Explanation-Driven Interventions for Artificial Intelligence Model Customization

Empowering End-Users to Tailor Black-Box AI in Rhinocytology

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Abstract. The integration of Artificial Intelligence (AI) in modern society is transforming how individuals perform tasks. In high-risk domains, ensuring human control over AI systems remains a key design challenge. This article presents a novel End-User Development (EUD) approach for black-box AI models, enabling users to edit explanations and influence future predictions through targeted interventions. By combining explainability, user control, and model adaptability, the proposed method advances Human-Centered AI (HCAI), promoting a symbiotic relationship between humans and adaptive, user-tailored AI systems.

Keywords: Customization · Black-box AI · Model Reconfiguration · Explainable AI (XAI) · Human-AI symbiosis

1 Introduction

Artificial Intelligence (AI) has become an integral component of decision-support systems in numerous domains, including healthcare, finance, and law [16]. While AI models could enhance decision-making, their reliance on complex, often opaque, algorithms presents a significant barrier to adoption [16], especially in high-stakes applications such as medical diagnostics [6]. End-users—typically domain experts rather than AI specialists—require mechanisms to refine and adjust AI behavior to better align with their expertise and contextual knowledge.

Most AI systems follow a one-size-fits-all approach, with limited support for post-deployment customization [5]. This lack of adaptability can lead to misaligned recommendations, loss of trust, and decreased usability. End-User Development (EUD) for AI seeks to address this issue by enabling non-technical users to customize AI behavior according to their specific needs [12].

While the integration of EUD for AI has made substantial progress in fields such as the Internet of Things (IoT), education, and business analytics [11,20], AI-based

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decision-support systems—especially those powered by black-box models—remain challenging for users to modify. Current approaches to AI customization for end-users are (i) *Rule-Based Customization* [11], (ii) *Low-Code / No-Code AI* [20], and (iii) *Human-AI Collaboration Interfaces* [8,22]. The first one involves the definition from the user of if-this-then-that conditions to influence AI outputs. On the other hand, the platforms that adopt *Low-Code / No-Code AI* allow users to build and deploy AI models without programming (e.g., AutoML tools), but they do not enable real-time intervention on model behavior post-deployment. Lastly, *Human-AI Collaboration Interfaces* enable users to validate and/or override the system's predictions without affecting its future behavior. These approaches do not fully address the need for an interactive and iterative refinement of AI behavior based on human expertise. Using professionals' knowledge and expertise to refine AI reasoning can be a valuable resource to improve the system's performance while building a stronger symbiotic relationship between the two parties [15,8].

Creating AI-based systems that embody these characteristics can foster collaboration, establishing a symbiotic relationship between humans and AI. Symbiotic Artificial Intelligence (SAI) is a specialization of Human-Centered AI [26] and aims at supporting humans instead of replacing them. This implies creating solutions that reflect humans' needs and preferences by integrating intervention paradigms, transparency, and fairness by design focusing on augmentation rather than automation [17,8].

This research proposes a novel intervention-based User Interface (UI) within the *Rhino-Cyt* platform, designed to empower rhinocytologists to modify AI-generated classifications and explanations. This proposal aims at embodying the *EUDability* construct [4] by introducing an innovative explanation-driven EUD approach, allowing end-users to adjust AI classifications, edit AI-generated explanations, and indirectly refine and tailor the AI model through the mechanism of *interventions* [24]. This approach goes beyond rule-based or component-based customization, offering a *human-in-the-loop* model refinement paradigm. Thus, Rhino-Cyt involves rhinocytologists as its end-user developers, supporting them in reaching the goal of diagnosing.

The rest of the article is structured as follows. Section 2 discusses prior research in EUD for AI, explainability, and human-AI collaboration, also presenting Rhino-Cyt. Section 3 presents the design of the intervention-based UI, detailing its interaction flow and impact on AI adaptation. Section 4 positions Rhino-Cyt within existing EUD for AI taxonomies and compares it with other customization paradigms. Section 5 concludes this article by summarizing its key contributions and outlining the next steps.

2 Background and Related Work

This section reviews prior research on EUD for AI, explainability as a mechanism for EUD, and human-AI collaboration in decision-support systems.

2.1 End-User Development for AI

EUD encompasses a range of methods, techniques, tools, and socio-technical environments that empower non-professionals to engage in activities usually reserved for professionals in ICT-related areas, including the ability to create, modify, extend, and test digital artifacts without requiring specialized knowledge in conventional software engineering practices [3]. A systematic literature review by Esposito et al. categorized existing EUD for AI approaches into five key paradigms [11]:

1. *Component-Based:* Users assemble predefined AI components through visual programming interfaces.
2. *Rule-Based:* Users are allowed to modify AI behavior through "if-then" rules.
3. *Wizard-Based:* Step-by-step guidance simplifies AI customization, presenting the task as a sequence of operations that guide users throughout the overall activity.
4. *Template-Based:* Users adjust pre-built AI models by modifying parameters.
5. *Workflow and Data Diagrams:* Users define AI processes using flow-based representations.

While these approaches are effective for tasks such as building AI models from scratch or configuring predefined automation rules, they offer limited support for modifying existing black-box AI models. *Explanation-driven interventions* extend EUD for AI by introducing a new paradigm. Instead of requiring users to manipulate AI model components or logic directly, this proposal allows them to edit AI-generated explanations, *indirectly* refining the model's behavior over time.

In this regard, explainability has rarely been explored as an active mechanism for EUD. EXplainable Artificial Intelligence (XAI) seeks to make AI model decisions more interpretable and transparent [16,23]. Through XAI, users can understand AI decisions, deciding whether to rely on its predictions or potentially recognize (and mitigate) biases by assessing its reasoning [16].

In most AI-assisted decision systems, explanations are static, not allowing users to modify them to influence future AI behavior. Our proposal introduces a novel editable explanation mechanism where users can modify explanations associated with AI classifications, provide domain-specific refinements to ensure AI-generated explanations align with expert knowledge, and influence future AI behavior indirectly.

2.2 Human-AI Collaboration in Decision Support Systems

AI-based decision-support systems, especially in medicine, often follow a *human-on-the-loop* paradigm, where users oversee the decision-making process by interacting with AI outputs to merely validate its decisions [25,8,13]. This translates into a validation-based collaboration, where experts review AI predictions but have no direct manipulation mechanism for modifying the AI's reasoning process [8].

Our proposal aims at filling this gap following the model of human–AI interaction proposed by Desolda et al. [7], moving beyond this by enabling direct, explanation-driven interventions, ensuring that AI's decision-making processes evolve alongside domain experts, fostering a symbiosis among humans and AI [8]. Establishing proper collaboration mechanisms between humans and AI is crucial to guarantee that professionals are aware of the processes that lead to outputs.

2.3 Rhino-Cyt: an AI-based system for Rhinocitology

Our proposal leverages a case study in the context of rhinocytology (a subfield of medical cytology) [9,10]. Currently, the diagnostic process in rhinocytology is mainly based on direct observation under the microscope, which requires a prolonged effort by rhinocytologists [14,7].

Rhino-Cyt is an AI-assisted environment for the classification of nasal cytology samples that supports its end-user developers, i.e., medical professionals, in diagnosing inflammatory and allergic conditions [10]. It employs AI models (namely, a CNN) to automate the cytological examination by segmenting histological samples of the nasal mucosa, identifying and classifying individual cells based on nine cytotypes [10,14]: (i) ciliated, (ii) muciparous, (iii) basal cells, (iv) striated cells, (v) neutrophils, (vi) eosinophils, (vii) mast cells, (viii) lymphocytes, (ix) metaplastic cells.

3 Design of the Intervention-Based User Interface

Rhino-Cyt introduces an innovative intervention-based UI that allows rhinocytologists to refine AI-assisted classifications, presented in Fig. 1. Users can *intervene* modifying decisions and explanations, unlike conventional AI customization methods, which rely on rule-based or low-code paradigms [24].

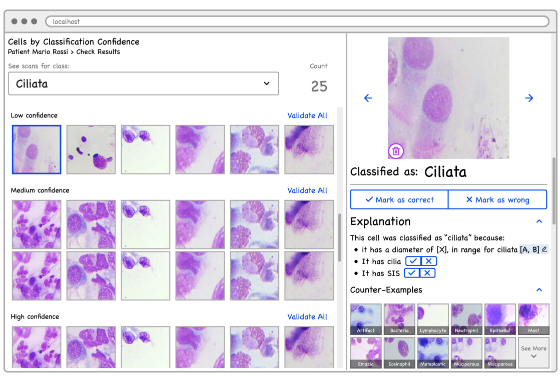

Fig. 1: The user interface for allowing black-box AI model tailoring implemented in Rhino-Cyt

This section details the design principles, UI components, and interaction workflow, demonstrating how the system aligns with EUD for AI by offering an explanation-driven intervention mechanism.

3.1 Design Rationale and Principles

The design of the Rhino-Cyt intervention UI follows three core principles derived from EUD for AI research [11], which emphasize the human intervention that leads to the AI customization while minimizing humans' cognitive load. The referred principles are:

1. *Intervention-Based Interaction*. The system allows logged users to adjust AI classifications and explanations tracking any modifications.

2. *Explainability-Driven Customization*. The system supports it by allowing users to refine AI-generated justifications without requiring them to modify raw model parameters or write explicit rules. Instead, the interface leverages editable explanations as a means of customization, enabling domain experts to adjust and improve AI-generated reasoning based on their medical expertise.
3. *Minimal Cognitive Load for Domain Experts*. The system is designed to minimize the cognitive load for domain experts by providing guided interventions that simplify the interaction process and reduce the need for technical expertise. AI adaptation occurs implicitly through user feedback, allowing the model to refine its reasoning without requiring manual retraining.

3.2 User Interface Components

The elements of Rhino-Cyt's UI (Fig. 1) that allow users to intervene on AI decisions consist of the following key components

1. The *Classification Details and Interventions Panel* presents AI-generated classifications, allowing users to review system decisions. If necessary, users can override AI's decisions by selecting an alternative category which is incorporated into the system, contributing to the continuous adaptation and improvement of the AI's future performance.
2. The *Editable Explanation Area* displays the AI-generated justifications of its classifications, providing transparency into the decision-making process. Users can modify these justifications to guarantee they align more closely with their expertise. Any edits made by users directly influence the AI's reasoning model, refining its approach and shaping future justifications.

3.3 Interaction Workflow: How Users Intervene in AI Decisions

The Rhino-Cyt intervention workflow is structured as a three-step process.

Step 1: Reviewing AI-Generated Classification and Explanation. Upon analyzing a nasal cytology sample, the AI presents a predicted classification and a textual explanation justifying the classification.

Step 2: User Intervention via Adjustment or Explanation Editing. The users have two options for intervention: they can either override the AI classification by selecting an alternative label or modify the AI-generated explanation to reflect expert reasoning more accurately, or both.

Step 3: Model Adaptation and Visualization of Impact. The system logs interventions and updates the AI's explanation model.

This workflow enables AI adaptation to be progressive, ensuring the model evolves alongside experts' knowledge, thus creating a human-in-the-loop customization mechanism for AI-supported decision-making.

3.4 Underlying AI Model Adaptation

Our proposal balances manual user intervention with an automated model refinement process based on users' feedback, thus providing an example of both an *adaptable* and *adaptive* system [12].

The platform continuously logs user interactions, capturing every action performed by users. This includes explicit feedback on the AI model's predictions, where users can either accept the suggested classification or reject it and make modifications. The collected feedback is then leveraged to initiate the retraining of the AI model.

To enhance the adaptivity and adaptability of the AI system, several techniques can be employed, ranging from online learning [1,27] to reinforcement learning from human feedback [18], leveraging detailed explanation obtained either from a gray-box model (as the one presented by Desolda et al. [7]) or through large-language models. Specifically, user feedback on explanations helps refine the AI model in different ways. If there is a direct, one-to-one relationship between an explanation and the model's decision-making process—as seen in decision trees—the model can be updated immediately. In contrast, when using more complex models, such as deep learning, the feedback is transformed into additional data points that contribute to adjusting the model's internal parameters.

4 Positioning Explanation-Driven Interventions as an EUD Tool for AI

The Rhino-Cyt intervention UI introduces a novel approach to EUD for AI, using editable explanations as an AI customization mechanism. This section explores Rhino-Cyt's classification within the current EUD for AI landscape, comparing it with existing AI customization approaches while also examining its impact on human-AI symbiosis. Rhino-Cyt's main features are summarized in Table 1 and described below to highlight the customization aspects of the interaction workflow.

It enables end-users to customize its functionalities through explanation-driven intervention. Based on the information highlighted in the explanation, users can take actions such as marking the explanation as accurate or incorrect or adjusting the feature values used in the reasoning process. This approach puts physicians in control by allowing them to refine the system's outputs and justifications, enhancing its performance, especially in cases involving outliers. In this context, user actions can represent feedback for the system that can adapt its behavior over time.

To classify Rhino-Cyt within the existing EUD for AI landscape, we adopt a recent framework proposed by Esposito et al. [11], which categorizes EUD AI solutions based on the dimensions presented in Table 2.

To illustrate the novelty of Rhino-Cyt, we compare it with three common AI customization paradigms: rule-based customization, no-code model building, and collaboration interfaces. The comparison is reported in Table 3.

Explanation-Driven Intervention enables users to manipulate the reasoning of the AI model by modifying the explanations. This approach becomes particularly effective in the medical context because no technical expertise is required: professionals can

Table 1: A summary of the main features of Rhino-Cyt's intervention-based UI

Feature	Rhino-Cyt's Intervention UI
Customization Approach	Explanation-driven intervention
User Control	Freeform modifications of AI outputs and justifications
Impact on Model Behavior	Direct, real-time adaptation
Technical Expertise Required	None (domain expertise only)

Table 2: Classification of the intervention-based UI according to [11]

EUD Dimension	Rhino-Cyt Implementation
Composition Paradigm	Explanation-driven, rule-based intervention
Target Users	Domain experts (rhinocytologists)
Technology	AI-assisted medical diagnostics
Usage	Single-user, with potential for collaborative interventions
Customization Level	Tailoring and indirect model refinement
Approach Output	AI model adaptation via explanation modifications

Table 3: Comparison between the three common customization paradigms and the Rhino-Cyt intervention-based UI.

Approach	Customization Scope	Technical Expertise Required	Impact on AI Model
Rule-Based AI Customization	Predefined rule sets	Moderate	Direct, deterministic changes
No-Code AI Model Building	Component-based visual programming	Low	Configures AI before deployment
Human-AI Collaboration Interfaces	Users validate/override AI outputs	None	No direct AI adaptation
Explanation-Driven Intervention	Editable explanations influence AI reasoning	None	Indirect, adaptive refinements over time

redirect and refine the systems' behavior merely by relying on their knowledge and background in their field. This approach enables adaptive learning ensuring the model evolves in alignment with expert reasoning.

Trust calibration is a major challenge in AI-assisted decision support, particularly in high-stakes domains like medicine [19]. More specifically, AI systems must be created ensuring that users do not simply accept AI recommendations blindly—or, conversely, dismiss them outright [2,21,6]. Our proposal tackles this challenge by allowing users to engage with the AI's reasoning process rather than just its final outputs. Instead of simply overriding a classification, experts can refine the reasoning behind it, fostering a symbiotic relationship in which both the user and the AI system learn in the process [8]. Through explanation-driven interventions, users' refinements gradually steer the AI model toward better, safer, and more reliable predictions. This approach positions AI as a collaborative partner, learning from domain expertise in a way that strengthens both accuracy and user confidence.

5 Conclusions and Future Work

This article proposed *explanation-driven interventions* as an EUD tool for black-box AI systems, illustrated through their adoption in Rhino-Cyt, a system aiding rhinocytologists in cell counting tasks. Unlike traditional AI customization methods that relegate domain experts to passive reviewers, explanation-driven interventions empowers them to directly manipulate AI-generated outputs and explanations, without any programming expertise. This work contributes to ongoing research in human-centered AI and AI-assisted decision supports EUD systems have the potential to bridge the gap between AI automation and expert oversight. Future work includes evaluating the usability and effectiveness of Rhino-Cyt through user studies, identifying improvement areas, and extending support to multi-user collaboration. Better methods for tracking intervention impact and mitigating user errors are also needed. Another key direction is assessing how editable explanations affect model performance, accuracy, and user cognitive load. Structured evaluations could clarify whether this approach enhances trust and understanding more than traditional rule-based customization. Finally, explanation-driven interventions hold promise beyond medicine, with potential in domains like law and finance where professionals must interpret and refine AI reasoning.

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