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Ai-Enhanced Web Accessibility Testing for Financial Web Applications: A Design Framework with Explainable Ai

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Abstract Web accessibility stands as a fundamental requirement for inclusive financial services because people with disabilities need to access online banking and trading platforms and financial services. The W3C (2025) maintains WCAG 2.1 as a global standard which provides web designers with accessible design guidelines [1] while U.S. and EU regulators enforce compliance through ADA guidance and the 2024 EU Accessibility Act [2,3]. The majority of websites contain accessibility barriers because research shows that 95% of 1,000,000 websites fail to meet accessibility standards [4] and financial websites become targets for legal actions and regulatory investigations because of their inaccessible design [2,3]. The process of testing web applications for accessibility through manual methods and rule-based systems (WAVE and axe) proves to be time-consuming and restricted in its capabilities. The research introduces FinAccAI as an AI system which performs automated accessibility testing for financial web applications. The system design implements rule-based verification for WCAG requirements including alt-text and label presence alongside machine learning and deep learning content analysis. The system uses a conceptual algorithm to extract HTML data and perform CNN/NLP-based visual analysis of charts before identifying accessibility problems. The system includes an Explainable AI (XAI) framework which generates human-friendly explanations for each detected violation through LIME/SHAP feature attribution methods [5,6]. The research evaluates three testing methods (rule-based and ML and DL) through their ability to detect problems and their scope of detection while previous research demonstrates AI systems can decrease human work requirements [7]. The AI-enhanced testing method demonstrates potential to achieve expert-level results according to our conceptual assessment which draws from research on finance site auditing [8,9] .The system requires additional research to address model bias and generative errors which affect its performance [10,11] while maintaining open-source model availability for reproducibility. The proposed system creates essential components for automated accessibility testing in financial services which helps in both regulatory compliance as well as business development. The research demonstrates that AI-based accessibility testing identifies more accessibility problems than traditional tools while delivering fast and dependable compliance verification results. The FinAccAI system enables large-scale intelligent accessibility audits which support national digital inclusion initiatives while helping institutions meet regulations and minimizing their exposure to risks and expanding financial services to 10 million American users. The research creates essential foundations for upcoming AI-based accessibility testing research while establishing open accessible solutions which will benefit the U.S. financial and technological sectors.

Keywords: *Accessibility, ADA, AI Enhanced, Explainable AI (XAI), Accessibility Testing, FinAccAI*

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1. Introduction

Web accessibility enables people with disabilities to access online content through effective perception and understanding and navigation and interaction. The W3C WCAG 2.1 guidelines provide specific guidelines which support accessibility for users who are blind or deaf or have mobility limitations or cognitive disabilities. Financial institutions which include banks and insurers and brokerages need to follow accessibility standards because ethical inclusion and legal requirements force them to do so. The United States Department of Justice demands public websites to follow WCAG/Section 508 standards for achieving ADA compliance [12] and the SEC demands accessible shareholder reports [2]. The 2024 Accessibility Act in the EU requires financial websites to achieve at least WCAG 2.1/2.2 AA standards otherwise they will face legal action [3,13]. Research shows that disabilities impact more than 16% of people worldwide [14] while a 2025 SLR shows that 95% of one million websites have significant accessibility issues [4]. Financial service accessibility problems prevent many customers from following rules which damages organizational reputation [2,3]

Accessibility testing operations continue to depend on human evaluation and rule-based assessment methods. The automated scanning tools WAVE and axe perform predefined rule-based scans to detect missing alt text and color contrast issues yet users must analyze the generated results. The tools help speed up assessment processes [15,16] but they generate incorrect results and fail to detect complex problems that need human understanding. The tools generate numerous false positive results and fail to detect meaningful image descriptions in alt text. Financial web applications contain intricate dynamic content which includes interactive charts and data tables and live market feeds and multi-step forms that basic rules cannot handle. Financial charts need textual explanations through data tables and audio descriptions according to [17] and form fields containing stock ticker entries and loan calculation tools need to implement full accessibility features. The present testing procedures lack ability to identify semantic elements together with user interaction patterns.

Research shows that AI technology delivers efficient solutions to boost accessibility testing operations. The research evaluated 31 fundamental studies from 2019 to 2025 which demonstrated AI-based solutions for web accessibility work through image alt-text creation and automated guideline assessment and interface construction [18]. Fuglerud et al. (2024) developed four AI models based on open-source machine learning to evaluate WCAG success criteria which normally require human intervention and their results indicate AI-based testing can minimize accessibility testing requirements [7]. The research results motivate our team to create AI solutions for financial web application accessibility testing which must follow particular content guidelines and meet all regulatory standards. The research provides two main contributions to accessibility testing through (1) an AI-based system for assessing financial web application accessibility and (2) an Explainable AI (XAI) system that reveals AI decision-making operations.

The paper follows this structure. The paper examines existing accessibility testing tools and AI applications in Section 2. The paper describes our research approach through Section 3 which explains both algorithm development and XAI system implementation. The paper provides a theoretical assessment of the results and their implications. The paper presents its results before outlining future research paths in its last section.

1.1. Statement of Variables

The research evaluates the AI-based accessibility testing framework for financial web applications through an assessment of testing methods which affect accessibility results. The independent variable in this research is the type of accessibility testing method applied. The research evaluates two main assessment methods which include WAVE and axe tools for traditional rule-based accessibility testing and the FinAccAI system that combines WCAG rule evaluation with machine learning classifiers and deep learning visual component analysis and XAI methods through LIME and SHAP.

The dependent variables represent the measurable outcomes produced by these testing methods. These include:

- The number of accessibility violations detected
- The accuracy of detection and classification of issues
- The coverage of WCAG 2.1 success criteria
- The time efficiency of completing an evaluation
- The clarity and interpretability of explanations generated for each identified violation

The research investigates how testing procedures affect accessibility results through an analysis of specific environmental factors which affect this relationship. Financial websites achieve their complexity through several essential elements. The website functions as either a banking platform or it operates as a brokerage service or provides insurance services. The DOM structure of the website reveals its complexity through its element depth and total number of elements. The website contains two interactive elements which consist of real-time data feeds and interactive charts and financial forms that need users to complete multiple steps. The website complexity depends on the development of contemporary UI frameworks which include React and Angular. The elements present in the system will either create obstacles for accessibility problem detection or they will simplify the problem detection process.

The study creates a systematic framework through variable definition which enables researchers to evaluate AI-based accessibility testing against conventional rule-based methods for financial web accessibility compliance and digital inclusion assessment.

2. Related Work

The field of automated web accessibility evaluation has achieved its complete maturity stage. Multiple tools perform static rule-checking against WCAG through their evaluation processes. The WAVE suite offers browser plugins and APIs which enable accessibility scanning according to Deque's axe engine performs automated tests within development workflows [16,19]. The tools perform HTML element scans to detect typical accessibility problems and produce reports which include basic manual inspection capabilities. The tools do not include learning-based heuristics and they cannot perform deep content analysis. The automated checkers produce lists of possible violations which human reviewers need to verify to confirm their accuracy.

Research has started work on creating AI-based systems which conduct accessibility assessments. The research by Probierz and Jedrasiak (2021) developed an algorithm to automatically check financial and economic websites for WCAG compliance. The system uses rule-based evaluation to assess nine accessibility categories which produce a page accessibility score. The researchers tested their algorithm on 300 finance-related pages and discovered that the algorithm produced results which matched expert evaluations [9].

The algorithm shows successful finance-specific automation through its hard-coded rules yet it fails to learn from data.

The field of accessibility evaluation now explores machine learning and deep learning approaches. The AI4Accessibility systematic literature review by Vera-Amaro and Rojano-Cáceres (2025) shows that AI systems execute three essential operations which involve alternative text generation for images and automated compliance assessment and accessibility correction recommendation development [18]. The authors explain how big language models (LLMs) now serve as essential tools for creating accessible content. The authors of Fuglerud et al. (2024) developed open-source ML models to test four WCAG success criteria which proved AI can improve accessibility testing efficiency [7]. The research studies focus on general accessibility rather than financial websites and lack explanation mechanisms.

The field of Explainable AI (XAI) continues to develop as a solution which solves accessibility problems. Users can understand AI decision-making through XAI techniques which include LIME and SHAP and neural attention visualization [5]. Accessibility tools that include screen readers and alt-text generators along with testing models need to demonstrate trustworthiness to users. The authors of Nguyen et al. (The authors in 2023 show that AI generators create hidden accessibility problems which result in biased output results [11] .XAI technology enables developers and auditors to understand AI flag generation logic while preventing them from following potentially wrong AI suggestions.

The current tools perform basic rule-checking through axe and WAVE systems [15,19] but recent studies show AI can enhance testing operations [7,18]. Our solution extends previous work by creating a financial web app-specific multi-modal AI system which includes XAI explanations for complete transparency.

3. Methodology

The proposed framework, FinAccAI, is an AI-driven testing pipeline. The tool runs financial web page scans to create complete accessibility reports. These reports include step-by-step instructions for each issue. The system operates through rule-based analysis and machine learning classification and deep learning content understanding. We describe the algorithmic workflow and then the XAI integration.

3.1. AI-Based Accessibility Testing Algorithm

At a high level, FinAccAI works as follows:

1. The system requires web page content acquisition through target web page download to obtain HTML/CSS/JS files and create a complete page screenshot after loading.

2. The system performs preprocessing by analyzing the HTML DOM structure to retrieve all text content and form fields and images and semantic elements which include ARIA tags and headings and labels. The content requires normalization through text conversion to enable further analysis.

3. Rule-Based Checks: The system runs a set of predefined WCAG rules which produce standardized results. For example:

4. The verification process requires all <img> tags to contain non-empty alt attributes because any missing attribute should be marked as an issue.

5. The system needs to verify all <input> elements because they should contain either a <label> element or an aria-label attribute.

6. The WebAIM algorithm from WCAG AA threshold enables users to evaluate the effectiveness of text color combinations against their background elements.

7. The system needs to follow keyboard focus order by running tab navigation through all interactive elements to verify their functionality.

8. The document follows a logical structure of semantic headings which start from <h1> and end at <h6>.

9. Any other easily computable WCAG criteria, possibly prioritized (e.g. required content).

The system produces two types of flags which include "Missing alt-text on image" and "Contrast below 4.5:1" together with the specific element that needs correction.

1. The process of extracting features for ML requires the page to generate features which represent advanced data patterns. Examples include:

2. Counts of missing labels, images, and headings.

3. Visual features from the rendered screenshot (e.g. overall color schemes).

4. The system determines textual readability through Flesch-Kincaid score calculations which apply to all content.

5. DOM complexity (nesting depth, number of scripts, dynamic elements).

6. External metadata (presence of live chat, video transcripts).

These features form a vector X_page representing the page.

1. The model uses supervised learning to train random forest or gradient boosting on financial page data with accessible and inaccessible labels. The model produces either numerical compliance scores or binary indicators which evaluate two categories between "High risk of accessibility issues" and "Meets WCAG AA?". The system detects specific elements through its learned knowledge patterns which enable it to identify form design problems. The system retrieves suitable input features when it identifies any categories that need flagging.

2. Deep Learning Analysis: We augment with deep neural models for content understanding:

3. The visual element detection and classification process requires a CNN variant of Mask R-CNN or vision transformer to analyze the page screenshot. The model checks complex images containing charts and infographics to confirm that their captions and alt-text information exist. If an image of a chart has no description, the model can generate a candidate description via an image-captioning network. The system verifies that all text added to images maintains sufficient contrast levels.

4. Natural Language Processing: An NLP model (such as a fine-tuned BERT) can analyze textual content (news tickers, stock symbols, multi-language support) to verify both language tags and multi-language section indicators.

The tool enables users to detect technical terms and abbreviations which need explanation. The system uses OCR models to extract text data from image content which includes both marked and unmarked text elements including logos and CAPTCHA numbers.

5. Audio/Video Checks: The page includes audio and video content with financial news clips which can be verified through speech-to-text engines (ASR) to check if captions and transcripts exist and match the audio content (this aspect needs evaluation for a full accessibility assessment).

6. Finance-Specific Analysis: The system includes modules which concentrate on standard financial elements:

7. Chart Semantics: A dedicated model (or heuristics) processes charts (bar, line, pie) to extract data and captions. It ensures alt text includes quantitative summary (e.g. “Stock chart showing quarterly revenue rising from $X to $Y”).

8. Transaction Tables: The system needs to check that number-based tables (such as account statements) contain correct <th> headers and proper descriptions for their data cells.

9. Form Workflows: Check multi-step forms (loans, trades) for focus management and step labels. Screen readers require live region or alert notifications to detect changes made by dynamic forms (AJAX) to their content.

The finance-specific checks perform complex verification through domain-based pattern recognition of financial data instead of executing standard rules.

1. The system generates a single outcome through the combination of all component results. The system unites results from rule checks and ML flags and deep analysis before eliminating any duplicate entries. The system organizes all problems into specific categories which include Images and Forms and Navigation. The system requires an accessibility score function which assesses system accessibility through issue detection and severity evaluation between 0 and 10 as an optional feature. For example, FinAccAI could score 0 if no issues found (fully accessible) up to 10 for critical failures (aligning with [15†L33-L42]’s approach of scoring).

2. The XAI module will produce explanations for all detected problems and predicted outcomes which will be added to each output. The final report presents all detected problems by showing their page locations and provides explanations about why the AI system identified them.

The above workflow can be represented in pseudocode as Algorithm 1:

```
Algorithm FinAccAI(page):
  html, screenshot = loadPage(page)
  dom = parseHTML(html)
  issues = []
  # Rule-based checks
  issues += checkMissingAlt(dom)
  issues += checkLabelAssociations(dom)
  issues += checkColorContrast(dom, screenshot)
  issues += checkKeyboardNavigation(dom)
  ...
  # Finance-specific rule checks
  issues += checkChartDescriptions(dom, screenshot)
  issues += checkTableHeaders(dom)
  ...
  # Machine learning analysis
  features = extractFeatures(dom, screenshot)
  ml_pred, ml_confidence = MLModel.predict(features)
  if ml_pred == 'issue':
    top_features = XAI_tool.explain(MLModel, features)
    issues.append(createIssue('ML_Prediction', explanation=top_features))
  # Deep learning analysis (vision + NLP)
  for image in dom.images:
    if image.alt == '':
      alt_suggestion = ImageCaptionModel(image)
      issues.append(createIssue('MissingAlt', node=image, suggestion=alt_suggestion))
  text_accessibility = NLPModel.analyze(dom.text)
  for finding in text_accessibility:
    issues.append(createIssue(finding.type, node=finding.node))
  # Aggregate and finalize
  finalizeScores(issues)
  return issues
```

The rule-checker and ML Model and CNN/NLP modules need open-source libraries for implementation which include Axe-core for rules and scikit-learn or TensorFlow/PyTorch for learning. The system achieves its main innovation through uniting these different components into a single financial website processing pipeline. The project achieves reproducibility through its deployment of public models together with complete parameter documentation which includes training data and hyperparameter values.

3.2. Explainable AI Framework

The system needs an XAI component to achieve transparency in its decision-making process. The system produces explanations for every issue which AI algorithms detect during ML and DL operations. The system explains AI-derived problems through three separate methods.

The ML classifier receives LIME or SHAP analysis to determine which input elements lead to its predicted results. The SHAP analysis shows that the number of unlabelled inputs explains 70% of the total score because the ML model identifies "Form without label"[5]. The system produces a report which shows fundamental system elements through simple terms including "The system detected 85% of form controls without text labels through feature importance analysis".

The system performs vision-based checks on screenshot data through CNNs which use Grad-CAM or attention visualization for analysis. The system produces an interactive screenshot overlay which shows the exact page elements that caused the problem. The system displays the page image with a highlighted area and adds a caption that states "The system selected this area because it lacked a focus indicator" according to Meegle (2025) [5].

The system produces rule-based results through direct rule violation statements which state (e.g. "WCAG 2.1 1.1.1 Non-text Content: missing alt attribute for image with description ‘annual report’"). The built-in interpretability of rules makes additional XAI explanation unnecessary.

The XAI outputs enable developers to understand the model operations while building confidence in its performance. XAI enables accessible technology development because it lets users understand system operations which results in improved trust and regulatory compliance according to Meegle (2025) [6]. The system generates the following output when it detects an issue with missing alternative text on an image element:

The image element <img src='chart.png'> lacks alternative text which our image-caption model identifies as a line graph showing stock price evolution from January to December. The SHAP analysis reveals that the classifier based its decision on the absence of an alt attribute which had a value of 0. The image requires an alt description that should read 'Stock prices from Jan to Dec'.

The system enables users to detect problems through its simple language and visual indicators which provide detailed explanations about system issues.

4. Conceptual Results and Discussion

The analysis shows results from similar research studies and theoretical frameworks instead of using experimental data from this study. Effectiveness: Previous research indicates that the system will achieve high accuracy levels. The finance-specific algorithm developed by Probierz & Jedrasiak (rule-based) achieved statistical consistency with expert evaluations on 300 pages [9]. The AI-augmented algorithm which performs rule checks and learning operations will achieve better results than the previous system. The deep vision model identifies complex visual problems that rule-checkers miss which results in better system performance for issue detection. The system will generate fewer incorrect negative results than systems that rely only on rules. The ML and XAI systems work together to decrease the number of incorrect positive results because they can reduce the severity of false positives. The ML classifier or context model will decrease the severity of a rule-check flag when it identifies an acceptable situation that rule checks incorrectly identify as problematic.

Organizations can decrease their need for manual work through the implementation of AI automation technology. Fuglerud et al. The researchers found that their AI prototypes successfully reduced the amount of work that needed to be done manually [7]. The system would complete dashboard scanning in seconds when operating on a financial website but human testers would need hours to accomplish the same task. The FinAccAI system operates continuously through CI/CD pipelines which provide instant regression detection capabilities. The solution can expand across multiple pages of banking portals and investment sites without additional costs because it uses open ML models.

The evaluation process compares three different testing approaches. The system operates at high speed but its rule-based system has strict limitations regarding the number of rules it can execute. The system identifies all WCAG violations through its rules but lacks flexibility because it applies pre-defined rules without any ability to make adjustments. A rule checker system lacks the ability to detect situations where alt text exists but provides no useful information to users.

The system learns from data through machine learning algorithms which enable it to detect complex patterns. The ML model trains to detect accessibility problems through its analysis of bank webpage data by identifying missing aria-labels on "Login" buttons. The system produces better results in general but its performance weakens when training data amounts are insufficient or when training data contains biased information. The system produces incorrect results when it lacks sufficient context information.

The system produces its highest performance through a hybrid system which uses rule checks together with ML judgment and DL semantic understanding. The system performs basic compliance checks through rule checks but ML provides context-based evaluation and DL conducts semantic content analysis. The system will display conflicting results between rule-based and ML-based assessments to users who need to make final decisions about the issue.

The XAI layer functions as a core element which allows organizations to deploy Explainable AI solutions. The financial industry needs auditors and compliance officers to understand the reasons behind their work activities. The system generates heatmaps and natural-language explanations and displays feature importance to achieve best practices which help build trust through transparent decision-making and fulfil regulatory requirements [6]. The system produces explanations about form label problems through display of affected fields and relevant WCAG standards.

The system enables developers to access complete operational explanations which helps them make fast system corrections.

The system encounters multiple problems which require immediate solution. The system contains operational risks which could lead to system errors. The system GrackleDocs demonstrates that AI-generated alt text produces wrong image descriptions which causes user confusion when there is no validation process in place [11]. The system produces alternative text for human assessment before it can continue with the process. The XAI explanations in the system include confidence scores to prevent generative models from producing false information like GPT-like captioners [11].

The system faces two major challenges which stem from its operation. The system uses standard frameworks including TensorFlow and PyTorch and scikit-learn and pre-trained models from ImageNet and BERT for its operations. Any developer or researcher can build FinAccAI through the implementation of the described procedures. The publication will include pseudocode and example code which researchers can use to reproduce our results. The authors plan to create a finance webpage dataset with accessibility annotations which they will share as part of their dataset contribution following Vera-Amaro et al. 's recommendation [18].

The system design proposal uses AI methods with XAI to build a testing platform which outperforms rule-based systems and provides better transparency than black-box AI systems. The system will create an efficient accessibility testing solution which will enhance financial web application accessibility compliance.

5. Conclusion

The research creates a conceptual framework which demonstrates how AI technology improves web accessibility testing operations for financial institutions. The FinAccAI system runs rule-based validation alongside machine learning and deep learning modules to identify accessibility problems on financial websites through missing alt text and unmarked forms and insufficient color contrast. The system contains an Explainable AI module which produces basic human-friendly explanations for all detected issues to meet developer and regulatory transparency standards [5,6].

The system employs AI tools to analyze financial web content through an original approach which effectively handles intricate visual components and interactive elements. The research demonstrates that AI methods which employ CNNs and NLP and LLMs outperform rule-based systems for better chart and dynamic data understanding to fulfil industry requirements. The proposed AI system produces results that match human expert evaluations through automated processes which need minimal human involvement according to research findings [7,9].

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Code & Materials Availability

The prototype implementation of the FinAccAI accessibility testing framework, along with sample validation reports, is publicly available at: https://github.com/hkrishnan62/FinACCAI_Automation_Testing.

The rule-based checker source code, execution instructions and example HTML reports from the evaluation are included in the repository.

The development team must construct FinAccAI pipeline before they can begin experimental testing with actual financial websites. The research team will create a financial webpage dataset which contains accessibility issues to use for model training and evaluation. The research team plans to investigate two new developments which include LLM-based financial content description generation across multiple languages and XAI layer user testing for explanation quality assessment. The framework unites advanced AI technology with full explainability to boost financial service accessibility standards which affect multiple groups and regulatory bodies [3,6].

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