Scaffolding Human Learning by Shaping Visual Environment

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Motivation And Contribution

‣ **Challenges for Online Learning Support.**

- In-time teacher guidance is often unavailable in ubiquitous online learning environments
- Our solution: proactively supporting learners by **adaptively modifying the learning environment** based on learner behavior.

‣ **Research Questions of Environment Shaping.**

- **What** kind of guidance/learning support is needed?
- **When** do students need support?

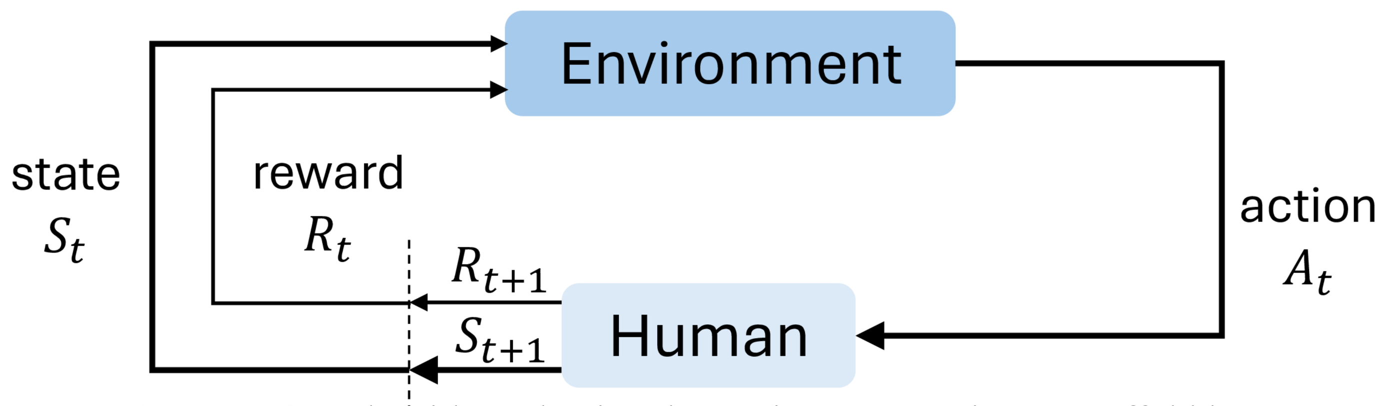


Figure: Our algorithm: shaping the environment action to scaffold human learning modeled in Markov Decision Process (MDP).

Contributions

‣ We introduce environment shaping as pedagogical experience manipulation, expanding AI-assisted learning beyond on-demand help.

‣ We instantiate this framework in VEX VR, using large visual models to detect learner difficulty and generate adaptive visual interventions. We introduce a VLM-agent simulation framework for reproducible evaluation, with promising preliminary results.

Methods

1) Model The Learner-Environment Loop

$M = (S, A, P, R)$, $\quad s_t = (g_t, m_t, c_t)$

g: gaze, m: mouse, c: code; progress $f(s_t)$ is inferred from behavior.

2) Decide Whether Guidance Is Needed

$a_t = intervene(s_t) \text{ if } f(s_t) < \tau; \quad \emptyset \text{ otherwise}$

3) Estimate Intervention Effect And Shape Visuals

$P(s'|s,a) = N(s,a,s')/\sum_{s''} N(s,a,s'')$

$r_t = R(s_t, a_t, s_{t+1})$

Actions: pop-up hints, code/object/area highlighting, or no-op.

When To Provide Support And What To Provide?

‣ We formulate learning as a **Markov decision process (MDP)**, where learner states are inferred from multimodal behavioral signals and actions correspond to environment-level interventions such as **adaptive visual highlighting**.

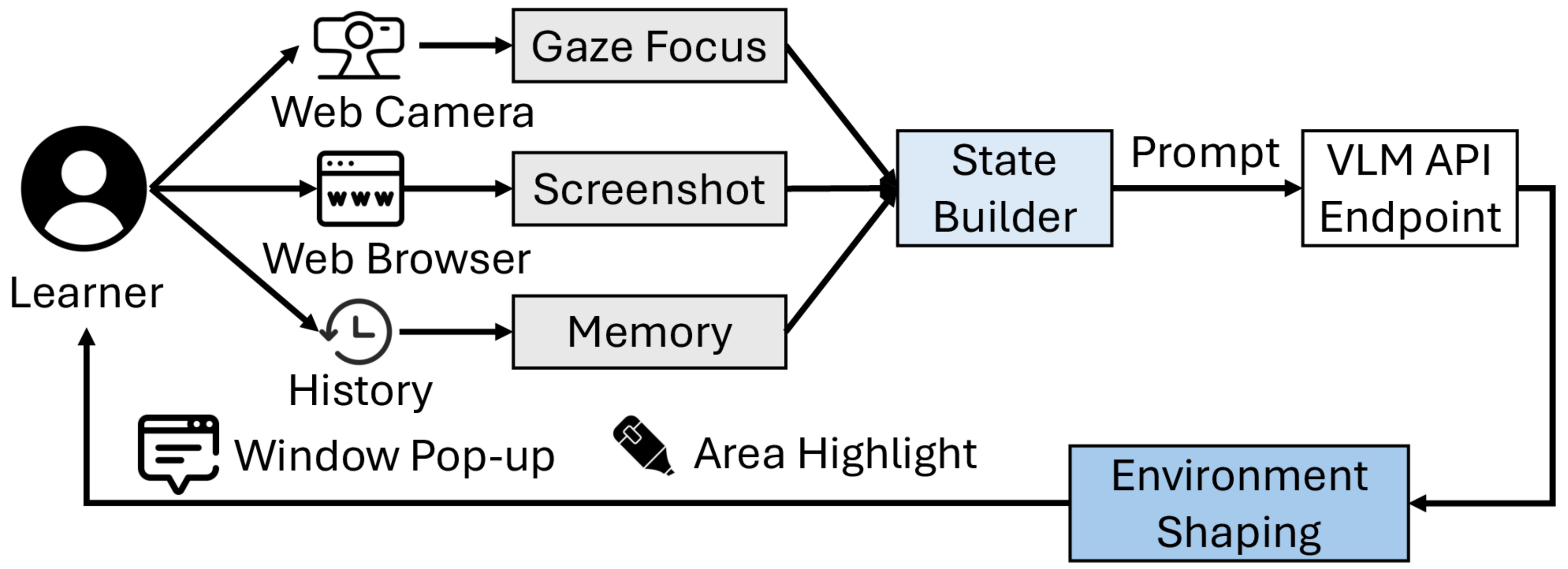
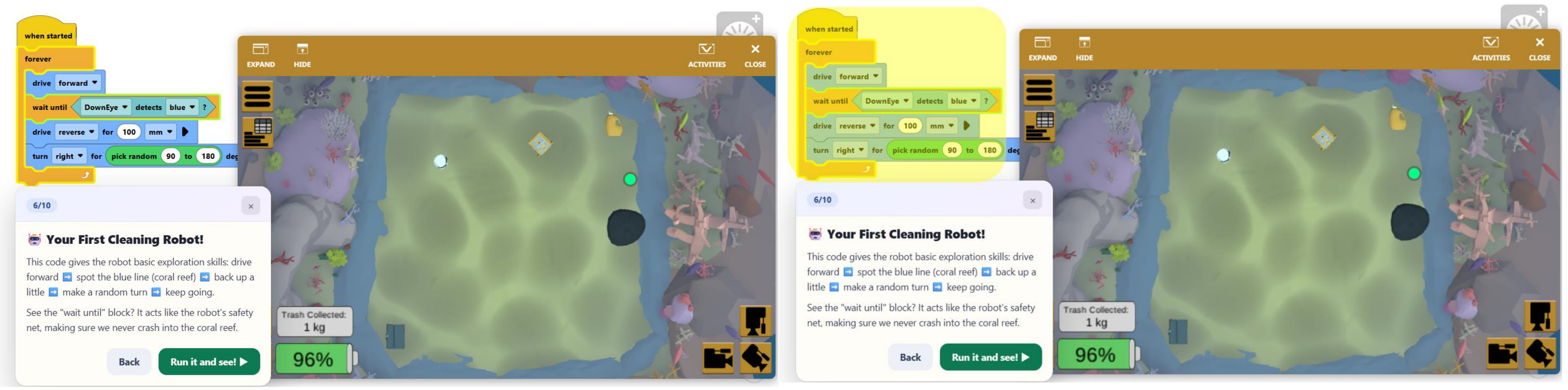


Figure: Our system: a general MDP-based implementation.

‣ The browser extension executes the selected intervention by displaying **textual hints** in pop-up windows or **highlighting** relevant regions, thereby providing real-time feedback.

Figure: left: pop-up window; right: area highlighting.



What Is Our Studied Learning Platform?

‣ VEX VR is extensively used in programming education and has reached over 1.45 million users cross 151 countries.

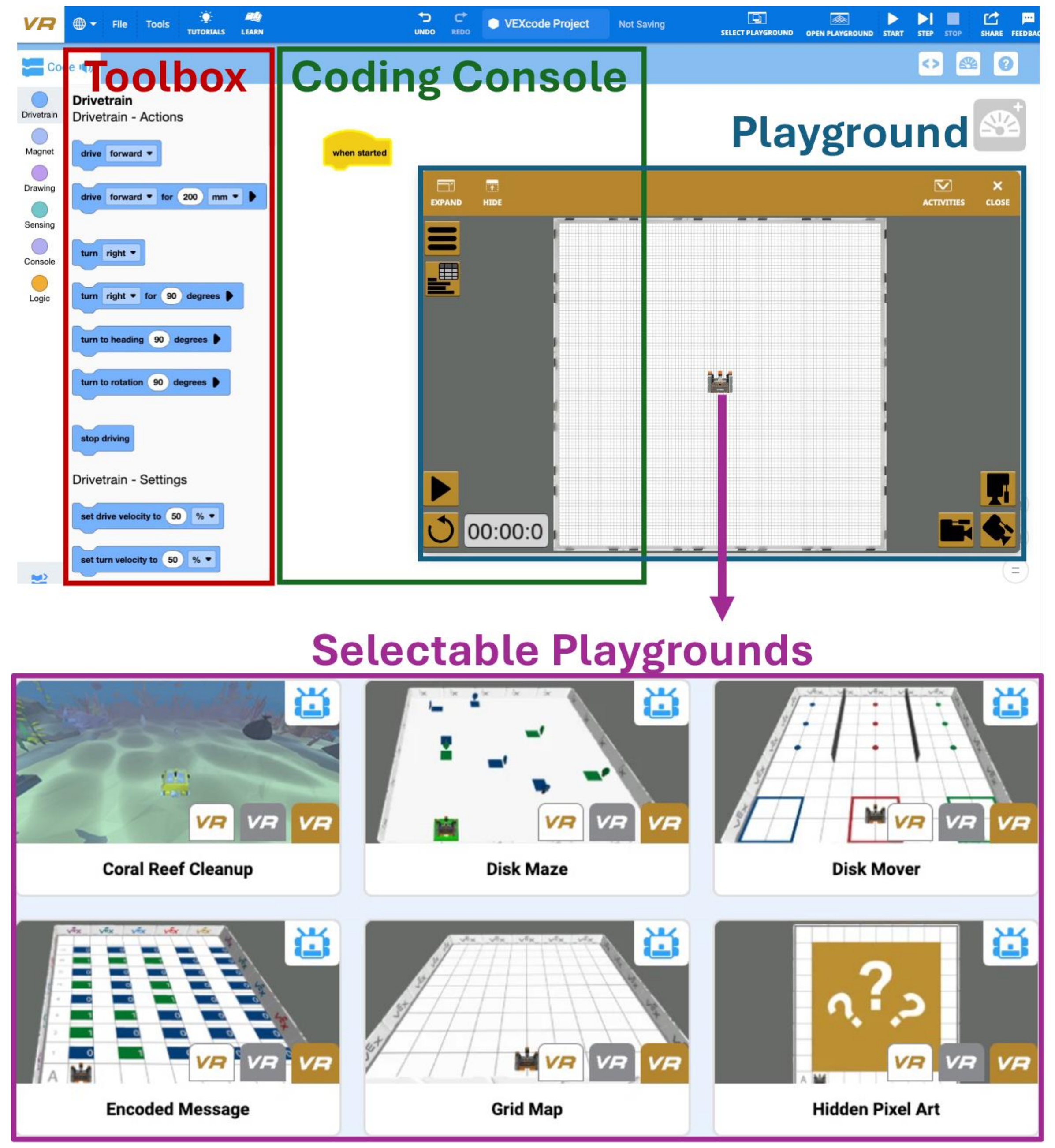


Figure: Illustration of Vex VR Testbed. It is generally divided into three components of toolbox, coding console, and playground.

How Effective Is Our Method For AI-Simulated Learners?

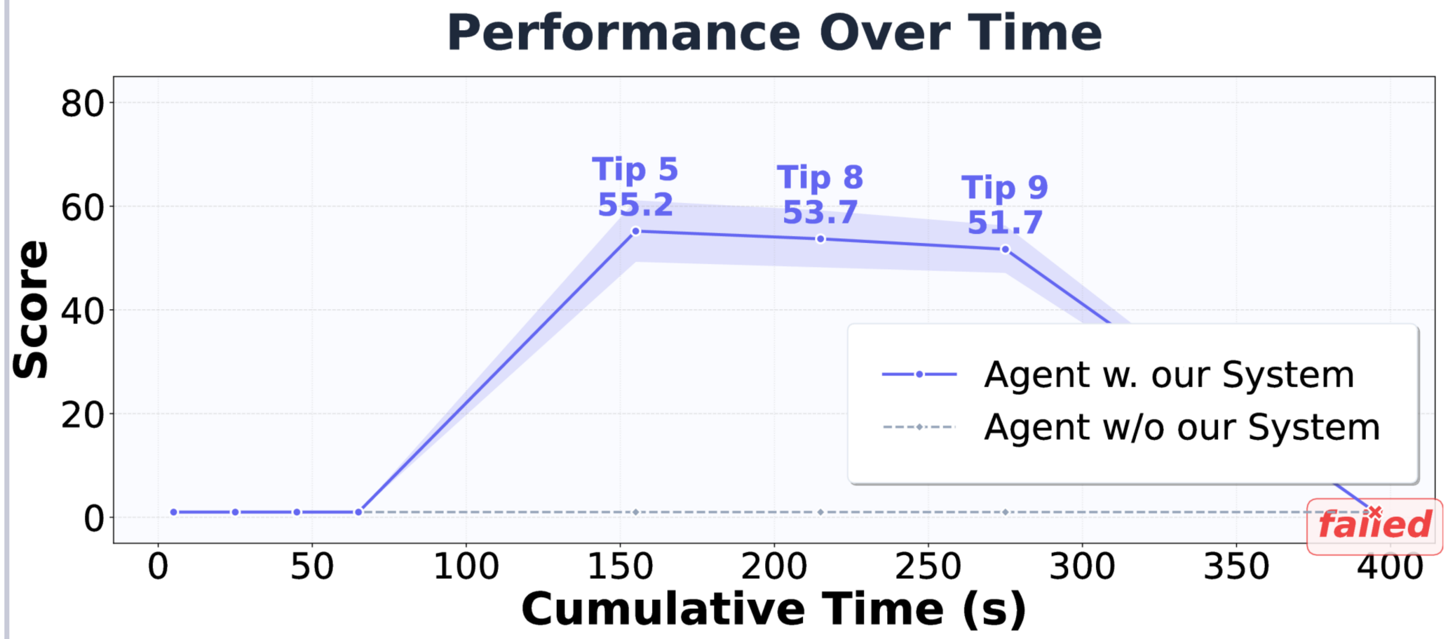


Figure: Learning curve of the GUI agent.

‣ We use a large vision model-based GUI agent to simulate learners. Our results show that **unguided exploration** fails to find effective steps (stuck in trivial behavior), while **our guidance helps the agent initially**.

Conclusions

‣ Proactive shaping supports learners without interrupting cognitive flow.

‣ **MDP framing** unifies state sensing, visual intervention, and progress reward.

‣ In **VEX VR**, VLM-guided cues reach **55.2kg after tip 5**; unguided exploration remains hard.

‣ Next: improve long-horizon focus retention and run controlled human studies.

Key References

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