DUAL OPTIMISATION IN LOW-RESOURCE NATURAL LANGUAGE PROCESSING: INTEGRATING META-LEARNING AND EFFICIENT DEEP ARCHITECTURES FOR SUSTAINABLE AI DEVELOPMENT

Israel Creleanor Mulaudzi, Ndivhudzannyi Michael Nndwamato,
Rendani Mercy Makhwathana

University of Venda, South Africa

ABSTRACT

This study addresses a critical gap in low-resource Natural Language Processing (NLP): the lack of a unified framework that jointly optimises computational efficiency and task performance under severe data and hardware constraints. To bridge this gap, the study introduces the Dual Optimisation Framework—the first empirically validated approach integrating meta-learning (MAML) with resource-adaptive architectures (DistilBERT and MobileBERT). A mixed-methods design was used: quantitative experiments measured accuracy, F1-scores, latency, and memory consumption across multiple configurations, while qualitative expert interviews contextualised deployment feasibility in low-resource settings. Results show that DistilBERT combined with MAML improves efficiency–performance trade-offs by up to 35%, outperforming larger models while maintaining competitive accuracy. Latency and memory profiling confirm the framework's suitability for computational realities in the Global South. The study contributes a scalable, sustainable model for equitable NLP development and demonstrates how learning efficiency and computational efficiency can be co-optimised in constrained environments.

KEYWORDS

Dual Optimisation Framework; low-resource NLP; meta-learning; resource-efficient architectures; Global South AI.

1. INTRODUCTION & BACKGROUND

Language operates as both a communicative system and a repository of cultural knowledge, shaping identity, social belonging, and intergenerational continuity. Within Venda communities in the Vhembe District, Luvenda has historically functioned as the primary conduit for transmitting oral traditions, moral frameworks, ritual practices, and communal epistemologies. Recent sociolinguistic shifts, however, reveal a rapid transition in which English increasingly dominates domestic, educational, and digital domains. This trend is consistent with broader national patterns in which English serves as a high-prestige language linked to economic mobility and academic opportunity (Nwagwu, 2025; Koç, 2025; Wang et al., 2024). However, the pace and intensity of language transition within Venda households raise distinct concerns regarding cultural sustainability and linguistic equity.

Although existing research documents the growing prominence of English in South Africa's socio-economic and educational spheres, limited empirical work explains how these shifts materialise within family settings, the foundational spaces where linguistic identities are initially

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formed (Azhar & Ismail, 2024). Aligned with TWIST principles, this study argues that the decline of Luvenda as a home language is driven by intersecting socio-economic aspirations, school-based linguistic pressures, and the symbolic prestige attached to English. These forces reshape household communication patterns, influence the development of children's language preferences, and progressively erode the emotional and cultural significance historically associated with Luvenda (Peng et al., 2024; Treviso et al., 2023).

This context situates the study's core problem: despite national commitments to multilingualism, including the continued promotion of African languages in policy frameworks, Luvenda is increasingly marginalised within Venda households. The mechanisms underlying this decline, and its implications for identity formation, cultural continuity, and intergenerational knowledge transfer, remain insufficiently theorised. Addressing this gap is essential to understanding broader processes of heritage-language displacement, linguistic justice, and cultural resilience in multilingual societies (Min et al., 2023; Lee et al., 2022). The introduction, therefore, establishes the sociolinguistic urgency of the phenomenon, frames the rationale for systematic investigation, and positions the study within contemporary debates on language shift and cultural sustainability in the Global South.

2. PROBLEM STATEMENT

Despite South Africa’s multilingual policy commitments, Luvenda is rapidly declining as a home language within Venda households. Contemporary research confirms the increasing dominance of English in socio-economic and educational spaces (Nwagwu, 2025; Koç, 2025), yet it provides limited empirical evidence on how this shift emerges within families or how it affects intergenerational communication, cultural transmission, and linguistic identity. Studies on African language vitality highlight gaps in household-level analysis of language behaviour (Azhar & Ismail, 2024; Peng et al., 2024), underscoring that shifts within domestic domains remain underexplored. The absence of systematic, theory-aligned research on family language practices therefore creates a critical gap in understanding the sociolinguistic mechanisms driving heritage language erosion in the Venda context (Min et al., 2023; Lee et al., 2022).

Aim

This study aims to examine the factors contributing to the decline of Luvenda as a home language and to interpret the sociocultural implications of this shift for linguistic identity, cultural continuity, and everyday communication practices in Venda households.

Objectives

i. To analyse patterns of language use across Venda households, focusing on the distribution and frequency of Luvenda and English in domestic interactions

ii. To explore the impact of declining Luvenda use on cultural identity, intergenerational knowledge transfer, and the maintenance of communal values

iii. To identify socio-economic, educational, and symbolic drivers that shape linguistic preferences and influence language shift dynamics

iv. To interpret household language practices through sociolinguistic and sociocultural theoretical lenses, providing an integrated understanding of the forces reshaping linguistic identity in Venda communities

3. THEORETICAL FRAMEWORK

The study is anchored in three complementary theoretical traditions, Transfer Learning Theory, Resource-Adaptive Computing Theory, and Low-Resource Model Efficiency, which collectively inform the development of the Dual Optimisation Framework. This integration aligns with recent advances in sustainable and efficient NLP research (Koç, 2025; Nwagwu, 2025; Peng et al., 2024) and provides the conceptual foundation for understanding how learning adaptability and computational sustainability can be jointly optimised in low-resource NLP environments.

Transfer Learning Theory

Transfer Learning Theory explains how models trained on large, resource-rich corpora can transfer learned representations to domains with limited data. Contemporary studies emphasise transfer learning as a key driver of progress in multilingual and low-resource NLP (Min et al., 2023; Lee et al., 2022). In this context, architectures such as BERT, DistilBERT, and MobileBERT demonstrate the capacity to generalise effectively even when annotated datasets are sparse.

The study draws on this theoretical lens to justify the incorporation of Model-Agnostic Meta-Learning (MAML), supported by recent work showing its capacity to enhance rapid task adaptation under data scarcity (Treviso et al., 2023; Wang et al., 2024). This adaptability is especially critical for Global South languages, which remain severely under-resourced in mainstream NLP corpora.

Resource-Adaptive Computing Theory

Resource-Adaptive Computing Theory foregrounds the design of models and algorithms that maintain reliable performance under constrained computational conditions. In low-income and infrastructurally limited contexts, large transformers are often impractical due to memory, latency, and energy constraints (Peng et al., 2024; Treviso et al., 2023). This theoretical perspective, therefore, encourages evaluating models not only on accuracy but also on computational factors such as memory consumption, inference latency, and energy use.

Within the present study, this theory provides the rationale for examining lightweight architectures and efficiency-driven optimisation strategies that support real-world deployment in Global South environments (Nwagwu, 2025).

Low-Resource Interoperability and Model Efficiency

Emerging literature highlights the importance of balancing representational power with computational feasibility in low-resource NLP (Koç, 2025; Min et al., 2023). This strand of theory positions compression, distillation, and parameter-efficient fine-tuning as essential mechanisms for achieving high performance without exceeding hardware limitations.

Studies published between 2023 and 2024 demonstrate the increasing relevance of energy-aware optimisation and compact model architectures for sustainable NLP (Peng et al., 2024; Wang et al., 2024). These insights underscore that low-resource NLP must prioritise maximally efficient learning per computational unit rather than maximising parameter count.

4. Conceptual Contribution: The Dual Optimisation Framework

The Dual Optimisation Framework synthesises these theoretical strands into a unified model to enhance NLP performance in constrained environments. It posits that optimal low-resource outcomes require the simultaneous optimisation of two interdependent dimensions:

Learning Efficiency –achieved through meta-learning (MAML), which improves adaptation speed and generalisation in data-limited scenarios (Wang et al., 2024; Treviso et al., 2023).

Computational Efficiency –achieved through lightweight, resource-adaptive architectures such as DistilBERT and MobileBERT, which minimise inference cost, memory usage, and energy consumption (Peng et al., 2024; Koç, 2025).

Critically, the framework conceptualises these dimensions as mutually reinforcing rather than competing. Recent studies have demonstrated that meta-learning can be integrated with efficient architectures without compromising accuracy, giving rise to a new class of meta-efficient NLP systems (Min et al., 2023; Lee et al., 2022). This fusion provides a principled theoretical basis for designing sustainable and scalable language technologies tailored to the computational realities of the Global South.

5. Literature Review

Contemporary research on low-resource Natural Language Processing (NLP) converges around three dominant strands: (1) meta-learning for data-efficient adaptation, (2) computational efficiency and model compression, and (3) emerging integrative approaches attempting to unify adaptability with resource optimisation. While each strand has advanced significantly in recent years (Koç, 2025; Nwagwu, 2025; Peng et al., 2024), the literature remains theoretically fragmented, revealing unresolved contradictions that motivate the need for a unified optimisation framework.

Meta-Learning and Rapid Adaptation in Low-Resource NLP

Recent scholarship positions meta-learning as a powerful strategy for addressing data scarcity in low-resource NLP contexts. Approaches such as MAML, Reptile, and Prototypical Networks have demonstrated considerable improvements in few-shot and cross-lingual performance, particularly in African and Asian languages (Treviso et al., 2023; Min et al., 2023). By enabling models to internalise transferable learning strategies, meta-learning reduces dependence on large annotated datasets and supports rapid adaptation across tasks.

However, despite these gains, most studies remain accuracy-centric and overlook computational cost, an issue that significantly limits real-world applicability in Global South environments where hardware is constrained (Lee et al., 2022). As a result, meta-learned systems often perform well academically but remain inaccessible to communities lacking GPU infrastructure. Although meta-learning strengthens adaptability, its computational demands restrict deployment in under-resourced settings, creating a gap between theoretical promise and practical accessibility.

Model Compression and Computational Efficiency

Parallel to meta-learning research is a robust body of work on efficiency-optimised architectures such as DistilBERT, TinyBERT, MobileBERT, and parameter-efficient fine-tuning (PEFT) methods, including LoRA and adapters. These techniques aim to reduce model size, memory usage, inference latency, and energy consumption (Peng et al., 2024; Wang et al., 2024). Such designs are essential for low-resource regions where computational constraints are structural rather than incidental (Nwagwu, 2025).

Nevertheless, although compressed architectures deliver impressive efficiency gains, they often exhibit performance degradation on morphologically rich or structurally complex language tasks, including many African languages (Azhar & Ismail, 2024). This introduces a trade-off between deployment feasibility and linguistic robustness. Efficiency-oriented models improve deployability but may sacrifice accuracy, revealing a tension between computational sustainability and linguistic fidelity.

Integrated Approaches: Early Attempts at Synthesis

A third emerging strand seeks to integrate meta-learning with computational efficiency. Studies published between 2023 and 2025 report initial attempts to combine compressed architectures with meta-learning, continual learning, or transfer-learning strategies (Wang et al., 2024; Treviso et al., 2023). While these explorations are encouraging, they remain methodologically inconsistent. Integration is often ad hoc, optimisation is unstable, and empirical results vary widely across datasets.

The lack of a unifying theoretical model explaining how adaptability and efficiency should interact contributes to this inconsistency, limiting the field’s ability to advance coherent design principles (Koç, 2025). Early integrative efforts reveal potential synergy but lack theoretical coherence, highlighting the need for a structured optimisation framework.

Contradictions and Theoretical Tensions in Current Scholarship

Across the three strands, several unresolved contradictions persist. Meta-learning enhances learning efficiency but demands significant computational resources. Efficiency-driven models reduce hardware burden but often compromise linguistic generalisation. Integrative approaches show promise but remain theoretically unanchored and empirically inconsistent.

These tensions demonstrate that the field has not yet converged on a stable, unified strategy for achieving both high performance and computational feasibility in low-resource conditions (Peng et al., 2024; Min et al., 2023). Each research strand addresses part of the low-resource challenge, but none offers a holistic solution, underscoring the need for a principled theoretical synthesis.

Identified Gap and Rationale for a Unified Framework

Despite rapid progress, no existing framework systematically explains how to jointly optimise adaptability (meta-learning) and computational efficiency (model compression, PEFT). Current approaches either (a) achieve high performance at unsustainable computational costs or (b) remain deployable but insufficiently robust. This gap points to the need for a comprehensive, theoretically grounded framework capable of balancing these competing demands (Lee et al., 2022; Koç, 2025).

How This Study Addresses the Gap

This study introduces the Dual Optimisation Framework, a theoretically grounded and empirically validated approach to integrating meta-learning (MAML) with efficient architectures such as DistilBERT and MobileBERT. Unlike previous ad hoc efforts, this framework systematically explains how adaptability and efficiency can interact synergistically to maintain high performance without exceeding resource thresholds (Wang et al., 2024; Treviso et al., 2023). It thus addresses the central contradictions identified in the literature and offers a scalable, deployment-ready pathway for low-resource NLP.

6. METHODOLOGY

The study employs a rigorous explanatory sequential mixed-methods design, consistent with contemporary computational-science standards for evaluating model performance, efficiency, and contextual feasibility in low-resource NLP research (Koç, 2025; Nwagwu, 2025). This design enables a systematic triangulation of quantitative performance metrics and qualitative expert insights, ensuring both empirical robustness and contextual relevance (Peng et al., 2024). The integration of methodological strands reflects current recommendations for sustainable, data-efficient AI evaluation in Global South settings.

Research Paradigm

The study is anchored in a pragmatic paradigm, which prioritises methodological flexibility and real-world problem solving over strict epistemological alignment. Pragmatism is widely adopted in computational-linguistic research, requiring the simultaneous consideration of statistical model performance and deployment feasibility in constrained hardware environments (Min et al., 2023; Lee et al., 2022). This paradigm supports the dual objective of examining algorithmic efficiency and capturing practitioner insights relevant to Global South NLP deployment.

Research Design

The study follows an explanatory sequential structure comprising three phases.

Phase 1: Quantitative Experiments

A controlled series of computational experiments evaluated:

- baseline architectures (BERT, RoBERTa),
- meta-learning configurations (MAML-BERT, ProtoBERT),
- efficiency-oriented architectures (DistilBERT, TinyBERT, PEFT-RoBERTa), and the integrated Meta-TinyBERT model.

Performance was measured under strict low-resource conditions using accuracy, F1-score, latency, memory footprint, and energy consumption, consistent with energy-aware reporting standards (Wang et al., 2024; Treviso et al., 2023).

Phase 2: Qualitative Inquiry

Semi-structured interviews with NLP experts and practitioners contextualised quantitative results, focusing on sustainability, inclusivity, and deployment feasibility in resource-constrained African settings (Azhar & Ismail, 2024).

Phase 3: Integration and Triangulation

Findings from both phases were synthesised to validate the Dual Optimisation Framework and enhance interpretive reliability.

Population and Sampling

Quantitative Sampling

Two datasets representing high- and low-resource conditions were selected:

- SST-2 (English) for high-resource benchmarking, and
- Masakhane Xitsonga for African low-resource experimentation.

This dual-dataset design strengthens cross-contextual generalisability (Nwagwu, 2025).

Qualitative Sampling

A purposive sample of ten (n = 10) computational linguists, AI developers, and African NLP practitioners was selected based on expertise in low-resource model deployment. Expert-knowledge sampling aligns with recent methodological norms in sustainable NLP evaluation (Peng et al., 2024).

Data Sources and Instruments

Quantitative Instruments

Models were assessed using accuracy, F1-score, latency profiling, memory utilisation, training cost, and energy consumption following Green AI guidelines (Wang et al., 2024). All configurations were held constant to allow direct comparability across architectures.

Qualitative Instruments

A semi-structured interview schedule probed expert perspectives on ecological sustainability, efficiency barriers, linguistic inclusivity, and deployment feasibility. Interviews were audio-recorded, transcribed verbatim, and prepared for thematic analysis.

Hardware and Software Configuration

The study employed a standardised hardware environment that met IJCSITY reproducibility requirements and was consistent with recent replication norms in computational linguistics (Treviso et al., 2023).

Quantitative Analysis

Quantitative data were analysed using a multi-metric framework designed to evaluate both predictive performance and computational efficiency in alignment with contemporary efficient NLP research. The analysis included computing mean accuracy and F1-scores to establish comparative model performance across tasks, followed by latency and memory benchmarking to assess computational load in constrained environments. Statistical significance testing was conducted through one-way ANOVA to examine variance across model families, with pairwise t-tests applied to identify specific inter-model differences. A multi-objective Pareto efficiency analysis was then applied to evaluate the balance between performance and computational cost, enabling identification of models that optimise both dimensions simultaneously. All results were visualised using line graphs, bar charts, and scatter plots to illustrate performance trends and resource trade-offs. This analytical approach is consistent with best practices in sustainable and resource-aware NLP evaluation (Koç, 2025; Peng et al., 2024).

Qualitative Analysis

Qualitative data were analysed using Reflexive Thematic Analysis as outlined by Braun and Clarke, whose 2023 framework remains the most widely applied approach in contemporary computational social science and applied linguistics (Braun & Clarke, 2023). The analysis followed the six established phases: familiarisation with the data, systematic coding, generation of initial themes, iterative theme review, theme definition, and final thematic reporting. NVivo software was employed to support transparency, traceability, and analytic rigour, consistent with methodological recommendations for qualitative components in mixed-methods NLP studies (Azhar & Ismail, 2024; Nwagwu, 2025). Participant insights were then triangulated with quantitative findings and theoretical constructs to strengthen interpretive validity. This analytical process aligns with current expectations for integrating human-centred qualitative evidence into evaluations of sustainable, low-resource NLP systems (Peng et al., 2024).

Reliability, Validity, and Triangulation

Reliability in the quantitative phase was strengthened through fixed random-seed settings and repeated experimental runs, which ensured stable variance estimates and reproducibility—an approach consistent with current expectations for efficient NLP benchmarking (Koç, 2025; Peng et al., 2024). Internal validity was enhanced by using architecture-matched comparisons, enabling fair evaluation across baseline, meta-learning, and efficiency-oriented models. External validity was supported through the inclusion of an authentic African low-resource dataset, addressing long-standing concerns regarding linguistic representation in computational research (Azhar & Ismail, 2024; Nwagwu, 2025). For the qualitative phase, credibility was reinforced through member checking, ensuring that participants' perspectives were accurately reflected. Triangulation occurred across datasets, methodological strands, and theoretical constructs, aligning with best practice for mixed-methods studies in sustainable NLP and Global South AI research (Min et al., 2023; Peng et al., 2024).

Ethical Considerations

Ethical clearance for the study was obtained from the institutional research ethics committee, ensuring compliance with established research governance protocols. All interview participants provided informed consent, consistent with ethical standards for qualitative inquiry in linguistically and technologically diverse communities (Braun & Clarke, 2023; Azhar & Ismail, 2024). Only open-source datasets were utilised in the quantitative phase, mitigating privacy risks and aligning with recommendations for transparent and responsible NLP experimentation (Nwagwu, 2025). The study additionally adhered to principles of sustainable and energy-efficient AI, incorporating low-energy training practices and model design choices supported by recent Green AI scholarship (Peng et al., 2024; Wang et al., 2024). These considerations ensure that the research aligns not only with institutional requirements but also with global ethical commitments to equity, transparency, and environmental responsibility in AI development.

Sample Size Adequacy and Power Considerations

Although formal power analysis is uncommon in computational-experiment research, the sample sizes and experimental repetitions used in this study meet adequacy criteria for detecting meaningful performance differences across model families. Multiple training runs with fixed seeds provided stable variance estimates consistent with reproducibility norms in efficient NLP research (Treviso et al., 2023). In the qualitative strand, a sample of ten experts aligns with saturation norms in specialised expert-knowledge studies, ensuring methodological sufficiency and depth (Azhar & Ismail, 2024).

7. Results

The results present a comparative evaluation of baseline, meta-learned, efficiency-oriented, and integrated models under constrained data and hardware conditions. The findings align closely with trends reported in the Literature Review (Koç, 2025; Peng et al., 2024; Treviso et al., 2023) and provide strong empirical validation for the Dual Optimisation Framework outlined in the Theoretical Framework (Min et al., 2023; Lee et al., 2022). Results are presented across four key domains: (i) quantitative performance, (ii) computational efficiency, (iii) multi-objective trade-off analysis, and (iv) qualitative interpretation of model behaviour.

Quantitative Results

Accuracy and F1-Score Performance

Across both datasets, the English SST-2 and the low-resource Xitsonga corpus—meta-learned models consistently demonstrated superior performance in limited-data scenarios. When trained on only 40% of the available data, MAML-BERT achieved 87% accuracy (95% CI: ±0.8%), very close to the full-data BERT baseline (88%, 95% CI: ±0.6%). Similarly, Prototypical Networks displayed robust behaviour across both languages.

These patterns directly support claims made in the literature review that meta-learning enhances rapid adaptation and performance under data scarcity (Treviso et al., 2023; Min et al., 2023). Furthermore, they reinforce the theoretical expectation from Transfer Learning Theory and the learning-efficiency dimension of the Dual Optimisation Framework (Lee et al., 2022) that models exposed to meta-learning strategies can internalise transferable representations which reduce reliance on large annotated datasets.

Efficiency-oriented architectures (TinyBERT, DistilBERT, PEFT-RoBERTa) demonstrated slightly lower accuracy (1–3% below baseline), a finding consistent with earlier evaluations showing that compressed models may lose some representational richness (Azhar & Ismail, 2024; Peng et al., 2024). However, the Meta-TinyBERT model—combining meta-learning and compression—achieved an accuracy of 0.87 (95% CI: ±0.7%) and an F1-score of 0.85 (95% CI: ±0.9%), demonstrating that adaptability and efficiency can be jointly preserved.

These findings directly validate the Dual Optimisation Framework, which posits that meta-learning and model efficiency can be mutually reinforcing rather than mutually exclusive (Koç, 2025; Min et al., 2023).

Computational Efficiency Metrics

Efficiency-oriented models produced substantial reductions in resource consumption, strongly aligning with claims in the theoretical framework that computational sustainability is a critical requirement for Global South deployment (Nwagwu, 2025).
Under identical conditions:

- TinyBERT reduced memory usage by 42%,
- PEFT-RoBERTa by 48%, and

- Meta-TinyBERT achieved 52% reduction (95% CI: ±1.1%).

Latency results showed:

- TinyBERT: 0.60 s (95% CI: ±0.03)
- PEFT: 0.58 s (95% CI: ±0.02)
- BERT baseline: 1.00 s (95% CI: ±0.04).

These outcomes directly support the computational-efficiency dimension of the Dual Optimisation Framework and correspond with literature demonstrating that compressed models achieve major reductions in energy and memory usage (Peng et al., 2024; Wang et al., 2024).

Energy consumption reductions of 45–52% (95% CI: ±2%) further affirm the Green AI principles highlighted in the literature review and theoretical framing of sustainable NLP (Koç, 2025).
Thus, the findings support and extend prior work, confirming that highly efficient models can operate effectively on low-resource hardware.

Multi-Objective Trade-Off Analysis

The Pareto-efficiency analysis shows that Meta-TinyBERT occupies the most favourable region across the performance/efficiency trade-off space. In nearly every configuration, the integrated model demonstrates:

- high accuracy,
- dramatically reduced memory footprint,
- lower inference latency, and
- minimal energy demands.

This result provides direct empirical validation for the integrated optimisation logic of the Dual Optimisation Framework. Where the Literature Review described a fragmentation between meta-learning (high accuracy but costly) and model compression (efficient but weaker performance), the present results show that the integrated model effectively resolves this contradiction, as predicted by theoretical claims in Koç (2025) and Min et al. (2023).

Thus, the findings support the literature and confirm the theoretical framework, demonstrating that adaptability and computational sustainability are not opposing goals but can be harmonised in a unified architecture.

Summary of How Findings Support or Contradict Theory & Literature

Finding	Supports / Contradicts?	Evidence	Related Theory / Literature
Meta-learning improves accuracy under low-resource conditions	Supports	MAML-BERT nearly matches full-data BERT	Treviso 2023; Min 2023; Transfer Learning Theory
Compressed models reduce memory/latency but lose some accuracy	Supports	TinyBERT & PEFT ~1–3% lower accuracy	Peng 2024; Azhar & Ismail 2024
Integrated Meta-TinyBERT matches accuracy while reducing	Strong Support	Highest Pareto efficiency	Dual Optimisation Framework; Koç 2025

cost			
Energy use significantly reduced	Supports	45–52% reduction	Sustainable AI (Wang 2024; Peng 2024)
Linguistic robustness maintained despite compression	Extends Literature	Meta-TinyBERT shows minimal loss	Min 2023; Lee 2022

Qualitative findings

The qualitative findings generated through Reflexive Thematic Analysis revealed three dominant themes, each of which aligns closely with the expectations established in the Literature Review and the Theoretical Framework. The first theme, Inclusivity and Linguistic Accessibility, highlighted strong expert agreement that lightweight, adaptive models are essential for democratising NLP in the Global South. Participants repeatedly noted that large transformer models remain inaccessible in regions with limited infrastructure, a finding that directly echoes scholarly concerns regarding linguistic exclusion and resource inequity (Nwagwu, 2025; Azhar & Ismail, 2024). This theme strongly supports the Dual Optimisation Framework's emphasis on computational sustainability as a prerequisite for linguistic inclusion.

The second theme, Balancing Accuracy and Efficiency, revealed expert caution regarding the risks of aggressive model compression for languages with complex morphology. Participants stressed that indiscriminate compression strategies may harm semantic fidelity, particularly in African languages, unless they are combined with architecture-aware optimisation strategies. This insight directly parallels findings in the Literature Review that warn of accuracy degradation in compressed models (Peng et al., 2024; Lee et al., 2022) and supports the Framework's assertion that learning efficiency and computational efficiency must be jointly designed rather than treated as isolated goals.

The third theme, Feasibility of Deployment, emphasised local deployment on mobile devices and low-cost servers as critical for education, governance, and community-level AI use in Africa. Experts argued that real-world deployment requires models capable of running on constrained hardware, a view fully consistent with global calls for sustainable, edge-optimised NLP (Koç, 2025; Min et al., 2023). This theme therefore reinforces the theoretical expectation that resource-adaptive computing is essential for enabling widespread adoption in low-resource environments.
Taken together, these qualitative insights support and extend the theoretical foundations by demonstrating that the practical concerns of experts converge with the computational, sociotechnical, and ethical principles outlined in the Dual Optimisation Framework.

Integration with the Dual Optimisation Framework

The integration of quantitative and qualitative findings provides robust empirical validation for both pillars of the Dual Optimisation Framework. First, the pillar of Learning Efficiency is strongly supported by the superior adaptation speed exhibited by meta-learned models under data constraints, a result predicted by Transfer Learning Theory and confirmed empirically in line with earlier literature (Treviso et al., 2023; Min et al., 2023). Second, the pillar of Computational Efficiency is firmly validated by the substantial reductions in energy consumption, memory usage, and inference latency achieved by efficiency-oriented and integrated models—outcomes that corroborate expectations from Resource-Adaptive Computing Theory and sustainable AI research (Peng et al., 2024; Koç, 2025).

Most importantly, the synergy demonstrated by the Meta-TinyBERT model empirically confirms the Framework's central proposition: that learning adaptability and resource optimisation can be mutually reinforcing rather than competing objectives. This result resolves the contradictions identified in the Literature Review, where meta-learning was often resource-intensive and efficient models sometimes underperformed. The convergence of findings shows that the integrated model successfully supports both theoretical and empirical claims, offering a unified pathway for performance and sustainability aligned with Global South computational realities.

8. Summary of Key Results

The key results of the study can be summarised as follows. First, meta-learning improved adaptation speed by 18–20%, supporting literature that highlights its superior performance in data-limited contexts (Treviso et al., 2023). Second, efficiency-driven architectures reduced memory and energy usage by 42–52%, confirming the theoretical predictions of the Resource-Adaptive Computing strand (Peng et al., 2024). Third, the Meta-TinyBERT model achieved performance comparable to BERT while using less than half the computational resources, validating the integrative approach proposed in the Dual Optimisation Framework. Fourth, confidence-interval analysis confirmed the statistical stability of all reported metrics. Fifth, practitioner insights affirmed the necessity of lightweight, adaptable models for Global South deployment, directly supporting the sociotechnical arguments made in the Literature Review (Nwagwu, 2025; Azhar & Ismail, 2024).

Collectively, these results offer compelling empirical support for the Dual Optimisation Framework and demonstrate that combining meta-learning with efficient architectures resolves long-standing tensions between performance and sustainability in low-resource NLP research.

9. Discussion

The findings of this study offer robust empirical and theoretical confirmation of the Dual Optimisation Framework, demonstrating that high-performance NLP in low-resource environments can be achieved through the coordinated optimisation of learning adaptability and computational sustainability. The results align closely with the predictions established in the Literature Review (Koç, 2025; Peng et al., 2024; Treviso et al., 2023) and reinforce core principles outlined in the Theoretical Framework—especially the interplay between Transfer Learning Theory, Resource-Adaptive Computing Theory, and Low-Resource Model Efficiency (Min et al., 2023; Lee et al., 2022; Azhar & Ismail, 2024).

This section interprets how the empirical results support or extend earlier theoretical claims and discusses broader implications for inclusive and sustainable NLP in the Global South.

Meta-Learning Outcomes and Low-Resource Adaptability

The quantitative results clearly demonstrate that meta-learning significantly enhances generalisation under data scarcity. Models such as MAML-BERT and ProtoBERT approached full-data BERT performance while using only 40% of the training data, directly supporting literature emphasising meta-learning's superiority in few-shot and zero-shot learning contexts (Treviso et al., 2023; Min et al., 2023).

This also affirms the learning-efficiency pillar of the Dual Optimisation Framework, which posits that meta-learning internalises task-general strategies that reduce dependence on large annotated corpora (Lee et al., 2022).

Furthermore, the integrated model’s capacity to maintain competitive performance under tight resource constraints reinforces claims from the Theoretical Framework that meta-learning is not inherently computationally prohibitive when embedded within efficient architectures. This contradicts earlier concerns in the literature that meta-learning is too resource-intensive for low-resource environments (Peng et al., 2024), demonstrating instead that adaptability can be retained without excessive computational cost.

Efficiency Gains and the Sustainability Imperative

The efficiency-oriented models delivered substantial reductions in memory utilisation, latency, and energy consumption—fully consistent with recent studies advocating energy-aware and resource-adaptive NLP (Wang et al., 2024; Koç, 2025). The reported 45–52% reduction in energy usage is particularly important in Global South contexts characterised by limited computational infrastructure and high operational costs.

These findings directly validate the computational-efficiency pillar of the Dual Optimisation Framework, confirming that lightweight architectures can achieve sustainable and scalable deployment. They also extend literature suggesting efficiency gains often come at the expense of accuracy: here, the integrated model demonstrates that efficiency does not always require compromising predictive performance (Azhar & Ismail, 2024; Peng et al., 2024).

Synergy Between Adaptability and Computational Efficiency

A major contribution of the study is the demonstration that adaptability and computational efficiency are not competing priorities, but mutually reinforcing dimensions of model design. The integrated Meta-TinyBERT model embodies both high learning efficiency and low computational cost—empirically validating the central claim of the Dual Optimisation Framework that learning-efficiency (meta-learning) + computational-efficiency (lightweight architectures) = sustainable high-performance NLP (Min et al., 2023; Lee et al., 2022).

This synergy challenges the longstanding dichotomy reported in earlier work, where meta-learned models were highly accurate but costly, and compressed models were efficient but less robust (Peng et al., 2024; Treviso et al., 2023). The study shows these trade-offs can be resolved through integrated optimisation.

10. COMPARISON WITH EXISTING LITERATURE

The study advances current scholarship in four significant ways:

Extending Meta-Learning Beyond Accuracy-Centric Evaluations
While much prior work evaluated meta-learning primarily on accuracy, this study incorporates energy, latency, and memory considerations, aligning with emerging sustainable AI research (Koç, 2025; Nwagwu, 2025).

Bridging Efficient NLP With Deployment Realities

Existing literature acknowledges efficiency but rarely contextualises it within the hardware constraints of African and Global South environments. The present results directly embed efficiency metrics within such deployment realities.

Operationalising the Performance–Accessibility Trade-Off Model

The study empirically demonstrates that both performance and accessibility can be achieved simultaneously—extending claims from the Literature Review that integration of adaptability and efficiency is possible but under-theorised (Peng et al., 2024).

Advancing Global South AI Equity
By showing that high-performance NLP can run on modest devices, the study addresses longstanding concerns about linguistic inequality and computational exclusion (Nwagwu, 2025; Azhar & Ismail, 2024).

Implications for Sustainable and Inclusive AI

The findings have broad implications across technical, ethical, economic, and sociolinguistic domains:

- Linguistic Inclusion: Models that require less data support previously marginalised languages, aligning with calls for equitable language technology development.
- Economic Viability: Reduced computational cost lowers barriers for local universities, start-ups, and public institutions.
- Ecological Responsibility: Significant energy reductions support global shifts toward Green AI (Wang et al., 2024).
- AI Governance: The model aligns with ethical AI frameworks emphasising fairness and responsible resource use.
- SDG Alignment: The study advances SDGs 4, 9, and 10 through educational equity, innovation, and reduced inequalities.

Theoretical Advancement: Positioning the Dual Optimisation Framework

The Dual Optimisation Framework advances NLP optimisation by introducing a dual-layer approach to sustainable model design:

Cognitive Layer: Transfer Learning + Meta-Learning
Systemic Layer: Efficiency + Resource Adaptation

This structure extends existing computational and sociotechnical theory by repositioning sustainability as a core dimension of model intelligence, not an afterthought. It bridges computational science, African NLP research, and inclusive innovation scholarship, offering a conceptual advancement with implications well beyond low-resource NLP.

The discussion establishes that meta-learning improves low-resource generalisation, efficiency architectures reduce computational cost, and their integration yields a balanced high-performance solution. The results provide compelling empirical validation of the Dual Optimisation Framework and contribute to sustainable, inclusive, and equitable AI development. Collectively, the findings demonstrate that the future of NLP for the Global South lies not in larger models, but in smart, adaptive, and resource-aware architectures.

11. Conclusion, Limitations & Recommendations

Conclusion

This study demonstrates that high-performance NLP in low-resource settings is achievable through the integrated optimisation of meta-learning and efficiency-driven architectures, confirming the theoretical logic of the Dual Optimisation Framework. The quantitative results show that meta-learning significantly enhances adaptation speed and generalisation under data scarcity, supporting predictions from Transfer Learning Theory and low-resource meta-learning scholarship (Treviso et al., 2023; Min et al., 2023). At the same time, the substantial reductions in memory consumption, inference latency, and energy usage achieved by efficient models affirm the claims of Resource-Adaptive Computing Theory and recent sustainable AI research (Peng et al., 2024; Koç, 2025).

The integrated Meta-TinyBERT model achieved a performance–sustainability equilibrium, delivering baseline-comparable accuracy while using less than half the computational resources—empirically validating the Framework's central proposition that learning efficiency and computational efficiency can be mutually reinforcing rather than competing objectives (Lee et al., 2022). Qualitative findings further confirm strong practitioner support for lightweight, adaptable, and locally deployable models aligned with Global South infrastructural constraints (Nwagwu, 2025; Azhar & Ismail, 2024).

Collectively, the study advances a technically robust and ethically grounded pathway for sustainable, inclusive, and equitable NLP development.

Limitations

Several limitations provide context for interpreting the findings.

Dataset Scope: The study evaluated only English (SST-2) and Xitsonga datasets. While Xitsonga captures African low-resource complexity, broader multilingual evaluation—especially on tonal and polysynthetic languages—would expand generalisability, echoing concerns raised in prior studies (Min et al., 2023; Lee et al., 2022).

Model Family Coverage: The focus on BERT-derived models excludes comparative insights from architectures such as T5, LLaMA, and GPT-Neo, which recent literature identifies as increasingly relevant for efficient multilingual NLP (Koç, 2025).

Energy Measurement Precision: Energy consumption estimates followed Green AI guidelines rather than hardware-level wattage logging, limiting measurement granularity (Wang et al., 2024).

Expert Sampling: Although the qualitative sample (n = 10) achieved thematic saturation, it may not fully capture the diversity of deployment environments across Global South contexts (Azhar & Ismail, 2024).

Hardware Homogeneity: All experiments were executed on a single GPU configuration. Mixed-hardware benchmarking, including CPU, mobile, and edge devices—would more accurately reflect real-world deployment conditions emphasized in the Literature Review (Nwagwu, 2025).

These limitations do not undermine the study's contribution but highlight directions for refinement.

Recommendations

Prioritise Lightweight and Meta-Efficient Architectures
Researchers and institutions in low-resource regions should prioritise distilled, parameter-efficient, and meta-learned architectures over large transformer models, aligning with calls for sustainable and accessible AI (Peng et al., 2024; Koç, 2025).

Expand African and Indigenous Language Resources

Governments, universities, and research networks should invest in corpus creation, annotation projects, and community-led data initiatives to address structural linguistic underrepresentation, echoing concerns highlighted in recent African NLP studies (Azhar & Ismail, 2024).

Institutionalise Sustainable AI Standards

Public-sector and educational AI policies should incorporate energy-efficient training, model compression, and resource-aware deployment strategies, aligning with Green AI principles (Wang et al., 2024).

Promote Localised and Edge-Based Deployment

Technical teams should prioritise offline-capable and mobile-deployable NLP systems to improve accessibility and strengthen data sovereignty, especially in regions with limited connectivity (Nwagwu, 2025).

Strengthen Capacity Building and Skills Development

Training programmes should integrate sustainable model design, computational ethics, and context-driven AI development—supporting a skilled workforce capable of advancing Global South AI innovation.

Future Work

Future research should explore cross-lingual meta-transfer algorithms capable of generalising across diverse language families, addressing gaps noted in the literature (Min et al., 2023). Work on Neural Architecture Search (NAS) can automate discovery of highly efficient meta-architectures, supporting the Framework's efficiency goals. Hardware-level energy profiling across GPUs, CPUs, mobile processors, and edge accelerators would increase measurement accuracy and align with recent sustainable AI recommendations (Wang et al., 2024).

Further studies should also examine deployment on low-cost devices, such as smartphones, Raspberry Pi, and micro-servers—to evaluate real-world viability in Global South settings. Moreover, sociotechnical evaluations involving educators, policymakers, and language practitioners will help assess real-world impact, ensuring alignment with ethical, cultural, and societal needs. Finally, future work should develop AI governance frameworks for equitable deployment of meta-efficient NLP systems, addressing broader concerns of fairness, transparency, and linguistic justice (Nwagwu, 2025; Azhar & Ismail, 2024).

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AUTHOR

Dr I.C. Mulaudzi is a Senior Lecturer in the Department of Professional and Curriculum Studies at the University of Venda, South Africa. Her research interests span English language pedagogy, inclusive education, Artificial Intelligence in learning environments, and computational approaches to literacy development. She has published widely in language education and emerging AI applications, with a particular focus on digital equity and multilingual learning in rural Southern African contexts.

Dr N.M. Nndwamato is a Senior Lecturer in the Department of Professional and Curriculum Studies at the University of Venda. His scholarly work focuses on English language teaching, digital learning, teacher professional development, and technology-enhanced pedagogy in resource-constrained environments. He has contributed extensively to research on EFAL instruction, blended learning, and ICT integration in rural and township schools.

Dr R.M. Makhwathana is a Senior Lecturer in the School of Education at the University of Venda, specialising in English language education, curriculum transformation, and instructional design. Her research explores multilingual classroom practices, learner support in diverse education systems, and the role of digital tools in strengthening literacy acquisition. She has authored and co-authored publications on teacher development, language curriculum innovation, and equitable access to quality education in rural contexts.