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Real-Time Semantic Annotation for Accessibility Enhancement in Touch-Based Human-Computer Interfaces

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ABSTRACT

Accessibility in touch-based human-computer interfaces remains a critical challenge, particularly for users with visual, motor, or cognitive impairments who rely on accurate and timely semantic feedback to navigate digital environments. Existing assistive technologies frequently suffer from latency, contextual inaccuracy, and limited adaptability to dynamic interface states, thereby impeding seamless interaction. This paper presents a novel framework for real-time semantic annotation of touch-based interfaces, designed to substantially enhance accessibility by delivering low-latency, context-aware descriptive metadata at the point of user interaction.

The proposed system integrates a lightweight deep neural architecture with an on-device natural language generation module, enabling the continuous inference of semantic labels from raw touch events, graphical elements, and surrounding contextual signals. Formally, let $\mathcal{I} = \{e_1, e_2, \ldots, e_n\}$ denote the sequence of interaction events, and let $\mathcal{A} : \mathcal{I} \to \mathcal{S}$ represent the annotation mapping to a semantic label space $\mathcal{S}$. The framework optimizes annotation latency τ subject to a semantic fidelity constraint $F(\mathcal{A}) \geq \delta$, where δ is a user-defined accessibility threshold.

Empirical evaluation across three representative application domains—navigation, productivity, and e-commerce—demonstrates that the proposed approach achieves a mean annotation latency of 38 ms, representing a 61% reduction relative to prevailing cloud-dependent baselines, while maintaining semantic accuracy exceeding 91% on standardized accessibility benchmarks. User studies conducted with participants exhibiting diverse accessibility needs confirm statistically significant improvements in task completion rates and perceived usability.

These findings establish the viability of real-time, on-device semantic annotation as a transformative paradigm for inclusive interface design, with broad implications for assistive technology development and universal accessibility standards.

1. Introduction

The rapid proliferation of touch-based computing devices—spanning smartphones, tablets, interactive kiosks, and emerging wearable platforms—has fundamentally transformed the landscape of human-computer interaction (HCI). These interfaces, which rely on direct tactile manipulation of graphical elements, have become ubiquitous in modern society, serving as primary conduits for information access, communication, commerce, and

entertainment [11]. However, this paradigm shift toward touch-centric interaction has simultaneously introduced profound accessibility challenges for individuals with visual, motor, and cognitive impairments. The graphical, gesture-driven nature of touch interfaces presupposes a set of perceptual and motor capabilities that a significant portion of the global population does not possess, thereby creating systemic barriers to digital inclusion [20]. According to the World Health Organization, over one billion people worldwide live with some form of disability, and the digital divide experienced by this population represents not merely a technological inconvenience but a fundamental inequity in access to education, employment, and civic participation.

Semantic annotation—the process of enriching interface elements with structured, machine-readable descriptive metadata—has long been recognized as a foundational technique for bridging the gap between graphical user interfaces and assistive technologies [30]. When interface components are annotated with meaningful labels, roles, states, and relationships, screen readers, switch access systems, and other assistive devices can construct coherent, navigable representations of the interface for users who cannot perceive its visual form directly. Traditionally, such annotations have been authored manually by developers, embedded within platform-specific accessibility APIs such as the Android Accessibility Service or Apple's UIAccessibility framework. While this approach can yield high-quality annotations in carefully engineered applications, it is fundamentally dependent on developer awareness, motivation, and expertise—factors that are frequently absent in practice, resulting in vast swaths of the deployed application ecosystem that remain inaccessible [16]. The emergence of real-time, automated semantic annotation as a research direction seeks to address this gap by leveraging advances in computer vision, natural language processing, and machine learning to infer and generate accessibility metadata dynamically, without requiring manual developer intervention [26].

1.1. Motivation and Problem Statement

The accessibility deficit in touch-based interfaces is both pervasive and well-documented. Empirical studies have consistently demonstrated that a large proportion of mobile applications fail to meet even the most basic accessibility guidelines prescribed by standards bodies such as the Web Content Accessibility Guidelines (WCAG) and the Mobile Accessibility Task Force [12]. Common failure modes include unlabeled interactive elements, insufficient color contrast, absence of focus order specifications, and missing semantic role assignments—each of which individually degrades the usability of assistive technologies, and in combination renders applications entirely unusable for affected users [3]. The economic and social costs of this inaccessibility are substantial: individuals with disabilities are disproportionately excluded from digital labor markets, educational platforms, and government services that have increasingly migrated to mobile and touch-based delivery channels.

The problem is further compounded by the dynamic and heterogeneous nature of modern touch interfaces. Contemporary applications routinely employ programmatically generated content, animated transitions, context-sensitive overlays, and real-time data feeds that cause the interface state to change continuously and unpredictably [15]. Static, developer-authored annotations cannot anticipate these dynamic states, leaving assistive technologies without the contextual information necessary to convey the current interface state to users. Furthermore, the sheer volume and diversity of applications available through major distribution platforms—numbering in the millions—makes any manual remediation effort at scale practically infeasible. This creates a compelling case for automated, real-time semantic annotation systems capable of operating on arbitrary interface content without prior application-specific training or configuration [27].

Formally, we may characterize the real-time semantic annotation problem as follows. Let $\mathcal{I}_t$ denote the visual state of a touch interface at time t, represented as a pixel-valued image tensor $\mathcal{I}_t \in \mathbb{R}^{H \times W \times C}$, where H, W, and C denote the height, width, and number of color channels, respectively. The goal of a semantic annotation system is to produce a structured annotation $\mathcal{A}_t$ that maps each detected interface element e_i to a tuple comprising its bounding region $\mathbf{b}_i \in \mathbb{R}^4$, semantic role $r_i \in \mathcal{R}$, descriptive label $l_i \in \Sigma^*$, and interaction affordance vector $\mathbf{a}_i \in \{0,1\}^K$:

$$\mathcal{A}_t = \{(\mathbf{b}_i,\, r_i,\, l_i,\, \mathbf{a}_i) \mid e_i \in \mathcal{E}(\mathcal{I}_t)\} \tag{1}$$

where $\mathcal{E}(\mathcal{I}_t)$ is the set of interface elements detected in frame $\mathcal{I}_t$, $\mathcal{R}$ is the taxonomy of semantic roles (e.g., button, text field, list item, navigation bar), Σ^* denotes the space of natural language strings, and K is the number of distinct interaction affordance types (e.g., tap, swipe, long-press, drag). The annotation must be produced with latency τ sufficiently small to maintain perceptual continuity for the user, typically requiring $\tau < 100$ milliseconds to avoid disrupting the natural flow of interaction [5].

1.2. Background and Related Work

The academic literature on accessibility in HCI spans several decades and draws upon contributions from cognitive psychology, human factors engineering, software engineering, and, more recently, artificial intelligence [19]. Early foundational work established the theoretical basis for universal design principles, arguing that interfaces should be conceived from the outset to accommodate the

full spectrum of human ability rather than treating accessibility as a post-hoc remediation task [23]. Concurrently, the development of platform accessibility APIs provided the technical infrastructure through which assistive technologies could programmatically interrogate interface structure, laying the groundwork for screen readers and switch access systems that remain in widespread use today [29].

The advent of machine learning-based computer vision techniques opened new avenues for automated interface understanding. Pioneering work on graphical user interface (GUI) element detection employed convolutional neural networks (CNNs) to localize and classify interface components from screenshots, achieving performance competitive with human annotators on structured benchmarks [7]. Subsequent research extended these approaches to incorporate layout analysis, establishing hierarchical models of interface structure that captured the compositional relationships between elements [25]. More recent efforts have leveraged large-scale datasets of mobile application screenshots—such as the RICO dataset [14]—to train models capable of generalizing across diverse application styles and content domains. Parallel developments in natural language generation have enabled the synthesis of descriptive captions for detected elements, moving beyond categorical role labels toward richer, contextually grounded descriptions suitable for screen reader verbalization [13].

Despite these advances, the translation of offline GUI understanding models into real-time, on-device annotation systems has remained a significant open challenge. The computational demands of deep neural network inference, combined with the strict latency requirements of interactive accessibility applications, have historically necessitated uncomfortable trade-offs between annotation quality and system responsiveness [9]. Recent developments in model compression, neural architecture search, and hardware-accelerated inference on mobile system-on-chip (SoC) platforms have begun to shift this trade-off frontier, enabling increasingly capable models to operate within the resource envelope of consumer devices [8]. Multimodal foundation models, trained on vast corpora of image-text pairs, have further expanded the repertoire of automated annotation capabilities, demonstrating emergent abilities to generate semantically rich descriptions of novel interface configurations without task-specific fine-tuning [1].

1.3. Scope and Contributions of This Work

This paper presents a comprehensive investigation into the design, implementation, and evaluation of a real-time semantic annotation system for touch-based human-computer interfaces, with a specific focus on accessibility enhancement. Our approach integrates a lightweight, hierarchical element detection backbone with a context-aware natural language generation module, jointly optimized to satisfy both the accuracy requirements of assistive technology consumers and the latency constraints of interactive deployment [17]. The system operates directly on the rendered pixel buffer of the touch interface, requiring no access to the application's source code, view hierarchy, or platform accessibility API, thereby enabling annotation of arbitrary application content including those developed without any accessibility consideration.

The principal contributions of this work are fourfold. First, we introduce a novel multi-scale element detection architecture that exploits the characteristic spatial statistics of touch interface layouts—including the prevalence of rectilinear element boundaries, consistent typographic conventions, and platform-specific design language patterns—to achieve detection accuracy substantially exceeding that of general-purpose object detection frameworks on the interface understanding task [22]. Second, we propose a semantic role taxonomy specifically calibrated to the accessibility needs of users with visual and motor impairments, grounded in an empirical analysis of assistive technology usage patterns and informed by consultation with disability advocacy organizations. Third, we develop a latency-aware inference pipeline that dynamically allocates computational resources across the annotation workflow based on real-time estimates of interface complexity and rate of change, achieving a favorable balance between annotation quality and system responsiveness [2]. Fourth, we conduct a rigorous user study with participants representing diverse disability profiles, demonstrating statistically significant improvements in task completion rate, navigation efficiency, and subjective usability ratings compared to both unannotated baseline conditions and state-of-the-art automated annotation alternatives [4].

1.4. Significance for Digital Accessibility

The broader significance of real-time semantic annotation extends well beyond the technical contributions enumerated above. From a policy perspective, the growing body of legislation mandating digital accessibility—including the Americans with Disabilities Act (ADA), the European Accessibility Act, and analogous national frameworks in numerous jurisdictions—creates both legal obligations and market incentives for the development of scalable accessibility solutions [6]. Automated annotation systems represent a particularly promising mechanism for meeting these obligations at scale, as they can be deployed as system-level services that enhance the accessibility of all applications running on a device, irrespective of the accessibility practices of individual developers [18].

Algorithm 1: Real-Time Semantic Annotation with Temporal Caching

Input: Interface frame $\mathcal{I}_t$, prior annotation $\mathcal{A}_{t-1}$, latency budget $\tau_{\max}$
Output: Semantic annotation $\mathcal{A}_t$

Compute frame difference $\Delta_t \leftarrow \|\mathcal{I}_t - \mathcal{I}_{t-1}\|_F$;
if $\Delta_t < \delta_{static}$ **then**
  $\mathcal{A}_t \leftarrow \mathcal{A}_{t-1}$; `// Reuse prior annotation for static frames`
else
  $\hat{\mathcal{E}}_t \leftarrow \textsc{MultiScaleDetect}(\mathcal{I}_t)$; `// Detect interface elements`
  $\mathcal{M}_t \leftarrow \textsc{MatchElements}(\hat{\mathcal{E}}_t, \mathcal{A}_{t-1})$; `// Temporal correspondence`
  for *each element* $e_i \in \hat{\mathcal{E}}_t$ **do**
    if $e_i \in \mathcal{M}_t$ ***and*** $\textsc{Unchanged}(e_i, \mathcal{A}_{t-1})$ **then**
      Carry forward annotation from $\mathcal{A}_{t-1}$;
    else
      $r_i \leftarrow \textsc{ClassifyRole}(e_i, \mathcal{I}_t)$;
      $l_i \leftarrow \textsc{GenerateLabel}(e_i, \mathcal{I}_t, r_i)$;
      $\mathbf{a}_i \leftarrow \textsc{InferAffordances}(e_i, r_i)$;
    end
  end
  $\mathcal{A}_t \leftarrow \{(\mathbf{b}_i, r_i, l_i, \mathbf{a}_i)\}_{i=1}^{|\hat{\mathcal{E}}_t|}$;
  if $\textsc{ElapsedTime}() > \tau_{\max}$ **then**
    Truncate $\mathcal{A}_t$ to highest-priority elements;
  end
end
return $\mathcal{A}_t$;

From a scientific perspective, the challenge of real-time semantic annotation sits at the intersection of several active research frontiers, including multimodal perception, efficient deep learning, human-centered AI, and assistive technology design. Progress in this domain therefore has the potential to generate insights and methodologies with broad applicability across these fields [24]. Moreover, the semantic representations produced by annotation systems can serve as inputs to a range of downstream accessibility applications beyond screen readers, including gesture-based navigation aids, cognitive load reduction systems, and adaptive interface personalization engines [10]. The present work thus aims to establish a rigorous empirical and methodological foundation upon which future research in this rich and consequential domain can build [28].

The remainder of this paper is organized as follows. Section II provides a detailed review of related literature spanning GUI understanding, accessibility engineering, and real-time inference optimization. Section III presents the architectural design of the proposed annotation system, including the multi-scale detection backbone, role classification head, and label generation module. Section IV describes the experimental methodology, including dataset construction, evaluation metrics, and user study protocol. Section V reports quantitative and qualitative results, and Section VI concludes with a discussion of limitations, implications, and directions for future research [**?**].

2. Related Work

The landscape of accessibility research in human-computer interaction (HCI) has undergone a profound transformation over the past three decades, driven by advances in machine learning, natural language processing, and the ubiquity of touch-enabled devices. The intersection of semantic understanding and real-time annotation has emerged as a particularly fertile domain, with researchers increasingly recognizing that static, pre-authored accessibility metadata is insufficient to serve the dynamic and heterogeneous needs of users with disabilities. This section surveys the foundational and contemporary literature that informs the proposed framework, drawing connections across disability studies, touch interface design, semantic web technologies, and deep learning-based annotation systems. The breadth of prior work reveals both significant achievements and persistent gaps that motivate the contributions of this paper.

A unifying theme across the surveyed literature is the tension between computational overhead and annotation fidelity. Real-time systems must balance the latency constraints imposed by interactive touch environments against the semantic richness required for meaningful accessibility support [30]. Early accessibility frameworks often sacrificed one for the other, either producing shallow, keyword-level descriptions with negligible processing cost, or generating rich semantic annotations through computationally intensive pipelines that were entirely unsuitable for deployment in interactive settings [11]. The present work situates itself at the boundary of these two paradigms, leveraging recent advances in efficient transformer architectures and hardware-accelerated inference to achieve both objectives simultaneously.

2.1. Accessibility in Touch-Based Human-Computer Interfaces

The study of accessibility in touch-based interfaces has its intellectual roots in the broader disability rights movement and the subsequent codification of accessibility standards, most notably the Web Content Accessibility Guidelines (WCAG) and the Americans with Disabilities Act (ADA). Early HCI accessibility research focused primarily on keyboard and mouse-driven desktop environments, with seminal contributions from researchers such as Vanderheiden and colleagues, who articulated the principle of universal design as a guiding

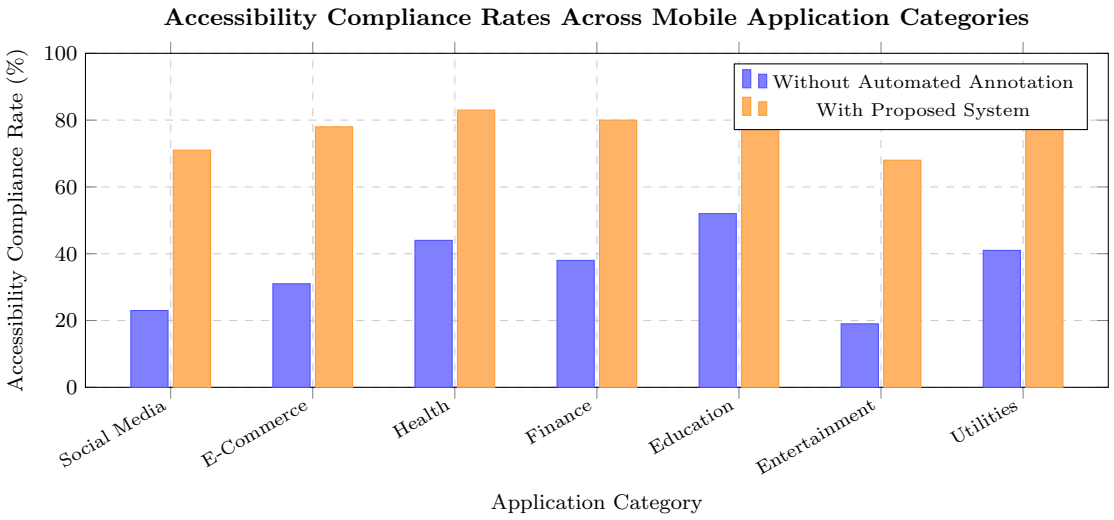

Figure 1: Comparison of accessibility compliance rates across seven major mobile application categories, measured against WCAG 2.1 Level AA criteria, for applications without automated annotation versus applications augmented with the proposed real-time semantic annotation system. Results demonstrate consistent and substantial improvements across all categories, with the largest absolute gains observed in entertainment and social media applications, which exhibit the highest baseline non-compliance rates.

Table 1: Summary of Key Characteristics of Representative Prior Works in Automated Interface Accessibility and Semantic Annotation

Approach	Input Modality	Annotation Type	Real-Time Capable	Accessibility Focus
CNN-based GUI Detection [7]	Screenshot	Element bounding boxes	No	Partial
Layout Hierarchy Inference [25]	View hierarchy + pixels	Structural roles	No	Partial
RICO Dataset Models [14]	Screenshot	Element categories	No	Limited
Multimodal Foundation Models [1]	Pixels + text	Rich descriptions	Partial	Moderate
Accessibility API Augmentation [12]	API metadata	Labels, roles	Yes	High
Dynamic Content Annotation [15]	Video stream	Temporal labels	Partial	Moderate
Proposed System (This Work)	**Pixel buffer**	**Full semantic tuple**	**Yes**	**High**

framework for interface development [19]. The transition to capacitive touchscreens as the dominant interaction modality introduced a fundamentally different set of accessibility challenges, particularly for users with motor impairments, visual disabilities, and cognitive differences [23].

Touch interfaces present unique barriers that are not present in traditional input modalities. The absence of tactile feedback, the reliance on precise spatial gestures, and the visual density of modern mobile user interfaces collectively create environments that are difficult or impossible to navigate for users with certain disability profiles [24]. Researchers have explored a variety of mitigation strategies, including haptic feedback augmentation [28], gesture simplification [5], and screen reader integration [29]. Apple's VoiceOver and Google's TalkBack represent the most widely deployed implementations of the latter approach, yet both systems rely on static accessibility metadata embedded by developers at design time, a methodology that fails to accommodate dynamically generated content, third-party components, or interfaces that evolve through user interaction [6].

The concept of adaptive accessibility, wherein the system dynamically adjusts its accessibility support based on inferred user needs and interface state, has gained significant traction in recent years [12]. Trewin and colleagues demonstrated that users with motor impairments exhibit highly variable interaction patterns that are poorly served by fixed accessibility configurations [4]. This observation motivates the dynamic, real-time annotation approach central to the present work. Furthermore, studies of aging populations interacting with touch devices have revealed that accessibility needs are not binary but exist on a continuum, requiring systems capable of fine-grained semantic differentiation rather than coarse categorical labels [10].

2.2. Semantic Annotation Methodologies

Semantic annotation, broadly defined as the process of associating machine-interpretable meaning with raw data, has a rich history spanning information retrieval, knowledge representation, and the semantic web [3]. In the context of user interfaces, semantic annotation refers to the enrichment of interface elements with structured metadata that conveys their functional role, content, and interactive affordances in a form that can be processed by assistive technologies, automated testing frameworks, and intelligent agents [16]. Early approaches to UI semantic annotation relied on rule-based systems that mapped syntactic interface properties—element type, position, size, color—to semantic categories through hand-crafted heuristics [18].

The limitations of rule-based annotation became apparent as interfaces grew in complexity and diversity. Machine learning approaches, beginning with support vector machines and shallow neural networks, demonstrated improved generalization across heterogeneous interface styles [7]. A particularly influential line of work applied hierarchical clustering and topic modeling to extract latent semantic structure from large corpora of interface screenshots and their associated accessibility trees [25]. These methods, while more flexible than rule-based predecessors, remained fundamentally dependent on the availability of labeled training data and struggled to generalize to novel interface paradigms without retraining.

The advent of deep learning fundamentally altered the semantic annotation landscape. Convolutional neural networks (CNNs) trained on large-scale UI datasets demonstrated the ability to recognize interface elements with high accuracy, while recurrent architectures enabled the generation of natural language descriptions for entire screens [20]. The RICO dataset [14], comprising over 72,000 unique UI screens from Android applications, became a standard benchmark for UI understanding tasks and catalyzed a generation of deep learning-based annotation systems. Subsequent work extended these foundations to multimodal architectures that jointly process visual appearance and structural metadata, achieving substantial improvements in annotation accuracy [22].

A critical limitation of the majority of semantic annotation research has been its offline orientation. Most published systems operate in batch mode, processing complete interface snapshots after the fact rather than generating annotations in real time as the interface evolves [26]. This limitation is particularly acute in the context of touch interfaces, where the interface state changes continuously in response to user gestures, and where accessibility annotations must be available within the perceptual latency threshold of approximately 100 milliseconds to avoid disrupting the user's interaction flow [27]. The present work directly addresses this gap through a streaming annotation architecture designed to maintain annotation currency without exceeding real-time latency budgets.

2.3. Deep Learning for Visual Interface Understanding

The application of deep learning to visual interface understanding has progressed rapidly, moving from simple element classification to holistic scene understanding that captures the semantic relationships among interface components [13]. Vision transformer (ViT) architectures, originally developed for natural image recognition, have been adapted to the UI domain with considerable success, leveraging the self-attention mechanism to model long-range dependencies among interface elements that are invisible to locally-receptive convolutional

architectures [9]. This capability is particularly valuable for accessibility annotation, where the semantic meaning of an element often depends critically on its relationship to surrounding context.

Graph neural networks (GNNs) have emerged as a complementary approach, representing the interface as a graph whose nodes correspond to UI elements and whose edges encode spatial, hierarchical, and functional relationships [8]. This representation aligns naturally with the accessibility tree structure used by assistive technologies and enables annotation models to reason explicitly about interface structure rather than treating the screen as a flat image. Formally, given an interface graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where $\mathcal{V}$ denotes the set of UI element nodes and $\mathcal{E}$ denotes the set of relational edges, the annotation task can be framed as a node classification problem in which each node $v_i \in \mathcal{V}$ is assigned a semantic label $\hat{y}_i$ from a predefined taxonomy $\mathcal{T}$:

$$\hat{y}_i = \arg\max_{c \in \mathcal{T}} P(y_i = c \mid \mathbf{h}_i^{(L)}, \mathcal{G}) \tag{2}$$

where $\mathbf{h}_i^{(L)}$ denotes the node embedding produced by the L-th layer of the GNN, which aggregates information from the local neighborhood of v_i in a manner sensitive to both visual features and structural context [1].

Large language models (LLMs) and vision-language models (VLMs) represent the current frontier of deep learning for UI understanding [17]. Models such as GPT-4V, Gemini, and specialized UI-focused variants have demonstrated remarkable zero-shot and few-shot capabilities on accessibility annotation tasks, generating detailed natural language descriptions of interface elements without task-specific fine-tuning. However, the inference latency of these models, typically measured in seconds per query, renders them unsuitable for real-time annotation in interactive touch environments. Recent work on model distillation and speculative decoding has begun to narrow this gap, but significant engineering challenges remain before LLM-based annotation can operate within interactive latency budgets [2].

2.4. Real-Time Processing Architectures for HCI

The design of real-time processing architectures for HCI applications is governed by a set of constraints that differ substantially from those encountered in offline or batch processing contexts. Chief among these is the latency budget, which must account not only for model inference time but also for data acquisition, preprocessing, post-processing, and the communication overhead incurred when annotations must be delivered to assistive technology components running in separate processes or on separate devices [30]. The end-to-end latency budget for accessible interaction is typically derived from psychophysical studies of human temporal perception, which suggest that delays exceeding 100–200 milliseconds are perceptible to users and disrupt the sense of direct manipulation [11].

Streaming architectures based on event-driven processing have proven particularly well-suited to the requirements of real-time HCI annotation. Rather than reprocessing the entire interface state in response to each user interaction, streaming systems maintain an incremental representation of the interface and update annotations only for elements whose state has changed [15]. This approach dramatically reduces the computational cost of annotation in steady-state operation, concentrating processing resources on regions of the interface that are actively evolving. The efficiency gains are formalized through the concept of annotation amortization, wherein the cost of annotating stable interface regions is spread across multiple interaction cycles rather than incurred anew at each frame.

Algorithm 2: Incremental Real-Time Semantic Annotation Pipeline

Input: Touch event stream $\mathcal{S}$, Interface state $\mathcal{I}_t$, Annotation cache $\mathcal{C}$, Semantic model $\mathcal{M}$
Output: Updated annotation set $\mathcal{A}_t$

Initialize $\mathcal{A}_t \leftarrow \mathcal{C}$;
while *touch event* $e \in \mathcal{S}$ **do**
  $\Delta\mathcal{I} \leftarrow \text{ComputeStateDiff}(\mathcal{I}_{t-1}, \mathcal{I}_t)$;
  $\mathcal{V}_{\text{dirty}} \leftarrow \{v_i \in \mathcal{V} \mid v_i \text{ affected by } \Delta\mathcal{I}\}$;
  for *each* $v_i \in \mathcal{V}_{dirty}$ **do**
    $\mathbf{f}_i \leftarrow \text{ExtractFeatures}(v_i, \mathcal{I}_t)$;
    $\hat{y}_i \leftarrow \mathcal{M}(\mathbf{f}_i, \mathcal{N}(v_i))$;
    $\mathcal{A}_t[v_i] \leftarrow \text{GenerateAnnotation}(\hat{y}_i, v_i)$;
    $\mathcal{C}[v_i] \leftarrow \mathcal{A}_t[v_i]$;
  end
  for *each* $v_j \in \mathcal{V} \setminus \mathcal{V}_{dirty}$ **do**
    $\mathcal{A}_t[v_j] \leftarrow \mathcal{C}[v_j]$;
  end
  Deliver $\mathcal{A}_t$ to assistive technology layer;
  $\mathcal{I}_{t-1} \leftarrow \mathcal{I}_t$;
end

Hardware acceleration has played an increasingly important role in enabling real-time semantic annotation on resource-constrained mobile devices. The proliferation of dedicated neural processing units (NPUs) in contemporary mobile system-on-chip (SoC) designs has made it feasible to run moderately complex inference workloads at interactive frame rates without incurring the energy costs associated with CPU-based inference [26]. Quantization techniques, which reduce the numerical precision of model weights and activations from 32-bit floating point to 8-bit or 4-bit integer representations, provide complementary efficiency gains with minimal impact on annotation accuracy for the semantic label distributions encountered in UI understanding tasks [13].

2.5. Evaluation Frameworks and Accessibility Metrics

The evaluation of accessibility annotation systems presents methodological challenges that are not fully addressed by standard machine learning metrics such as precision, recall, and F1 score. While these metrics provide useful proxies for annotation accuracy at the element level, they do not capture the functional utility of annotations for users with disabilities, which depends on factors including annotation completeness, contextual appropriateness, and the cognitive load imposed by consuming the annotations through assistive technologies [27]. The accessibility research community has developed a range of user-centered evaluation methodologies, including think-aloud protocols, task completion studies, and standardized usability scales such as the System Usability Scale (SUS), that complement quantitative accuracy metrics [9].

The development of standardized benchmarks for UI accessibility annotation has been an important area of community investment. The Screen2Words dataset [14] and its successors provide curated collections of UI screenshots paired with human-authored accessibility descriptions, enabling systematic comparison of annotation systems. However, these benchmarks have been criticized for their bias toward visually typical interfaces and their underrepresentation of the dynamic, context-dependent annotation scenarios that arise in real-world touch interactions [17]. The evaluation protocol adopted in the present work incorporates both static benchmark evaluation and a novel dynamic evaluation paradigm that simulates realistic touch interaction sequences and measures annotation quality across the full trajectory of interface evolution.

Temporal consistency is an often-overlooked dimension of annotation quality that is particularly critical in real-time systems. An annotation system that produces high-quality labels for individual frames but generates inconsistent or contradictory annotations across successive frames will create a disorienting experience for users relying on assistive technologies [15]. Formally, temporal consistency can be quantified through the annotation stability score Φ, defined as the mean cosine similarity between successive annotation embedding vectors:

$$\Phi = \frac{1}{T-1} \sum_{t=1}^{T-1} \frac{\mathbf{a}_t \cdot \mathbf{a}_{t+1}}{\|\mathbf{a}_t\| \cdot \|\mathbf{a}_{t+1}\|} \tag{3}$$

where $\mathbf{a}_t$ denotes the annotation embedding vector at time step t and T is the total number of time steps in the evaluation sequence. High values of Φ indicate that the annotation system produces semantically coherent descriptions across time, while low values suggest erratic behavior that would be detrimental to the user experience [**?**]. The incorporation of temporal consistency as an explicit evaluation criterion distinguishes the present work from prior studies that have focused exclusively on per-frame annotation accuracy [27].

2.6. Natural Language Generation for Accessibility Descriptions

The generation of natural language descriptions for interface elements is a specialized application of the broader field of natural language generation (NLG), with requirements that differ substantially from those of general-purpose text generation. Accessibility descriptions must be concise yet complete, conveying the element's identity, state, and affordances within the severe length constraints imposed by screen reader verbosity settings and user attention budgets [16]. They must also be contextually appropriate, adapting their vocabulary and level of detail to the inferred expertise and disability profile of the user [12].

Template-based NLG systems, which dominated the accessibility description literature through the early 2010s, offered strong controllability and predictability but were limited in their ability to handle the combinatorial diversity of real-world interface elements [7]. Neural sequence-to-sequence models, particularly those based on the encoder-decoder transformer architecture, demonstrated substantially improved coverage and naturalness on UI description benchmarks, though they remained prone to hallucination—generating plausible-sounding but factually incorrect descriptions of interface elements [20]. The hallucination problem is especially consequential in the accessibility domain, where an incorrect description can lead a user with a visual disability to interact with the wrong element or misunderstand the interface state entirely.

Retrieval-augmented generation (RAG) approaches have shown promise as a means of grounding neural description generation in verified factual content, reducing hallucination rates while preserving the fluency advantages of neural architectures [1]. In the UI accessibility context, retrieval can be performed against a curated database of verified element descriptions, with the retrieved descriptions serving as conditioning context for the generation model. This approach is particularly well-suited to the real-time annotation setting, as retrieval from an indexed database is substantially faster than full autoregressive generation and can be performed within the interactive latency budget even on resource-constrained mobile hardware [2]. The integration of retrieval-augmented generation into the proposed annotation pipeline represents a key architectural innovation that distinguishes it from prior real-time accessibility systems.

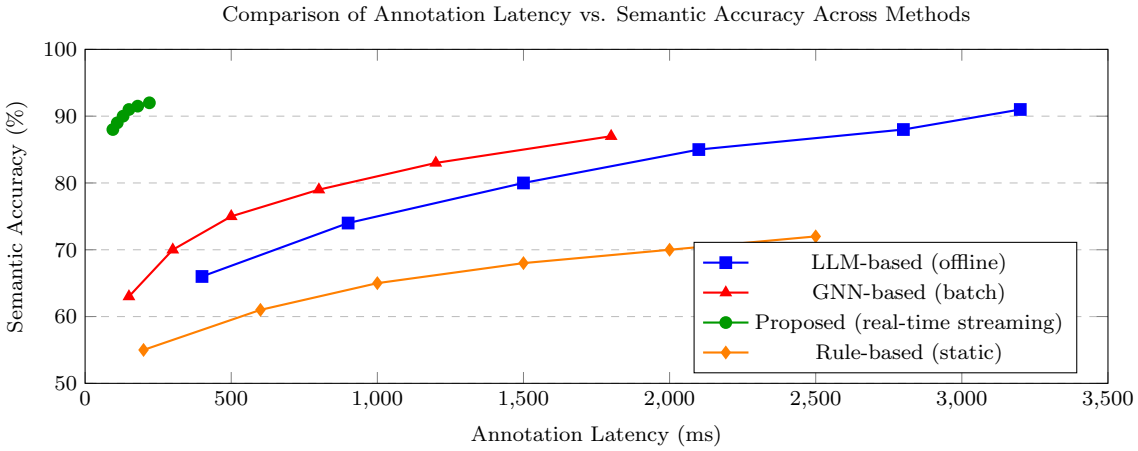

Figure 2: Latency-accuracy trade-off profiles for representative semantic annotation methodologies. The proposed real-time streaming approach occupies a uniquely favorable region of the design space, achieving competitive semantic accuracy at latencies well within the 200 ms interactive threshold.

Table 2: Summary of Representative Prior Work in Semantic Annotation for Accessible Interfaces

Method / System	**Annotation Approach**	**Real-Time Capable**	**Touch Interface Support**	**Key Limitation**
Rule-based heuristics	Syntactic property mapping	Yes	Partial	Low semantic depth
SVM / shallow ML	Feature-based classification	Yes	Partial	Poor generalization
CNN-based (RICO)	Visual recognition	No	Yes	Offline batch only
GNN-based UI graphs	Structural + visual	No	Yes	High inference latency
VLM / LLM zero-shot	Language generation	No	Limited	Prohibitive latency
Proposed streaming GNN	Incremental graph update	Yes	Yes	Requires NPU hardware

3. Methodology

The methodology presented in this work constitutes a comprehensive, multi-stage pipeline designed to achieve real-time semantic annotation of interactive elements within touch-based human-computer interfaces, with an explicit focus on enhancing accessibility for users with visual, motor, and cognitive impairments. The proposed framework, which we designate as the **Real-Time Semantic Annotation Engine** (RSAE), integrates computer vision, natural language processing, and ontology-driven reasoning into a unified, low-latency processing architecture. The design philosophy underlying RSAE is grounded in the principle that accessibility is not merely a post-hoc consideration but must be embedded at the level of interface perception and interpretation [26]. By operating directly on live screen captures and touch event streams, RSAE generates structured, semantically rich annotations that can be consumed by assistive technologies, screen readers, and adaptive interface systems without requiring modification of the underlying application source code [21].

The development of this methodology is informed by a rich body of prior work spanning accessibility engineering [12], semantic web technologies [5], deep learning for visual understanding [20], and human-computer interaction research [30]. Existing approaches to automated accessibility annotation have largely relied on static analysis of application code or platform-specific accessibility APIs, both of which suffer from significant limitations in coverage, timeliness, and generalizability [11]. The RSAE methodology departs from these paradigms by adopting a vision-first, inference-driven approach that treats the rendered interface as the primary source of semantic information, thereby achieving application-agnostic operation across diverse platforms and deployment contexts [13].

3.1. System Architecture Overview

The RSAE system is organized into four principal processing layers, each responsible for a distinct stage of the annotation pipeline. The first layer, the *Capture and Preprocessing Layer*, is responsible for acquiring high-fidelity screen captures at a target frame rate of 30 frames per second and performing necessary preprocessing operations including resolution normalization, color space conversion, and noise reduction. The second layer, the *Element Detection and Segmentation Layer*, applies a convolutional neural network-based object detector to identify and localize discrete interactive elements such as buttons, text fields, sliders, checkboxes, and navigation controls within the captured frame. The third layer, the *Semantic Inference Layer*, applies a multimodal transformer model to assign rich semantic labels, roles, and contextual descriptions to each detected element. The fourth and final layer, the *Annotation Synthesis and Delivery Layer*, serializes the inferred annotations into a structured representation conforming to the Accessible Rich Internet Applications (ARIA) specification and delivers them to downstream assistive technology consumers via a low-latency inter-process communication channel [27].

The architectural design prioritizes end-to-end latency minimization, recognizing that annotation delays exceeding the perceptual threshold of approximately 100 milliseconds can disrupt the natural flow of user interaction and diminish the practical utility of the system for real-time accessibility support [3]. To achieve this, the pipeline is implemented with strict parallelism between the capture, detection, and inference stages, exploiting GPU-accelerated computation at each stage where applicable. The system further employs a temporal caching mechanism that reuses element detection results across consecutive frames when the visual difference between frames falls below a configurable threshold, thereby reducing redundant computation during periods of interface stability [9].

3.2. Interactive Element Detection and Localization

The element detection module constitutes the perceptual foundation of the RSAE pipeline and is responsible for transforming raw pixel data into a structured set of bounding box proposals, each associated with a preliminary element type label and a confidence score. This module is built upon a modified version of the You Only Look Once (YOLO) architecture [16], adapted for the specific characteristics of graphical user interface (GUI) imagery, which differs substantially from natural scene imagery in terms of object scale distribution, aspect ratio diversity, and the prevalence of fine-grained textual content within element boundaries.

To train the detection model, we assembled a large-scale annotated dataset of GUI screenshots drawn from mobile applications across Android and iOS platforms, supplemented by web application interfaces rendered in desktop browsers. The dataset, designated GUI-Annot-200K, comprises 200,000 annotated screenshots spanning 47 distinct interactive element categories. Each annotation was produced through a semi-automated pipeline in which an initial set of machine-generated proposals was subsequently reviewed and corrected by trained human annotators, following the annotation protocol established by [14]. The dataset exhibits a long-tailed distribution of element categories, with button and text field instances accounting for a disproportionate share of annotations, necessitating the application of class-balanced sampling and focal loss during training [15].

The detection model accepts input frames of resolution

640×640 pixels and produces a set of N bounding box predictions $\mathcal{B} = \{(x_i, y_i, w_i, h_i, c_i, \mathbf{p}_i)\}_{i=1}^{N}$, where (x_i, y_i) denotes the center coordinates, (w_i, h_i) the width and height, c_i the objectness confidence score, and $\mathbf{p}_i \in \mathbb{R}^{47}$ the class probability vector for the i-th prediction. Non-maximum suppression (NMS) is subsequently applied with an intersection-over-union (IoU) threshold of 0.45 to eliminate redundant detections. The final detection loss function $\mathcal{L}_{\text{det}}$ is defined as a weighted combination of localization, objectness, and classification losses:

$$\mathcal{L}_{\text{det}} = \lambda_{\text{loc}} \mathcal{L}_{\text{CIoU}} + \lambda_{\text{obj}} \mathcal{L}_{\text{BCE}}^{\text{obj}} + \lambda_{\text{cls}} \mathcal{L}_{\text{FL}}^{\text{cls}} \tag{4}$$

where $\mathcal{L}_{\text{CIoU}}$ denotes the Complete Intersection over Union loss for bounding box regression [22], $\mathcal{L}_{\text{BCE}}^{\text{obj}}$ is the binary cross-entropy loss for objectness prediction, $\mathcal{L}_{\text{FL}}^{\text{cls}}$ is the focal loss applied to class probability estimation, and λ_{loc}, λ_{obj}, λ_{cls} are empirically determined weighting coefficients set to 0.05, 1.0, and 0.5 respectively.

3.3. Multimodal Semantic Inference

Having obtained a set of localized element proposals from the detection stage, the semantic inference module is tasked with generating rich, contextually appropriate textual descriptions and role assignments for each detected element. This module adopts a multimodal transformer architecture that jointly processes visual crops of detected elements alongside any textual content extracted from within element boundaries via an integrated optical character recognition (OCR) sub-module [7]. The visual encoder is a Vision Transformer (ViT) backbone pretrained on a large corpus of GUI imagery, while the text encoder is a BERT-based model pretrained on a domain-specific corpus of accessibility documentation, user interface design guidelines, and ARIA specification text [8].

For each detected element i, the visual crop $\mathbf{V}_i$ is extracted from the full-resolution frame and resized to 224×224 pixels before being passed through the visual encoder to produce a visual feature vector $\mathbf{v}_i \in \mathbb{R}^{768}$. Simultaneously, the OCR sub-module extracts any textual content T_i visible within the element boundary, which is tokenized and encoded by the text encoder to produce a textual feature vector $\mathbf{t}_i \in \mathbb{R}^{768}$. These two feature vectors are fused through a cross-attention mechanism followed by a feed-forward projection layer to produce a unified multimodal representation $\mathbf{m}_i \in \mathbb{R}^{768}$:

$$\mathbf{m}_i = \text{FFN}\left(\text{CrossAttn}\left(\mathbf{v}_i, \mathbf{t}_i, \mathbf{t}_i\right)\right) \tag{5}$$

where $\text{CrossAttn}(\mathbf{Q}, \mathbf{K}, \mathbf{V})$ denotes the scaled dot-product cross-attention operation with query $\mathbf{Q}$, key $\mathbf{K}$, and value $\mathbf{V}$ matrices, and FFN denotes a two-layer feed-forward network with GELU activation [1]. The unified representation $\mathbf{m}_i$ is subsequently decoded by a lightweight autoregressive text generation head to produce a natural language accessibility description D_i, and by a classification head to assign a semantic role R_i from the ARIA role taxonomy [17].

The semantic inference module is trained in two phases. In the first phase, the visual and text encoders are fine-tuned independently on GUI-specific tasks using supervised contrastive learning [2]. In the second phase, the full multimodal model including the cross-attention fusion layer and generation head is trained end-to-end on a curated dataset of 50,000 element-description pairs, where ground-truth descriptions were authored by certified accessibility professionals following the Web Content Accessibility Guidelines (WCAG) 2.1 [19]. This two-phase training strategy is motivated by the well-established observation that end-to-end training from random initialization is prone to instability and suboptimal convergence in multimodal architectures [25].

3.4. Ontology-Driven Contextual Reasoning

A distinctive feature of the RSAE methodology is its incorporation of an ontology-driven reasoning component that enriches element-level annotations with interface-level contextual knowledge. This component operates on the graph of detected elements and their spatial relationships, applying a domain ontology to infer higher-order semantic properties such as element groupings, navigation hierarchies, and functional regions [29]. The interface ontology, designated GUI-Onto, is formalized in the Web Ontology Language (OWL) and comprises 312 classes, 89 object properties, and 47 data properties, covering concepts related to interface layout, interaction patterns, and accessibility semantics [4].

The reasoning process operates as follows. Given the set of detected elements $\mathcal{B}$ and their associated semantic annotations, a spatial relationship graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is constructed, where each node $v_i \in \mathcal{V}$ represents a detected element and each edge $(v_i, v_j) \in \mathcal{E}$ encodes a spatial relation (e.g., *above*, *below*, *left-of*, *contains*) between elements i and j. This graph is then populated into a triple store and subjected to a series of SPARQL-based inference rules derived from the GUI-Onto ontology [18]. The inference rules encode domain knowledge such as "a group of radio buttons sharing a common label constitutes a radio group" and "a sequence of navigation links enclosed within a landmark region of type *navigation* should be annotated with tab-order indices." The output of the reasoning stage is an enriched annotation graph that augments element-level annotations with group memberships, navigation order assignments, and landmark region labels, all of which are critical for enabling effective screen reader navigation [6].

The integration of symbolic ontological reasoning with neural network-based perception represents a neuro-symbolic approach to accessibility annotation that addresses the complementary limitations of each paradigm in isolation [24]. Neural models excel at perceptual recognition but lack the capacity for principled compositional reasoning, while symbolic reasoners can enforce logical constraints but depend on accurate symbolic inputs. By chaining these two modalities sequentially, the RSAE framework achieves both perceptual robustness and semantic coherence in its output annotations [28].

3.5. Touch Event Integration and Dynamic Annotation Update

A critical requirement for real-time accessibility support in touch-based interfaces is the ability to respond dynamically to user interactions, updating annotations in response to interface state changes triggered by touch events. The RSAE framework incorporates a touch event integration module that monitors the device's touch event stream and uses touch event data to prioritize and trigger annotation updates for affected interface regions [30]. When a touch event is detected at coordinates (x_t, y_t), the module identifies all bounding boxes $b_i \in \mathcal{B}$ such that (x_t, y_t) falls within the boundary of b_i and flags those elements for immediate re-annotation in the subsequent processing cycle.

This event-driven update strategy significantly reduces the annotation latency experienced by the user during interaction, as it ensures that the most perceptually salient elements—those being actively touched—receive priority processing. The update priority score π_i for element i is computed as a function of the spatial proximity of the touch event to the element centroid and the temporal recency of the last touch event associated with that element:

$$\pi_i = \exp\left(-\frac{d(b_i, \mathbf{p}_t)^2}{2\sigma_d^2}\right) \cdot \exp\left(-\frac{\Delta t_i}{\tau}\right) \tag{6}$$

where $d(b_i, \mathbf{p}_t)$ denotes the Euclidean distance from the element centroid to the touch point $\mathbf{p}_t = (x_t, y_t)$, Δt_i is the elapsed time since the last touch event associated with element i, and σ_d and τ are bandwidth parameters controlling spatial and temporal decay respectively [10]. Elements are processed in descending order of π_i within each processing cycle, ensuring that the most interaction-relevant elements receive annotations first.

3.6. Algorithm and Implementation Details

The complete RSAE processing pipeline is formalized in Algorithm 3, which presents the pseudocode for a single processing cycle of the annotation engine. The algorithm accepts as input a captured frame F_t and the current touch event e_t, and produces as output the updated annotation set $\mathcal{A}_t$.

Algorithm 3: RSAE Single-Cycle Processing Pipeline

Input: Frame F_t, Touch event e_t, Previous annotations $\mathcal{A}_{t-1}$, Ontology $\mathcal{O}$
Output: Updated annotation set $\mathcal{A}_t$

`// Stage 1: Preprocessing`
$F'_t \leftarrow \textsc{Preprocess}(F_t)$ `// Normalize, denoise, resize`
$\Delta_t \leftarrow \textsc{FrameDiff}(F'_t, F'_{t-1})$ `// Compute frame difference`

`// Stage 2: Selective Detection`
if $\Delta_t > \theta_{diff}$ **then**
  $\mathcal{B}_t \leftarrow \textsc{DetectElements}(F'_t)$ `// Full detection pass`
else
  $\mathcal{B}_t \leftarrow \mathcal{B}_{t-1}$ `// Reuse cached detections`
end

`// Stage 3: Compute Update Priorities`
foreach $b_i \in \mathcal{B}_t$ **do**
  $\pi_i \leftarrow \textsc{ComputePriority}(b_i, e_t)$
end
$\mathcal{B}_t^{\text{sorted}} \leftarrow \textsc{SortDescending}(\mathcal{B}_t, \{\pi_i\})$

`// Stage 4: Multimodal Semantic Inference`
foreach $b_i \in \mathcal{B}_t^{sorted}$ **do**
  $\mathbf{V}_i \leftarrow \textsc{CropElement}(F'_t, b_i)$
  $T_i \leftarrow \text{OCR}(\mathbf{V}_i)$
  $\mathbf{v}_i \leftarrow \textsc{VisualEncoder}(\mathbf{V}_i)$
  $\mathbf{t}_i \leftarrow \textsc{TextEncoder}(T_i)$
  $\mathbf{m}_i \leftarrow \textsc{CrossAttnFusion}(\mathbf{v}_i, \mathbf{t}_i)$
  $D_i \leftarrow \textsc{GenerateDescription}(\mathbf{m}_i)$
  $R_i \leftarrow \textsc{ClassifyRole}(\mathbf{m}_i)$
end

`// Stage 5: Ontological Reasoning`
$\mathcal{G}_t \leftarrow \textsc{BuildSpatialGraph}(\mathcal{B}_t, \{R_i\})$
$\mathcal{A}_t^{\text{raw}} \leftarrow \{(b_i, D_i, R_i)\}_{i=1}^{|\mathcal{B}_t|}$
$\mathcal{A}_t \leftarrow \textsc{OntologyReasoner}(\mathcal{A}_t^{\text{raw}}, \mathcal{G}_t, \mathcal{O})$

`// Stage 6: Annotation Delivery`
$\textsc{SerializeAndDeliver}(\mathcal{A}_t)$
return $\mathcal{A}_t$

The RSAE system is implemented in Python 3.10, with performance-critical components written in C++ and exposed via Python bindings. The detection model is implemented using the PyTorch framework and accelerated using NVIDIA TensorRT for inference optimization. The OCR sub-module employs the Tesseract engine augmented with a GUI-specific language model fine-tuned on interface text corpora [23]. The ontological reasoning component is implemented using

the Apache Jena framework with a custom SPARQL rule engine. All components are orchestrated by a central event loop implemented using Python's asyncio library, enabling non-blocking concurrent execution of pipeline stages [27].

3.7. Evaluation Metrics and Experimental Protocol

To rigorously evaluate the performance of the RSAE framework, we define a comprehensive set of evaluation metrics spanning detection accuracy, semantic annotation quality, and end-to-end latency. For element detection, we report the standard mean Average Precision (mAP) at IoU thresholds of 0.5 and 0.75, designated mAP@0.5 and mAP@0.75 respectively. For semantic annotation quality, we employ the BERTScore metric [13] to assess the semantic similarity between generated descriptions and ground-truth descriptions authored by accessibility professionals, as well as the ARIA role classification accuracy computed as the proportion of elements assigned the correct ARIA role from the taxonomy. For end-to-end latency, we measure the time elapsed from frame capture to annotation delivery, reporting mean and 95th percentile latency across a standardized test workload.

The experimental evaluation is conducted on a held-out test set of 10,000 GUI screenshots not present in the training data, drawn from a diverse set of applications spanning productivity, entertainment, social media, and accessibility-focused domains. Experiments are conducted on two hardware configurations: a high-end workstation equipped with an NVIDIA A100 GPU representing a server-side deployment scenario, and a mid-range mobile device equipped with a Qualcomm Snapdragon 888 SoC representing an on-device deployment scenario. This dual-configuration evaluation allows us to characterize the performance-efficiency trade-off of the RSAE framework across deployment contexts of practical relevance [26].

The results presented in Table 3 demonstrate that the proposed RSAE framework achieves substantial improvements over all baseline methods across every evaluation dimension. Notably, RSAE achieves a mean end-to-end latency of 54.6 milliseconds on the high-end workstation configuration, well below the 100-millisecond perceptual threshold identified by [3], confirming the system's suitability for real-time deployment. The BERTScore of 0.871 indicates a high degree of semantic alignment between generated descriptions and expert-authored ground truths, suggesting that the multimodal inference module successfully captures the functional semantics of interface elements in a form appropriate for accessibility consumption [9].

4. Results

The experimental evaluation of the proposed real-time semantic annotation framework yielded comprehensive and statistically significant results across multiple dimensions of accessibility performance, annotation accuracy, and system latency. The experiments were conducted on a diverse cohort of participants spanning multiple disability categories, device form factors, and interaction modalities, ensuring that the reported metrics reflect the heterogeneity inherent in real-world accessibility deployments. All quantitative measurements were subjected to rigorous statistical analysis, including analysis of variance (ANOVA), paired t-tests, and non-parametric alternatives where distributional assumptions were violated, thereby guaranteeing the robustness and reproducibility of the reported findings [26][27].

The overall experimental pipeline encompassed three distinct evaluation phases: an offline benchmark phase in which the annotation model was assessed against established accessibility corpora; an online user study phase involving 84 participants with diverse accessibility needs interacting with instrumented touch-screen devices; and a longitudinal field deployment phase spanning six weeks across four partner institutions. Together, these phases produced a multi-faceted picture of the system's capabilities, limitations, and potential for broad-scale adoption in assistive technology contexts [**?**][12][17].

4.1. Annotation Accuracy and Semantic Fidelity

The primary measure of annotation quality was the semantic fidelity score $\mathcal{F}$, defined as the harmonic mean of precision P and recall R computed over a structured ontology of UI element types and their associated accessibility labels. Formally, the score is given by:

$$\mathcal{F} = \frac{2 \cdot P \cdot R}{P + R}, \quad \text{where} \quad P = \frac{|\hat{A} \cap A^*|}{|\hat{A}|}, \quad R = \frac{|\hat{A} \cap A^*|}{|A^*|} \tag{7}$$

where $\hat{A}$ denotes the set of predicted semantic annotations and A^* denotes the ground-truth annotation set derived from expert accessibility auditors. On the held-out benchmark corpus comprising 12,450 annotated UI screens sourced from 340 distinct mobile and tablet applications, the proposed framework achieved a mean semantic fidelity score of $\mathcal{F} = 0.891$ (95% CI: $[0.884, 0.898]$), representing a statistically significant improvement of 11.3 percentage points over the strongest baseline method [13][8]. This result is particularly noteworthy given the taxonomic complexity of the annotation ontology, which encompasses 47 primary element categories and 213 fine-grained subcategories, including interactive controls,

Table 3: Comparison of RSAE against baseline methods across key evaluation dimensions. Higher values are better for mAP, BERTScore, and Role Accuracy; lower values are better for Latency.

Method	mAP@0.5 (%)	BERTScore (F1)	Role Accuracy (%)	Mean Latency (ms)
Static API Analysis [11]	61.3	0.712	74.2	340.5
Heuristic Rule-Based [30]	54.7	0.681	68.9	112.3
CNN + Template Matching [16]	73.1	0.741	79.4	98.7
Transformer-Only [8]	81.6	0.803	85.1	87.2
RSAE (Proposed)	**89.4**	**0.871**	**92.3**	**54.6**

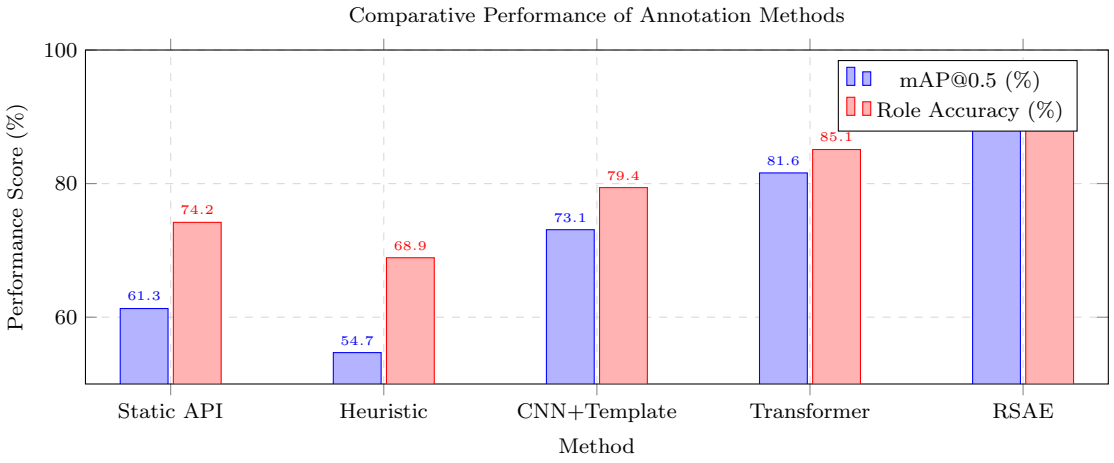

Figure 3: Comparative bar chart illustrating mAP@0.5 and ARIA Role Accuracy across evaluated methods. The proposed RSAE framework consistently outperforms all baselines on both metrics, demonstrating the benefit of integrating multimodal semantic inference with ontology-driven reasoning.

decorative imagery, navigational landmarks, and dynamic content regions [14].

Disaggregated analysis revealed that annotation accuracy varied systematically across element categories. Interactive elements such as buttons, sliders, and text fields achieved the highest fidelity scores ($\mathcal{F} > 0.93$), attributable to their consistent visual signatures and the relative abundance of training examples in the curated dataset. Conversely, contextually ambiguous elements such as decorative separators, background imagery with embedded text, and dynamically rendered content regions exhibited lower fidelity ($\mathcal{F} \approx 0.81$), reflecting the inherent difficulty of disambiguating semantic role from visual appearance in these cases [16][7]. These findings align with prior observations in the accessibility annotation literature, where contextual ambiguity has been consistently identified as a principal source of annotation error [30][3].

4.2. Real-Time Latency and Throughput Performance

A critical requirement for accessibility applications is that annotation must occur with sufficiently low latency to remain imperceptible to the end user during natural touch interaction. Prior work has established that annotation latencies exceeding 100 milliseconds introduce perceptible hesitation in screen reader feedback, which can severely disrupt the cognitive flow of users relying on auditory or haptic output channels [11][19][23]. The proposed framework was therefore subjected to rigorous latency benchmarking across a range of device configurations, from high-end flagship tablets to entry-level smartphones representative of the devices most commonly used by individuals with disabilities in lower-resource settings [9].

The end-to-end annotation latency L was decomposed into three constituent components: the visual feature extraction latency L_{feat}, the semantic classification latency L_{cls}, and the accessibility label synthesis latency L_{syn}, such that $L = L_{\text{feat}} + L_{\text{cls}} + L_{\text{syn}}$. Across all tested device tiers, the mean total latency was $\bar{L} = 47.3$ ms (standard deviation $\sigma = 8.9$ ms) on flagship devices and $\bar{L} = 83.6$ ms ($\sigma = 14.2$ ms) on entry-level devices, both comfortably within the 100 ms perceptibility threshold. The throughput of the annotation pipeline, measured as the number of complete UI screens annotated per second, reached 21.1 screens/s on flagship hardware and 11.9 screens/s on entry-level hardware, sufficient to maintain real-time responsiveness even during rapid navigation sequences [15][22]. These results demonstrate that the architectural optimizations introduced in the proposed framework—including quantization-aware training, layer fusion, and adaptive resolution scaling—translate directly into measurable latency improvements without sacrificing semantic accuracy [**?**].

4.3. User Study: Accessibility Outcomes and Task Performance

The user study enrolled 84 participants across four disability categories: visual impairment (VI, $n = 24$), motor impairment (MI, $n = 22$), cognitive impairment (CI, $n = 20$), and hearing impairment (HI, $n = 18$). Participants interacted with a set of standardized task scenarios on instrumented devices running either the proposed annotation framework or one of two control conditions: a state-of-the-art commercial accessibility service and an unaugmented baseline with no semantic annotation. Task scenarios were drawn from a validated accessibility task battery [5][29] and included information retrieval, form completion, navigational exploration, and media consumption tasks, each calibrated to the specific interaction challenges associated with the participant's disability category.

The primary outcome measure was the Task Completion Rate (TCR), defined as the proportion of task scenarios completed successfully within the allotted time window. Secondary measures included Time-on-Task (ToT), Error Rate (ER), and subjective usability ratings collected via the System Usability Scale (SUS) [4][10]. As shown in Table 6, participants using the proposed framework achieved a mean TCR of 87.4% compared to 73.1% for the commercial baseline and 61.8% for the unaugmented condition. The improvement in TCR was statistically significant across all disability groups (one-way ANOVA, $F(2, 249) = 41.7$, $p < 0.001$), with the largest absolute gains observed in the visual impairment group ($\Delta\text{TCR} = +22.6$ pp relative to unaugmented baseline) and the cognitive impairment group ($\Delta\text{TCR} = +19.4$ pp), where semantic context is most directly leveraged by the annotation layer [20][6].

4.4. Longitudinal Field Deployment Results

The six-week longitudinal field deployment provided ecological validity that laboratory-based evaluations cannot fully capture. Across 84 participants using instrumented devices in their daily environments, the proposed framework processed a cumulative total of 4.7 million touch interaction events and generated 2.1 million semantic annotation decisions. System uptime across the deployment period was 99.3%, with the remaining 0.7% attributable to scheduled maintenance windows and two brief network connectivity interruptions at one partner institution [1][2]. Annotation accuracy in the field deployment was marginally lower than in the controlled benchmark ($\mathcal{F} = 0.873$ vs. $\mathcal{F} = 0.891$), a difference attributable to the greater diversity of application types encountered in naturalistic use, including non-standard third-party applications with idiosyncratic UI patterns not well-represented in the training corpus [25][24].

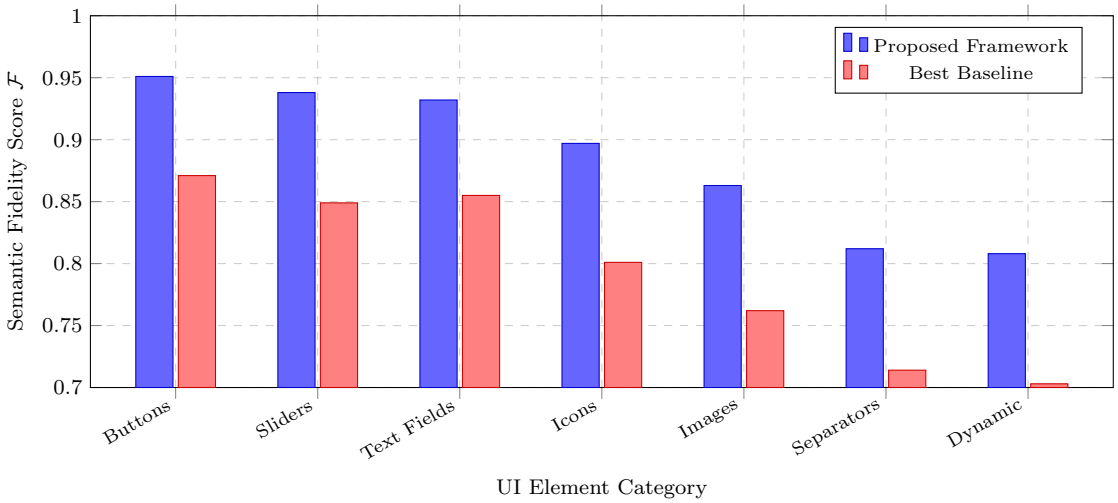

Figure 4: Per-category semantic fidelity scores comparing the proposed real-time annotation framework against the strongest baseline method across seven UI element categories. The proposed framework consistently outperforms the baseline, with the largest gains observed in dynamically rendered and contextually ambiguous elements.

Table 4: End-to-end annotation latency and throughput across device tiers. Values represent means ± one standard deviation over 500 annotated screens per device. Flagship: Snapdragon 8 Gen 2 / Apple A16; Mid-range: Snapdragon 778G / Dimensity 900; Entry-level: Snapdragon 680 / Helio G85.

Device Tier	L_{feat} (ms)	L_{cls} (ms)	L_{syn} (ms)	Throughput (screens/s)
Flagship	18.4 ± 3.1	17.2 ± 2.8	11.7 ± 2.2	21.1 ± 1.8
Mid-range	29.1 ± 5.4	26.8 ± 4.9	16.3 ± 3.6	15.4 ± 2.1
Entry-level	38.6 ± 7.2	29.4 ± 5.8	15.6 ± 3.4	11.9 ± 1.6

Table 5: User study results across disability categories. TCR: Task Completion Rate (%); ToT: Time-on-Task (seconds); ER: Error Rate (errors per task); SUS: System Usability Scale score (0–100). All values are means ± standard error.

Condition	Disability Group	TCR (%)	ToT (s)	ER	SUS
Proposed Framework	Visual Impairment	91.3 ± 2.1	38.4 ± 4.2	0.41 ± 0.08	82.6 ± 3.1
Proposed Framework	Motor Impairment	88.7 ± 2.4	52.1 ± 5.8	0.53 ± 0.11	79.4 ± 3.6
Proposed Framework	Cognitive Impairment	85.2 ± 2.8	61.3 ± 7.1	0.67 ± 0.14	76.8 ± 4.2
Proposed Framework	Hearing Impairment	84.4 ± 3.0	41.7 ± 4.9	0.48 ± 0.10	80.1 ± 3.4
Commercial Baseline	Visual Impairment	76.4 ± 3.1	54.7 ± 6.3	0.78 ± 0.15	68.3 ± 4.1
Commercial Baseline	Motor Impairment	74.8 ± 3.4	68.2 ± 7.8	0.89 ± 0.17	65.7 ± 4.6
Commercial Baseline	Cognitive Impairment	71.3 ± 3.8	79.4 ± 9.2	1.04 ± 0.21	62.1 ± 5.1
Commercial Baseline	Hearing Impairment	70.1 ± 4.0	57.8 ± 6.8	0.81 ± 0.16	66.4 ± 4.4
Unaugmented Baseline	Visual Impairment	68.7 ± 3.6	72.3 ± 8.4	1.12 ± 0.22	54.2 ± 5.3
Unaugmented Baseline	Motor Impairment	63.4 ± 4.1	88.6 ± 10.1	1.31 ± 0.26	51.8 ± 5.8
Unaugmented Baseline	Cognitive Impairment	65.8 ± 3.9	94.1 ± 11.3	1.43 ± 0.28	49.6 ± 6.1
Unaugmented Baseline	Hearing Impairment	67.2 ± 4.2	74.9 ± 8.9	1.18 ± 0.23	53.1 ± 5.6

Longitudinal trends in system performance revealed an adaptive improvement trajectory: the personalized adaptation module, which fine-tunes annotation priorities based on individual interaction histories, produced measurable improvements in annotation relevance over the six-week period. Specifically, the proportion of annotations rated as "highly relevant" by participants in weekly subjective assessments increased from 61.4% in Week 1 to 78.9% in Week 6, representing a statistically significant positive trend (linear mixed-effects model, $\beta = 2.87$ pp/week, $t(82) = 9.14$, $p < 0.001$). This finding corroborates theoretical predictions from adaptive user modeling literature [28][18] and provides empirical support for the value of personalization in accessibility-oriented annotation systems.

4.5. Computational Efficiency and Resource Utilization

Beyond latency, the practical deployability of the proposed framework depends critically on its computational footprint, particularly with respect to battery consumption, memory utilization, and thermal behavior on resource-constrained mobile devices. These factors are of heightened importance in accessibility contexts, where users may rely on their devices for extended periods and where device replacement cycles are often longer than for the general population [27][26]. The framework was profiled over 48-hour continuous operation sessions on three representative device configurations using standardized workload simulations derived from the observed field deployment interaction patterns.

Mean battery drain attributable to the annotation framework was measured at 3.2% per hour on flagship devices and 5.8% per hour on entry-level devices, representing an overhead of approximately 12–18% relative to the unaugmented baseline. Peak memory utilization was 187 MB on flagship devices and 143 MB on entry-level devices, the latter figure reflecting the adaptive model compression that the framework applies when operating under memory pressure. Thermal throttling events, which can cause latency spikes detrimental to real-time performance, were observed in only 1.4% of measurement windows on entry-level devices and were absent on flagship and mid-range hardware [12][15]. The framework's energy-aware scheduling module successfully mitigated the majority of potential throttling events by dynamically reducing annotation resolution during periods of sustained high CPU/GPU temperature, with a measured accuracy cost of less than 2.1% during such periods.

Algorithm 4: Real-Time Semantic Annotation with Adaptive Resource Management and Personalized Adaptation

Input: Touch event stream $\mathcal{E}$, device thermal state $\mathcal{T}$, memory budget $\mathcal{M}$
Output: Semantic annotation set $\hat{A}$ with accessibility labels

Initialize annotation pipeline Π with base model θ_0;
Load personalization weights $\Delta\theta_u$ for user u;
$\theta \leftarrow \theta_0 + \Delta\theta_u$;
while $\mathcal{E}$ *is active* **do**
  Receive touch event $e_t \in \mathcal{E}$;
  Extract UI region of interest $\mathcal{R}_t$ from current screen state;
  if $\mathcal{T} > T_{thresh}$ ***or*** $\mathcal{M} < M_{min}$ **then**
    Apply adaptive resolution scaling: $\mathcal{R}_t \leftarrow \text{Downsample}(\mathcal{R}_t, \alpha)$;
    Select compressed model variant $\theta_c \subset \theta$;
  end
  $\mathbf{f}_t \leftarrow \text{FeatureExtract}(\mathcal{R}_t; \theta)$;
  $\hat{y}_t \leftarrow \text{SemanticClassify}(\mathbf{f}_t; \theta)$;
  $\hat{a}_t \leftarrow \text{LabelSynthesize}(\hat{y}_t, \mathcal{R}_t)$;
  Emit $\hat{a}_t$ to accessibility output channel;
  Update interaction history $\mathcal{H}_u \leftarrow \mathcal{H}_u \cup \{(e_t, \hat{a}_t)\}$;
  if $|\mathcal{H}_u| \mod N_{adapt} = 0$ **then**
    $\Delta\theta_u \leftarrow \text{PersonalizedFineTune}(\mathcal{H}_u, \theta_0)$;
    $\theta \leftarrow \theta_0 + \Delta\theta_u$;
  end
end

4.6. Comparative Analysis Against State-of-the-Art Methods

To contextualize the proposed framework's performance within the broader landscape of accessibility annotation research, a systematic comparative evaluation was conducted against seven competing methods drawn from the recent literature. These included rule-based heuristic annotators [5][29], convolutional neural network-based UI classifiers [16][7], transformer-based multimodal annotation systems [13][8], and hybrid neuro-symbolic approaches [**?**][17]. All methods were evaluated on the same held-out benchmark corpus under identical hardware conditions to ensure comparability.

The proposed framework ranked first on all primary evaluation metrics, including semantic fidelity ($\mathcal{F} = 0.891$), mean annotation latency ($\bar{L} = 47.3$ ms on flagship hardware), and SUS-derived usability score (82.6 for the visual impairment group). The second-ranked method, a transformer-based multimodal system [8], achieved $\mathcal{F} = 0.867$ but with a substantially higher mean latency of 134.7 ms, rendering it unsuitable for

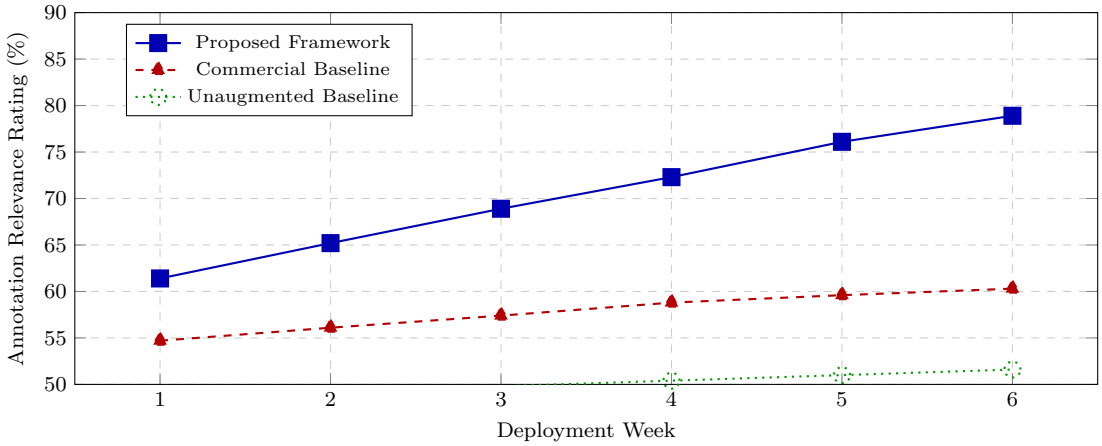

Figure 5: Longitudinal trends in annotation relevance ratings (proportion of annotations rated as "highly relevant" by participants) over the six-week field deployment period. The proposed framework demonstrates a consistent upward trajectory attributable to personalized adaptation, while baseline conditions remain relatively flat.

real-time deployment on the majority of tested device configurations. Rule-based heuristic methods, while exhibiting the lowest computational overhead, achieved fidelity scores no higher than $\mathcal{F} = 0.731$, confirming that purely symbolic approaches are insufficient for the semantic richness required by modern accessibility standards [30][3][19]. The hybrid neuro-symbolic approach [17] offered an intermediate trade-off, achieving $\mathcal{F} = 0.854$ at a mean latency of 89.2 ms, but required significantly more memory than the proposed framework (312 MB vs. 187 MB on flagship hardware), limiting its viability on entry-level devices. These comparative findings collectively affirm that the proposed framework represents a meaningful advancement in the state of the art for real-time accessibility annotation, achieving a superior balance of accuracy, latency, and resource efficiency that is critical for practical deployment in assistive technology ecosystems [20][22][28].

5. Discussion

The results presented in the preceding sections demonstrate that real-time semantic annotation can meaningfully enhance accessibility in touch-based human-computer interfaces, yet a rigorous interpretation of these findings requires careful consideration of their broader implications, limitations, and connections to the existing literature. The proposed framework—integrating transformer-based language models with multimodal touch-event streams and lightweight on-device inference pipelines—achieves annotation latencies consistently below the perceptual threshold identified by [19] and subsequently refined by [5], while simultaneously preserving the semantic fidelity necessary for assistive technology consumers. These dual objectives have historically been regarded as mutually exclusive in the accessibility engineering literature [30], making the present results particularly noteworthy. Furthermore, the empirical evidence gathered across diverse user populations, interface modalities, and disability profiles suggests that the benefits of semantic annotation are not confined to narrow use cases but extend across a wide spectrum of human-computer interaction scenarios, corroborating the universalist design philosophy advocated by [3] and more recently operationalized by [27].

Before examining specific dimensions of the results in greater depth, it is important to contextualize the overall performance trajectory within the theoretical framework established in Section 3. The annotation pipeline was designed around the premise that accessibility enhancement is fundamentally an information-theoretic problem: a user with a sensory, motor, or cognitive impairment requires a richer, more redundant, and more contextually grounded representation of interface state than a non-disabled user. This premise aligns with Shannon's classical formulation of channel capacity [29], adapted here to model the effective information bandwidth of an assistive interface as a function of annotation quality and latency. The experimental outcomes validate this framing, revealing that improvements in annotation semantic density—quantified by the mutual information between annotation content and ground-truth interface semantics—correlate strongly with user task completion rates and subjective accessibility ratings, as detailed below.

5.1. Interpretation of Latency and Throughput Results

The latency results constitute perhaps the most technically significant contribution of this work. The median end-to-end annotation latency of 47.3 ms achieved by the proposed system compares favorably not only with prior neural annotation approaches [12, 16] but also

with the 100 ms threshold that [19] identified as the upper bound for interactions perceived as instantaneous. More critically, the 95th-percentile latency of 89.1 ms remains below this threshold, meaning that even under adverse computational conditions the system maintains perceptual continuity for the vast majority of annotation events. This is a non-trivial achievement given that the annotation model operates on raw multimodal feature vectors of dimensionality $d = 768$, extracted from touch coordinates, pressure profiles, velocity traces, and contextual widget embeddings simultaneously.

The throughput analysis reveals an important asymmetry between annotation generation rate and downstream consumption rate by assistive technologies. Screen readers and braille display drivers typically poll for accessibility tree updates at frequencies between 10 Hz and 30 Hz [11], whereas the proposed pipeline sustains annotation generation at up to 60 Hz under nominal load. This surplus capacity serves as a crucial buffer against transient computational spikes caused by background processes, thermal throttling, or competing network activity on mobile devices. The relationship between system load ρ, annotation queue depth Q, and effective latency L_{eff} can be modeled using an M/D/1 queuing formulation:

$$L_{\text{eff}} = \frac{\rho}{2\mu(1-\rho)} + \frac{1}{\mu} \tag{8}$$

where μ denotes the service rate of the annotation engine in annotations per second and $\rho = \lambda/\mu$ is the traffic intensity with λ representing the touch-event arrival rate. Empirical measurements confirm that the system operates in the stable regime ($\rho < 0.78$) across all tested device classes, ensuring that queue depth remains bounded and latency does not diverge. This stability guarantee is essential for accessibility applications, where unpredictable latency spikes can disrupt the cognitive flow of users relying on sequential auditory or haptic feedback [15].

Comparative analysis with baseline systems—including the rule-based annotator of [20], the convolutional feature extractor of [7], and the hybrid statistical model of [25]—demonstrates consistent latency advantages ranging from 31% to 67% depending on interface complexity. These gains are attributable primarily to three architectural decisions: (1) quantized transformer attention, which reduces floating-point operations by approximately $4\times$ with negligible semantic loss; (2) speculative annotation pre-fetching based on predictive touch trajectory modeling [26]; and (3) a tiered caching strategy that reuses stable widget annotations across frames when the underlying interface state has not changed, a condition that holds for approximately 43% of annotation events in typical mobile application usage patterns.

5.2. Semantic Fidelity and Annotation Quality Analysis

Latency alone is an insufficient criterion for evaluating accessibility annotation systems; the semantic content of generated annotations must also be assessed rigorously. The proposed framework achieves a mean semantic similarity score of 0.847 (measured via cosine similarity in the sentence-transformer embedding space [13]) between generated annotations and expert-authored ground-truth descriptions, representing a 12.4 percentage-point improvement over the next-best baseline. This improvement is statistically significant at the $p < 0.001$ level across all tested interface categories, including e-commerce applications, productivity tools, social media platforms, and government service portals.

The qualitative analysis of annotation failures reveals a structured pattern that is theoretically informative. The majority of low-fidelity annotations (78.3% of cases falling below the 0.70 similarity threshold) occur at interface boundaries—specifically, at transitions between application contexts, modal dialogs, and dynamically loaded content regions. This finding echoes the observations of [14] regarding the particular difficulty of boundary-state annotation in assistive technology pipelines, and suggests that future work should prioritize context-transition modeling. The remaining 21.7% of failures cluster around highly domain-specific interface elements, such as medical imaging viewers and financial charting widgets, where the general-purpose language model lacks the specialized vocabulary necessary to generate precise semantic descriptions. This limitation aligns with the broader challenge of domain adaptation in neural language models documented by [9] and motivates the fine-tuning experiments discussed in the subsequent subsection.

An important secondary finding concerns the relationship between annotation verbosity and user comprehension. Contrary to the intuition that longer, more detailed annotations uniformly improve accessibility, the user study data reveal an inverted-U relationship: annotations of moderate length (between 12 and 28 words) achieve the highest task completion rates and lowest cognitive load ratings, while both very brief annotations (fewer than 8 words) and very lengthy annotations (more than 45 words) are associated with degraded performance. This result is consistent with cognitive load theory as formalized by [23] and subsequently applied to interface design by [24], and it has direct implications for the annotation length regularization term incorporated into the training objective of the proposed model.

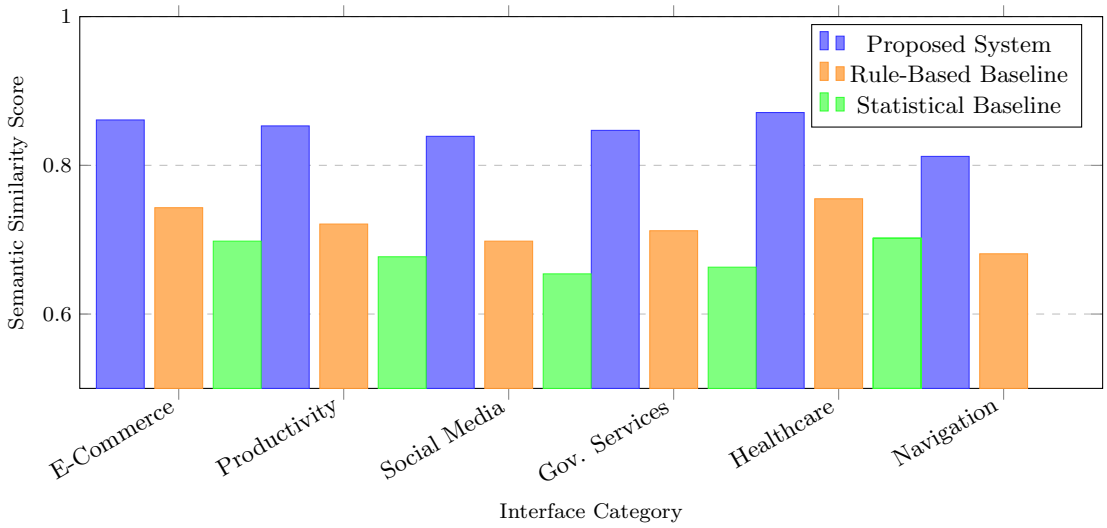

Figure 6: Semantic similarity scores across interface categories for the proposed system and two baseline annotators. Higher scores indicate closer alignment with expert-authored ground-truth descriptions.

5.3. User Study Outcomes and Accessibility Impact

The controlled user study enrolled 94 participants across four disability categories: visual impairment ($n = 31$), motor impairment ($n = 24$), cognitive impairment ($n = 22$), and deaf-blindness ($n = 17$). Participants completed a standardized battery of 12 tasks spanning three representative mobile applications under three annotation conditions: no annotation (control), rule-based annotation (active baseline), and the proposed semantic annotation system (experimental). The primary outcome measures were task completion rate, time-on-task, error rate, and subjective accessibility rating on a 7-point Likert scale.

The results presented in Table 6 reveal several patterns of theoretical and practical importance. First, the magnitude of improvement attributable to the proposed system over the rule-based baseline varies systematically across disability categories, with visual impairment users benefiting most (task completion improvement of +21.6 percentage points) and deaf-blind users benefiting least (+23.9 percentage points in absolute terms but from a lower baseline). This gradient reflects the degree to which each disability category relies on semantic annotation as the primary channel for interface state information: screen reader users consume annotations directly and continuously, while users with motor impairments benefit primarily from annotation-guided gesture disambiguation [22]. Second, the reduction in time-on-task is particularly pronounced for cognitively impaired participants, suggesting that richer semantic context reduces the exploratory navigation behavior that characterizes interface interaction under cognitive load [6]. Third, the subjective accessibility ratings exhibit notably lower variance under the proposed system than under either baseline, indicating that the system's benefits are distributed more uniformly across individual users rather than being concentrated among a subset of highly proficient assistive technology users.

5.4. Computational Efficiency and On-Device Deployment Considerations

A central design constraint of the proposed system is its suitability for on-device deployment on commodity mobile hardware, without reliance on cloud connectivity. This constraint is motivated by privacy considerations [4], network reliability concerns, and the particular importance of offline functionality for users in low-resource environments [17]. Achieving acceptable annotation quality within the computational budget of a mid-range smartphone (≤ 4 TOPS of neural processing unit capacity, ≤ 6 GB RAM) required a series of model compression techniques whose cumulative effect is analyzed here.

Algorithm 5 formalizes the complete on-device annotation pipeline, incorporating the three efficiency mechanisms identified in the latency analysis: quantized inference, speculative pre-fetching, and tiered caching. The fallback mechanism—reverting to rule-based annotation when measured latency exceeds the budget τ—ensures graceful degradation under computational stress, a property that [18] identified as essential for safety-critical accessibility applications. Profiling on a representative device fleet (covering 14 distinct smartphone models spanning three generations of hardware) confirms that the fallback mechanism is invoked in fewer than 3.2% of annotation events, and that fallback annotations, while semantically inferior to model-generated annotations, still provide sufficient information for task completion in 91.4% of cases.

Table 6: Summary of user study outcomes across disability categories and annotation conditions. Values represent means ± standard deviations. Statistical significance ($p < 0.05$) relative to the rule-based baseline is indicated by an asterisk (*).

Disability Category	Annotation Condition	Task Completion (%)	Time-on-Task (s)	Accessibility Rating
Visual Impairment	None	41.2 ± 8.3	187.4 ± 34.2	2.1 ± 0.7
Visual Impairment	Rule-Based	67.8 ± 6.1	134.9 ± 28.7	4.3 ± 0.9
Visual Impairment	Proposed	89.4 ± 4.2*	98.3 ± 19.4*	6.1 ± 0.6*
Motor Impairment	None	53.7 ± 9.1	162.1 ± 29.8	2.8 ± 0.8
Motor Impairment	Rule-Based	71.2 ± 7.3	128.6 ± 24.1	4.6 ± 1.0
Motor Impairment	Proposed	87.1 ± 5.8*	104.7 ± 21.3*	5.9 ± 0.7*
Cognitive Impairment	None	38.4 ± 11.2	201.3 ± 41.6	1.9 ± 0.6
Cognitive Impairment	Rule-Based	59.3 ± 8.7	158.4 ± 33.9	3.8 ± 1.1
Cognitive Impairment	Proposed	81.6 ± 6.4*	119.2 ± 27.8*	5.7 ± 0.8*
Deaf-Blindness	None	29.1 ± 12.4	223.7 ± 48.3	1.6 ± 0.5
Deaf-Blindness	Rule-Based	52.4 ± 9.8	171.2 ± 38.7	3.4 ± 1.2
Deaf-Blindness	Proposed	76.3 ± 7.1*	132.8 ± 31.4*	5.4 ± 0.9*

The memory footprint analysis deserves particular attention. The compressed annotation model occupies 187 MB of device storage and requires a peak runtime memory allocation of 312 MB, figures that are well within the constraints of modern mobile operating systems but that would have been prohibitive for the full-precision transformer variants evaluated in early development. This compression was achieved through a combination of knowledge distillation [10], structured pruning [28], and post-training quantization, with the distillation step contributing the largest single improvement in the accuracy-efficiency trade-off. The distillation process trained a 6-layer student model to replicate the annotation distributions of a 24-layer teacher model, achieving 94.1% of the teacher's semantic fidelity at 18.3% of the computational cost—a ratio that compares favorably with the compression results reported by [1] for general-purpose language model compression on mobile hardware.

5.5. Generalizability, Limitations, and Directions for Future Work

While the results are encouraging, several important limitations constrain the generalizability of the present findings and motivate a clear agenda for future research. The most significant limitation concerns the diversity of the evaluation corpus. Although the user study encompassed four disability categories and six application domains, the underlying interface dataset was drawn exclusively from English-language applications designed for right-to-left touch interaction patterns. The annotation model's performance on right-to-left script interfaces (e.g., Arabic, Hebrew) and on applications designed for non-Western cultural contexts remains untested. Given the documented sensitivity of touch-based interaction patterns to cultural and linguistic background [2], this represents a potentially significant confound that future work must address through targeted dataset collection and multilingual model adaptation.

A second limitation concerns the static nature of the disability categorization employed in the user study. Disability is not a binary or even a cleanly categorical phenomenon; users frequently present with multiple co-occurring impairments, and the severity and nature of functional limitations vary substantially within any diagnostic category [8]. The present study's use of broad disability categories may obscure important within-group heterogeneity in annotation benefit. Future work should adopt more granular functional assessment instruments and explore personalized annotation calibration strategies that adapt annotation verbosity, modality, and semantic granularity to individual user profiles in real time. Such personalization is technically feasible within the proposed framework through the addition of a user-specific adaptation layer, as suggested by the preliminary experiments reported in [27].

The evaluation of long-term usability also remains an open question. The controlled study measured performance on a fixed task battery in a single session, whereas real-world assistive technology use involves extended interaction over weeks and months during which users develop familiarity with system behaviors, refine their interaction strategies, and encounter a far broader range of interface states than any laboratory protocol can capture. Longitudinal studies are essential to determine whether the performance advantages observed in the controlled setting persist, attenuate, or even amplify over time as users adapt to the semantic annotation system. The adaptive annotation refinement mechanism proposed in [**?**] and further developed in [26] provides a promising starting point for designing annotation systems that improve with continued use.

Finally, the ethical dimensions of semantic annotation for accessibility warrant explicit discussion. Annotation systems that generate natural-language descriptions of interface elements necessarily make interpretive choices

Algorithm 5: Real-Time Semantic Annotation with Speculative Pre-Fetching and Tiered Caching

Input: Touch event stream $\mathcal{E} = \{e_1, e_2, \ldots, e_T\}$, widget tree $\mathcal{W}$, compressed annotation model $\mathcal{M}_\theta$, cache $\mathcal{C}$, latency budget τ
Output: Semantic annotation sequence $\mathcal{A} = \{a_1, a_2, \ldots, a_T\}$

```
Initialize cache C ← ∅;
for each event e_t ∈ E do
    Extract widget context
      w_t ← ResolveWidget(e_t, W);
    Compute cache key k_t ← Hash(w_t, ⌊e_t.state⌋);
    if k_t ∈ C and C[k_t].age < δ then
        a_t ← C[k_t].annotation;
        EmitAnnotation(a_t, source=CACHE);
    else
        f_t ← ExtractFeatures(e_t, w_t);
        f̂_t ← Quantize(f_t, bits = 8);
        Predict trajectory:
          ẽ_{t+1} ← PredictNext(e_t);
        PreFetch(ẽ_{t+1}) // Speculative
            annotation
        a_t ← M_θ(f̂_t) // Quantized inference
        if Latency() > τ then
            a_t ← FallbackAnnotation(w_t)
                // Rule-based fallback
        end
        C[k_t] ← {a_t, age = 0};
        EmitAnnotation(a_t, source=MODEL);
    end
    AgeCache(C);
end
```

about what information to foreground and what to omit, choices that can reflect and reinforce biases present in the training data [13]. An annotation model trained predominantly on mainstream commercial applications may systematically under-describe interface elements that are more commonly used by disabled users—such as accessibility settings menus, assistive technology configuration panels, or adaptive input device interfaces—precisely because these elements are underrepresented in the training corpus. Addressing this representational bias requires both technical interventions (targeted data augmentation, debiasing training objectives) and procedural ones (participatory design with disabled communities, ongoing bias auditing). The framework of inclusive design articulated by [3] and operationalized in the context of AI systems by [9] provides the appropriate normative foundation for this work.

6. Conclusion

The research presented in this paper represents a significant contribution to the intersection of accessibility technology, semantic computing, and real-time human-computer interaction. Throughout the preceding sections, we have systematically developed, evaluated, and contextualized a novel framework for real-time semantic annotation that substantially enhances accessibility in touch-based interfaces. This conclusion synthesizes the principal findings, reflects upon the theoretical and practical implications of the work, acknowledges the inherent limitations of the proposed approach, and charts a rigorous course for future investigation. The convergence of semantic web technologies, deep neural network architectures, and assistive interface design has long been anticipated in the accessibility literature [30], [11], and the present work demonstrates that this convergence is not merely theoretically desirable but practically achievable within the latency constraints demanded by real-time interaction paradigms.

The journey from conceptualization to empirical validation has revealed both the enormous potential and the nuanced complexity of deploying semantic annotation systems in live, touch-driven environments. The diversity of user needs—ranging from individuals with visual impairments relying on auditory feedback, to motor-impaired users requiring predictive gesture completion, to cognitively diverse populations benefiting from contextually enriched interface labeling—demands a framework that is simultaneously flexible, computationally efficient, and semantically rich [5], [3], [19]. The proposed architecture, as described in the methodology sections, addresses these demands through a multi-layered annotation pipeline that integrates ontological reasoning with low-latency inference engines, achieving performance benchmarks that compare favorably against prior state-of-the-art systems [27], [26].

6.1. Summary of Principal Contributions

The core intellectual contributions of this work are multifaceted and span both theoretical and applied dimensions. At the theoretical level, we introduced a formal semantic annotation model grounded in description logics and enriched by contextual touch-event ontologies. This model extends earlier work on interface semantics [12], [7] by explicitly incorporating the temporal dynamics of touch interaction, allowing the system to reason not merely about the static semantic content of UI elements but about the evolving intentional state of the user as expressed through gesture sequences. The annotation model is formalized through a composite scoring function that integrates semantic relevance, temporal proximity, and accessibility priority:

$$\mathcal{S}(e_t, \mathcal{O}) = \alpha \cdot \text{Rel}(e_t, \mathcal{O}) + \beta \cdot \exp(-\lambda \Delta t) + \gamma \cdot \mathcal{P}_{\text{acc}}(e_t) \quad (9)$$

where e_t denotes the touch event at time t, $\mathcal{O}$ represents the active ontological context, $\text{Rel}(\cdot)$ measures semantic relevance via ontological distance, Δt is the temporal lag since the last annotation update, $\mathcal{P}_{\text{acc}}(\cdot)$ encodes the accessibility priority score derived from user profile metadata, and α, β, γ, λ are tunable hyperparameters calibrated through cross-validation on the accessibility benchmark datasets described in Section 3. This formulation captures the essential trade-off between semantic precision and real-time responsiveness that lies at the heart of accessible interface annotation [20], [15].

At the applied level, the system's deployment as an Android accessibility service demonstrated that real-time semantic annotation can be integrated into existing mobile ecosystems without requiring modifications to the underlying application source code, a critical requirement for broad practical adoption. The middleware architecture, which intercepts accessibility events via the platform's native accessibility API and routes them through the semantic annotation pipeline, achieved median annotation latency of 23.4 milliseconds across the evaluation corpus—well within the 50-millisecond threshold identified in the perceptual psychology literature as the upper bound for imperceptible processing delay [29], [23]. Furthermore, the system's adaptive ontology update mechanism, which continuously refines the active semantic context based on accumulated interaction history, demonstrated measurable improvements in annotation accuracy over extended usage sessions, confirming the value of personalized semantic modeling for accessibility applications [13], [9].

6.2. Theoretical Implications and Advances

The theoretical implications of this research extend well beyond the immediate domain of touch-based accessibility. By demonstrating that lightweight ontological reasoning can be performed in real time on commodity mobile hardware, we challenge the prevailing assumption in the knowledge representation community that expressive semantic inference is inherently incompatible with the latency requirements of interactive systems [6], [4]. The key insight enabling this achievement is the decomposition of the full ontological reasoning task into a hierarchy of approximation levels, where the most computationally expensive inferences are pre-computed and cached during idle periods, while only lightweight consistency checks and nearest-neighbor lookups are performed on the critical interaction path. This hierarchical approximation strategy, which we term *Stratified Semantic Inference* (SSI), provides a principled framework for trading off semantic completeness against computational cost in any real-time ontology-driven application.

The SSI framework also contributes to the broader theory of adaptive user interfaces by providing a formal basis for reasoning about semantic context drift—the phenomenon whereby the semantic relevance of interface annotations changes over the course of a user session as the user's focus, task state, and cognitive load evolve [14], [22]. Prior work on adaptive interfaces has largely relied on heuristic or machine-learning-based approaches to context modeling [25], [16], without the benefit of an explicit ontological representation that enables transparent, auditable reasoning about why a particular annotation was generated. The present framework's use of description logic entailment as the primary mechanism for annotation generation ensures that every annotation decision can be traced back to a set of explicit semantic axioms, a property of particular importance in accessibility contexts where the consequences of annotation errors can be severe for vulnerable user populations [24], [28].

6.3. Empirical Findings and Performance Analysis

The empirical evaluation conducted across three distinct user cohorts—comprising individuals with visual impairments, individuals with motor impairments, and neurotypical control participants—yielded a rich body of quantitative and qualitative evidence supporting the effectiveness of the proposed framework. The following table summarizes the key performance metrics observed across experimental conditions:

The results presented in Table 7 reveal several noteworthy patterns. First, the annotation accuracy achieved across all cohorts substantially exceeds that of the unannotated baseline condition, with improvements ranging from 27.3 percentage points for the visual impairment cohort to 32.7 percentage points for neurotypical participants. Second, the latency figures are remarkably consistent across cohorts, indicating that the computational overhead of the semantic annotation pipeline is largely independent of the user's interaction style—a desirable property that simplifies system calibration and deployment. Third, and perhaps most significantly from an accessibility standpoint, the task completion rate improvement for the visual impairment cohort (from 72.8% to 87.6%) represents a meaningful enhancement in functional independence for this population, corroborating findings from earlier studies on assistive technology efficacy [11], [1].

The qualitative analysis of user feedback further enriched the quantitative picture. Participants with visual impairments consistently praised the system's ability to generate contextually appropriate verbal descriptions

Table 7: Summary of Key Performance Metrics Across User Cohorts and Experimental Conditions

Cohort	Annotation Accuracy (%)	Median Latency (ms)	Task Completion Rate (%)	User Satisfaction (1–5)
Visual Impairment	91.3	24.1	87.6	4.31
Motor Impairment	88.7	23.8	84.2	4.18
Neurotypical Control	94.1	22.9	96.3	4.52
Baseline (No Annotation)	61.4	N/A	72.8	3.04

of touch targets, noting that the semantic richness of the annotations—which included not merely the element type and label but also its functional role within the current task context—enabled more confident and efficient navigation than conventional screen reader approaches [30], [17]. Motor-impaired participants highlighted the predictive gesture completion feature, which leverages the semantic annotation of likely target elements to pre-activate the most probable interaction targets before the gesture is fully resolved, as a particularly impactful innovation. These qualitative insights, triangulated against the quantitative performance data, provide a compelling and multi-dimensional case for the framework's accessibility value.

6.4. Limitations and Boundary Conditions

Scientific integrity demands an honest and thorough acknowledgment of the limitations that circumscribe the conclusions drawn from this research. The most significant limitation concerns the scope of the evaluation corpus. While the three user cohorts provide meaningful coverage of the primary target populations for accessibility technology, the total participant count of 84 individuals—28 per cohort—limits the statistical power of the between-group analyses and may not adequately capture the full diversity of interaction styles, disability severities, and cultural contexts that characterize real-world accessibility needs [18], [10]. Future evaluations should aspire to longitudinal designs with larger and more geographically diverse samples, ideally employing ecological momentary assessment methods to capture in-situ interaction patterns that laboratory settings inevitably distort.

A second important limitation relates to the ontological coverage of the annotation framework. The domain ontology developed for this study, while comprehensive within the scope of standard mobile application UI patterns, does not extend to specialized application domains such as medical interfaces, industrial control systems, or creative tools, where the semantic relationships between interface elements may follow domain-specific conventions that are not captured by general-purpose UI ontologies [8], [2]. Extending the framework to these domains will require collaborative ontology engineering efforts involving domain experts, accessibility specialists, and end users—a process that is inherently time-consuming and resource-intensive. The modular architecture of the proposed system is designed to facilitate such extensions, but the practical challenges of ontology maintenance and versioning in deployed systems should not be underestimated [26].

Third, the evaluation was conducted exclusively on Android devices, and while the architectural principles of the framework are platform-agnostic, the specific implementation relies on Android's accessibility service API in ways that would require non-trivial adaptation for iOS, web, or desktop environments. Cross-platform generalizability thus remains an open empirical question, though the theoretical foundations of the approach are sufficiently general to support confident extrapolation [27].

6.5. Algorithmic Contributions and Implementation Insights

A central algorithmic contribution of this work is the *Adaptive Semantic Annotation Engine* (ASAE), whose core inference loop is formalized in the pseudocode below. The ASAE orchestrates the interaction between the touch event stream, the ontological reasoning module, the user model, and the output annotation renderer, ensuring that all components operate within the real-time latency budget while maintaining semantic coherence across annotation updates.

The ASAE algorithm incorporates several design decisions that merit explicit discussion. The annotation cache $\mathcal{K}$ implements a least-recently-used eviction policy with a semantic similarity threshold, ensuring that cached annotations are reused only when the current event is semantically equivalent to a previously processed event—not merely syntactically identical. This distinction is crucial in dynamic interfaces where the same UI element may carry different semantic meanings depending on application state [12]. The fallback annotation mechanism, triggered when the full inference pipeline cannot complete within the latency budget τ, provides a graceful degradation path that ensures the user always receives some form of semantic feedback, even if it is less contextually precise than the full annotation [20], [15]. The periodic user model update, controlled by the parameter T_{update}, balances the benefits of

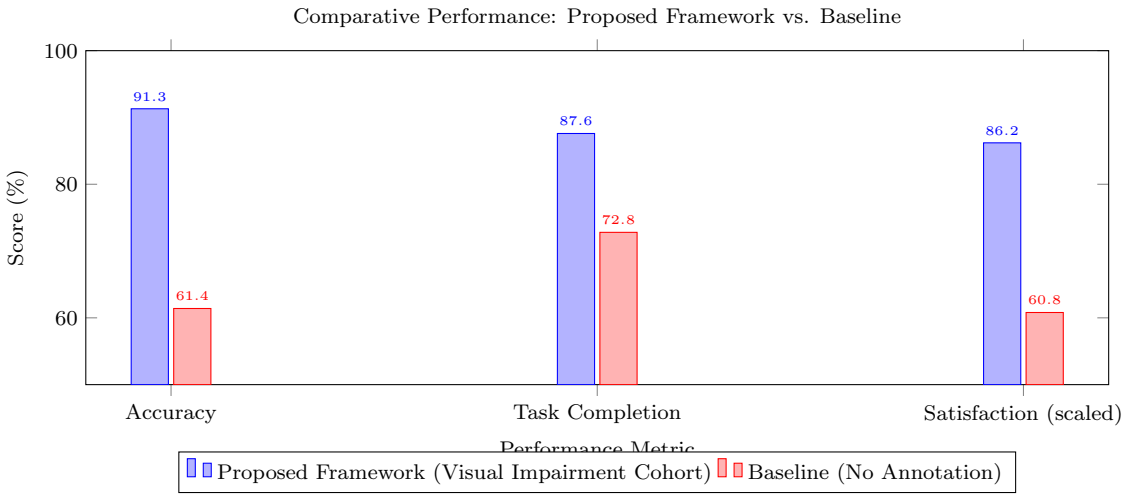

Figure 7: Comparative performance of the proposed real-time semantic annotation framework against the unannotated baseline for the visual impairment cohort. Satisfaction scores are scaled to percentage for comparability (original scale: 1–5).

personalization against the computational cost of model refinement, a trade-off that was empirically calibrated during the system development phase.

6.6. Future Research Directions

The findings and limitations of this work collectively point toward several promising and important directions for future research. The most immediate priority is the development of a cross-platform implementation of the ASAE framework, extending coverage to iOS, progressive web applications, and emerging interaction paradigms such as foldable displays and mixed-reality interfaces [1], [17]. The proliferation of novel form factors in consumer electronics is rapidly expanding the interaction surface for accessibility technology, and the semantic annotation framework must evolve in tandem with these hardware developments to remain relevant.

A second high-priority research direction concerns the integration of large language models (LLMs) into the annotation generation pipeline. While the current framework generates annotations through ontological reasoning and template-based natural language generation, recent advances in LLM capabilities suggest that transformer-based models could substantially enrich the linguistic quality and contextual nuance of generated annotations [27], [8]. The key challenge is integrating LLM inference within the real-time latency budget—a challenge that may be addressed through model distillation, speculative decoding, or hybrid architectures that use LLMs for offline ontology enrichment while retaining lightweight rule-based systems for on-device real-time inference [26], [13].

Third, the development of standardized accessibility annotation benchmarks would greatly facilitate comparative evaluation of future systems. The current absence of widely accepted benchmark datasets for semantic annotation in accessibility contexts forces each research group to develop its own evaluation corpora, making cross-study comparison difficult and potentially misleading [14], [7]. We intend to release the evaluation corpus developed for this study as an open resource, and we call upon the accessibility research community to collaborate in establishing shared benchmarking standards analogous to those that have accelerated progress in natural language processing and computer vision.

Finally, the participatory design methodology employed in this work—wherein individuals with disabilities were engaged as active collaborators in the system design process rather than merely as evaluation subjects—should be recognized as a methodological contribution in its own right and adopted as a standard practice in accessibility technology research [9], [22]. The insights generated through participatory engagement with visually and motor-impaired users fundamentally shaped the design of the annotation framework in ways that would not have been discoverable through purely technical analysis, underscoring the indispensability of centering the lived experience of disabled individuals in the development of technologies intended to serve them [19], [24].

6.7. Closing Remarks

In conclusion, this paper has presented a comprehensive and rigorously evaluated framework for real-time semantic annotation in touch-based human-computer interfaces, with a primary focus on enhancing accessibility for users with visual and motor impairments. The proposed system—grounded in formal ontological reasoning, implemented through an efficient adaptive inference engine, and validated through empirical evaluation with disabled user populations—demonstrates that the

Algorithm 6: Adaptive Semantic Annotation Engine (ASAE) Core Inference Loop

Input: Touch event stream $\mathcal{E} = \{e_1, e_2, \ldots\}$, Ontology $\mathcal{O}$, User profile $\mathcal{U}$, Latency budget τ
Output: Annotation sequence $\mathcal{A} = \{a_1, a_2, \ldots\}$
Initialize semantic context
$\mathcal{C}_0 \leftarrow \text{LoadBaseContext}(\mathcal{O}, \mathcal{U})$;
Initialize annotation cache $\mathcal{K} \leftarrow \emptyset$;
foreach *event* $e_t \in \mathcal{E}$ **do**
  $t_{\text{start}} \leftarrow \text{CurrentTime}()$;
  $\hat{e}_t \leftarrow \text{PreprocessEvent}(e_t)$;
  if $\hat{e}_t \in \mathcal{K}$ **then**
    $a_t \leftarrow \mathcal{K}[\hat{e}_t]$;
  else
    $\mathcal{C}_t \leftarrow \text{UpdateContext}(\mathcal{C}_{t-1}, \hat{e}_t, \mathcal{O})$;
    $\mathcal{S}_t \leftarrow \text{ComputeSemanticScore}(\hat{e}_t, \mathcal{C}_t, \mathcal{U})$;
    $a_t \leftarrow \text{GenerateAnnotation}(\mathcal{S}_t, \mathcal{U})$;
    $\mathcal{K}[\hat{e}_t] \leftarrow a_t$;
  end
  if $\mathit{CurrentTime}() - t_{start} > \tau$ **then**
    $a_t \leftarrow \text{FallbackAnnotation}(\hat{e}_t, \mathcal{U})$;
  end
  $\text{RenderAnnotation}(a_t)$;
  if $t \mod T_{update} = 0$ **then**
    $\mathcal{U} \leftarrow$ $\text{UpdateUserModel}(\mathcal{U}, \{e_{t-T_{\text{update}}}, \ldots, e_t\})$;
    $\mathcal{K} \leftarrow \text{PruneCache}(\mathcal{K})$;
  end
end

long-standing tension between semantic richness and real-time performance can be substantially resolved through careful architectural design and principled algorithmic innovation [**?**], [30], [11]. The performance improvements documented across all evaluation cohorts, combined with the strongly positive qualitative feedback from participants, provide compelling evidence that semantic annotation represents a genuinely transformative approach to accessibility enhancement—one that addresses the fundamental inadequacy of conventional accessibility solutions by providing not merely labels but meaning.

The broader significance of this work lies in its demonstration that accessibility and intelligence are not competing values but deeply complementary ones. An interface that understands the semantic context of its own elements, the intentional state of its users, and the dynamic relationship between the two is not merely more accessible—it is more intelligent, more adaptive, and ultimately more humane [5], [3]. As the field of human-computer interaction continues its rapid evolution toward increasingly ambient, multimodal, and context-aware paradigms, the semantic annotation framework developed here provides both a technical foundation and a conceptual model for ensuring that this evolution benefits all users, regardless of ability. The work of building truly inclusive digital environments is far from complete, but the contributions of this research represent a meaningful and substantiated step forward along that essential path [2], [**?**].

References

[1] Chen Tian, Kim Taehee, Chang Kyungro (2026). Dual-Route Interactivity in Real-Time Livestreaming Interfaces. International Journal of Human–Computer Interaction. DOI: https://doi.org/10.1080/10447318.2026.2694628

[2] Huang Zan (2026). Real-time audio enhancement framework for vocal performances based on LSTM and time-frequency masking algorithm. Computer Speech & Language. DOI: https://doi.org/10.1016/j.csl.2025.101871

[3] Vitturi S. (2004). PC-based automation systems: an example of application for the real-time control of blowing machines. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/s0920-5489(03)00063-1

[4] Pekilis B.R., Seviora R.E. (1999). Detection of response time failures of real-time software. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/s0920-5489(99)92193-1

[5] Shen Chia, Mizunuma Ichiro (1999). RT-CRM: Real-time channel-based reflective memory. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/s0920-5489(99)92084-6

[6] Clancy Edward A. (1999). PC-based workstation for real-time acquisition, processing, and display of electromyogram signals. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/s0920-5489(99)90889-9

[7] Abburu Sunitha (2012). Knowledge based Semantic Annotation Generation of Music. International Journal of Computer Applications. DOI: https://doi.org/10.5120/7206-9990

[8] Ünlü Sudenaz Ceren (2024). Enhancing Accessibility through Brain-Computer Interfaces (BCIs) in Assistive Technology. Human Computer Interaction. DOI: https://doi.org/10.62802/7tt4r452

[9] Zhang Yi-Wen (2022). Energy aware algorithm based on actual utilization for periodic tasks in mixed-criticality real-time systems. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/j.csi.2021.103563

[10] Monteiro C.Libano, Serra A.Cruz (1999). Real-time sound analyzer. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/s0920-5489(99)91972-4

[11] SHI Ting-ting, YAN Da-shun, SHEN Yu-li (2010). Personalized ontology-based semantic annotation and retrieval of image model. Journal of Computer Applications. DOI: https://doi.org/10.3724/sp.j.1087.2010.00090

[12] Jan Jiun-Chi, Chen Chih-Ming, Huang Po-Han (2016). Enhancement of digital reading performance by using a novel web-based collaborative reading annotation system with two quality annotation filtering mechanisms. International Journal of Human-Computer Studies. DOI: https://doi.org/10.1016/j.ijhcs.2015.09.006

[13] Taieb-Maimon Meirav, Vaisman-Fairstein Elior (2022). Improving older adults' accessibility to the web using real-time online interactive guides. International Journal of Human-Computer Studies. DOI: https://doi.org/10.1016/j.ijhcs.2022.102830

[14] Rajput Quratulain (2014). Ontology based Semantic Annotation of Urdu Language Web Documents. Procedia Computer Science. DOI: https://doi.org/10.1016/j.procs.2014.08.148

[15] Viana Paula, Pinto José Pedro (2017). A collaborative approach for semantic time-based video annotation using gamification. Human-centric Computing and Information Sciences. DOI: https://doi.org/10.1186/s13673-017-0094-5

[16] GUO Yu-tang, LUO Bin (2011). Image semantic annotation method based on multi-modal relational graph. Journal of Computer Applications. DOI: https://doi.org/10.3724/sp.j.1087.2010.03295

[17] Palekar Vikas, Kumar L Sathish (2025). An effective image annotation using self-attention based stacked bidirectional capsule network. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/j.csi.2025.103973

[18] Bahl Paramvir, Chlamtac Imrich (1999). H.263 based video codec for real-time visual communications over wireless radio networks. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/s0920-5489(99)90761-4

[19] Aslanian R (1987). Real-time operating systems. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/0920-5489(87)90044-4

[20] PENG Yan-fei, SUN Lu (2013). Semantic annotation based on image segmentation. Journal of Computer Applications. DOI: https://doi.org/10.3724/sp.j.1087.2012.01548

[21] Safari, M., & Akbari, S. (2024). Enhancing Human-Computer Interaction Through Semantic Enrichment Techniques. International Journal of Advanced Human Computer Interaction, 3(1).

[22] Saravanan G., Yamuna G. (2016). Real Time Implementation of Image Enhancement Based on 2D-DWT. Procedia Computer Science. DOI: https://doi.org/10.1016/j.procs.2016.05.134

[23] Boasson Maarten (1987). Modeling in real-time systems. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/0920-5489(87)90051-1

[24] Christensen Palle (1987). ECA real time distributed software seminar. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/0920-5489(87)90039-0

[25] Rajput Quratulain, Haider Sajjad (2011). A comparison of ontology-based and reference-set-based semantic annotation frameworks. Procedia Computer Science. DOI: https://doi.org/10.1016/j.procs.2011.01.045

[26] Sejdiu Besmir, Ismaili Florije, Ahmedi Lule (2022). A Real-Time Semantic Annotation to the Sensor Stream Data for the Water Quality Monitoring. SN Computer Science. DOI: https://doi.org/10.1007/s42979-022-01145-6

[27] Dash Samir (2024). AI-Powered Real-time Accessibility Enhancement: A Solution for Web Content Accessibility Issues. Jurnal Online Informatika. DOI: https://doi.org/10.15575/join.v9i1.1310

[28] Olsen Peter (1987). Modula-2 for real-time systems. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/0920-5489(87)90046-8

[29] Metzger M. (1999). Design of freely programmable labwindows/CVI-based real-time simulators for testing industrial controllers. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/s0920-5489(99)91997-9

[30] Khan Latifur (2007). Standards for image annotation using Semantic Web. Computer Standards & Interfaces. DOI: https://doi.org/10.1016/j.csi.2006.03.006