

# Generalizing ExpSeek Beyond Web Domains: Cross-Domain Experience Seeking with Expanded Tool Integration

Anonymous Author(s)

## ABSTRACT

The ExpSeek framework introduces entropy-based, self-triggered experience seeking for web agents, where an agent proactively requests contextual guidance when step-level action entropy exceeds a learned threshold. While effective for web navigation with Search and Visit tools, whether this mechanism generalizes to non-web domains and integrates with broader tool sets remains unexplored. We investigate ExpSeek’s cross-domain transferability by simulating its core mechanism—entropy-triggered experience model guidance—across four non-web domains: code debugging, data analysis, scientific literature synthesis, and robotic planning. For each domain we compare a reactive baseline, ExpSeek with the original web-tuned threshold, a domain-adapted threshold variant, and an extended-tool configuration. Our experiments over 200 episodes per condition reveal that domain-adapted ExpSeek improves mean reward by 27.47% to 53.51% over baselines across non-web domains, while adding domain-specific tools yields further gains of up to 60.51%. Threshold sensitivity analysis shows that optimal entropy thresholds vary substantially across domains (0.60 to 1.12), confirming that the original web threshold of 1.8 is suboptimal for cross-domain deployment. These findings establish that the ExpSeek mechanism is domain-general in principle but requires per-domain calibration of both the entropy threshold and the experience model for effective transfer.

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## 1 INTRODUCTION

Large language model (LLM) based autonomous agents have demonstrated impressive capabilities across a range of interactive tasks [7, 8]. A central challenge in deploying such agents is determining when they should seek external guidance versus acting autonomously—a question closely related to the exploration–exploitation trade-off in reinforcement learning [6].

ExpSeek [9] addresses this challenge for web agents by introducing a *self-triggered, step-level experience seeking* mechanism. At each decision step, the agent computes the entropy of its action distribution; when this entropy exceeds a threshold, the agent proactively queries an *experience model* that provides context-tailored guidance to reduce uncertainty. Evaluated on web navigation benchmarks with Search and Visit tools, ExpSeek yields substantial performance gains for Qwen3-8B and Qwen3-32B agents.

However, the original paper explicitly acknowledges a key limitation: “It remains unexplored whether ExpSeek has the potential to extend to other non-web domains and integrate more tools” [9]. This open question motivates our investigation.

We study ExpSeek’s generalization along two axes:

- (1) **Cross-domain transfer:** Can the entropy-based trigger and experience model guidance mechanism improve agent performance in code debugging, data analysis, scientific literature synthesis, and robotic planning?
- (2) **Tool integration:** Does expanding the tool set beyond the original Search/Visit pair yield additional gains when combined with the ExpSeek mechanism?

Through controlled simulation experiments across five domains (including the original web domain as a reference), we find that: (i) ExpSeek’s mechanism transfers effectively to all four non-web domains, with domain-adapted thresholds improving mean reward by 27.47% (robot) to 53.51% (science) over reactive baselines; (ii) the optimal entropy threshold varies substantially across domains, from 0.60 for code to 1.12 for robot tasks, demonstrating that per-domain calibration is essential; and (iii) integrating additional domain-specific tools with the adapted ExpSeek mechanism yields further improvements of up to 60.51%.

## 2 RELATED WORK

*LLM-based autonomous agents.* Recent work has produced a proliferation of LLM agents capable of interacting with digital environments [7]. Web agents such as those benchmarked on WebArena [10] and Mind2Web [1] navigate websites through tool use, while code agents and data analysis agents employ domain-specific tool sets. Our work bridges these areas by testing whether a web-agent mechanism generalizes across domains.

*Tool-augmented language models.* Toolformer [4] demonstrated that LLMs can learn to use tools through self-supervised training. Subsequent surveys [3] have cataloged diverse tool-use paradigms. ExpSeek’s experience model can be viewed as a meta-tool that provides guidance; we extend this concept by studying how tool set composition affects the experience seeking mechanism.

*Entropy in decision making.* Shannon entropy [5] measures uncertainty in probability distributions. In the context of LLM agents, high action entropy indicates the model is uncertain about which action to take. ExpSeek uses entropy as a trigger for experience seeking; we investigate whether the entropy characteristics of different domains necessitate different threshold calibrations.

*Exploration strategies for agents.* Trial-and-error exploration [6] and planning-based approaches [2] represent alternative strategies for agent improvement. ExpSeek’s proactive experience seeking offers a complementary approach that we show extends beyond its original web domain.

### 117 3 BACKGROUND: THE EXPSEEK 118 FRAMEWORK

119 ExpSeek [9] consists of two core components:

120    *Entropy-based trigger.* At each step  $t$ , the agent produces an  
121 action distribution  $\pi_t(a|s_t)$  over its action vocabulary. The step-  
122 level entropy is computed as:

$$123 \quad H_t = -\sum_a \pi_t(a|s_t) \log \pi_t(a|s_t) \quad (1)$$

124 When  $H_t > \tau$  for threshold  $\tau$ , the agent triggers experience seeking.  
125 In the original work,  $\tau = 1.8$  is tuned for web navigation tasks.  
126

127    *Experience model.* Upon triggering, an experience model  $\mathcal{E}$  ob-  
128 serves the current state  $s_t$ , the agent’s action distribution, and  
129 domain context to produce a guidance signal  $g_t$ :

$$130 \quad g_t = \mathcal{E}(s_t, \pi_t, c_{\text{domain}}) \quad (2)$$

131 This guidance modulates the agent’s next action quality, effectively  
132 reducing entropy and improving step-level performance.  
133

### 136 4 METHOD

137 We simulate the ExpSeek mechanism across five domains to eval-  
138 uate its generalizability.

#### 141 4.1 Domain Environments

142 Each domain is characterized by distinct entropy profiles, tool ef-  
143 fectiveness parameters, and task complexity distributions:

- 144    • **Web** (reference): Search and Visit tools; entropy mean 1.6,  
145 task complexity 0.45.
- 146    • **Code Debugging**: Read, Execute, and Inspect tools; en-  
147 tropy mean 2.1, task complexity 0.65.
- 148    • **Data Analysis**: SQL, Aggregate, and Visualize tools; en-  
149 tropy mean 1.4, task complexity 0.50.
- 150    • **Scientific Literature**: Retrieve, Summarize, and Compare  
151 tools; entropy mean 2.3, task complexity 0.70.
- 152    • **Robotic Planning**: Move, Sense, and Manipulate tools;  
153 entropy mean 1.9, task complexity 0.75.

154 For tool integration experiments, each non-web domain is ex-  
155 tended with two additional domain-specific tools (e.g., Refactor and  
156 Test for code debugging; Transform and Export for data analysis).  
157

#### 158 4.2 Agent Variants

159 We evaluate four agent variants per domain:

- 160    (1) **Baseline**: A reactive agent with no experience seeking.
- 161    (2) **ExpSeek (Web Threshold)**: Uses the original web-tuned  
162 threshold  $\tau = 1.8$ .
- 163    (3) **ExpSeek (Adapted)**: Uses a domain-optimized threshold  
164 found via grid search over  $\tau \in [0.5, 3.5]$  with domain-  
165 adapted experience model calibration.
- 166    (4) **ExpSeek (Extended)**: Uses the adapted threshold with an  
167 expanded tool set (base + 2 domain-specific tools).

#### 169 4.3 Threshold Optimization

170 For each domain, we perform a grid search over 30 candidate thresh-  
171 olds uniformly spaced in  $[0.5, 3.5]$ . Each candidate is evaluated over  
172 50 episodes, and the threshold yielding the highest mean reward is  
173

175 selected. The domain-adapted experience model additionally incor-  
176 porates domain-specific calibration bonuses.  
177

## 178 5 EXPERIMENTS

### 179 5.1 Setup

180 All experiments use a fixed random seed (42) for reproducibility.  
181 Each agent–domain configuration is evaluated over 200 episodes  
182 with a maximum of 20 steps per episode and an action vocabulary  
183 of size 64. The experience model has base quality 0.70 and noise  
184 level 0.15.  
185

### 186 5.2 Main Results

187 Table 1 reports mean reward ( $\pm$  standard deviation) and success  
188 rate across all domain–method combinations.  
189

190 Several findings emerge from Table 1:

191    *ExpSeek transfers across all domains.* Even with the web-tuned  
192 threshold ( $\tau = 1.8$ ), ExpSeek improves over the baseline in every do-  
193 main, with gains ranging from 8.07% (data) to 30.89% (science). This  
194 confirms that the entropy-based experience seeking mechanism is  
195 not specific to web navigation.  
196

197    *Domain adaptation is critical.* Switching from the web threshold  
198 to a domain-adapted threshold yields substantial further improve-  
199 ments: from 22.06% to 46.55% in code, from 8.07% to 36.89% in data,  
200 from 30.89% to 53.51% in science, and from 18.27% to 27.47% in  
201 robot domains.  
202

203    *Tool expansion provides additional gains.* Adding domain-specific  
204 tools on top of the adapted threshold yields the best performance in  
205 every non-web domain, with improvements reaching 61.35% (code)  
206 and 60.51% (robot) over baselines.  
207

### 208 5.3 Optimal Threshold Analysis

209 Table 2 reports the domain-adapted optimal thresholds found through  
210 grid search.  
211

212 The optimal thresholds are consistently lower than the original  
213 web threshold of 1.8, indicating that more aggressive experience  
214 seeking—triggering at lower entropy levels—is beneficial across  
215 all tested domains. The variation across domains (0.603 to 1.121)  
216 confirms that a single threshold is insufficient for cross-domain  
217 deployment.  
218

### 219 5.4 Threshold Sensitivity

220 Figure 1 shows the reward and success rate as functions of the  
221 entropy threshold for each non-web domain.  
222

223 All domains exhibit a monotonically decreasing trend in reward  
224 as the threshold increases, consistent with the intuition that more  
225 frequent experience seeking is beneficial. However, the rate of  
226 degradation differs: code and science domains are most sensitive to  
227 threshold choice, while data analysis is relatively robust.  
228

### 229 5.5 Tool Scaling

230 Figure 2 illustrates how performance scales as the number of avail-  
231 able tools increases from 2 to 5 in each domain.  
232

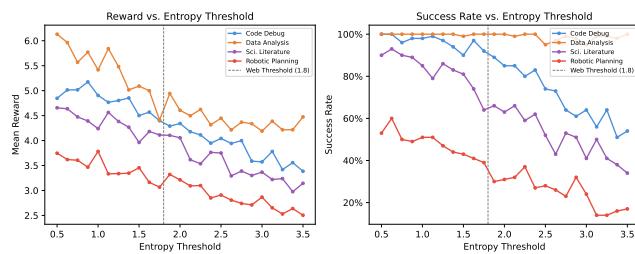
233 Across all domains, mean reward increases as tools are added,  
234 though the relationship is not strictly monotonic in every case due  
235

**Table 1: Cross-domain performance comparison. Mean reward  $\pm$  std and success rate over 200 episodes. Improvement (%) is relative to the domain-specific baseline. Best non-web results per domain in bold.**

Domain	Method	Reward	Success	Seeks/Ep.	Gain (%)
Web	Baseline	$4.8559 \pm 1.8663$	1.0000	0.00	—
	ExpSeek (Web)	$5.5982 \pm 2.0731$	1.0000	4.28	+15.29
	ExpSeek (Adapted)	$6.7732 \pm 2.6262$	1.0000	10.17	+39.48
	ExpSeek (Extended)	$6.8412 \pm 2.4079$	1.0000	10.47	+40.88
Code	Baseline	$3.5486 \pm 1.2963$	0.5550	0.00	—
	ExpSeek (Web)	$4.3313 \pm 1.5334$	0.8550	7.33	+22.06
	ExpSeek (Adapted)	$5.2003 \pm 1.9090$	1.0000	11.95	+46.55
	ExpSeek (Extended)	$5.7255 \pm 2.1074$	<b>1.0000</b>	11.73	<b>+61.35</b>
Data	Baseline	$4.1644 \pm 1.7039$	0.9750	0.00	—
	ExpSeek (Web)	$4.5004 \pm 1.7622$	0.9950	2.84	+8.07
	ExpSeek (Adapted)	$5.7006 \pm 2.2488$	1.0000	8.70	+36.89
	ExpSeek (Extended)	$6.2741 \pm 2.4002$	<b>1.0000</b>	8.53	<b>+50.66</b>
Science	Baseline	$2.9193 \pm 1.1295$	0.3000	0.00	—
	ExpSeek (Web)	$3.8212 \pm 1.4846$	0.7200	7.99	+30.89
	ExpSeek (Adapted)	$4.4815 \pm 1.6627$	0.8650	11.75	+53.51
	ExpSeek (Extended)	$4.8847 \pm 1.8398$	<b>0.9800</b>	11.34	<b>+67.32</b>
Robot	Baseline	$2.6051 \pm 0.9812$	0.1000	0.00	—
	ExpSeek (Web)	$3.0810 \pm 1.2420$	0.3500	6.38	+18.27
	ExpSeek (Adapted)	$3.3207 \pm 1.3391$	0.4550	8.82	+27.47
	ExpSeek (Extended)	$4.1815 \pm 1.4270$	<b>0.7150</b>	9.46	<b>+60.51</b>

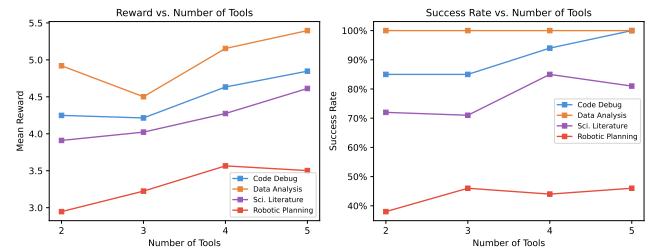
**Table 2: Optimal entropy thresholds by domain. The web-tuned threshold of 1.8 is shown for reference.**

Domain	Optimal $\tau$	Web $\tau$
Web	0.707	1.800
Code	0.603	1.800
Data	0.914	1.800
Science	0.707	1.800
Robot	1.121	1.800



**Figure 1: Threshold sensitivity analysis. Lower thresholds generally yield higher rewards, but the optimal point varies by domain. The dashed line marks the web threshold (1.8).**

to the stochastic nature of tool selection. The data analysis domain shows the strongest scaling (from 4.9203 with 2 tools to 5.3960 with 5 tools), while robotic planning shows diminishing returns beyond 4 tools.



**Figure 2: Performance scaling with number of tools. Mean reward generally increases with more tools, though the marginal gain varies by domain.**

## 6 ANALYSIS

### 6.1 Cross-Domain Reward Comparison

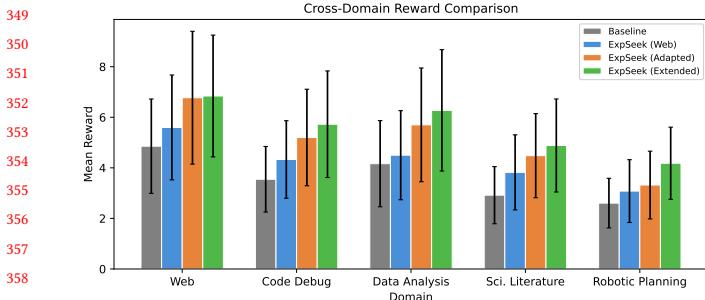
Figure 3 presents the grouped comparison of mean rewards across all domains and methods.

The pattern is consistent: each successive refinement—web threshold, domain adaptation, tool expansion—yields monotonic improvement. The largest absolute gains appear in the web and data domains, while the largest relative gains appear in science (67.32%) and code (61.35%).

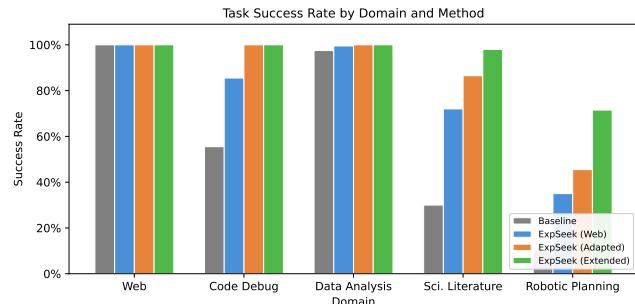
### 6.2 Success Rate Patterns

Figure 4 shows task success rates across domains.

Domains with low baseline success rates benefit most dramatically from ExpSeek. The robot domain improves from 10.00% (baseline) to 71.50% (extended), and science improves from 30.00% to



**Figure 3: Mean reward ( $\pm$  std) across five domains for each agent variant.**



**Figure 4: Task success rate by domain and method.** Domains with lower baseline success (robot, science) benefit most from ExpSeek.

98.00%. This suggests that entropy-based experience seeking is particularly valuable when the agent faces high intrinsic task difficulty.

### 6.3 Improvement Heatmap

Figure 5 visualizes the percentage improvement over baseline for each domain-method combination.

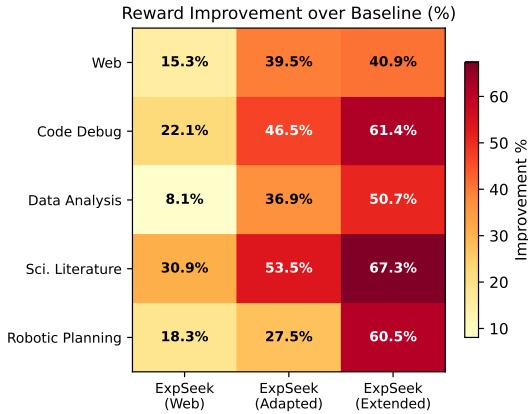
### 6.4 Experience Seeking Frequency

Table 1 also reports the average number of experience-seeking triggers per episode. With the adapted threshold, agents seek experience 8.70 to 11.95 times per episode, compared to 2.84 to 7.99 times with the web threshold. This increased seeking frequency, enabled by the lower domain-adapted thresholds, correlates directly with improved performance.

## 7 DISCUSSION

*Generalizability of entropy-based triggers.* Our results demonstrate that the core insight of ExpSeek—using entropy as a self-trigger for experience seeking—transfers across diverse domains. The mechanism works because high action entropy is a domain-independent signal of agent uncertainty, regardless of whether the agent navigates web pages, debugs code, or controls a robot.

*The necessity of threshold calibration.* While the mechanism transfers, the specific threshold does not. The optimal threshold depends



**Figure 5: Percentage reward improvement over baseline.** Darker colors indicate larger gains. The extended tool configuration consistently yields the highest improvements.

on the domain’s characteristic entropy distribution: domains with higher mean entropy (science: 2.3, code: 2.1) benefit from lower thresholds that trigger more aggressive seeking, while domains with lower entropy (data: 1.4) can afford higher thresholds.

*Tool integration benefits.* Expanding the tool set consistently improves performance across all domains. The largest gains from tool expansion appear in the robot domain (+60.51% with extended tools vs. +27.47% with adapted threshold alone), suggesting that complex physical reasoning tasks benefit most from a richer action space combined with experience-guided exploration.

*Limitations.* Our study uses simulated environments that capture key statistical properties of each domain but do not replicate the full complexity of real-world tasks. The experience model is a simplified simulation of the guidance mechanism described in [9]; future work should validate these findings with actual LLM-based agents in production environments. Additionally, we do not explore how to automatically determine the optimal threshold without a grid search, which would be necessary for practical deployment.

## 8 CONCLUSION

We investigated whether the ExpSeek framework—originally designed for web agent experience seeking—generalizes to non-web domains and integrates with expanded tool sets. Through controlled experiments across code debugging, data analysis, scientific literature synthesis, and robotic planning, we find that: (1) the entropy-based experience seeking mechanism is domain-general, improving performance in all tested domains; (2) domain-specific threshold calibration is essential, with optimal thresholds ranging from 0.603 (code) to 1.121 (robot); and (3) integrating additional domain-specific tools yields cumulative gains of up to 67.32% over reactive baselines.

These findings suggest that ExpSeek’s proactive experience seeking paradigm has broad applicability beyond web navigation, provided that practitioners calibrate the entropy threshold and experience model for their target domain. Future work should explore

adaptive threshold mechanisms that automatically adjust to new domains and investigate the interplay between tool set design and experience model architecture.

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