Unsupervised Partner Design Enables Robust Ad-hoc Teamwork

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Abstract

We introduce *Unsupervised Partner Design (UPD)* – a population-free, multi-agent reinforcement learning framework for robust ad-hoc teamwork that adaptively generates training partners without requiring pretrained partners or manual parameter tuning. UPD constructs diverse partners by stochastically mixing an ego agent's policy with biased random behaviours and scores them using a variance-based learnability metric that prioritises partners near the ego agent's current learning frontier. We show that UPD can be integrated with unsupervised environment design, resulting in the first method enabling fully unsupervised curricula over both level and partner distributions in a cooperative setting. Through extensive evaluations on Overcooked-AI and the Overcooked Generalisation Challenge, we demonstrate that this dynamic partner curriculum is highly effective: UPD consistently outperforms both population-based and population-free baselines as well as ablations. In a user study, we further show that UPD achieves higher returns than all baselines and was perceived as significantly more adaptive, more human-like, a better collaborator, and less frustrating.

1 Introduction

Robust cooperation with unknown partners, or ad-hoc teamwork (Stone et al. 2010, AHT), is key for building general-purpose multi-agent systems. Training agents for AHT is costly because existing methods typically require large populations of diverse partners (Strouse et al. 2021; Zhao et al. 2023; Yu et al. 2023; Li et al. 2023; Wang et al. 2025). Efficient end-to-end training (Yan et al. 2023, E3T) mitigates this problem by generating partner policies as stochastic mixtures of the ego policy, but still requires careful tuning of mixture parameters to the evaluation setting. In parallel, unsupervised environment design (Dennis et al. 2020, UED) and dual curriculum design (Jiang et al. 2021, DCD) methods have shown that adaptive curricula over environment parameters can yield efficient learning and robust generalisation. Recent work highlighted the importance of joint partner and environment generalisation, but also the inability of current models to achieve it (Ruhdorfer et al. 2025).

In this work, we present the first approach that unifies AHT and UED by constructing curricula over the joint partner–environment space. To this end, we propose *Unsupervised Partner Design (UPD), a lightweight, population-free AHT algorithm that adaptively selects partner parameters based on the ego agent's current learning frontier, enabling efficient and robust zero-shot coordination.* We view UPD not only as a new algorithm, but as a general framework for partner generation, where prior approaches – such as training a best response against a diverse population and E3T – emerge as special cases with fixed, non-adaptive partner distributions. When combined with existing UED algorithms, UPD enables the first joint open-ended partner–environment curriculum learning method for AHT. Our contributions are:

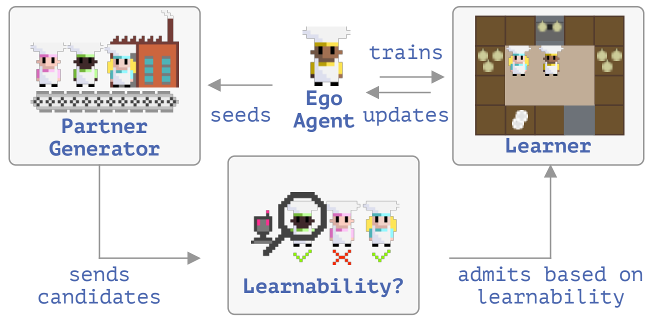

Figure 1: *Unsupervised partner design* is a novel population-free, multi-agent learning framework for ad-hoc teamwork that uses learnability to find optimal training partners for the ego agent to generate an open-ended curriculum.

1. We introduce **Unsupervised Partner Design (UPD)**, a new framework for ad-hoc teamwork via partner-space curriculum learning, generating diverse partners on-the-fly without pre-trained populations.
2. We design a **flexible partner generation framework** that combines stochastic mixture sampling with Dirichlet-biased randomisation to capture both competence variability and systematic behavioural biases. We integrate this with a return-variance-based selection mechanism to construct partner curricula adaptively.
3. We provide **comprehensive empirical evaluations** on Overcooked-AI (Carroll et al. 2019) and the Overcooked Generalisation Challenge (Ruhdorfer et al. 2025, OGC) across strong population-based and population-free baselines, diverse evaluation populations, and humans. UPD consistently outperforms baselines across key metrics.

2 Related Work

2.1 Ad-hoc Teamwork

AHT was explored in a wide range of multi-agent reinforcement learning (RL) environments (Carroll et al. 2019; Bard et al. 2020; Kurach et al. 2020). Popular AHT methods, such as fictitious co-play (Strouse et al. 2021, FCP) or maximum entropy population-based training (Zhao et al. 2023, MEP), rely on pretraining diverse partner populations and optimising best-response policies for these (Yu et al. 2023; Lou et al. 2023; Rahman et al. 2023). Recent works introduced curriculum learning to adaptively select training partners from populations based on scoring functions (Erlebach and Cook 2024; You et al. 2025). Parallel efforts incorporated open-ended learning objectives to dynamically expand partner diversity (Li et al. 2023; Wang et al. 2025), but still involved growing partner populations over time. A notable exception is E3T (Yan et al. 2023), which generates partners on the fly as mixtures of the ego and a random policy. While this approach does not require any partner population and thus significantly reduces the computational overhead, it still requires careful tuning of mixture coefficients between the ego and random policy for each task and evaluation scenario. In contrast, we propose a lightweight population-free approach that adaptively generates diverse partner behaviours without fixed parameters or pre-trained populations, and integrates seamlessly into current curriculum learning frameworks.

2.2 Unsupervised Environment Design

UED (Dennis et al. 2020) adaptively generates training environments tailored to an agent's capabilities, and has proven effective for improving generalisation. Unlike domain randomisation (Tobin et al. 2017, DR), UED generates environments to target an agent's learning frontier. Existing UED methods mainly focus on single-agent settings and rely on regret-based objectives to guide environment generation (Wang et al. 2019, 2020; Dennis et al. 2020; Jiang, Grefenstette, and Rocktäschel 2021; Jiang et al. 2021; Parker-Holder et al. 2022; Li, Varakantham, and Li 2023; Beukman et al. 2024). Extensions to multi-agent settings are limited: Samvelyan et al. (2023) focused on competitive settings and Ruhdorfer et al. (2025) proposed a cooperative multi-agent UED benchmark, but no method. Recent works reframed UED as a learnability-driven problem, replacing regret approximations with scoring functions that directly measure environments' learning potential (Rutherford et al. 2024; Monette et al. 2025). However, no prior work explored the parameterisation of partner policies. We extend unsupervised design to partner policies, introducing adaptive partner generation as a population-free curriculum mechanism. Furthermore, our method integrates naturally with standard UED approaches, enabling joint unsupervised partner and environment design for robust zero-shot cooperation.

3 Preliminaries

3.1 Reinforcement Learning

In this work we adopt the formalism of the *decentralised under-specified partially observable Markov decision process* (Dec-UPOMDP) of Ruhdorfer et al. (2025) given by the tuple $\mathcal{M} = \langle \mathcal{N}, A, \Omega, \Theta, \mathcal{S}^{\mathcal{M}}, \mathcal{T}^{\mathcal{M}}, O^{\mathcal{M}}, \mathcal{R}^{\mathcal{M}}, \gamma \rangle$. The term *under-specified* reflects that the Dec-UPOMDP defines a family of environments, where each fully-specified instance $\mathcal{M}_\theta$ (a *level*) corresponds to a particular choice of environment parameters $\theta \in \Theta$. UPOMDPs (Dennis et al. 2020) are useful as they give a formalism for training agents over a distribution of levels as given by Θ.

Within Dec-UPOMDP, $\mathcal{N}$ is the set of agents, A the set of actions, Ω the set of observations, and the set of true states in the environment is given by $\mathcal{S}^{\mathcal{M}}$. At each time step t in a given level $\mathcal{M}_\theta$, each agent $i \in \mathcal{N}$ receives an observation $o_t^i \in \Omega$ via the observation function $O : \mathcal{S} \times \mathcal{N} \to \Omega$. The agents produce a joint action $\boldsymbol{a}_t = (a_t^{(1)}, \dots, a_t^{(n)})$ where $a^{(i)} \in A$. They then observe a shared reward $R(s, \boldsymbol{a})$ and the environment transitions according to the transition function $\mathcal{T} : \mathcal{S} \times \mathcal{A}^1 \times \cdots \times \mathcal{A}^n \times \Theta \to \Delta(\mathcal{S})$, which maps to a probability distribution over next states.

A trajectory τ is a sequence of states and joint actions. Slightly abusing notation, we denote $R(\tau)$ to be the undiscounted sum of rewards obtained by following τ. The agents maximise the expected discounted sum of rewards:

$$J(\pi^{(1)}, \dots, \pi^{(n)}) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t^{(1)}, \dots, a_t^{(n)})\right]. \quad (1)$$

We explore fully-specified (Overcooked-AI) and under-specified (OGC) environments in our experiments. In case of a fully-specified environment, the formalism reduces to a Dec-POMDP (Oliehoek and Amato 2016).

3.2 Dual Curriculum Design and Learnability

Algorithms for solving (Dec-)UPOMDPs can be understood under the framework of dual curriculum design (Jiang et al. 2021, DCD), where learning agents are trained on levels generated by a level generator and selected by a curator. Methods mainly differ in how they implement the generator and curator. Prioritised level replay (Jiang, Grefenstette, and Rocktäschel 2021, PLR) creates levels at random and samples them based on a score function. PAIRED (Dennis et al. 2020) uses a teacher-student setup. REPAIRED (Jiang et al. 2021) combines both ideas. In contrast, Rutherford et al. (2024) introduced sampling for learnability (SFL) in which randomly generated levels are scored using a learnability function to guide curriculum construction more effectively. Specifically, they define the score as $\ell_{sr} = p(1-p)$, where p is the success rate for a level θ with binary outcomes. The intuition is that if agents always fail or succeed on a level, ℓ_{sr} will be zero, i.e. learnability will only be high for levels that are at the agent's learning frontier. Monette et al. (2025) extended this to continuous rewards by weighting return variance around the mean. Given empirical variance σ and mean μ, with $\mathcal{N}$ denoting the Gaussian probability density function:

$$\ell_{\text{gauss}} = \sigma_\theta \cdot \mathcal{N}(\mu_\theta \mid \mu, \sigma^2). \quad (2)$$

In their work, the authors argued that this weighing stabilises learning as it downweights levels that are far from the mean.

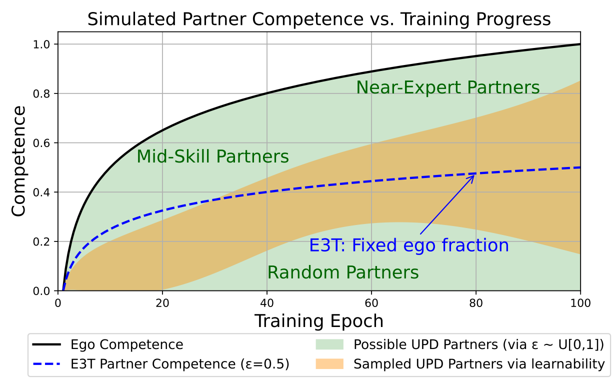

Figure 2: As ego competence improves over training (black), E3T generates partners using a fixed mixture coefficient (here $\epsilon = 0.5$), resulting in a fixed fraction of ego competence (blue). In contrast, UPD samples $\epsilon \sim \mathcal{U}(0, 1)$ (green) and filters partners using a learnability criterion, leading to a dynamic range of partner competences (orange).

3.3 Efficient End-To-End Training for Human-AI Cooperation

We propose a novel AHT algorithm based on E3T (Yan et al. 2023). E3T learns an ego policy π_{ego} that is robust to novel partners by constructing a partner policy π_p per episode, corresponding to the mixture of the current policy π_{ego} and a uniformly random policy π_r via a mixing coefficient ϵ:

$$\pi_p = \epsilon \pi_r + (1 - \epsilon)\pi_{\text{ego}}, \quad \text{where } \epsilon \in [0, 1]. \tag{3}$$

Importantly, Yan et al. (2023) chose the value of ϵ depending on the layout and the cooperation partner. **One of the key novelties of our work is that we adapt ϵ on the fly without requiring any task knowledge.**

4 Unsupervised Partner Design

Unsupervised partner design (UPD) is a framework and an end-to-end learning algorithm that adaptively generates and selects cooperation partners based on their learnability potential. Our key insight is to apply DCD not at the level of environments but directly in the space of partner policies. UPD requires two components: (1) a partner generator and (2) an adaptive selection criterion to build an open-ended curriculum (see Figure 1). Unlike existing approaches, such as E3T, that use fixed mixture coefficients for partner generation, our method samples and scores partners to build an adaptive curriculum over diverse partners (see Figure 2). As such, UPD can be understood as a generalisation of prior AHT methods: Popular population-based approaches, such as FCP or MEP, correspond to sampling from a fixed, static partner set instead of a partner generator, while E3T represents a special case with a fixed mixture coefficient ($\epsilon = c$) and no adaptation to the ego agent's learning progress.

4.1 Online Partner Generation

We extend the E3T partner generation strategy by introducing additional stochasticity and behavioural bias. To introduce partner stochasticity, we leverage the insight that a

Algorithm 1: Unsupervised Partner Design Training

Require: Environment $\mathcal{E}$, ego agent policy π_{ego}, partner policy generator $\mathcal{G}_{\text{p}}$, number of evaluation rollouts N, rollout length L, learnability buffer size K

Initialize empty partner buffer $\mathcal{B}$
while not converged **do**
  for each partner sampling iteration **do**
    Sample partner: $\pi_{\text{p}} \sim \mathcal{G}_{\text{p}}(\pi_{\text{ego}})$ (Alg. 2)
    Get N rollouts of length L for pairing $(\pi_{\text{ego}}, \pi_{\text{p}})$
    Collect returns $R_1, \ldots, R_N$ for pairing
    Compute learnability score: $\ell = \text{Var}(R_1, \ldots, R_N)$
    Store (ℓ, π_{p}) into buffer $\mathcal{B}$
  end for
  Get top K policies from $\mathcal{B}$ with highest learnability
  for each PPO update step **do**
    Sample partner π_{p} from the selected K
    Collect trajectories $(\pi_{\text{ego}}, \pi_{\text{p}})$
    Update ego policy π_{ego} using PPO
  end for
end while

Algorithm 2: Partner Policy Generator $\mathcal{G}_{\text{p}}$

Require: Ego policy π_{ego}

Sample mixing parameter $\epsilon \sim \mathcal{U}(0, 1)$
With probability p_{bias}:
  Sample bias mask $m \sim \text{Dirichlet}(\alpha \cdot \mathbf{1}_A)$
Otherwise:
  Set $m = \mathbf{1}_A / A$
Construct random policy π_r using bias mask m
Return mixture partner policy $\pi_p = \epsilon \pi_r + (1 - \epsilon)\pi_{\text{ego}}$

fixed value of ϵ can be suboptimal across different stages of training. Early in learning, more competent partners help task learning, while later, more random partners provide coordination challenges. Thus, rather than fixing ϵ, we first sample ϵ from a uniform distribution throughout training. Then, our curator selects partners based on their learnability score. This exposes the ego agent to a range of competencies aligned with its current learning stage.

Moreover, in many cooperative domains such as Overcooked-AI, partner variability extends beyond only competence: Partners may exhibit systematic behavioural biases – for instance, human partners tend to show preferences for certain actions (Yu et al. 2023), or display increased propensity for `stay` actions (Carroll et al. 2019). Capturing such biases is important for training robust AHT policies. To accommodate both competence and behavioural diversity, we design a two-component partner generator:

1. **Variable Mixing:** For each partner, we sample a mixing coefficient $\epsilon \sim \mathcal{U}(0, 1)$, allowing partners to range from fully random ($\epsilon = 1$) to fully ego ($\epsilon = 0$).
2. **Bias Masking:** We sample a bias mask $m \sim Dir(\alpha \cdot \mathbf{1}_A)$ from the Dirichlet distribution over A, producing biased random policies with persistent action preferences.

This partner generation mechanism enables online creation of a diverse set of potential partners covering diverse competence and behavioural traits. However, it also raises the question: At learning step t, how should one pick the partner parameters to facilitate optimal learning?

4.2 Sampling Partners for Learnability

While we generate a diverse set of partners, not all partners are equally useful for learning. Following prior insights into learnability-based curricula, we hypothesise that we can score partners for their learnability potential. We adapt the notion of sampling-for-learnability (SFL) in that, at every step of the learning process, we sample many partners using Alg. 2, score them for their learnability potential using rollouts in the environment, and then select partners with a high learnability score using a partner buffer $\mathcal{B}$ (see Alg. 1).

Since cooperative settings often lack binary success, we use a generalised learnability score function based on the variance of returns across rollouts for candidate partner π_p:

$$\ell_{\text{var}} = \text{Var}_{\tau\sim(\pi,\pi_p)}\left[R(\tau)\right], \quad \text{where } R \in [0, R_{max}]. \quad (4)$$

Low variance indicates either consistent failure or mastery; high variance suggests that the ego agent sometimes succeeds: ℓ_{var} is highest when exactly half of the collected returns are 0 and half are R_{max}, i.e. when the agent is sometimes successful and sometimes not. This aligns with curriculum learning principles, where tasks of intermediate difficulty (high variance) drive maximal learning progress (Florensa et al. 2018; Tzannetos et al. 2023). This variance-based scoring naturally extends the success-rate-based definitions used for binary-outcome tasks in previous work (Rutherford et al. 2024), but unlike Monette et al. (2025), does not downweight performance extremes, therefore, reflecting the AHT goal of preparing agents for both best- and worst-case partners.

4.3 Training Loop

The full UPD training process alternates between partner generation, learnability scoring, and learning (see Alg. 1):

1. **Partner Sampling:** Generate multiple partner policies using the biased stochastic generator (Alg. 2).
2. **Learnability Scoring:** For each sampled partner, collect multiple rollouts and compute the learnability score.
3. **Partner Selection:** Select the top K partners with the highest learnability scores to form a training buffer.
4. **Policy Update:** Train the ego agent using any RL method with partners sampled from the buffer.

This procedure forms an evolving curriculum over partner policies, adaptively focusing training on those partners where learning potential remains highest. Crucially, and in contrast to prior work, this is achieved without pre-defining any fixed partner diversity or hand-tuning of ϵ.

4.4 Joint Unsupervised Design Learning

For challenges that require generalisation across levels and partners (e.g. the OGC), our method can be easily integrated into off-the-shelf UED learning algorithms, specifically into SFL to construct a joint learning algorithm that samples and scores a level-policy pair. We denote this algorithm Joint

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Algorithm 3: Adjusted Sampling for JUPD

Require: Underspecified Env. $\mathcal{E}$, Env. Parameter Dist. Θ
1: Sample free parameters of the environment $\theta \sim \Theta$
2: Sample partner policy: $\pi_{\text{p}} \sim \mathcal{G}_{\text{p}}$ (Alg. 2)
3: Roll out N episodes in $\mathcal{E}(\theta)$ for pairing $(\pi_\theta, \pi_{\text{p}})$
4: Collect returns $R_1, \ldots, R_N$ for pairing
5: $\ell_{CV^2} = \text{Var}(R_1, \ldots, R_N)/\text{Mean}(R_1, \ldots, R_N)^2$
6: Store $(\ell_{CV^2}, \pi_{\text{p}}, \theta)$ into buffer $\mathcal{B}$
7: {Continue as in Alg. 1}

UPD (JUPD). For this, we reuse our notion of learnability above and adjust Alg. 1 by replacing the learnability scoring loop with the one shown in Alg. 3: We sample a level $\theta \sim \Theta$ and a partner policy $\pi_{\text{p}} \sim \mathcal{G}_{\text{partner}}$, then score the joint tuple $(\pi_{\text{ego}}, \pi_{\text{p}}, \theta)$ and store it in the buffer $\mathcal{B}$. To ensure that learnability scores remain comparable across levels with varying reward scales, we adopt a coefficient-of-variation squared (CV^2) formulation, which normalises return variance by the squared mean per θ:

$$\ell_{CV^2} = \frac{\text{Var}_{\tau\sim(\pi,\pi_p,\theta)}[R(\tau,\theta)]}{\left(\mathbb{E}_{\tau\sim(\pi,\pi_p,\theta)}[R(\tau,\theta)]\right)^2}. \quad (5)$$

This yields a scale-invariant metric, since CV^2 can be used to compare variability across datasets, or, in our case, levels. Together, this establishes a joint partner-level curriculum, as envisioned by Ruhdorfer et al. (2025). The key advantage of our approach is that adding UPD into SFL adds no additional computational cost besides simple parameter sampling.

5 Experiments

Our experiments seek to answer several questions: **RQ1** Does UPD learn robust AHT policies? **RQ2** Do all components of UPD matter? **RQ3** How do humans rate UPD? **RQ4** Can UPD be integrated into UED algorithms?

5.1 RQ1: Ad-Hoc Teamwork in Overcooked-AI

We first evaluated UPD in Overcooked-AI (Carroll et al. 2019), a well-established benchmark for AHT. We considered the five standard layouts: Cramped Room (CRoom), Asymmetric Advantages (AA), Coordination Ring (CR), Counter Circuit (CC), and Forced Coordination (FC). For each method, we trained six independent seeds and evaluated coordination with novel partners. Coordination was assessed in an AHT setting by pairing agents with evaluation populations containing diverse partner policies.

To construct challenging and diverse evaluation populations, we were inspired by related works (Wang et al. 2025) and we combined hardcoded agents, human-inspired planning models, and agents trained using BRDiv (Rahman et al. 2023). A BRDiv population optimises self-play returns, while minimising cross-play compatibility. Such agents tend to adopt competent but incompatible strategies that can be difficult to cooperate with. Concretely, evaluation partners were drawn from four categories: (1) 3–4 BRDiv agents (Rahman et al. 2023) trained for self-play but incompatible in cross-play, (2) probabilistic planning agents following

Method	CRoom	AA	CR	CC	FC	Average
SP	$64.0\pm$ 11.2	$64.4\pm$ 21.6	$25.2\pm$ 6.4	$14.5\pm$ 4.7	$33.4\pm$ 8.7	$40.4\pm$ 10.5
FCP	$44.2\pm$ 10.3	$68.6\pm$ 26.7	$48.2\pm$ 12.9	$14.4\pm$ 4.1	$\mathbf{50.6 \pm 6.7}$	$45.2\pm$ 11.2
MEP	$100.5\pm$ 12.1	$136.2\pm$ 19.7	$40.3\pm$ 3.8	$12.7\pm$ 8.7	48.8 ± 2.5	$67.8\pm$ 9.6
E3T	$101.3\pm$ 8.0	$127.9\pm$ 21.0	$58.4\pm$ 5.2	$55.0\pm$ 5.8	$41.3\pm$ 6.7	$76.8\pm$ 9.7
UPD w/o bias	$102.1\pm$ 6.7	$159.9\pm$ 23.0	$66.2\pm$ 6.0	57.1 ± 6.7	$44.4\pm$ 5.7	$85.6\pm$ 11.1
UPD w/o ℓ	106.9 ± 6.4	164.0 ± 28.4	68.9 ± 7.4	$\mathbf{64.5 \pm 8.5}$	$45.7\pm$ 4.4	90.0 ± 11.0
UPD (Ours)	$\mathbf{108.1 \pm 5.5}$	$\mathbf{181.4 \pm 15.1}$	$\mathbf{69.2 \pm 7.2}$	$\mathbf{64.5 \pm 8.7}$	48.7 ± 3.7	$\mathbf{94.4 \pm 8.1}$

Table 1: Average returns (mean $\pm$ std.) against the evaluation populations. We average over both starting positions in the environment. The best results are in **bold**, second-best are underlined. On average, UPD outperforms all baselines. Our ablated UPD w/o ℓ, performs the second-best. This highlights the advantages of online partner generation and learnability scoring.

human-inspired heuristics (Wang et al. 2025), (3) hardcoded agents performing task subsets (e.g., onion-only workers) (Yu et al. 2023), and (4) random or stay agents as worst-case partners. Each layout used between 4–9 such partners (nine for CRoom, eight for AA, CR, CC, and four for FC), with fewer for FC due to its restrictive dynamics that limit viable hard-coded partner strategies.

We compared UPD against four baselines that, together, cover the most widely and successfully used AHT algorithms in Overcooked-AI: (1) A self-play baseline trained using IPPO (de Witt et al. 2020). (2) E3T using their reported hyperparameters: $\epsilon = 0.5$ for CRoom, AA, CR, and CC, and $\epsilon = 0.0$ for FC. (3) MEP agents using an entropy coefficient of $\alpha = 0.01$ and a population size of 48. (4) FCP agents trained as a best response to a population of size 48. We ensured a fair comparison by tuning MEP and FCP: First, our populations were larger than in the original works, which improves performance (Yu et al. 2023). Second, during best-response training, we allowed extended training up to 1×10^8 environment steps (two times more than UPD) to ensure convergence. Third, for best-response training, we fine-tuned the learning rate per layout (from $1\mathrm{e}{-3}$, $3\mathrm{e}{-4}$ and $1\mathrm{e}{-4}$). In contrast, we found that UPD works with one set of hyperparameters on all layouts.

We used the same recurrent policy base for all methods. For E3T and UPD, we added the partner model proposed by E3T. Training used 512 envs (400 steps/env), 5×10^7 total timesteps, with reward shaping for the first 3×10^7. For UPD, we used a partner buffer size of $|\mathcal{B}| = 512$, $N = 10$ evaluation rollouts per partner, Dirichlet parameter $\alpha = 1.0$, and refreshed the buffer fully every fourth training loop. Details on hyperparameters, compute infrastructure, additional results and training curves can be found in the Appendix.

Table 1 shows that UPD outperforms all baselines, achieving the highest average return when paired with diverse, unseen partners. Other methods struggle to generalise, likely due to the high behavioural diversity and competence range of the evaluation population. These findings are further supported by human evaluation results presented later in **RQ3**.

Figure 3 shows that UPD favours different ϵ values across layouts, often diverging from the fixed values used in E3T. In layouts with more rigid cooperation conventions (e.g., CR, CC, FC), UPD gravitates towards lower ϵ; in more flexible layouts (e.g., CRoom, AA), it prefers more stochastic partners. **This demonstrates that UPD dynamically adjusts partner competence based on task demands**.

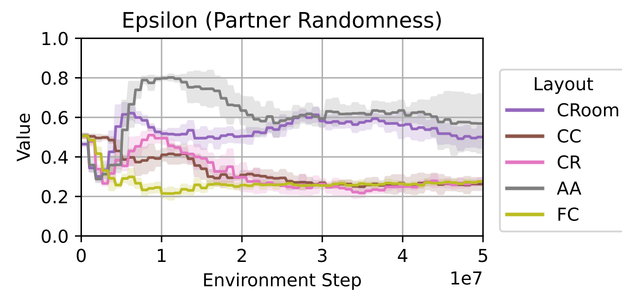

Figure 3: We compare how ℓ_{var} favours different ϵ values across different layouts during training. For layouts that are known to feature narrower coordination challenges (CC, CR & FC), UPD favours ϵ closer to self-play, while for CRoom and AA, UPD favours more random partners.

Figure 4 reveals that UPD induces emergent convention-breaking: early in training, partners exhibit directional biases (e.g., favouring "right"), but later shift to the opposite preference. We hypothesise this increases return variance by violating the ego agent's expectations of partner behaviour. This effect is consistent across layouts and seeds. While prior zero-shot coordination approaches often require hand-engineered mechanisms for convention-breaking (Hu et al. 2020), we find that **convention-breaking-like phenomena organically emerge in UPD**.

5.2 RQ2: Ablations

We also compared with two ablations in Table 1 (Bottom): *UPD w/o bias* uses a uniformly random policy π_r for partner mixing, while *UPD w/o* ℓ removes learnability scoring and instead samples random partners per rollout. Each variant still produces competitive AHT agents, but their combination in full UPD yields the best results – confirming that both stochastic bias and adaptive selection contribute meaningfully. Interestingly, *UPD w/o* ℓ performs quite well, likely because the online partner generator alone induces a natural curriculum by sampling a broad spectrum of partner competencies. Notably, E3T can be viewed as an additional ab-

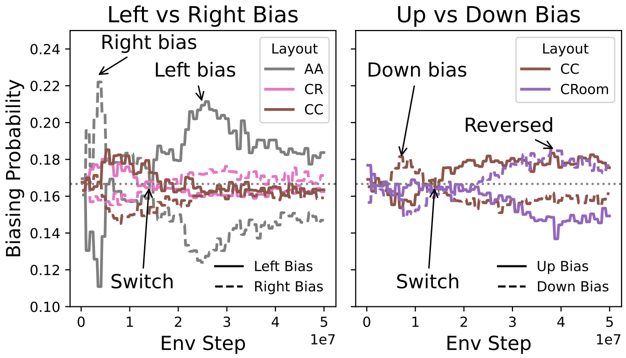

Figure 4: Directional action biases added in partner generation over training. We find that **UPD induces emergent symmetry breaking**, with partners initially biased toward one convention (e.g., left) before switching. These shifts reflect adaptive curriculum dynamics and highlight how maximising learnability encourages convention exploration.

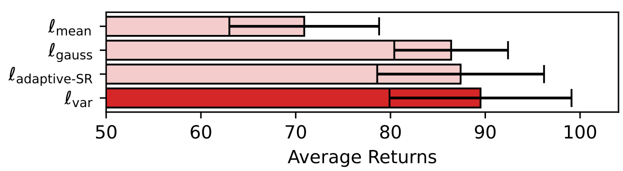

Figure 5: Performance of all learnability functions against the evaluation population averaged over layouts. Our simple ℓ_{var} performs equally or better than more complicated measures. Additionally, the UPD is robust to the learnability function as long as the function is reasonable.

lation: It uses a fixed partner generator and no learnability criterion. UPD outperforms all three ablations, underscoring the benefits of dynamic, learnability-driven curricula.

Next, we examined how different learnability functions affect partner selection and training performance. Specifically, we asked: Does our proposed variance-based score ℓ_{var} induce effective curricula? and How sensitive is UPD to the choice of learnability function? We evaluated four functions across the five Overcooked-AI layouts from RQ1 using the following comparisons: (1) $\ell_{\text{mean}} = \mathbb{E}_{\tau\sim(\pi,\pi_p)}[R(\tau)]$, selects partners with higher expected returns. (2) We adapted the success-rate-based learnability of Rutherford et al. (2024) to continuous rewards by thresholding returns at the median, i.e. using an estimated pseudo-success rate:

$$\ell_{\text{adaptive-SR}} = p \cdot (1 - p), \tag{6}$$

$$\text{where } p = 1 \text{ if } R(\tau) > \text{Median, else } 0. \tag{7}$$

(3) The Gauss-weighted formulation of (Monette et al. 2025). (4) Our ℓ_{var}. Together, these cover naive reward-driven and other selection strategies identified in related works.

As shown in Figure 5, our ℓ_{var} achieves the highest performance. Notably, UPD remains robust across alternative functions – as long as they avoid pathological cases (e.g., self-play). Contrary to prior findings (Monette et al. 2025), we observe that, at least for partner selection, **more complex learnability functions used in UED offer no clear benefit**.

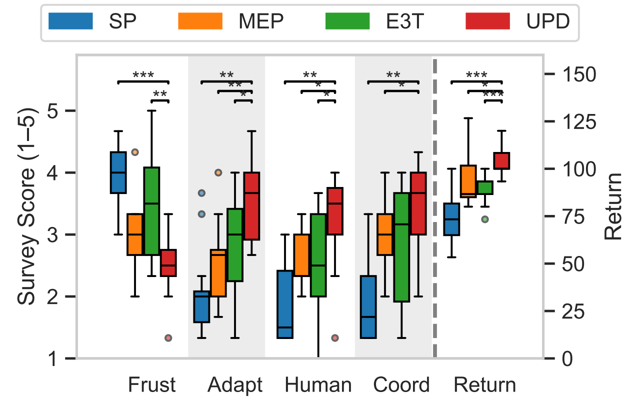

Figure 6: Human evaluation of partners: Frust = 'frustrating?' (↓), Adapt = 'adapted well?' (↑), Human = 'human-like?' (↑), Coord = 'coordinated well?' (↑). We performed one-sided Wilcoxon signed-rank tests on individual survey questions and one-sided paired t-tests on return, comparing UPD to each baseline. Significance levels are Holm-Bonferroni-corrected per question to account for the three comparisons ($* = p < 0.05$, $** = p < 0.01$, $*** = p < 0.001$). Results show that UPD is rated significantly higher on most survey items and yields the highest average return.

5.3 RQ3: Human-AI Teamwork Study

As a final experiment on Overcooked-AI, we evaluated how UPD performs with humans in a double blind user study. We evaluated four representative agents – SP, MEP, E3T, and UPD – on three layouts with challenging coordination dynamics: AA, CR, and CC. Twelve participants (ages 26–34, five female) were recruited, each playing all agent-layout combinations in randomised order. We collected a total of 144 games, with 36 games being played per method. A tutorial session preceded the trials, and compensation was provided per institutional ethics guidelines. The institutional ethics review board approved the study.

Figure 6 shows that **UPD achieves significantly higher returns than all baselines when interacting with humans** (right), and is also preferred across most subjective survey items (left): participants found **UPD significantly more adaptive, more human-like, a better collaborator, and less frustrating to work with**. To evaluate overall subjective preference, we aggregated individual responses across all survey items. The ratings showed high internal consistency (Cronbach's $\alpha = 0.938$), justifying the use of a composite score. Based on these aggregates, UPD was significantly preferred over all other agents (Wilcoxon signed-rank tests, Holm-Bonferroni-corrected, $p < 0.05$ in all cases). UPD is preferred by both artificial and human partners.

Method	CRoom	CR	FC	Average
DR-DR	86.4 ± 7.2	53.6 ± 8.3	9.7 ± 2.4	49.9 ± 5.1
CEC	41.4 ± 9.2	20.3 ± 7.0	12.7 ± 3.5	23.9 ± 6.4
SFL-E3T	81.7 ± 7.8	41.1 ± 10.1	7.4 ± 2.5	44.0 ± 5.1
JUPD (Ours)	$\mathbf{97.0 \pm 7.4}$	$\mathbf{60.0 \pm 6.1}$	$\mathbf{17.1 \pm 4.2}$	$\mathbf{58.9 \pm 5.9}$

Table 2: Results (mean $\pm$ std.) for joint unsupervised environment and partner generalisation on the 5x5 OGC. JUPD outperforms competitive baselines on this challenging benchmark. The best results are in **bold**, second-best are underlined. In CRoom, agents perform near baselines that are trained on a single layout specifically, but generally, performance lags behind.

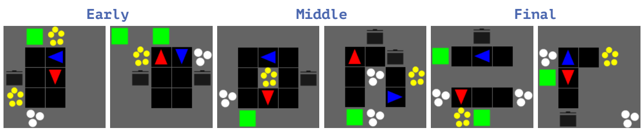

Figure 7: Levels in the JUPD buffer over time.

5.4 RQ4: Joint Environment and Partner Design

One of our central goals was to design a lightweight algorithm that could integrate seamlessly with existing UED methods. To test this, we evaluated UPD within the OGC (Ruhdorfer et al. 2025) – a particularly difficult environment where levels are randomly generated and not guaranteed to be solvable, placing a heavy burden on the UED mechanism.

We implemented our joint method, JUPD, by combining UPD with SFL: we replaced the standard partner/environment sampling in Alg. 1 with the joint sampling and scoring procedure described in Alg. 3. To ensure tractability, we used the 5×5 version of the OGC and trained all methods for 10^9 steps using 1,024 parallel environments. Evaluation was performed using held-out level-partner combinations and held-out layouts with adjusted evaluation populations from **RQ1**.

We compared JUPD against several baselines that combine level and partner generation:

- **DR-DR** randomly samples partners and levels.
- **Cross-Environment-Cooperation (CEC)** selects levels at random and plays in self-play. CEC has shown great success if the level generator is close to the evaluation layouts (Jha et al. 2025).
- **SFL-E3T** combines the best of the literature and selects levels using SFL and creates E3T partners with $\epsilon = 0.5$[1].

As shown in Table 2, JUPD outperforms all baselines across all layouts, achieving the highest average return in this challenging setting. Unlike DR-DR and CEC, which lack structured partner adaptation, or SFL-E3T, which uses static partner generation, JUPD dynamically adapts both level and partner difficulty during training. Sampled levels over time are visualised in Figure 7.

Note that due to slight differences in observations between Overcooked-AI and the OGC, the results in Tables 1 and 2 should be compared with caution.

[1]We use $\epsilon = 0.5$ as it is a common choice in related works.

6 Discussion & Limitations

UPD introduces a general curriculum framework for AHT that mirrors the philosophy of DCD: Just as DCD adapts level difficulty, UPD adapts partner difficulty through online generation and selection. As such, UPD unifies prior AHT approaches – such as E3T, FCP, and MEP – as special cases under fixed generators or static populations, while also achieving stronger performance. Beyond improved performance, UPD produces emergent behaviours like symmetry breaking and task-specific adaptation without explicit design, positioning unsupervised partner shaping as a promising tool for generalisable multi-agent cooperation.

While effective, UPD currently targets discrete action spaces and captures only a subset of possible behavioural diversity – mainly competence and low-level action biases. Extending UPD with richer generators (e.g., using latent-conditioned policies (Eysenbach et al. 2019)) could enable partners with more diverse preferences, intentions, or goals. We see this as a promising direction for future work in open-ended learning for cooperative AI.

Finally, our results underscore the importance of human evaluation: While UPD consistently outperforms baselines, some methods (e.g., MEP vs. E3T) rank differently when paired with humans than with artificial agents. This highlights a persistent gap: agent-agent evaluation alone may not reliably predict human-agent alignment, making user studies essential for measuring collaboration capabilities.

7 Conclusion

We introduced Unsupervised Partner Design (UPD) – a novel, population-free framework for ad-hoc teamwork that uses a learnability-driven curriculum in the partner policy space. By integrating with unsupervised environment design, UPD supports joint adaptation over both tasks and partners, addressing a key challenge in multi-agent generalisation. We reported extensive evaluations showing that UPD enables robust zero-shot coordination without pre-trained partners or manual tuning, outperforming strong baselines on Overcooked-AI. We also evaluated UPD with humans and found that it not only achieves significantly higher returns than all baselines but was also perceived as significantly more adaptive, more human-like, a better collaborator, and less frustrating. Taken together, our work shows that unsupervised, variance-based partner creation and selection offer a scalable path toward more adaptive multi-agent systems.

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A Infrastructure & Tools

We ran our experiments on a server system equipped with NVIDIA H100-NVL GPUs with 94GB of memory and AMD EPYC 9454 CPUs. All training runs are executed on a single GPU only. We trained our models using JAX (Bradbury et al. 2018), Flax (Heek et al. 2023) and Optax (DeepMind et al. 2020). In terms of tools, we did our analysis using NumPy (Harris et al. 2020), Pandas (Team 2020), SciPy (Virtanen et al. 2020) and Matplotlib (Hunter 2007). Our single-file IPPO implementation is based on the one provided by JaxMARL (Rutherford et al. 2023).

Our experiments only require a fraction of the computing power this system offers. At a minimum, our experiments are reproducible using GPUs with 16GB of memory, possibly even less. Overcooked-AI experiments run on the order of minutes while experiments on the OGC usually take a couple of hours but finish in well under a day.

B Reproducibility Statement

To reproduce our work, we provide all key hyperparameters as well as hyperparameter ranges in this document. Our code is available under https://git.hcics.simtech.uni-stuttgart.de/public-projects/UPD.

Category	**Hyperparameter**
# Environments	512
Total timesteps	5×10^7
Reward shaping horizon	3×10^7
Learning rate	1×10^{-3}
Learning rate annealing	Linear
Seeds used	0 - 5
PPO hyperparameters	
PPO rollout length	400 steps
PPO epochs	6
Minibatches per update	8
Discount factor (γ)	0.99
GAE parameter (λ)	0.95
Clipping threshold (ϵ)	0.2
Entropy coefficient	0.01
Value loss coefficient	1.0
Gradient norm clipping	0.5
Architecture (shared for actor and critic)	
Embedding layers	2
Actor layers	4
Critic layers	4
Fully connected layer size	256
GRU hidden size	256
Activation	Tanh
Layer normalization	Enabled
Partner modeling (E3T/UPD only)	
Auxiliary model depth	4 layers (size 64)
MOA loss coefficient	1.0
Trajectory history length	5 steps
Action embedding size	256
Prediction normalization	L2 norm
UPD-specific parameters	
# generated agents	8192
Buffer size ($\|\mathcal{B}\|$)	512
N	10
Buffer refresh frequency	4 training loops

Table 3: Hyperparameters used in Overcooked-AI experiments (e.g. for SP, FCP, MEP, E3T and UPD).

Category	Hyperparameter Range
Total timesteps	5×10^7, $\underline{1 \times 10^8}$
Reward shaping	3×10^7, $\underline{5 \times 10^7}$
Learning rate	$\mathbf{1 \times 10^{-3}}$, 3×10^{-4}, 1×10^{-4}
PPO epochs	$\underline{4}$, **6**
PPO minibatches	$\underline{4}$, 6, **8**
Layernorm?	**True**, False
UPD-specific parameters	
Buffer size ($\lvert\mathcal{B}\rvert$)	128, 256, **512**
N	3, **10**
Buffer refresh freq.	1, 2, **4**

Table 4: Training and architecture hyperparameters search space used in the Overcooked-AI experiments for SP, E3T and UPD. We put the choice in **bold**. For FCP and MEP, we sometimes found slightly different hyperparameters <u>in which case we underline them</u>. To decide which parameters to keep, we looked at evaluation results with a BRDiv population as a cheap proxy. Some hyperparameters were only tuned for FCP and MEP, such as total timesteps and reward shaping horizon. For OGC experiments, we reused the above-found hyperparameters in bold and only added more environments (1024), steps (1×10^9), and actor and critic layers (1 extra; see text).

C Additional Training Details

C.1 Reinforcement Learning Details

We employ independent PPO (de Witt et al. 2020; Schulman et al. 2017) for all methods in the main paper. We give an overview over all hyperparameters in Table 3.

For all methods we conducted small preliminary hyperparameter searches to arrive at the hyperparameters in question. We show the ranges in Table 4.

Experiments on the OGC used the exact same hyperparameters with one small difference: we use an additional actor and critic layer (5 each) and train in 1,024 environments for 1×10^9 total timesteps.

C.2 Neural Network Architecture

We employ a recurrent actor-critic architecture. The model comprises a shared encoder, a recurrent processing module, and separate heads for policy and value estimation.

Each agent's observation is passed through a feedforward encoder consisting of a linear layer followed by a configurable number of fully connected layers (default: two layers). Each layer contains 256 hidden units with either ReLU or Tanh activations, optionally followed by layer normalisation. The resulting representation is used as input to the recurrent module.

Temporal dependencies are captured using a Gated Recurrent Unit (GRU) (Cho et al. 2014) with a hidden state size of 256. The recurrent hidden state is reset at environment terminal states. The GRU output serves as a temporal embedding and is shared by both the actor and critic heads.

The policy head processes the recurrent embedding through four fully connected layers with 256 units each and nonlinear activations. A final linear layer outputs unnormalized logits over discrete actions, defining a categorical action distribution. The value head also uses the recurrent embedding as input and applies four fully connected layers with 256 units each, followed by a scalar output representing the state value estimate.

We employ the *other agent modelling network* proposed by E3T. This auxiliary module models the behaviour of their teammate. Each agent receives the past five state-action pairs of the other agent. Observations and actions are embedded and passed through a four-layer multilayer perceptron (64 units per layer) to predict the teammate's next action distribution. The prediction is L2-normalised and concatenated with the agent's own embedding before being fed into the policy head. This auxiliary loss is optimised using a cross-entropy objective and weighted by a tunable coefficient. This is consistent with the original formulation (Yan et al. 2023).

D Additional Environment Details

D.1 Overcooked-AI

Overcooked-AI is a multi-agent coordination benchmark based on the Overcooked video game, originally proposed by Carroll et al. (2019). It features two-player cooking tasks requiring temporal coordination and spatial reasoning. Agents must pick up ingredients, cook them in pots, and serve dishes, with partial observability and sparse rewards. The action space is discrete, consisting of six actions: move up, down, left, right, interact, and stay.

We use the five standard layouts commonly used in ad-hoc teamwork literature (also see Figure 8): Cramped Room (CRoom), Asymmetric Advantages (AA), Coordination Ring (CR), Counter Circuit (CC), and Forced Coordination (FC). We use the implementation provided by JaxMARL and keep all reward settings at their defaults (sparse reward for serving, shaped reward for intermediate actions where indicated). For training, we use sparse reward settings by default, but enable reward shaping during the first 3×10^7 timesteps. During the shaped reward phase, agents receive a reward of 3 for placing an ingredient into a pot, 3 for picking up a plate while a soup is cooking, and 5 for picking up a ready soup.

D.2 The Overcooked Generalisation Challenge

The Overcooked Generalisation Challenge (OGC) (Ruhdorfer et al. 2025) extends Overcooked-AI to assess zero-shot generalisation across both partner and level distributions. Instead of training on fixed layouts, the environment includes a procedural level generator that produces randomised kitchens with varying topology and difficulty.

The challenge is particularly demanding because many generated layouts are unsolvable or require nontrivial conventions to coordinate efficiently.

In our work, we use a 5×5 version of the OGC to reduce computational cost while preserving task diversity. This generator randomly samples kitchen structure (walls, counters, item placement) and goal configurations (e.g., number of

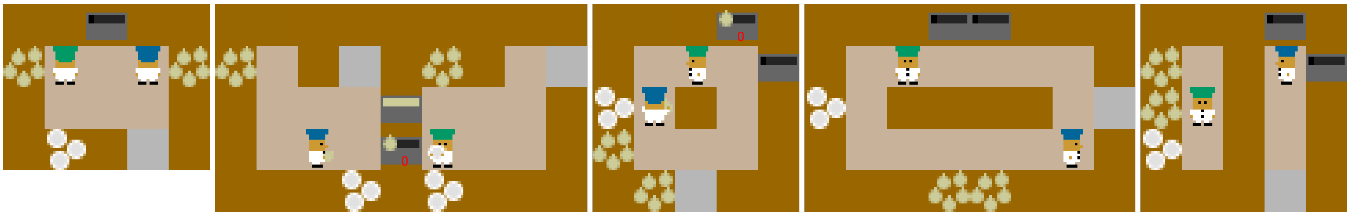


Figure 8: We reprint the five evaluation layouts of the non-Jax Overcooked version using the figure of Carroll et al. (2019). From left to right: CR, AA, CR, CC and FC.

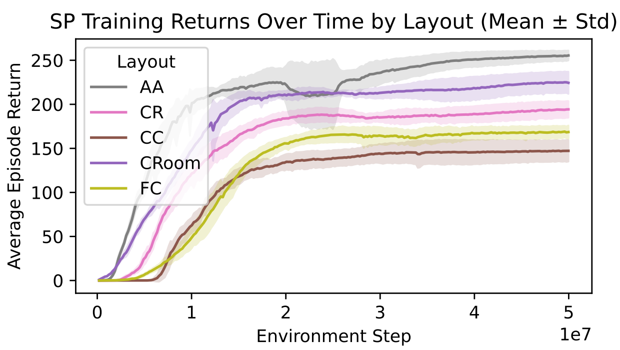


Figure 9: SP training curves. We average over 6 seeds and show standard deviation.

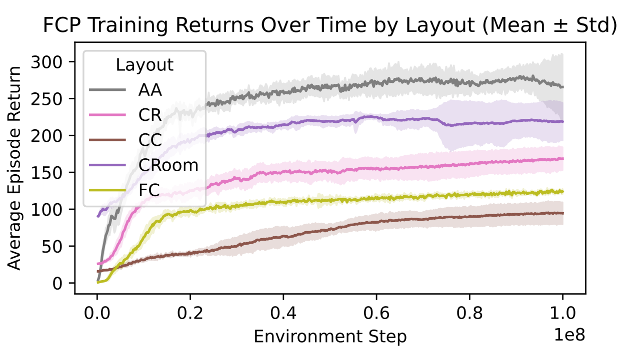


Figure 10: FCP training curves. We average over 6 seeds and show standard deviation.

onions per soup). The generator first generates a layout with walls at the border and then randomly samples a wall budget between 1 and 10. With this budget, the system then places walls randomly. The generator also randomly adds a dividing wall or additional walls at the side in order to narrow the layout. After this, the system places items on walls. Lastly, both agents are placed on a free tile.

We evaluate performance on a fixed subset of small layouts used in the OGC benchmark and compare agents based on average return when paired with held-out agents across these generated environments.

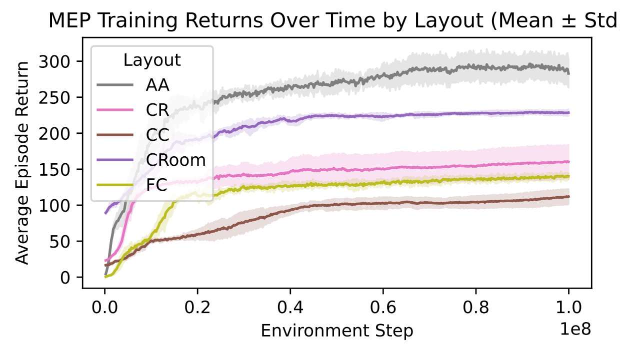


Figure 11: MEP training curves. We average over 6 seeds and show standard deviation.

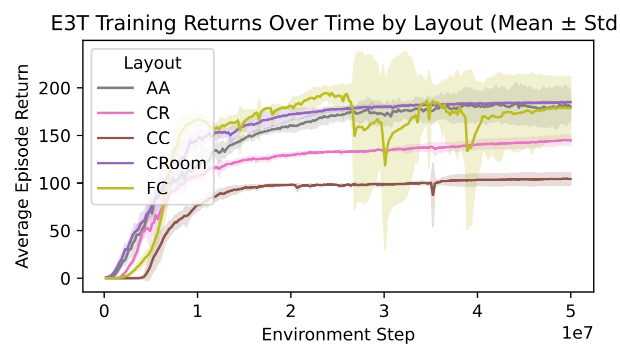


Figure 12: E3T training curves. We average over 6 seeds and show standard deviation.

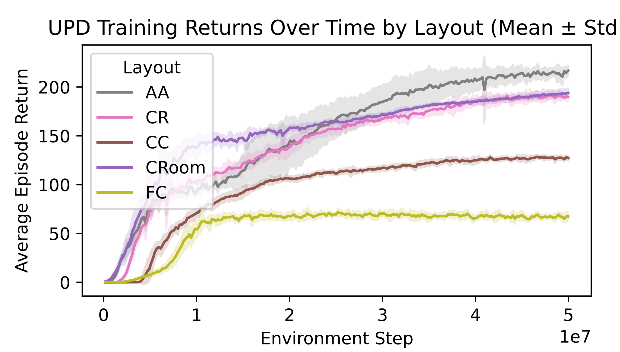


Figure 13: UPD training curves. We average over 6 seeds and show standard deviation.

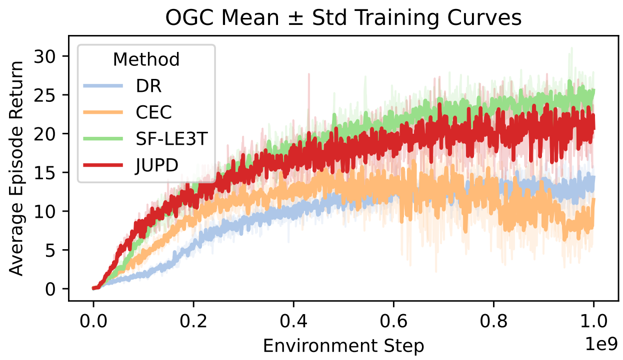


Figure 14: OGC training curves. We average over 6 seeds and show standard deviation for all three methods.

E Training Curves

We display the received training returns for all Overcooked-AI methods in Figures 9 (SP), 10 (FCP), 11 (MEP), 12 (E3T) and 13 (UPD). Note that these returns must be interpreted with caution. For FCP and MEP, they display the returns with their respective populations. For UPD and E3T, they display the received training returns based on the generated partner. In any case, all the Figures show methods converging stably. Also note that many methods achieve higher training returns compared to UPD, but, as has been established in the literature (Carroll et al. 2019), this isn't necessarily predictive of test returns with unknown partners.

In Figure 14, we display training returns for all four OGC methods. We see all methods converging. Only CEC appears to experience a drop in performance at the end. Again, note that training performance is not predictive of test-time performance: Methods that sample levels by learnability (SFL-E3T, JUPD) might sample harder levels than methods that do not (DR, CEC), and both SFL-E3T as well as JUPD do not play in a self-play setting.

F Partner Curriculum Dynamics

To better understand how UPD identifies effective training partners throughout learning in Overcooked-AI, we visualise learnability scores across training, similar to prior work (Rutherford et al. 2024; Monette et al. 2025). For three respective layouts (CR, AA and FC), we evaluate a trained ego agent at three points during training (at 2/5, 4/5, and the end) by rolling out with 8,192 randomly generated partners (see Figures 15, 16, 17). We select these three layouts as they are representative: both CRoom and CC behave very similarly to the CR case. We compute learnability using the same variance-based metric as during training and plot it against the corresponding mean return. Across all settings, we observe that learnability does not concentrate on the highest- or lowest-returning partners, nor does it peak where most partners lie. Instead, learnability is high for partners with intermediate difficulty. We observe that for most levels, the generated partners fall into low-return and low-learnability buckets. This suggests that our hypothesis – that not all partners are optimal for training – is correct: Most partners score low on the learnability metric. Instead, UPD ranks partners from middle-return buckets highest, in which only a few partners resign.

Finally, unlike prior work on level-space curricula with binary outcomes (Rutherford et al. 2024; Monette et al. 2025), we observe that agents in our setting rarely score zero reward with any partner. Due to this and the continuous reward structure, we find that our learnability analysis plot conveys information not only through its shape but also via its rightward shift over time. For instance, in Figure 16, the lowest-scoring partner improves from around 20 to 120 mean return between early and middle training. This shift suggests that the ego agent's capabilities expand over time and that UPD adapts by sampling increasingly competent partners. In doing so, UPD not only identifies informative partners but also tracks the agent's learning progress, adjusting the curriculum accordingly. A notable exception arises in tasks with strong interdependence, such as FC (see Figure 17).

G Additional Results

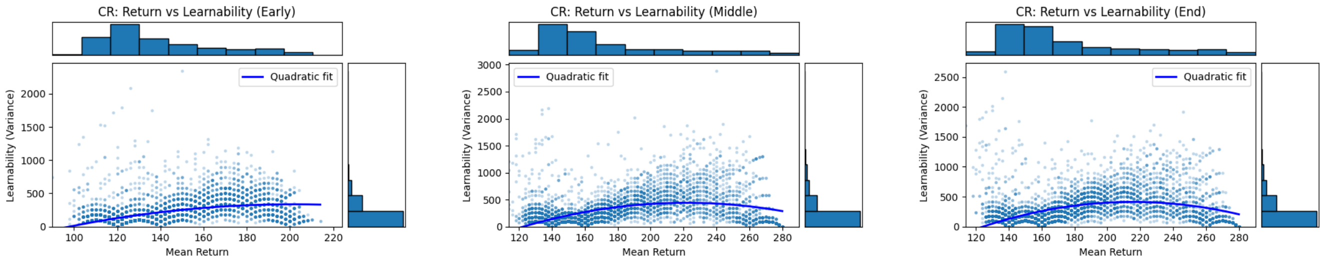
In Figure 18, we display additional results for how UPD performs with different partners. On average and with most partners, UPD performs best. UPD is only slightly outperformed by MEP with the onion agent, however, as also discussed in the main paper, UPD outperforms MEP in all other regards.

H Additional Notes on Alternative Learnability Fomulations

Our experiments showed that UPD is highly effective in training agents for AHT, and is robust under different formulations of learnability as long as they do not collapse to the self-play setting. Additionally, we demonstrated that UPD can be integrated into standard UED enabling fully unsupervised curricula over both environment and partner distributions. While we explored several learnability functions, many alternatives remain. One natural baseline is to prioritise the hardest partners – those with the lowest average return – as explored in prior work (Zhao et al. 2023; Li et al. 2023; You et al. 2025). However, both theoretically and in preliminary experiments, we find this approach leads to adversarial dynamics. Specifically, in Overcooked-AI, it heavily favours near-random partners (i.e., $\epsilon \to 1$), while in the OGC, it favours unsolvable levels. In both cases, learning stagnates. This is because our setting involves an open-ended partner generator, unlike prior work, which relies on pre-trained or bounded populations that implicitly cap adversarial behaviour. In such constrained settings, prioritising "hard" examples remains within the space of feasible coordination, whereas in (J)UPD, unconstrained difficulty selection can collapse the training signal entirely.

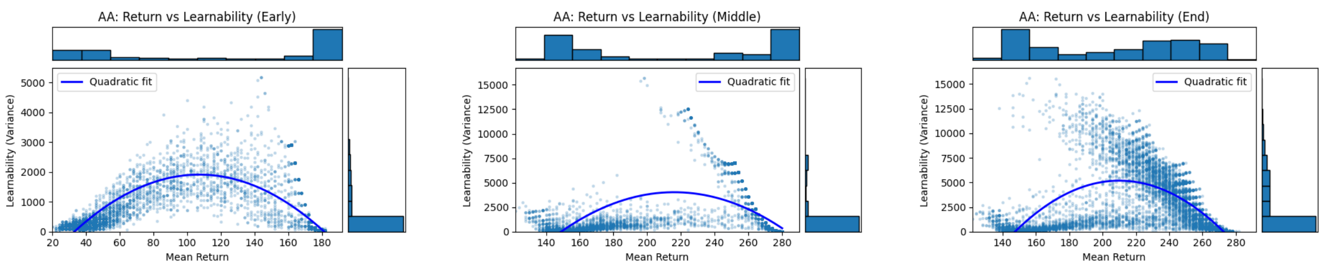
I Additional User Study Details

We employed a within-subjects design: each participant interacted with all 4 agents (SP, MEP, E3T, UPD) across 3 Overcooked layouts (Asymmetric Advantages, Cramped Room, Counter Circuit). Each agent-layout pair was played once, totalling 36 episodes per participant. Agent and layout



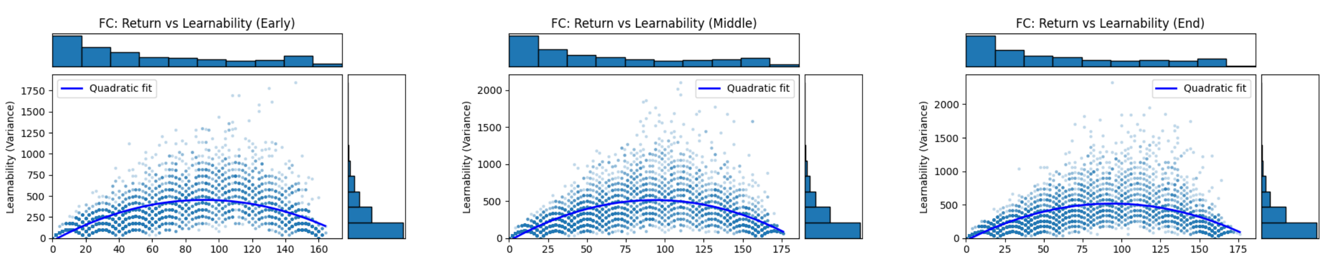
(a) Early (b) Middle (c) Final

Figure 15: Learnability vs. return over training in **Coordination Ring**.



(a) Early (b) Middle (c) Final

Figure 16: Learnability vs. return over training in **Asymmetric Advantages**.



(a) Early (b) Middle (c) Final

Figure 17: Learnability vs. return in **Forced Coordination**.

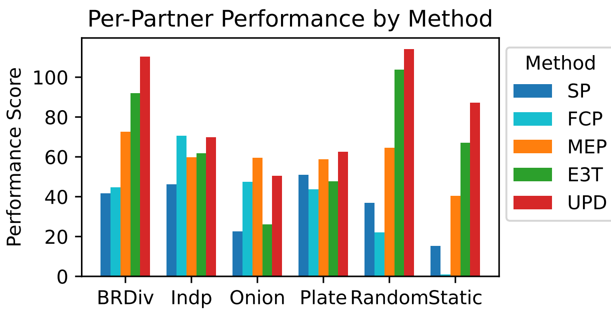


Figure 18: Per-Partner results averaged over layouts in Overcooked-AI. UPD outperforms other methods with most partners. Some methods show similar or even slightly better performance with the Onion and the independent planning agent. However, these methods are not consistently better than UPD.

order were randomised per user. Each full study lasted between 18 and 35 minutes, and participants completed a short tutorial prior to the main study.

The study was conducted via a web-based interface using the `NiceWebRL` framework[2]. We recruited 12 participants (5 female; aged 26–34) for the user study. The study was approved by our institutional ethics review board, and all participants gave informed consent. Compensation was provided per institutional guidelines. Participants controlled their character using a keyboard layout (arrow keys, space and the s key). Participants were not informed about the agent identities to avoid bias (double-blind). After each agent interaction, participants rated the agent using seven 5-point Likert-scale questions (strongly disagree, disagree, neutral, agree, strongly agree). The questions were:

1. I enjoyed playing with the agent.
2. I felt that the agent's ability to coordinate with me was: (very poor, poor, neutral, good, very good)
3. The agent adapted to me when making decisions.
4. The agent frequently got in my way. *(negative)*
5. The agent was consistent in its actions.
6. The agent's actions were human-like.
7. The agent's behaviour was frustrating. *(negative)*

We additionally allowed users to give free-form feedback at the end of the study. Responses were numerically mapped from 1 to 5. Negative-valence questions were inverted before aggregation for our analysis on the overall subjective preference. To assess internal consistency of the question responses, we computed Cronbach's $\alpha = 0.938$, suggesting strong reliability. This justifies aggregating scores across questions to produce a single subjective preference score per agent.

We ran one-sided Wilcoxon signed-rank tests comparing UPD to each baseline. To control for multiple comparisons, we applied Holm–Bonferroni correction within each question. We also tested the aggregated preference scores using the same procedure. Performance (reward) was analysed via one-sided paired t-tests with Holm correction. We provide bar plots for each survey question, showing Likert response distributions per agent, available in Figure 19

[2]https://github.com/KempnerInstitute/nicewebrl

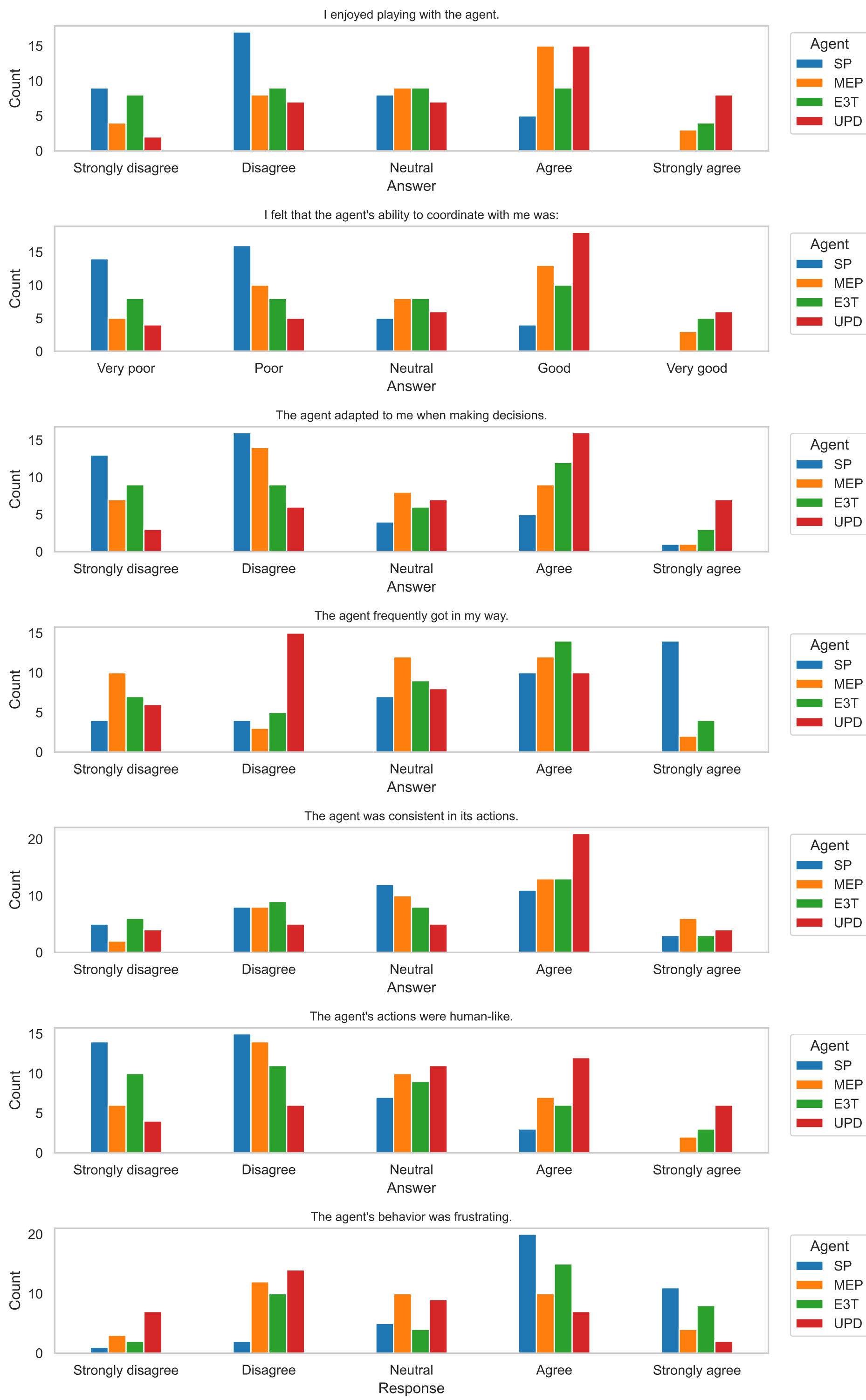


Figure 19: Distribution of human ratings for each survey question across all agents. Each bar represents the number of responses given to each Likert item (x-axis), with colors indicating the agent. Questions are grouped vertically and include both subjective impressions (e.g., enjoyment, consistency) and collaboration quality (e.g., coordination, frustration).