Research Statement — Yi-Chi Liao

yichi.liao@inf.ethz.ch | yichiliao.com

Interactive systems are increasingly powered by AI, yet most interfaces remain static once deployed, unable to adapt to users or contexts. My research develops **human-in-the-loop optimization (HILO)** methods that **enable interactive systems to learn from human behavior and adapt interfaces during use**. For example, I introduce optimization techniques that allow input methods to adapt to individuals' movements, and design tools that infer aesthetic preferences to optimize for design outcomes. Rather than assuming a fixed interface can serve all users and contexts, I view interaction as an **ongoing optimization process**, in which humans and AI jointly shape the interface. My long-term vision is to build **streamlined human-AI collaborative systems** in which interfaces continuously evolve by learning from human interaction.

Introduction

Designing interactive systems (e.g., graphical interfaces, input techniques, design tools) has always been a central yet challenging task in Human-Computer Interaction (HCI) and human-centered computing. A key difficulty is the magnitude of the design space. For example, consider designing a mouse-to-cursor transfer function that maps mouse movement to cursor position with only four parameters; even if each parameter is discretized into just 10 levels, the design space already contains *10^4 combinations*. Designers usually navigate such vast spaces through iterative prototyping and user testing until they find an effective solution. Yet, promising designs can be missed in this process. Moreover, this "one-design-fits-all" workflow assumes that a well-crafted interface can serve all users and contexts, which is increasingly incompatible with today's interfaces. For example, many mixed-reality interfaces require personalization, while the user experience in gaming devices and design tools can greatly benefit from customization. AI-driven systems add further complexity, as they are operated via open-ended prompts rather than carefully designed interactions.

I believe the future of HCI lies ***not in perfecting fixed interfaces***, but in ***creating intelligent systems that adapt, and even re-create themselves for different users during use***. This raises a core research challenge: *how can we develop machine learning-based optimization methods that allow interactive systems to efficiently learn from noisy human behavior and optimize for individuals in real time?*

Prior work in human-in-the-loop optimization (HILO) has enabled interfaces to adapt through an iterative optimization process: the system proposes an interface, the user interacts with it, the system observes performance and proposes a refined interface. Despite their promise, existing HILO approaches remain limited in scope, require many iterations to converge, and are difficult to scale with data.

Research Contributions

My research follows three interlinked directions: (1) I develop methods that expand HILO's scope to complex, real-world interactions [1-5]. (2) I enhance the efficiency of HILO by leveraging data from prior users [6-7]. (3) I scale HILO methods by allowing them to incorporate ever-growing data [8-9].

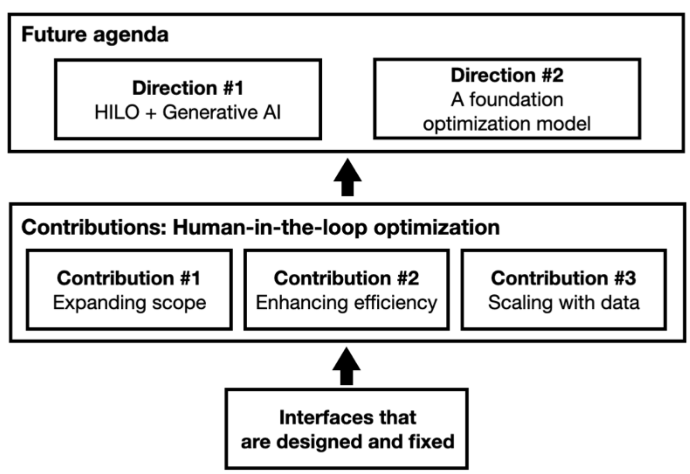

Figure 1. Overview of my research agenda: transitioning from pre-designing interfaces to human-in-the-loop optimization (HILO) and, ultimately, to future human-AI collaborative systems that optimize complex interface designs.

1. Broadening HILO's *Scope*: beyond Single Design Objectives

Typical HILO work focuses on tasks with a single design objective; for example, push-button design optimizes solely for input accuracy [5] (Figure 2a). However, user experience in real-world interfaces is usually governed by multiple design goals. For instance, the experience of selecting a target in VR depends on both input accuracy and efficiency; similarly, a webpage must balance information density with visual comfort. Thus, the limitation of only handling one design objective severely restricts HILO's scope.

To overcome this, **I integrated multi-objective optimization into HILO,** which offered a crucial advantage: instead of searching for a single design that maximizes one objective, it **identified a set of designs that achieve Pareto-optimal performances** across multiple objectives. These solutions represented the best trade-offs: improving one design objective necessarily worsens another. For example, multi-objective optimization can identify all design variants of an input technique that optimally balance accuracy and speed, or webpage layouts that best trade off information density and readability. By identifying this Pareto-optimal set, the optimization process offered designers and users a range of options rather than a single solution, allowing them to select the design that matches their priorities across different objectives.

Figure 2. *I developed methods that broaden HILO from single- to multi-objective tasks: (a) A typical HILO workflow that optimizes push-button design solely for input accuracy [5]. (b–d) Integrating multi-objective optimization into HILO, demonstrated on haptic display design [3], AR interface layouts [1], and VR target selection techniques [4].*

Extending HILO from single to multiple objectives greatly broadens the range of applications. For example, it enables the personalization of haptic displays that must balance information transfer rate and recognition accuracy [3] (Figure 2b), the adaptation of mixed-reality interfaces based on multiple objectives [1] (Figure 2c), and the optimization of several input techniques in VR [4] (Figure 2d) and on touchscreens [2], which have to consider diverse performance metrics. These works broaden the scope of HILO and demonstrate its applicability to complex interaction design challenges. Our user studies showed that users benefit from the flexibility of selecting final designs based on their priorities across different design objectives. In addition, designs produced by the optimizer achieve higher performance than manually created designs, while significantly reducing designers' effort.

Figure 3. *I developed methods that enhance HILO's efficiency by leveraging prior experience. (a) Prior optimization data enables rapid adaptation in movement-based cursor control using wrist-worn devices [7]. (b) Prior preference data supports efficient personalization of image filters [6]. (c) A continual HILO framework goes beyond a fixed dataset, continually accumulating knowledge across unlimited users for mid-air keyboard adaptation [8].*

2. Enhancing HILO's *Efficiency:* Leveraging Prior Experience

Current HILO workflows often require extensive user evaluation on various design candidates before identifying an optimal solution. For example, optimizing a VR input technique [4] (Figure 2d) can take up to 60 minutes. The fundamental challenge is that optimizers typically lack prior knowledge of the task and must search the design space from scratch for each user, leading to slow convergence. However, many interactions require rapid personalization (e.g., text entry, VR input) where long optimization processes are impractical. Therefore, these interactions usually rely on explicit calibration steps before use, which disrupt the user experience and do not guarantee optimal performance.

I developed a novel method that **stores previous users' evaluation data as prior user models**. These models predict expected performance for new users given an interface candidate, **allowing the optimizer to propose effective designs** from the start and thus enabling rapid interface adaptation [7]. Applied to wrist-worn input interactions, this approach identifies personalized settings within only three iterations (Figure 3a). Moreover, it outperforms manual calibration in both efficiency and performance, effectively eliminating the need for explicit calibration.

I further extended this approach to preference-based tasks, demonstrating it on visual filter design [6] (Figure 3b). The underlying method is preferential optimization: it relies on preference comparisons (i.e., selecting the preferred design among alternatives) rather than noisy human ratings on different designs. However, preferential optimization without prior experience usually needs many comparisons to reach a satisfied design. By leveraging prior preference models from other users, our method enables efficient filter optimization for new users with few iterations. These works establish a generalized approach for improving HILO's efficiency, enabling real-time interface adaptation.

3. *Scaling* HILO: Ever-Growing Data and Synthetic Interactions

The above works have shown that HILO can be enhanced by experience. However, they do not scale indefinitely. Two challenges remain: (1) current systems cannot incorporate ever-growing data and (2) large-scale interaction data collection remains expensive and difficult.

The above works rely on a fixed dataset of prior users. As this pool grows, so does the computational cost during deployment, preventing it from leveraging ever-increasing prior experience. This further constrains generalizability: when new users deviate from the prior users' behaviors, the optimizer cannot adapt effectively. An ideal HILO system should instead continually evolve, improving its performance as more user experience becomes available.

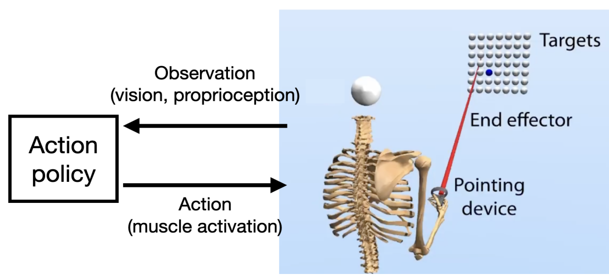

Figure 4. Synthetic users with human's musculoskeletal structure driven by an action policy model, enabling large-scale interaction data generation. I demonstrated the concept on a target selection interaction in VR [9].

I proposed a **continual HILO framework** that enables optimizers to incorporate ever-growing experience and improve across users over time [8]. At its core was a model that captured population-level user characteristics and continuously updated itself with new user data. Importantly, such a model was a neural network, *enabling it to integrate large-scale data without increasing computational cost.* I deployed this approach for mid-air keyboard personalization in VR (Figure 3c). Results showed that the system not only outperformed existing baselines, but also improved its performance with more users.

Another crucial step toward scalability lies in the data itself. Collecting human interaction data to serve as priors remains costly, making it difficult to scale beyond small datasets. To address this limitation, I developed **synthetic users that simulate human behavior**, enabling scalable data generation without human involvement. These synthetic users have human musculoskeletal models and action policies learned through reinforcement learning, allowing them to produce realistic interaction behaviors. Together, these components generate large-scale interaction data at minimal cost. Building on this, I introduced a target inference model trained entirely on synthetic interactions [9] (Figure 4), which enables adaptive target suggestions to support selection in VR. This project demonstrates that simulation can serve as a scalable data foundation for future adaptive interfaces.

To summarize, my contributions establish a foundation for HILO by (1) broadening its application scope, (2) improving its adaptation efficiency, and (3) scaling HILO approaches with data.

Research Agenda

Looking ahead, my goal is to extend HILO into more general human-AI collaborative systems: systems in which AI iteratively improves and generates interfaces that optimize user experience. To advance this vision, my research moves in two complementary directions: (1) integrating HILO with generative AI to broaden the scope, and (2) developing a general-purpose optimization model that learns from interactions at scale.

Direction 1: Integrating HILO and Generative AI

A key requirement of current HILO approaches is that they operate in a well-defined design space, typically one that can be expressed through a fixed set of parameters. Examples include the parameters governing input techniques or the position and size of UI elements. However, real-world interface design is often far more complex, open-ended, and cannot be easily parameterized. Designing a complete webpage or a full application interface, for instance, cannot be easily reduced to a fixed set of parameters.

Generative models offer a promising alternative. They can produce complex interface artifacts (e.g., full graphical interfaces or interactive webpages) directly from textual prompts, without requiring an explicitly defined design space. However, this workflow introduces a new challenge: the prompt space is nearly unbounded. As a result, achieving a desired outcome often requires extensive trial and error. Conceptually, both prompt-based generation and traditional interface optimization share the same core problem: efficiently searching within a vast design space, whether parameterized or open-ended.

To address this, **I will integrate HILO optimization with generative AI.** In such systems, the generative AI iteratively produces and refines candidate interfaces, users interact with and evaluate these candidates, and the system adapts its generation strategy based on evaluation outcomes (e.g., objective function values). Rather than relying on extensive manual prompt engineering, designers provide minimal guidance, while the system learns and improves through interaction.

I will investigate optimization at multiple levels: at the intent level, the system automatically refines prompts for optimizing the user experience. At the latent level, the system explores abstract qualities, such as balance, cohesiveness, or style, that are difficult to explicitly articulate in text prompts. At the model level, the generative model adapts across users and contexts, incorporating cumulative feedback into its generative behavior. These capabilities extend HILO beyond predefined design spaces into open-ended domains. I envision a future where generative systems become active collaborators that actively anticipate goals and evolve themselves by learning from human interactions.

Direction 2: A Foundation Optimization Model for Interactive Systems

While prior experience can enhance HILO, current approaches remain interaction-specific: data collected from one interaction benefits only that same interaction. For instance, prior data on mid-air typing accelerates adaptation for new users in mid-air typing, but offers no benefit for optimizing a different interaction. **I aim to develop a foundation optimization model that learns from optimizing a wide range of interfaces and applies this knowledge to new design tasks more efficiently.**

Analogous to large models in language (e.g., GPT) or vision (e.g., DALL·E), which capture transferable patterns across contexts, this foundation optimization model will learn the general principles of interaction optimization: how to adjust interfaces based on user behavior and performance across diverse devices, modalities, and environments. This would constitute the first step toward a unified model for general interface optimization. Scalability is central to this vision; I will train a deep neural model that learns to propose interface designs based on large-scale evaluation data collected across interactions and users. The model will learn to interpret observed evaluation outcomes and generate design candidates predicted to perform well. Synthetic users will play a critical role by producing realistic and diverse interaction data at scale, dramatically reducing dependence on human evaluation.

Ultimately, this direction seeks to establish a foundation model that enables efficient, cross-domain interface optimization that generalizes across users, devices, and contexts.

REFERENCES

[1] Yao Song, Christoph Gebhardt, **Yi-Chi Liao**, Christian Holz. “Preference-Guided Multi-Objective UI Adaptation.” *Proceedings of the 2025 ACM Symposium on User Interface Software and Technology (UIST)*. 2025.
[2] **Yi-Chi Liao**, George B Mo, John J Dudley, Chun-Lien Cheng, Liwei Chan, Per Ola Kristensson, Antti Oulasvirta. “Practical approaches to group-level multi-objective Bayesian optimization in interaction technique design.” *ACM Collective Intelligence*, *3*(1). 2024.
[3] **Yi-Chi Liao**, John J Dudley, George B Mo, Chun-Lien Cheng, Liwei Chan, Antti Oulasvirta, Per Ola Kristensson. "Interaction design with multi-objective Bayesian optimization." *IEEE Pervasive Computing* 22.1 (2023): 29-38.
[4] Liwei Chan, **Yi-Chi Liao**, George B Mo, John J Dudley, Chun-Lien Cheng, Per Ola Kristensson, Antti Oulasvirta. "Investigating positive and negative qualities of human-in-the-loop optimization for designing interaction techniques." *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 2022. **Honorable Mention Award.**
[5] **Yi-Chi Liao**, Sunjun Kim, Byungjoo Lee, Antti Oulasvirta. "Button simulation and design via FDVV models." *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 2020.
[6] Zhipeng Li, **Yi-Chi Liao**, Christian Holz. “Efficient Visual Appearance Optimization by Learning from Prior Preferences.” *Proceedings of the 2025 ACM Symposium on User Interface Software and Technology (UIST)*. 2025.
[7] **Yi-Chi Liao**, Ruta Desai, Alec M Pierce, Krista E Taylor, Hrvoje Benko, Tanya R Jonker, Aakar Gupta. "A meta-Bayesian approach for rapid online parametric optimization for wrist-based interactions." *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 2024.
[8] **Yi-Chi Liao**, Paul Streli, Zhipeng Li, Christoph Gebhardt, Christian Holz. “Continual Human-in-the-Loop Optimization.” *Proceedings of the 2025 Conference on Human Factors in Computing Systems (CHI)*. 2025. **Honorable Mention Award.**
[9] Hee-Seung Moon, **Yi-Chi Liao**, Chenyu Li, Byungjoo Lee, Antti Oulasvirta."Real-time 3D target inference via biomechanical simulation." *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 2024. **Honorable Mention Award.**