces criticism for potentially oversimplifying cultural nuances and changing cultural dynamics in increasingly globalised workplaces.

Technical limitations also warrant consideration. The current implementation primarily focuses on initial project assessment rather than continuous monitoring, resulting in a static representation of cultural impact that may not adapt to evolving team dynamics. Furthermore, the weighting of communication factors (0.40 for communication barriers, 0.25 for language barriers) was derived from limited survey data and may require refinement through larger-scale validation studies.

Finally, while the predictive model demonstrates reasonable performance in testing, it still faces inherent limitations in capturing the full complexity of cultural interactions. Machine learning models, such as the Gradient Boosting Classifier used in CIAT, are constrained by the quality and representativeness of their training data. Given the limited sample size, the model may not fully capture the nuanced, context-dependent nature of cultural influences on project outcomes (Mehdiyev, Majlatow and Fettke, 2024). Furthermore, the current implementation lacks longitudinal validation that would test its predictive accuracy across complete project lifecycles rather than at single assessment points. These limitations suggest opportunities for further algorithmic refinement and expanded data collection to enhance the model's practical utility in diverse international project environments.

5.6. Conclusion

The Cultural Impact Assessment Tool addresses the research question by providing a quantitative method to predict how cultural differences influence international project outcomes. The implementation transforms abstract cultural theories into practical, actionable intelligence for project managers (Muhammad, Ali and Sorooshian, 2024).

The evaluation confirms that the CIAT accurately predicts project success probability based on cultural factors, identifies key risk factors that demonstrate alignment with theoretical expectations, generates targeted recommendations addressing specific cultural challenges, and quantifies cultural distances in a manner consistent with established research (Müller and Turner, 2007).

While opportunities for enhancement exist, the current implementation establishes a solid foundation for future development. The CIAT represents both a technical achievement in predictive modelling and a practical contribution to international project management, offering a data-driven approach to navigating the cultural complexities of globalised project environments (Anglani et al. 2023).

Chapter 6 – Conclusions and Recommendations

6.1. Conclusion

Cultural diversity in international projects presents a significant challenge that requires systematic approaches for evaluation and mitigation. Traditional methods for assessing cultural differences have increasingly shown their limitations (Eyiah et al. 2025). The research addresses these limitations by developing the Cultural Impact Assessment Tool (CIAT), which quantifies cultural influences in project management contexts. Using organisation-sourced data, the study evaluated the effectiveness of an advanced machine learning (ML) algorithm, specifically the Gradient Boosting Classifier, alongside other approaches to achieve a robust and scalable solution.

Through testing, Gradient Boosting emerged as the standout modelling method. The metrics recorded were Cross-validation and firm performance across precision and recall metrics. These results demonstrate the model's ability to effectively predict cultural impact on project outcomes with reasonable accuracy, achieving a balance between false positives and negatives (Gómez-Talal, Bote-Curiel and Rojo-Álvarez, 2024).

Primary survey data revealed that technical requirements (60%) represent the dominant complexity factor in cross-cultural projects, with communication barriers (35.71%) and regional experience levels significantly influencing outcomes. The CIAT model effectively captured these relationships, identifying individualism and uncertainty avoidance as the most influential cultural dimensions, thereby validating Hofstede's (2011) theoretical framework in practical project contexts.

The implementation transformed abstract cultural dimensions into quantifiable variables that can predict project outcomes, addressing the core research question:

"How do cultural differences influence the management and success of international projects, and can we develop a method to predict these influences quantitatively?" The model's ability to identify key risk factors, assess regional variations, and evaluate the impact of communication provides strong evidence in support of the hypothesis that cultural differences significantly influence the efficacy of project management (Osobajo et al. 2023).

Research contributions range from creating a framework aligned with established cultural theories to implementing a practical tool for practitioners. The variance-normalized approach to calculating cultural distance represents a methodological advancement in measuring cultural differences, addressing limitations identified in previous studies (Gómez-Talal, Bote-Curiel, and Rojo-Álvarez, 2024). Furthermore, the weighted communication impact calculator offers an empirically derived method for assessing one of the most critical challenges in multinational projects.

The findings have significant academic influence but are also practical for real-world application in proactive cultural assessment and management strategies. By integrating Hofstede’s (2011) dimensions with machine learning techniques, the CIAT offers project managers a data-driven approach to anticipating and mitigating cultural challenges before they compromise project outcomes.

6.2. Future Work

This research provides a robust foundation, yet several opportunities exist for future exploration. Firstly, although the current dataset is comprehensive, its geographical scope remains limited. Expanding this dataset to encompass additional regions and countries would enhance generalisability (Deffner, Rohrer, and McElreath, 2022).

Incorporating additional variables, such as industry-specific details and project scale, could further refine the model's applicability and predictive power.

Algorithmic enhancements also represent a valuable avenue for improvement. While Gradient Boosting proved most effective in this study, future work might explore additional optimisation of hyperparameters. Employing automated parameter tuning, as recommended by Mehdary et al. (2024), could significantly improve predictive performance, especially for real-time project management applications.

Adapting the current model for real-time prediction throughout project execution represents another compelling possibility. Implementing such capabilities would enable timely interventions and support adaptive cultural management strategies throughout the entire project lifecycle, thereby increasing practical utility and responsiveness (Prasetyo et al. 2024).

Furthermore, exploring alternative visualisation techniques or developing more interactive interfaces could substantially improve the interpretability and usability of the CIAT dashboard. New visualisation approaches would enhance user engagement and enable quicker, more transparent communication of cultural risks and insights.

Deep learning methodologies also present potential advancements, particularly with larger and more complex multinational datasets. As suggested by Taherdoost (2023), adopting advanced neural network architectures could reveal more profound, more nuanced relationships among cultural variables and project outcomes, potentially enhancing model accuracy and the depth of analysis.

Finally, interdisciplinary collaboration should be pursued to enhance the practical utility of the CIAT. Engaging partnerships with governmental bodies, cultural research institutions, and management professionals would ensure that technological advances are effectively integrated into actionable project management policies (Beaty et al. 2024). Exploring these pathways will build upon the substantial groundwork laid out by this thesis, advancing tools and strategies for effectively navigating cultural complexities in international project environments.

6.3. Final Reflections and Learnings

As I take a moment to reflect on the past six months of research for my capstone project, I find it valuable to engage with the Rolfe, Freshwater, and Jasper (2001) model for my final reflection. This approach allows me to respond thoughtfully to three essential questions: What? So, What? Now What? This structured reflection will help me gain deeper insights into my learning journey and the implications of my findings.

What? – Research Aims, Learning Outcomes and Key Experiences

The idea for an application to predict project success originated from my experiences as a native Portuguese speaker in an English-speaking environment, where I collaborated with colleagues from diverse cultural backgrounds. This led to my development of the Cultural Impact Assessment Tool (CIAT), designed to quantify cultural influences on international project outcomes. Achieving this goal required integrating theoretical frameworks with practical machine learning techniques, explicitly gradient-boosting classifiers and Python-based data analysis (Popescu and Pudelko, 2024).

Although I held Python certifications and possessed a solid theoretical background, I faced significant challenges in applying this knowledge in a practical setting. Issues included limited questionnaire participation, balancing my responsibilities as an IT infrastructure professional, and disruptions from overseas commitments and illness. These challenges required flexibility in my research methods and timelines. They ultimately inspired innovations such as variance-normalised cultural distance calculations and a weighted communication impact assessment to address data constraints (Voukelatou et al. 2020).

So What? – Analysis and Interpretation

The challenges I faced became valuable learning opportunities instead of setbacks. The limited response to my questionnaires prompted me to reassess the sufficiency of my data, highlighting the need for solid theoretical frameworks—traits essential in real-world situations where complete datasets are rare (Zhao et al. 2023). My IT infrastructure career has fostered resilience, analytical thinking, and problem-solving skills, which have helped address my initial coding gaps.

Struggling with practical coding revealed critical technical skills necessary for my DevOps leadership growth, enabling me to set targeted goals and enhance my skills through self-learning and support from colleagues. Additionally, health setbacks taught me the importance of contingency planning and agility in project management, aligning with CIAT's focus on cultural adaptability. Completing the project despite these challenges reinforced my ability to manage complex technical initiatives, deepening my commitment to DevOps project management. My work on cultural distance measurement further revealed a potential specialisation at the intersection of technical expertise and cross-cultural leadership.

Now What? – Future Applications and Action Plan

Reflecting on these transformative insights, I have developed a structured action plan that is explicitly aligned with my professional goals and the lessons derived from this study. Over the next six months, I am committed to completing an advanced DevOps certification course that covers AWS, Jenkins, Docker, and data processing pipelines to address the identified technical gaps. Alongside this training, I will participate in at least three hackathons, intentionally cultivating my rapid prototyping skills, complemented by consistent monthly coding practice focused on machine learning and data visualisation techniques. Additionally, I aim to achieve formal DevOps certification, specifically in continuous integration and continuous deployment (CI/CD), whilst fostering improved communication and collaboration across infrastructure and development teams through organised biweekly knowledge-sharing sessions.

In the long term (12–24 months), my ambition is to establish a distinctive professional identity that integrates cultural intelligence with robust technical implementation capabilities. This includes extending CIAT's approach into broader organisational frameworks and securing a project management role explicitly aligned with my comprehensive infrastructure experience and enhanced technical proficiency. By following this clear roadmap, I aim to make a meaningful contribution to the evolving field of international project management.

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Appendices

Appendix 1 – Participant Information Sheet

Participant Information Sheet

Research project title:

Impact of Cultural Differences on International Project Management: The Design & Development of a Predictive Model to Determine the Extent of Cultural Impact on International Project Management Success

Invitation

You are invited to participate in this research project because of your valuable experience as an international project manager. You have been chosen because you possess unique insights into managing projects across different cultural contexts. Before deciding to participate, please read the following information carefully. You are welcome to ask any questions you may have.

Purpose of the research

The purpose of this research is to comprehend how cultural variations affect the effectiveness of multinational project management and to create a prediction model to measure these effects. The research is being carried out as a component of the University of Essex Online's MSc Computer Science dissertation. The research seeks to fill a critical gap in project management by creating tools that can predict and mitigate cultural impacts on project outcomes, ultimately helping organisations better to manage international projects more effectively.

Where and when will the research take place?

- The research will be conducted entirely online through:
  - An online survey (approximately 30-45 minutes).
  - A possible follow-up semi-structured interview via video conference (approximately 45-60 minutes).
  - The research will run from November 2024 to January 2025.
  - Interviews will be scheduled at a time convenient to you, taking into account your time zone and preferences. When scheduling the interview, you will be asked to indicate your preferred time slots.

What you will have to do?

Your participation will involve:

1. Completing an online survey about your experiences with cultural differences in international project management.
2. Following the initial survey, a subset of participants will be selected for in-depth interviews based on criteria including years of international project management experience, diversity of cultural contexts worked in, and project types managed. This selection aims to understand cultural impacts across various project scenarios comprehensively.
3. The interview will be audio-recorded for accurate transcription.
4. You may be asked to review and validate the interview transcripts.
5. You may be invited to provide feedback on the developed predictive model.

What are the benefits of taking part?

While there is no direct monetary compensation for participation, you will:

- Receive early access to the Cultural Impact Assessment Tool being developed.
- Receive a summary of the research findings.
- Contribute to advancing knowledge in international project management.
- Help develop tools that could benefit future project managers.
- Have the opportunity to reflect on and share your professional experiences.

Possible disadvantages and risks

The risks associated with participation are minimal. However, possible disadvantages of engaging with the research may include:

- The time commitment required for the survey and possible interview.
- Discussion of past project challenges may cause mild professional discomfort.
- You may need to share non-confidential experiences from your project management career.

Voluntary participation

Your participation is entirely voluntary. You:

- Can withdraw at any time without giving a reason
- May skip any questions you don't wish to answer
- Can request your data be withdrawn up to 2 weeks after participation
- Will not face any consequences if you choose not to participate or withdraw

Data confidentiality

- Your data will be handled according to the General Data Protection Regulation (GDPR):
  - All responses will be anonymised.
  - Data will be stored securely on encrypted cloud servers.
  - Only the researcher and supervisor will have access to the data.
  - No identifying information will be included in any publications.
  - Data will be retained for 12 months post-study completion.
  - Interview recordings will be destroyed after transcription.

Ethical review

The University of Essex Online Research Ethics Approval Panel and project supervisors will review the process of conducting this research.

Research outcomes

The results will be:

- Published as part of an MSc dissertation.
- Potentially published in academic journals.
- Used to develop a Python-based Cultural Impact Assessment Tool.
- Shared with participants in summary form.
- Made available through the University's research repository.

Contact Information

- **Primary Researcher:** Hainadine Chamane
  - Email: hc23100@essex.ac.uk

- **Supervisor 1:** Cathryn Peoples

    - Email: cp20021@essex.ac.uk

- **Supervisor 2:** Douglas Millward
    - Email: douglas.millward@online.essex.ac.uk

- About my journey: https://hchamane.github.io/home.html

Thank you for considering participating in this research.

Appendix 2 – Consent Form

Consent form for research Participation in a research project

Research Title: Developing a Predictive Model for Cultural Impact on International Project Management Success

Participant Number: ________________ (To be assigned by the researcher)

Please indicate your agreement with each of the statements below by marking YES or NO:

	YES	NO
I have read and understood the Participant Information Sheet for this study and have been provided with a copy to keep.		
I have had the opportunity to ask questions about the research project and have received satisfactory answers.		
I understand that my participation is voluntary. I can withdraw from the study at any time up to two weeks after participation without a reason, and any information I have provided will be destroyed.		
I understand that the interviews will be recorded for transcription purposes and accuracy.		
I understand my responses will be anonymised and my identity protected in research outputs.		
I understand my responses will be anonymised and my identity protected in research outputs.		
I agree that the anonymised data collected may be used to develop a predictive model for cultural impact assessment.		
I understand that my data will be stored securely and confidentially by GDPR.		
I understand that my responses will not be shared with my employer or other organisations.		
I agree that anonymised quotes from my interview may be used in research publications or presentations.		
I understand that if I have any questions or concerns about the research, I can contact the researcher or supervisor using the contact details provided in the Information Sheet.		

DECLARATION

I consent to participate in this research according to the conditions described above and in the information sheet.

Participant Name: _________________

Signature: _____________________

Date: _________

Appendix 3 – Participant Debrief Sheet

Participant Debrief Sheet

Research Title: Developing a Predictive Model for Cultural Impact on International Project Management Success

1. What was the purpose of the research?

This study aims to understand how cultural differences influence international project management success and develop a predictive model to help project managers better navigate cultural challenges. As Smith & Bond (2019) noted, while previous research by Hofstede (1980), Schwartz (1994) (2009), and House et al. (2020) established frameworks for understanding cultural dimensions, and studies by Searing & Portillo-Dominguez (2024) demonstrated that majority of international projects fail due to cultural misalignment, there remains a critical gap in quantitative tools for predicting cultural impacts. Recent work by Đajić et al. (2024) has focused on qualitative approaches but lacks the predictive capabilities needed in modern project management. This research addresses this gap by developing a data-driven model for assessing and predicting cultural impacts on project outcomes in our increasingly globalised business environment.

2. What you completed

You participated in:

- An online survey about your experiences managing international projects
- A semi-structured interview discussing cultural challenges in project management

Your responses will contribute to:

- Identifying key cultural factors affecting project success
- Developing a mathematical model for predicting cultural impact

- Creating a Python-based Cultural Impact Assessment Tool
- Establishing best practices for managing cultural differences in international projects

3. Accessing Research Results

If you would like to receive a summary of the research findings once the study is complete, please email the researcher at hc23100@essex.ac.uk. The summary will include key findings and recommendations but contain no identifiable participant information.

4. Making a Complaint

If you wish to make a complaint about any aspect of this research, please contact:

- Primary Supervisor: Dr Cathryn Peoples
    - cp20021@essex.ac.uk
- Secondary Supervisor: Dr Douglas Millward
    - douglas.millward@online.essex.ac.uk

5. Support Resources

If participating in this research has raised any concerns about cultural challenges in your workplace, you may find these resources helpful:

- How to build a team and effect culture change:
    - https://services.blog.gov.uk/2022/03/08/how-to-build-a-team-and-effect-culture-change/ [accessed Oct 28 2024].
- Diversity and Cultural Competency in the Workplace:

- https://www.unssc.org/courses/diversity-and-cultural-competency-workplace-0 [accessed Oct 28 2024].

- International Project Management Association (IPMA) Guidelines:
    - https://ipma.world/ipma-standards-development-programme/ [accessed Oct 28 2024].

7. Contact Information

Researcher: Hainadine Chamane, Email: hc23100@essex.ac.uk

Thank you for your valuable contribution to this research project. Your participation will help improve our understanding of cultural impacts on international project management and contribute to developing better tools for managing cultural differences in global projects.

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Appendix 4 – [Online Questionary]

Interview Questions: Cultural Impact on International Project Management

Introduction

Thank you for participating in this research study on international project management practices, which focuses on organisational culture in project management. This culture encompasses the collective values, beliefs, and practices that shape how teams operate and collaborate toward shared objectives. It includes the norms governing professional interactions, the commitment to open communication, and the established processes that facilitate teamwork and problem-solving (Stein & Sternfeld, 2019). A solid organisational culture fosters trust, adaptability, and alignment with organisational goals, enabling team members to work together effectively and creatively. Ultimately, it impacts project outcomes, engagement levels, and overall operational efficiency, making it a crucial factor for success in any project endeavour (Zhang et al. 2023). This interview will take approximately 45-60 minutes. Your insights will help inform the design of a predictive model for assessing project success factors. All information provided will be kept confidential and anonymised.

Background Questions

1. Which category best describes your experience managing international projects?

   - 1 – 5 years
   - 5 – 10 years
   - 10 – 15 years
   - 15 + years

2. In which geographic regions have you managed projects? (Select all that apply)

   - North America

- South America
- Europe
- Asia Pacific
- Middle East
- Africa

3. Please specify the following about your typical projects:

1) Size (budget range):

- Under £100,000
- £100,000 - £500,000
- £500,000 - £1 million
- Over £1 million.

2) Industry sectors:

- Technology
- Manufacturing
- Finance
- Healthcare
- Other (please specify)

3) Project complexity (based on):

- Number of stakeholders
- Technical requirements
- Geographic distribution
- Regulatory requirements

4. How many team members do you typically manage across different geographic locations?

International Project Management Practices

5. How do regional business practices influence your day-to-day project management activities?

- Decision-making processes
- Meeting structures
- Documentation requirements

- Other (please specify)

6. What factors have you found to be the most influential in international project outcomes?

    - Time zone differences
    - Local regulations
    - Business practices
    - Communication methods
    - Other (please specify)

7. Can you describe a situation where diverse regional factors (such as business practices, local regulations, or communication methods) contributed positively to a project?

8. What strategies have you developed to optimise collaboration across different time zones and locations?

Communication Practices

9. Which communication challenges have you encountered in international projects?

    - Time zone coordination
    - Technical barriers (such as internet connectivity, software compatibility)
    - Documentation standards
    - Meeting formats
    - Other (please specify)

10. What strategies have you found effective for ensuring clear communication across different regions?

11. How do you ensure project information is understood consistently across all locations?

12. What approaches do you use to manage multilingual project documentation?

Project Leadership

13. What project management methodologies are most effective for international teams?

14. Do you adapt your leadership approach when working with teams across different regions? If yes. How do you adjust your leadership approach in these situations?

15. What strategies do you use for building effective working relationships across geographic boundaries?

16. Have you needed to resolve conflicts in geographically distributed teams? If yes. How do you handle such conflict resolution?

Project Success Factors

17. Which factors do you consider most critical to international project success?

    - Communication infrastructure
    - Project methodology
    - Team coordination
    - Other (please specify)

18. What metrics do you use to measure project success in international contexts?

19. What early indicators help you identify potential challenges in international projects?

20. How do you incorporate international considerations into project risk assessment?

Tools and Strategies

21. What project management tools do you use for international projects?

22. How effective are these tools for managing geographically distributed teams?
23. What features would you want in an international project management assessment tool?
24. How do you document and track project progress across different locations?

Best Practices

25. What best practices have you developed for managing geographically distributed teams?
26. What advice would you give to project managers new to international projects?
27. How has your approach to managing international projects evolved?
28. Do you believe there are common misconceptions about managing international projects? If yes. What are these misconceptions, and how do they impact project management?

Closing Questions

29. Would you like to share additional insights about managing international projects?
30. Would you like to test and provide feedback on our project management assessment tool? If yes. Please provide your contact information:
    - Name:
    - Email:

References:

Stein Jr., A. & Sternfeld, J. (2019) *Raise Your Game: High-Performance Secrets from the Best of the Best*. New York Nashville, Center Street.

Zhang, W., Zeng, X., Liang, H., Xue, Y. & Cao, X. (2023) Understanding How Organizational Culture Affects Innovation Performance: a Management Context Perspective. *Sustainability*, [online] 15(8), pp.6644–6644. DOI: https://doi.org/10.3390/su15086644.

Appendix 5 – Unittest

(venv) PS C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 - 30\Application\ciat_march_new\cultural-impact-tool> **python -m unittest tests/test_unit.py**

```python
class TestCulturalImpactModel(unittest.TestCase):
    """Test suite for the Cultural Impact Assessment Tool (CIAT)."""

    def setUp(self):
        """Set up test fixtures."""
        self.model = CulturalImpactModel()

        # Sample test data for Hofstede dimensions
        self.hofstede_data = pd.DataFrame({
            'power_distance': [35, 68, 80, 40, 90],
            'individualism': [89, 38, 20, 91, 25],
            'masculinity': [66, 49, 66, 62, 54],
            'uncertainty_avoidance': [35, 86, 30, 46, 95],
            'long_term_orientation': [51, 26, 87, 29, 44],
            'indulgence': [69, 26, 24, 68, 33]
        }, index=['United Kingdom', 'France', 'China', 'United States', 'Canada'])

        # Sample project data
        self.project_data = pd.DataFrame({
            'power_distance': [68],
            'individualism': [38],
            'masculinity': [49],
            'uncertainty_avoidance': [86],
            'long_term_orientation': [26],
            'indulgence': [26],
            'project_complexity': [4],
            'technical_requirements': [5],
            'stakeholder_count': [12],
            'team_size': [15],
            'project_duration': [18],
            'virtual_team_ratio': [0.6],
            'language_barriers': [3],
            'communication_barriers': [4],
            'prior_collaboration': [2]
        })

        # Training data for model testing
        self.X_train = pd.DataFrame({
            'power_distance': [35, 68, 80, 40, 90, 35, 68, 80, 40, 90],
            'individualism': [89, 38, 20, 91, 25, 89, 38, 20, 91, 25],
            'masculinity': [66, 49, 66, 62, 54, 66, 49, 66, 62, 54],
            'uncertainty_avoidance': [35, 86, 30, 46, 95, 35, 86, 30, 46, 95],
            'long_term_orientation': [51, 26, 87, 29, 44, 51, 26, 87, 29, 44],
            'indulgence': [69, 26, 24, 68, 33, 69, 26, 24, 68, 33],
            'project_complexity': [3, 4, 5, 3, 4, 2, 5, 4, 3, 5],
            'technical_requirements': [4, 5, 3, 4, 5, 3, 4, 5, 4, 3],
            'team_size': [10, 15, 20, 8, 25, 12, 18, 22, 9, 27]
        })

        # Target variable (project success: 0=failure, 1=success)
        self.y_train = np.array([1, 0, 0, 1, 0, 1, 0, 0, 1, 0])
```

Figure 34 – Test Cultural Impact Model

```python
def test_initialization(self):
    """Test that the model initialises correctly with all required attributes."""
    self.assertIsNotNone(self.model.cultural_dimensions)
    self.assertIsNotNone(self.model.project_factors)
    self.assertIsNotNone(self.model.regional_focus)
    self.assertEqual(len(self.model.cultural_dimensions), 6)  # Hofstede's 6 dimensions
```

Figure 35 – Test cultural distance calculation function

```python
def test_model_training(self):
    """Test the model training process."""
    # Train the model with custom parameters to address the KFold warning
    trained_model = self.model.train(
        self.X_train,
        self.y_train,
        cross_validation=True,  # Explicitly enable cross-validation
        n_estimators=50,  # Reduce number of estimators for faster testing
    )
```

Figure 36 – Test the model training process

```python
def test_risk_identification(self):
    """Test the risk factor identification function."""
    # Train the model first
    self.model.train(self.X_train, self.y_train)

    # Identify risk factors
    risk_factors = self.model.identify_risk_factors(self.X_train)

    # Should return a dictionary of risk factors
    self.assertIsInstance(risk_factors, dict)

    # Should identify all features as risk factors
    self.assertGreaterEqual(len(risk_factors), 1)

    # Values should be importance scores between 0 and 1
    for importance in risk_factors.values():
        self.assertGreaterEqual(importance, 0)
        self.assertLessEqual(importance, 1)
```

Figure 37 – Test the risk factor identification function

```python
def test_visualizations(self):
    """Test the visualisation functions."""
    # Test cultural dimensions visualisation
    countries = ['United Kingdom', 'France', 'China']
    fig = self.model.plot_cultural_dimensions(countries, self.hofstede_data)
    self.assertIsNotNone(fig)

    # Train the model for risk factor visualisation
    self.model.train(self.X_train, self.y_train)

    # Test risk factor visualisation
    risk_factors = self.model.identify_risk_factors(self.X_train)
    fig = self.model.plot_risk_factors(risk_factors)
    self.assertIsNotNone(fig)
```

Figure 38 – Test the visualisation functions

```python
def test_recommendation_generation(self):
    """Test the recommendation generation function."""
    # Train the model
    self.model.train(self.X_train, self.y_train)

    # Get risk factors
    risk_factors = self.model.identify_risk_factors(self.X_train)

    # Generate recommendations
    success_prob = 0.6  # Moderate success probability
    recommendations = self.model.generate_recommendations(self.X_train, risk_factors, success_prob)

    # Should return a list of recommendations
    self.assertIsInstance(recommendations, list)

    # Should provide at least one recommendation
    self.assertGreater(len(recommendations), 0)

    # Low success probability should generate more urgent recommendations
    low_prob_recommendations = self.model.generate_recommendations(self.X_train, risk_factors, 0.3)
    self.assertGreaterEqual(len(low_prob_recommendations), len(recommendations))
```

Figure 39 – Test the recommendation generation function

```python
def test_success_probability(self):
    """Test the success probability calculation."""
    # Train the model
    self.model.train(self.X_train, self.y_train)

    # Calculate success probability
    success_prob = self.model.calculate_success_probability(self.project_data)

    # Should return a probability between 0 and 1
    self.assertGreaterEqual(success_prob, 0)
    self.assertLessEqual(success_prob, 1)
```

Figure 40 – Test the success probability calculation

2025-04-06 11:18:13,993 - INFO - CulturalImpactModel initialised
Diagnostic: Communication Barrier Impacts
Barriers: 1, Impact: 1.0
Barriers: 2, Impact: 1.0
Barriers: 3, Impact: 1.0
Barriers: 4, Impact: 1.0
Barriers: 5, Impact: 1.0
.2025-04-06 11:18:14,005 - INFO - CulturalImpactModel initialised
.2025-04-06 11:18:14,017 - INFO - CulturalImpactModel initialised
.2025-04-06 11:18:14,019 - INFO - CulturalImpactModel initialised
2025-04-06 11:18:14,020 - INFO - Training model with 10 samples
2025-04-06 11:18:14,020 - INFO - Unique values in target: [0 1]
2025-04-06 11:18:14,020 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:18:14,022 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 11:18:14,022 - INFO - Categorical features: []
2025-04-06 11:18:14,026 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:18:14,026 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:18:14,027 - INFO - Using Gradient Boosting Classifier

2025-04-06 11:18:14,093 - INFO - Validation accuracy: 1.0000
2025-04-06 11:18:14,093 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 -
30\Application\ciat_march_new\cultural-impact-tool\venv\Lib\site-
packages\sklearn\model_selection_split.py:805: UserWarning: The least populated class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
2025-04-06 11:18:14,476 - INFO - Cross-validation scores: [1. 1. 1. 1. 1.]
2025-04-06 11:18:14,476 - INFO - Mean CV score: 1.0000
2025-04-06 11:18:14,485 - INFO - Model saved to
C:\Users\hcham\AppData\Local\Temp\tmp8l377lxi.pkl
2025-04-06 11:18:14,501 - INFO - CulturalImpactModel initialised
2025-04-06 11:18:14,501 - INFO - Model loaded from
C:\Users\hcham\AppData\Local\Temp\tmp8l377lxi.pkl
2025-04-06 11:18:14,501 - INFO - Making predictions for 1 instances
2025-04-06 11:18:14,504 - INFO - Making predictions for 1 instances
.2025-04-06 11:18:14,506 - INFO - CulturalImpactModel initialised
2025-04-06 11:18:14,507 - INFO - Training model with 10 samples
2025-04-06 11:18:14,508 - INFO - Unique values in target: [0 1]
2025-04-06 11:18:14,508 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:18:14,509 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 11:18:14,509 - INFO - Categorical features: []
2025-04-06 11:18:14,515 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:18:14,515 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:18:14,516 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:18:14,583 - INFO - Validation accuracy: 1.0000
2025-04-06 11:18:14,583 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 -
30\Application\ciat_march_new\cultural-impact-tool\venv\Lib\site-
packages\sklearn\model_selection_split.py:805: UserWarning: The least populated class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
2025-04-06 11:18:14,895 - INFO - Cross-validation scores: [1. 1. 1. 1. 1.]
2025-04-06 11:18:14,896 - INFO - Mean CV score: 1.0000
2025-04-06 11:18:14,896 - INFO - Making predictions for 10 instances
.2025-04-06 11:18:14,900 - INFO - CulturalImpactModel initialised
2025-04-06 11:18:14,901 - INFO - Training model with 10 samples
2025-04-06 11:18:14,901 - INFO - Unique values in target: [0 1]
2025-04-06 11:18:14,901 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:18:14,903 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 11:18:14,903 - INFO - Categorical features: []
2025-04-06 11:18:14,906 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:18:14,906 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:18:14,907 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:18:14,973 - INFO - Validation accuracy: 1.0000
2025-04-06 11:18:14,973 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 -
30\Application\ciat_march_new\cultural-impact-tool\venv\Lib\site-

```
packages\sklearn\model_selection\_split.py:805: UserWarning: The least populated class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
2025-04-06 11:18:15,268 - INFO - Cross-validation scores: [1. 1. 1. 1. 1.]
2025-04-06 11:18:15,268 - INFO - Mean CV score: 1.0000
.2025-04-06 11:18:15,270 - INFO - CulturalImpactModel initialised
.2025-04-06 11:18:15,271 - INFO - CulturalImpactModel initialised
2025-04-06 11:18:15,272 - INFO - Training model with 10 samples
2025-04-06 11:18:15,273 - INFO - Unique values in target: [0 1]
2025-04-06 11:18:15,273 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:18:15,274 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 11:18:15,275 - INFO - Categorical features: []
2025-04-06 11:18:15,278 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:18:15,278 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:18:15,279 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:18:15,343 - INFO - Validation accuracy: 1.0000
2025-04-06 11:18:15,344 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 - 30\Application\ciat_march_new\cultural-impact-tool\venv\Lib\site-packages\sklearn\model_selection\_split.py:805: UserWarning: The least populated class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
2025-04-06 11:18:15,686 - INFO - Cross-validation scores: [1. 1. 1. 1. 1.]
2025-04-06 11:18:15,686 - INFO - Mean CV score: 1.0000
.2025-04-06 11:18:15,688 - INFO - CulturalImpactModel initialised
2025-04-06 11:18:15,689 - INFO - Training model with 10 samples
2025-04-06 11:18:15,689 - INFO - Unique values in target: [0 1]
2025-04-06 11:18:15,690 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:18:15,691 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 11:18:15,692 - INFO - Categorical features: []
2025-04-06 11:18:15,695 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:18:15,696 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:18:15,697 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:18:15,761 - INFO - Validation accuracy: 1.0000
2025-04-06 11:18:15,762 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 - 30\Application\ciat_march_new\cultural-impact-tool\venv\Lib\site-packages\sklearn\model_selection\_split.py:805: UserWarning: The least populated class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
2025-04-06 11:18:16,068 - INFO - Cross-validation scores: [1. 1. 1. 1. 1.]
2025-04-06 11:18:16,068 - INFO - Mean CV score: 1.0000
2025-04-06 11:18:16,068 - INFO - Making predictions for 1 instances
.2025-04-06 11:18:16,072 - INFO - CulturalImpactModel initialised
2025-04-06 11:18:16,284 - INFO - Training model with 10 samples
2025-04-06 11:18:16,284 - INFO - Unique values in target: [0 1]
2025-04-06 11:18:16,284 - INFO - Preprocessing data with shape: (10, 9)
```

```
2025-04-06 11:18:16,286 - INFO - Numerical features: ['power_distance', 'individualism',
'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity',
'technical_requirements', 'team_size']
2025-04-06 11:18:16,286 - INFO - Categorical features: []
2025-04-06 11:18:16,290 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:18:16,290 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:18:16,291 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:18:16,355 - INFO - Validation accuracy: 1.0000
2025-04-06 11:18:16,355 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 -
30\Application\ciat_march_new\cultural-impact-tool\venv\Lib\site-
packages\sklearn\model_selection\_split.py:805: UserWarning: The least populated class in y has
only 4 members, which is less than n_splits=5.
  warnings.warn(
2025-04-06 11:18:16,651 - INFO - Cross-validation scores: [1. 1. 1. 1. 1.]
2025-04-06 11:18:16,651 - INFO - Mean CV score: 1.0000
.
----------------------------------------------------------------------
Ran 10 tests in 2.802s

OK
(venv) PS C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 -
30\Application\ciat_march_new\cultural-impact-tool> python -m unittest tests/test_unit.py
2025-04-06 11:30:33,077 - INFO - CulturalImpactModel initialised

Diagnostic: Communication Barrier Impacts
Barriers: 1, Impact: 1.0
Barriers: 2, Impact: 1.0
Barriers: 3, Impact: 1.0
Barriers: 4, Impact: 1.0
Barriers: 5, Impact: 1.0
.2025-04-06 11:30:33,090 - INFO - CulturalImpactModel initialised
.2025-04-06 11:30:33,103 - INFO - CulturalImpactModel initialised
.2025-04-06 11:30:33,104 - INFO - CulturalImpactModel initialised
2025-04-06 11:30:33,105 - INFO - Training model with 10 samples
2025-04-06 11:30:33,105 - INFO - Unique values in target: [0 1]
2025-04-06 11:30:33,105 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:30:33,107 - INFO - Numerical features: ['power_distance', 'individualism',
'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity',
'technical_requirements', 'team_size']
2025-04-06 11:30:33,107 - INFO - Categorical features: []
2025-04-06 11:30:33,111 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:30:33,111 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:30:33,112 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:30:33,180 - INFO - Validation accuracy: 1.0000
2025-04-06 11:30:33,181 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 11:30:33,453 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 11:30:33,454 - INFO - Mean CV score: 1.0000
2025-04-06 11:30:33,461 - INFO - Model saved to
C:\Users\hcham\AppData\Local\Temp\tmp6hghxozr.pkl
2025-04-06 11:30:33,477 - INFO - CulturalImpactModel initialised
```

2025-04-06 11:30:33,477 - INFO - Model loaded from
C:\Users\hcham\AppData\Local\Temp\tmp6hghxozr.pkl
2025-04-06 11:30:33,477 - INFO - Making predictions for 1 instances
2025-04-06 11:30:33,480 - INFO - Making predictions for 1 instances
.2025-04-06 11:30:33,484 - INFO - CulturalImpactModel initialised
2025-04-06 11:30:33,486 - INFO - Training model with 10 samples
2025-04-06 11:30:33,486 - INFO - Unique values in target: [0 1]
2025-04-06 11:30:33,487 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:30:33,488 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 11:30:33,488 - INFO - Categorical features: []
2025-04-06 11:30:33,491 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:30:33,492 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:30:33,492 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:30:33,528 - INFO - Validation accuracy: 1.0000
2025-04-06 11:30:33,529 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 11:30:33,529 - INFO - Using 4-fold cross-validation based on class distribution
2025-04-06 11:30:33,654 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 11:30:33,655 - INFO - Mean CV score: 1.0000, Std: 0.0000
2025-04-06 11:30:33,655 - INFO - Making predictions for 10 instances
.2025-04-06 11:30:33,659 - INFO - CulturalImpactModel initialised
2025-04-06 11:30:33,660 - INFO - Training model with 10 samples
2025-04-06 11:30:33,660 - INFO - Unique values in target: [0 1]
2025-04-06 11:30:33,660 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:30:33,662 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 11:30:33,662 - INFO - Categorical features: []
2025-04-06 11:30:33,665 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:30:33,665 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:30:33,666 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:30:33,731 - INFO - Validation accuracy: 1.0000
2025-04-06 11:30:33,732 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 11:30:33,969 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 11:30:33,970 - INFO - Mean CV score: 1.0000
.2025-04-06 11:30:33,971 - INFO - CulturalImpactModel initialised
.2025-04-06 11:30:33,973 - INFO - CulturalImpactModel initialised
2025-04-06 11:30:33,974 - INFO - Training model with 10 samples
2025-04-06 11:30:33,974 - INFO - Unique values in target: [0 1]
2025-04-06 11:30:33,974 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:30:33,975 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 11:30:33,975 - INFO - Categorical features: []
2025-04-06 11:30:33,978 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:30:33,979 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:30:33,979 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:30:34,041 - INFO - Validation accuracy: 1.0000
2025-04-06 11:30:34,041 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 11:30:34,328 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 11:30:34,328 - INFO - Mean CV score: 1.0000

```
.2025-04-06 11:30:34,330 - INFO - CulturalImpactModel initialised
2025-04-06 11:30:34,331 - INFO - Training model with 10 samples
2025-04-06 11:30:34,333 - INFO - Unique values in target: [0 1]
2025-04-06 11:30:34,333 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:30:34,335 - INFO - Numerical features: ['power_distance', 'individualism',
'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity',
'technical_requirements', 'team_size']
2025-04-06 11:30:34,335 - INFO - Categorical features: []
2025-04-06 11:30:34,339 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:30:34,340 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:30:34,340 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:30:34,407 - INFO - Validation accuracy: 1.0000
2025-04-06 11:30:34,407 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 11:30:34,644 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 11:30:34,644 - INFO - Mean CV score: 1.0000
2025-04-06 11:30:34,645 - INFO - Making predictions for 1 instances
.2025-04-06 11:30:34,649 - INFO - CulturalImpactModel initialised
2025-04-06 11:30:34,867 - INFO - Training model with 10 samples
2025-04-06 11:30:34,868 - INFO - Unique values in target: [0 1]
2025-04-06 11:30:34,868 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 11:30:34,870 - INFO - Numerical features: ['power_distance', 'individualism',
'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity',
'technical_requirements', 'team_size']
2025-04-06 11:30:34,870 - INFO - Categorical features: []
2025-04-06 11:30:34,873 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 11:30:34,874 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 11:30:34,874 - INFO - Using Gradient Boosting Classifier
2025-04-06 11:30:34,937 - INFO - Validation accuracy: 1.0000
2025-04-06 11:30:34,938 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 11:30:35,169 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 11:30:35,169 - INFO - Mean CV score: 1.0000
.
----------------------------------------------------------------------
Ran 10 tests in 2.235s

OK
(venv) PS C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 -
30\Application\ciat_march_new\cultural-impact-tool> python -m unittest tests/test_unit.py
2025-04-06 12:21:44,634 - INFO - CulturalImpactModel initialised

Diagnostic: Communication Barrier Impacts
Barriers: 1, Impact: 1.0
Barriers: 2, Impact: 1.0
Barriers: 3, Impact: 1.0
Barriers: 4, Impact: 1.0
Barriers: 5, Impact: 1.0
.2025-04-06 12:21:44,675 - INFO - CulturalImpactModel initialised
.2025-04-06 12:21:44,690 - INFO - CulturalImpactModel initialised
.2025-04-06 12:21:44,692 - INFO - CulturalImpactModel initialised
2025-04-06 12:21:44,693 - INFO - Training model with 10 samples
2025-04-06 12:21:44,697 - INFO - Unique values in target: [0 1]
2025-04-06 12:21:44,697 - INFO - Preprocessing data with shape: (10, 9)
```

2025-04-06 12:21:44,699 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 12:21:44,699 - INFO - Categorical features: []
2025-04-06 12:21:44,704 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 12:21:44,705 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 12:21:44,707 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:21:44,792 - INFO - Validation accuracy: 1.0000
2025-04-06 12:21:44,792 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 12:21:45,031 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 12:21:45,031 - INFO - Mean CV score: 1.0000
2025-04-06 12:21:45,043 - INFO - Model saved to C:\Users\hcham\AppData\Local\Temp\tmpbxfch8km.pkl
2025-04-06 12:21:45,062 - INFO - CulturalImpactModel initialised
2025-04-06 12:21:45,062 - INFO - Model loaded from C:\Users\hcham\AppData\Local\Temp\tmpbxfch8km.pkl
2025-04-06 12:21:45,063 - INFO - Making predictions for 1 instances
2025-04-06 12:21:45,066 - INFO - Making predictions for 1 instances
.2025-04-06 12:21:45,069 - INFO - CulturalImpactModel initialised
2025-04-06 12:21:45,070 - INFO - Training model with 10 samples
2025-04-06 12:21:45,071 - INFO - Unique values in target: [0 1]
2025-04-06 12:21:45,071 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 12:21:45,072 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 12:21:45,072 - INFO - Categorical features: []
2025-04-06 12:21:45,076 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 12:21:45,077 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 12:21:45,077 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:21:45,113 - INFO - Validation accuracy: 1.0000
2025-04-06 12:21:45,113 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 12:21:45,114 - INFO - Using 4-fold cross-validation based on class distribution
2025-04-06 12:21:45,239 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 12:21:45,239 - INFO - Mean CV score: 1.0000, Std: 0.0000
2025-04-06 12:21:45,239 - INFO - Making predictions for 10 instances
.2025-04-06 12:21:45,243 - INFO - CulturalImpactModel initialised
2025-04-06 12:21:45,244 - INFO - Training model with 10 samples
2025-04-06 12:21:45,244 - INFO - Unique values in target: [0 1]
2025-04-06 12:21:45,245 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 12:21:45,246 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'team_size']
2025-04-06 12:21:45,246 - INFO - Categorical features: []
2025-04-06 12:21:45,251 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 12:21:45,252 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 12:21:45,252 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:21:45,323 - INFO - Validation accuracy: 1.0000
2025-04-06 12:21:45,323 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 12:21:45,563 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 12:21:45,563 - INFO - Mean CV score: 1.0000
.2025-04-06 12:21:45,565 - INFO - CulturalImpactModel initialised
.2025-04-06 12:21:45,568 - INFO - CulturalImpactModel initialised

```
2025-04-06 12:21:45,569 - INFO - Training model with 10 samples
2025-04-06 12:21:45,569 - INFO - Unique values in target: [0 1]
2025-04-06 12:21:45,569 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 12:21:45,570 - INFO - Numerical features: ['power_distance', 'individualism',
'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity',
'technical_requirements', 'team_size']
2025-04-06 12:21:45,571 - INFO - Categorical features: []
2025-04-06 12:21:45,574 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 12:21:45,574 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 12:21:45,575 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:21:45,637 - INFO - Validation accuracy: 1.0000
2025-04-06 12:21:45,637 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 12:21:45,923 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 12:21:45,923 - INFO - Mean CV score: 1.0000
.2025-04-06 12:21:45,925 - INFO - CulturalImpactModel initialised
2025-04-06 12:21:45,927 - INFO - Training model with 10 samples
2025-04-06 12:21:45,927 - INFO - Unique values in target: [0 1]
2025-04-06 12:21:45,927 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 12:21:45,928 - INFO - Numerical features: ['power_distance', 'individualism',
'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity',
'technical_requirements', 'team_size']
2025-04-06 12:21:45,928 - INFO - Categorical features: []
2025-04-06 12:21:45,932 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 12:21:45,933 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 12:21:45,934 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:21:45,997 - INFO - Validation accuracy: 1.0000
2025-04-06 12:21:45,998 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 12:21:46,232 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 12:21:46,232 - INFO - Mean CV score: 1.0000
2025-04-06 12:21:46,233 - INFO - Making predictions for 1 instances
.2025-04-06 12:21:46,237 - INFO - CulturalImpactModel initialised
2025-04-06 12:21:46,725 - INFO - Training model with 10 samples
2025-04-06 12:21:46,726 - INFO - Unique values in target: [0 1]
2025-04-06 12:21:46,726 - INFO - Preprocessing data with shape: (10, 9)
2025-04-06 12:21:46,727 - INFO - Numerical features: ['power_distance', 'individualism',
'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity',
'technical_requirements', 'team_size']
2025-04-06 12:21:46,727 - INFO - Categorical features: []
2025-04-06 12:21:46,733 - INFO - Data preprocessing complete. Output shape: (10, 9)
2025-04-06 12:21:46,733 - INFO - Preprocessed data shape: (10, 9)
2025-04-06 12:21:46,733 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:21:46,797 - INFO - Validation accuracy: 1.0000
2025-04-06 12:21:46,798 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 12:21:47,028 - INFO - Cross-validation scores: [1. 1. 1. 1.]
2025-04-06 12:21:47,028 - INFO - Mean CV score: 1.0000
.
----------------------------------------------------------------------
Ran 10 tests in 2.561s
```

Appendix 6 – Test Performance

(venv) PS C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 - 30\Application\ciat_march_new\cultural-impact-tool> python tests/**test_performance.py**

```
def run_performance_test():
    """
    Run performance tests on the Cultural Impact Assessment Tool to evaluate:
    1. Model accuracy and predictive performance
    2. Processing time for key operations
    3. Scalability with increasing dataset size
    """
    print("CULTURAL IMPACT ASSESSMENT TOOL - PERFORMANCE TEST")
    print("=" * 60)

    # Create directories for output
    os.makedirs("temp/performance", exist_ok=True)

    # Initialise the model
    model = CulturalImpactModel()

    # 1. Predictive Performance Test
    print("\n1. Testing Predictive Performance...")
    predictive_metrics = test_predictive_performance(model)
    print_predictive_metrics(predictive_metrics)

    # 2. Processing Time Test
    print("\n2. Testing Processing Time...")
    timing_results = test_processing_time(model)
    print_timing_results(timing_results)

    # 3. Scalability Test
    print("\n3. Testing Scalability...")
    scalability_results = test_scalability(model)
    plot_scalability_results(scalability_results)

    print("\nPerformance testing completed successfully!")
```

Figure 41 – Run performance tests

CULTURAL IMPACT ASSESSMENT TOOL - PERFORMANCE TEST
==
2025-04-06 12:21:56,251 - INFO - CulturalImpactModel initialised

1. Testing Predictive Performance...
  Training model on synthetic dataset...
2025-04-06 12:21:56,261 - INFO - Training model with 700 samples
2025-04-06 12:21:56,262 - INFO - Unique values in target: [0 1]
2025-04-06 12:21:56,262 - INFO - Preprocessing data with shape: (700, 15)

2025-04-06 12:21:56,267 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'stakeholder_count', 'team_size', 'project_duration', 'virtual_team_ratio', 'language_barriers', 'communication_barriers', 'prior_collaboration']
2025-04-06 12:21:56,267 - INFO - Categorical features: []
2025-04-06 12:21:56,273 - INFO - Data preprocessing complete. Output shape: (700, 15)
2025-04-06 12:21:56,274 - INFO - Preprocessed data shape: (700, 15)
2025-04-06 12:21:56,275 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:21:56,488 - INFO - Validation accuracy: 0.8143
2025-04-06 12:21:56,488 - INFO - Precision: 0.7408, Recall: 0.8143, F1: 0.7758
2025-04-06 12:21:57,490 - INFO - Cross-validation scores: [0.81428571 0.85 0.82142857 0.83571429 0.83571429]
2025-04-06 12:21:57,491 - INFO - Mean CV score: 0.8314
Model trained in 1.23 seconds
Making predictions on test data...
2025-04-06 12:21:57,491 - INFO - Making predictions for 300 instances

Predictive Performance Metrics:
- Accuracy: 0.8633
- Precision: 0.3333
- Recall: 0.1714
- F1 Score: 0.2264
- ROC-AUC: 0.7506
- Specificity: 0.9547

Confusion Matrix:
True Negative: 253, False Positive: 12
False Negative: 29, True Positive: 6

Training Time: 1.23 seconds

2. Testing Processing Time...
Testing cultural distance calculation time...
Average cultural distance calculation: 1.90 ms
Testing communication impact calculation time...
Average communication impact calculation: 1.32 ms
Testing prediction time...
2025-04-06 12:21:57,743 - INFO - Training model with 500 samples
2025-04-06 12:21:57,744 - INFO - Unique values in target: [0 1]
2025-04-06 12:21:57,744 - INFO - Preprocessing data with shape: (500, 15)
2025-04-06 12:21:57,747 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'stakeholder_count', 'team_size', 'project_duration', 'virtual_team_ratio', 'language_barriers', 'communication_barriers', 'prior_collaboration']
2025-04-06 12:21:57,748 - INFO - Categorical features: []
2025-04-06 12:21:57,751 - INFO - Data preprocessing complete. Output shape: (500, 15)
2025-04-06 12:21:57,751 - INFO - Preprocessed data shape: (500, 15)
2025-04-06 12:21:57,752 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:21:57,931 - INFO - Validation accuracy: 0.8000
2025-04-06 12:21:57,932 - INFO - Precision: 0.7522, Recall: 0.8000, F1: 0.7712
2025-04-06 12:21:58,788 - INFO - Cross-validation scores: [0.8 0.81 0.84 0.86 0.8]
2025-04-06 12:21:58,789 - INFO - Mean CV score: 0.8220

```
2025-04-06 12:21:58,789 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,792 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,795 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,798 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,801 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,806 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,808 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,810 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,813 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,816 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,819 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,822 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,824 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,827 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,829 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,832 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,836 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,839 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,842 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,844 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,846 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,848 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,851 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,856 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,859 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,861 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,864 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,866 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,870 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,873 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,876 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,879 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,882 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,884 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,889 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,891 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,894 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,896 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,899 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,902 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,907 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,909 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,911 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,914 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,916 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,964 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,968 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,972 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,975 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,977 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,979 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,982 - INFO - Making predictions for 1 instances
```

```
2025-04-06 12:21:58,984 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,989 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,991 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,993 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,996 - INFO - Making predictions for 1 instances
2025-04-06 12:21:58,999 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,001 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,005 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,007 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,009 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,011 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,014 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,016 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,020 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,023 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,026 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,028 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,030 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,033 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,037 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,040 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,043 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,045 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,047 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,050 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,055 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,057 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,060 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,062 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,065 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,067 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,071 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,074 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,077 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,079 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,082 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,084 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,089 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,091 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,094 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,097 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,099 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,102 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,107 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,109 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,111 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,114 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,116 - INFO - Making predictions for 1 instances
  Average prediction time: 3.31 ms
  Testing recommendation generation time...
  Average recommendation generation time: 0.09 ms
```

Operation Timing Results:
- Cultural Distance Calculation: 1.90 ms
- Communication Impact Assessment: 1.32 ms
- Prediction Time: 3.31 ms
- Recommendation Generation: 0.09 ms

3. Testing Scalability...
Testing with 100 samples...
2025-04-06 12:21:59,132 - INFO - Training model with 100 samples
2025-04-06 12:21:59,133 - INFO - Unique values in target: [0 1]
2025-04-06 12:21:59,133 - INFO - Preprocessing data with shape: (100, 15)
2025-04-06 12:21:59,137 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'stakeholder_count', 'team_size', 'project_duration', 'virtual_team_ratio', 'language_barriers', 'communication_barriers', 'prior_collaboration']
2025-04-06 12:21:59,137 - INFO - Categorical features: []
2025-04-06 12:21:59,140 - INFO - Data preprocessing complete. Output shape: (100, 15)
2025-04-06 12:21:59,141 - INFO - Preprocessed data shape: (100, 15)
2025-04-06 12:21:59,141 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:21:59,254 - INFO - Validation accuracy: 1.0000
2025-04-06 12:21:59,255 - INFO - Precision: 1.0000, Recall: 1.0000, F1: 1.0000
2025-04-06 12:21:59,830 - INFO - Cross-validation scores: [1.   0.9 0.95 0.85 0.8]
2025-04-06 12:21:59,831 - INFO - Mean CV score: 0.9000
Training time for 100 samples: 0.70 seconds
2025-04-06 12:21:59,831 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,835 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,839 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,841 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,844 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,847 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,849 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,853 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,856 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,859 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,862 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,864 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,867 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,872 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,875 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,878 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,881 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,883 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,888 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,891 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,894 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,896 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,899 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,903 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,906 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,909 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,911 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,914 - INFO - Making predictions for 1 instances

2025-04-06 12:21:59,917 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,921 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,924 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,927 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,929 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,932 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,936 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,939 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,942 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,945 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,948 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,951 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,955 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,958 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,961 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,964 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,967 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,972 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,975 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,977 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,980 - INFO - Making predictions for 1 instances
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2025-04-06 12:21:59,988 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,990 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,993 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,996 - INFO - Making predictions for 1 instances
2025-04-06 12:21:59,999 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,003 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,006 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,009 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,012 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,015 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,020 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,023 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,026 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,029 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,032 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,036 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,038 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,041 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,044 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,046 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,049 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,054 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,057 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,060 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,062 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,065 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,069 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,072 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,075 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,078 - INFO - Making predictions for 1 instances

2025-04-06 12:22:00,081 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,084 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,088 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,091 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,093 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,096 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,099 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,104 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,106 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,109 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,112 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,115 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,118 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,121 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,124 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,126 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,130 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,132 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,137 - INFO - Making predictions for 1 instances
2025-04-06 12:22:00,140 - INFO - Making predictions for 1 instances
  Average prediction time: 3.11 ms
  Testing with 500 samples...
2025-04-06 12:22:00,145 - INFO - Training model with 500 samples
2025-04-06 12:22:00,145 - INFO - Unique values in target: [0 1]
2025-04-06 12:22:00,145 - INFO - Preprocessing data with shape: (500, 15)
2025-04-06 12:22:00,150 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'stakeholder_count', 'team_size', 'project_duration', 'virtual_team_ratio', 'language_barriers', 'communication_barriers', 'prior_collaboration']
2025-04-06 12:22:00,150 - INFO - Categorical features: []
2025-04-06 12:22:00,156 - INFO - Data preprocessing complete. Output shape: (500, 15)
2025-04-06 12:22:00,156 - INFO - Preprocessed data shape: (500, 15)
2025-04-06 12:22:00,157 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:22:00,357 - INFO - Validation accuracy: 0.8900
2025-04-06 12:22:00,358 - INFO - Precision: 0.8616, Recall: 0.8900, F1: 0.8664
2025-04-06 12:22:01,336 - INFO - Cross-validation scores: [0.89 0.79 0.86 0.81 0.82]
2025-04-06 12:22:01,337 - INFO - Mean CV score: 0.8340
  Training time for 500 samples: 1.19 seconds
2025-04-06 12:22:01,337 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,341 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,343 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,346 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,348 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,352 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,355 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,358 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,360 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,363 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,367 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,372 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,374 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,377 - INFO - Making predictions for 1 instances

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2025-04-06 12:22:01,380 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,384 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,387 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,390 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,393 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,395 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,398 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,403 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,406 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,408 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,411 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,413 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,418 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,421 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,424 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,427 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,430 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,434 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,439 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,442 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,445 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,447 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,451 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:01,460 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,462 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,466 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,470 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,472 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,475 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,478 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,481 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,485 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:01,496 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,499 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,502 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,505 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,508 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,511 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,513 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,518 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,521 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,524 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,527 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,530 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,537 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,540 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,543 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:01,547 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,551 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,555 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,558 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,562 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,567 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,571 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,574 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,577 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,580 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,587 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,591 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,594 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,598 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,603 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,607 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,610 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,613 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,617 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,621 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,624 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,626 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,629 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,634 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,638 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,641 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,644 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,647 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,651 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,655 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,658 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,660 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,663 - INFO - Making predictions for 1 instances
2025-04-06 12:22:01,667 - INFO - Making predictions for 1 instances
  Average prediction time: 3.32 ms
  Testing with 1000 samples...
2025-04-06 12:22:01,673 - INFO - Training model with 1000 samples
2025-04-06 12:22:01,674 - INFO - Unique values in target: [0 1]
2025-04-06 12:22:01,674 - INFO - Preprocessing data with shape: (1000, 15)
2025-04-06 12:22:01,680 - INFO - Numerical features: ['power_distance', 'individualism',
'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity',
'technical_requirements', 'stakeholder_count', 'team_size', 'project_duration', 'virtual_team_ratio',
'language_barriers', 'communication_barriers', 'prior_collaboration']
2025-04-06 12:22:01,680 - INFO - Categorical features: []
2025-04-06 12:22:01,685 - INFO - Data preprocessing complete. Output shape: (1000, 15)
2025-04-06 12:22:01,686 - INFO - Preprocessed data shape: (1000, 15)
2025-04-06 12:22:01,686 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:22:01,981 - INFO - Validation accuracy: 0.8400
2025-04-06 12:22:01,981 - INFO - Precision: 0.7970, Recall: 0.8400, F1: 0.8160
2025-04-06 12:22:03,361 - INFO - Cross-validation scores: [0.84  0.81  0.88  0.87  0.855]
2025-04-06 12:22:03,361 - INFO - Mean CV score: 0.8510
  Training time for 1000 samples: 1.69 seconds
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2025-04-06 12:22:03,362 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,366 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,369 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,372 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,375 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,377 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,380 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,384 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,387 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,390 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,393 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,396 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,399 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,402 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,405 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,409 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,411 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,414 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,417 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,420 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,423 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,425 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,428 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,432 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,436 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,439 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,442 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,444 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:03,482 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,485 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,488 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,490 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,493 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,495 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,500 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,503 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,506 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,509 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,511 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,513 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:03,520 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,523 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:03,536 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,539 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,541 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,544 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,547 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,551 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,554 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,557 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,559 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,562 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:03,576 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,578 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,582 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,585 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,587 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:03,613 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,618 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,620 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,623 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,625 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,627 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,631 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,634 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,637 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:03,645 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,649 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,652 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,655 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,658 - INFO - Making predictions for 1 instances
2025-04-06 12:22:03,661 - INFO - Making predictions for 1 instances
  Average prediction time: 3.01 ms
  Testing with 2000 samples...
2025-04-06 12:22:03,667 - INFO - Training model with 2000 samples
2025-04-06 12:22:03,668 - INFO - Unique values in target: [0 1]

```
2025-04-06 12:22:03,668 - INFO - Preprocessing data with shape: (2000, 15)
2025-04-06 12:22:03,677 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'stakeholder_count', 'team_size', 'project_duration', 'virtual_team_ratio', 'language_barriers', 'communication_barriers', 'prior_collaboration']
2025-04-06 12:22:03,677 - INFO - Categorical features: []
2025-04-06 12:22:03,683 - INFO - Data preprocessing complete. Output shape: (2000, 15)
2025-04-06 12:22:03,684 - INFO - Preprocessed data shape: (2000, 15)
2025-04-06 12:22:03,684 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:22:04,146 - INFO - Validation accuracy: 0.8450
2025-04-06 12:22:04,146 - INFO - Precision: 0.8035, Recall: 0.8450, F1: 0.8140
2025-04-06 12:22:06,415 - INFO - Cross-validation scores: [0.845  0.82   0.8075 0.84   0.86  ]
2025-04-06 12:22:06,415 - INFO - Mean CV score: 0.8345
  Training time for 2000 samples: 2.75 seconds
2025-04-06 12:22:06,416 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,420 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,423 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,426 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,428 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,432 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,434 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,437 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,440 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,443 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,447 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,450 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,453 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,456 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,459 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,462 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,466 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,469 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,471 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,474 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,477 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,481 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,484 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,487 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,489 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,492 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,495 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,499 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,502 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,505 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,507 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,509 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,515 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,518 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,520 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,523 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,526 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,530 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:06,534 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,537 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,539 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,542 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,544 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,549 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,552 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,554 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,557 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,560 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,566 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,569 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,571 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,574 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,576 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,581 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,585 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,587 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,590 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,593 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,597 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,600 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,603 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,605 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,608 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,611 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,617 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,619 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,622 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,624 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,627 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,631 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,634 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,637 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,640 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,642 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,646 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,650 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,652 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,655 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,658 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,661 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,665 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,668 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,671 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,673 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,676 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,680 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,683 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,686 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,688 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,691 - INFO - Making predictions for 1 instances

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2025-04-06 12:22:06,694 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,699 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,701 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,704 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,707 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,709 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,715 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,718 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,720 - INFO - Making predictions for 1 instances
2025-04-06 12:22:06,723 - INFO - Making predictions for 1 instances
  Average prediction time: 3.09 ms
  Testing with 5000 samples...
2025-04-06 12:22:06,731 - INFO - Training model with 5000 samples
2025-04-06 12:22:06,731 - INFO - Unique values in target: [0 1]
2025-04-06 12:22:06,732 - INFO - Preprocessing data with shape: (5000, 15)
2025-04-06 12:22:06,756 - INFO - Numerical features: ['power_distance', 'individualism',
'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity',
'technical_requirements', 'stakeholder_count', 'team_size', 'project_duration', 'virtual_team_ratio',
'language_barriers', 'communication_barriers', 'prior_collaboration']
2025-04-06 12:22:06,756 - INFO - Categorical features: []
2025-04-06 12:22:06,760 - INFO - Data preprocessing complete. Output shape: (5000, 15)
2025-04-06 12:22:06,761 - INFO - Preprocessed data shape: (5000, 15)
2025-04-06 12:22:06,762 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:22:07,670 - INFO - Validation accuracy: 0.8610
2025-04-06 12:22:07,670 - INFO - Precision: 0.8232, Recall: 0.8610, F1: 0.8188
2025-04-06 12:22:12,047 - INFO - Cross-validation scores: [0.862 0.847 0.85  0.855 0.835]
2025-04-06 12:22:12,048 - INFO - Mean CV score: 0.8498
  Training time for 5000 samples: 5.32 seconds
2025-04-06 12:22:12,048 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,052 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,054 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,058 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,061 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,064 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,067 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,069 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,071 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,077 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,080 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,083 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,085 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,088 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,091 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,095 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,098 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,100 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,102 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,105 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,110 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,113 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,116 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,119 - INFO - Making predictions for 1 instances
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2025-04-06 12:22:12,121 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,124 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,128 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,131 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,133 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,136 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,139 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,145 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,148 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,152 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,155 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,160 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,163 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,166 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,168 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,171 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,174 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,178 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,181 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,184 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,187 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,190 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,194 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,197 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,199 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,202 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,204 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,209 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,212 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,215 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,218 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,221 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,228 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,234 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,239 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,247 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,252 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,257 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,264 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,268 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,272 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,275 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,278 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,282 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,286 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,290 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,294 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,298 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,303 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,307 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,311 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,315 - INFO - Making predictions for 1 instances

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2025-04-06 12:22:12,318 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,321 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,326 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,329 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,333 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,337 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,341 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,345 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,349 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,352 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,356 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,360 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,364 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,368 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,371 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,376 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,381 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,385 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,389 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,396 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,401 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,407 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,413 - INFO - Making predictions for 1 instances
2025-04-06 12:22:12,419 - INFO - Making predictions for 1 instances
  Average prediction time: 3.79 ms
  Scalability results plot saved to temp/performance/scalability_results.png

Performance testing completed successfully!
```

Appendix 7 – Test integration

(venv) PS C:\Users\hcham\Desktop\Essex\8. MSc Computing Project\Unit 9 - 30\Application\ciat_march_new\cultural-impact-tool> **python tests/test_integration.py**

```
CULTURAL IMPACT ASSESSMENT TOOL - INTEGRATION TEST
============================================================

1. Initialising Cultural Impact Model...
2025-04-06 12:22:21,976 - INFO - CulturalImpactModel initialised
  Model initialised successfully.

2. Loading test data...
  Loaded Hofstede data for 10 countries.
  Loaded training data with 100 samples.
  Loaded test project data.

3. Testing cultural distance calculation...
  Cultural distances between countries:
  - United States to United Kingdom: 1.0163
  - United States to China: 4.6386
  - Germany to France: 3.4571
  - Nigeria to South Africa: 3.8265
  - South Africa to France: 2.7517

4. Training the model...
2025-04-06 12:22:21,992 - INFO - Training model with 100 samples
2025-04-06 12:22:21,992 - INFO - Unique values in target: [0 1]
2025-04-06 12:22:21,993 - INFO - Preprocessing data with shape: (100, 15)
2025-04-06 12:22:21,995 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'stakeholder_count', 'team_size', 'project_duration', 'virtual_team_ratio', 'language_barriers', 'communication_barriers', 'prior_collaboration']
2025-04-06 12:22:21,996 - INFO - Categorical features: []
2025-04-06 12:22:22,001 - INFO - Data preprocessing complete. Output shape: (100, 15)
2025-04-06 12:22:22,001 - INFO - Preprocessed data shape: (100, 15)
2025-04-06 12:22:22,002 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:22:22,112 - INFO - Validation accuracy: 0.7500
2025-04-06 12:22:22,113 - INFO - Precision: 0.7353, Recall: 0.7500, F1: 0.7204
2025-04-06 12:22:22,113 - INFO - Using 5-fold cross-validation based on class distribution
2025-04-06 12:22:22,635 - INFO - Cross-validation scores: [0.75 0.8  0.75 0.85 0.75]
2025-04-06 12:22:22,635 - INFO - Mean CV score: 0.7800, Std: 0.0400
  Model trained successfully.

5. Calculating communication impact...
  Communication impact score: 1.0000

6. Assessing regional impact...
  Regional impact assessment:
  - Europe: Experience Level = High, Risk Level = Low
  - North America: Experience Level = Unknown, Risk Level = High
  - Asia-Pacific: Experience Level = Unknown, Risk Level = High
```

```
7. Identifying risk factors...
2025-04-06 12:22:22,640 - INFO - Training model with 100 samples
2025-04-06 12:22:22,640 - INFO - Unique values in target: [0 1]
2025-04-06 12:22:22,640 - INFO - Preprocessing data with shape: (100, 15)
2025-04-06 12:22:22,642 - INFO - Numerical features: ['power_distance', 'individualism', 'masculinity', 'uncertainty_avoidance', 'long_term_orientation', 'indulgence', 'project_complexity', 'technical_requirements', 'stakeholder_count', 'team_size', 'project_duration', 'virtual_team_ratio', 'language_barriers', 'communication_barriers', 'prior_collaboration']
2025-04-06 12:22:22,642 - INFO - Categorical features: []
2025-04-06 12:22:22,645 - INFO - Data preprocessing complete. Output shape: (100, 15)
2025-04-06 12:22:22,646 - INFO - Preprocessed data shape: (100, 15)
2025-04-06 12:22:22,647 - INFO - Using Gradient Boosting Classifier
2025-04-06 12:22:22,757 - INFO - Validation accuracy: 0.7500
2025-04-06 12:22:22,757 - INFO - Precision: 0.7353, Recall: 0.7500, F1: 0.7204
2025-04-06 12:22:23,269 - INFO - Cross-validation scores: [0.75 0.8  0.75 0.85 0.75]
2025-04-06 12:22:23,269 - INFO - Mean CV score: 0.7800
  Top 5 risk factors:
  1. num__individualism: 0.2147
  2. num__uncertainty_avoidance: 0.2105
  3. num__indulgence: 0.1439
  4. num__team_size: 0.1015
  5. num__long_term_orientation: 0.0959

8. Calculating project success probability...
2025-04-06 12:22:23,271 - INFO - Making predictions for 1 instances
  Success probability: 0.0004

9. Generating recommendations...
  Recommendations:
  1. Focus on team cohesion through virtual team-building and regular check-ins.
  2. Review and revise project plan to address cultural impact factors.
  3. Consider bringing in cultural experts or consultants for high-risk areas.

10. Testing model persistence...
2025-04-06 12:22:23,284 - INFO - Model saved to temp/ciat_model.pkl
  Model saved to temp/ciat_model.pkl
2025-04-06 12:22:23,306 - INFO - CulturalImpactModel initialised
2025-04-06 12:22:23,307 - INFO - Model loaded from temp/ciat_model.pkl
  Model loaded successfully.
2025-04-06 12:22:23,307 - INFO - Making predictions for 1 instances
2025-04-06 12:22:23,310 - INFO - Making predictions for 1 instances
  Original model prediction: 0.0004
  Loaded model prediction: 0.0004

11. Testing visualisation functions...
  Cultural dimensions visualisation saved to temp/cultural_dimensions.png
  Risk factors visualisation saved to temp/risk_factors.png

Integration test completed successfully!
```

Appendix 8 – GitHub Repositories

CIAT Repository: https://github.com/hchamane/CIAT

CSV files repository: https://github.com/hchamane/CIAT/tree/main/ciat/data

Test images generated: https://github.com/hchamane/CIAT/tree/main/temp