

AI-Enabled Passive Sensing for Forecasting Warfighter Mental Health Risk and Readiness-Relevant Change

Toward proactive, continuous behavior and mental health monitoring to support warfighter readiness

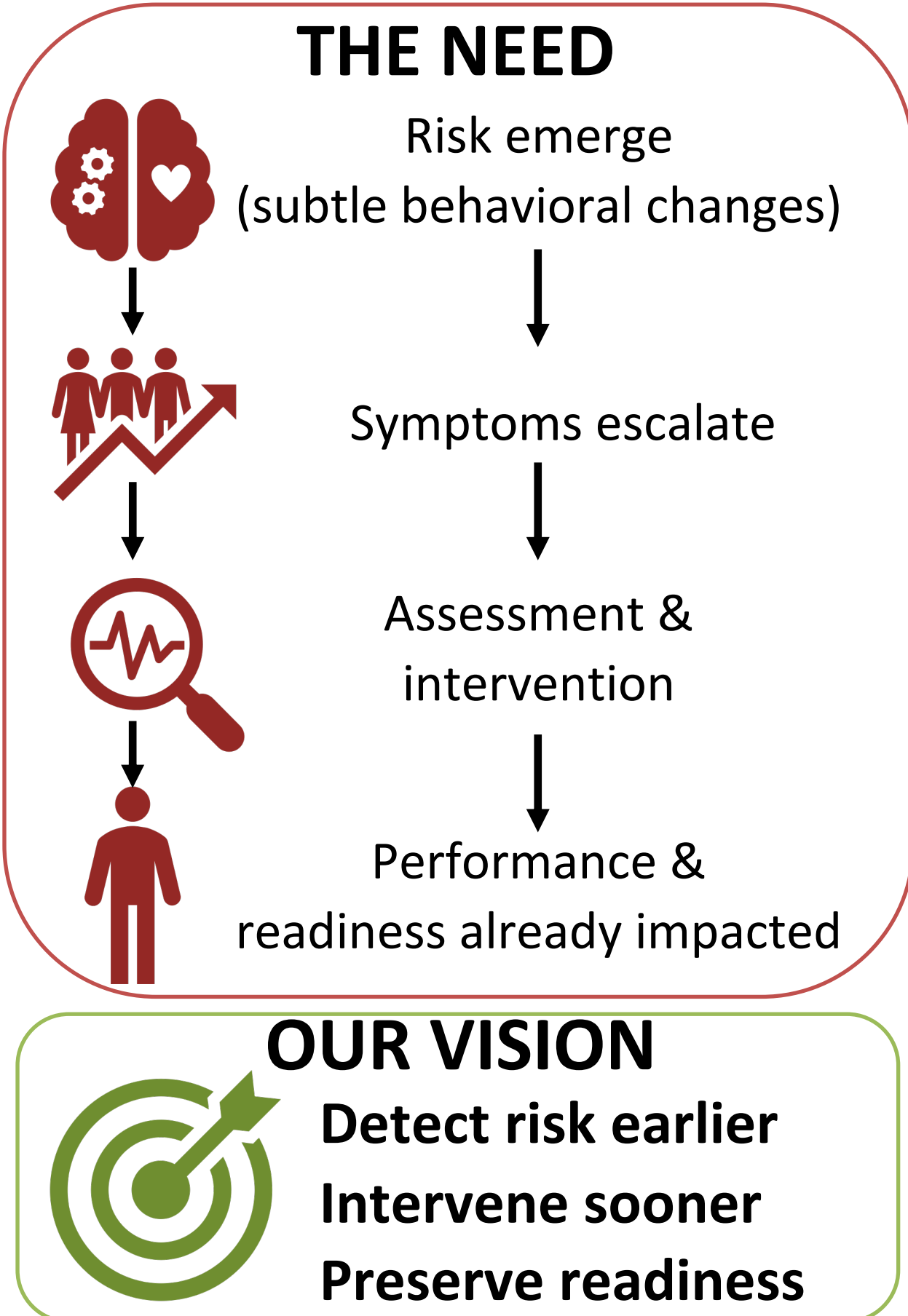
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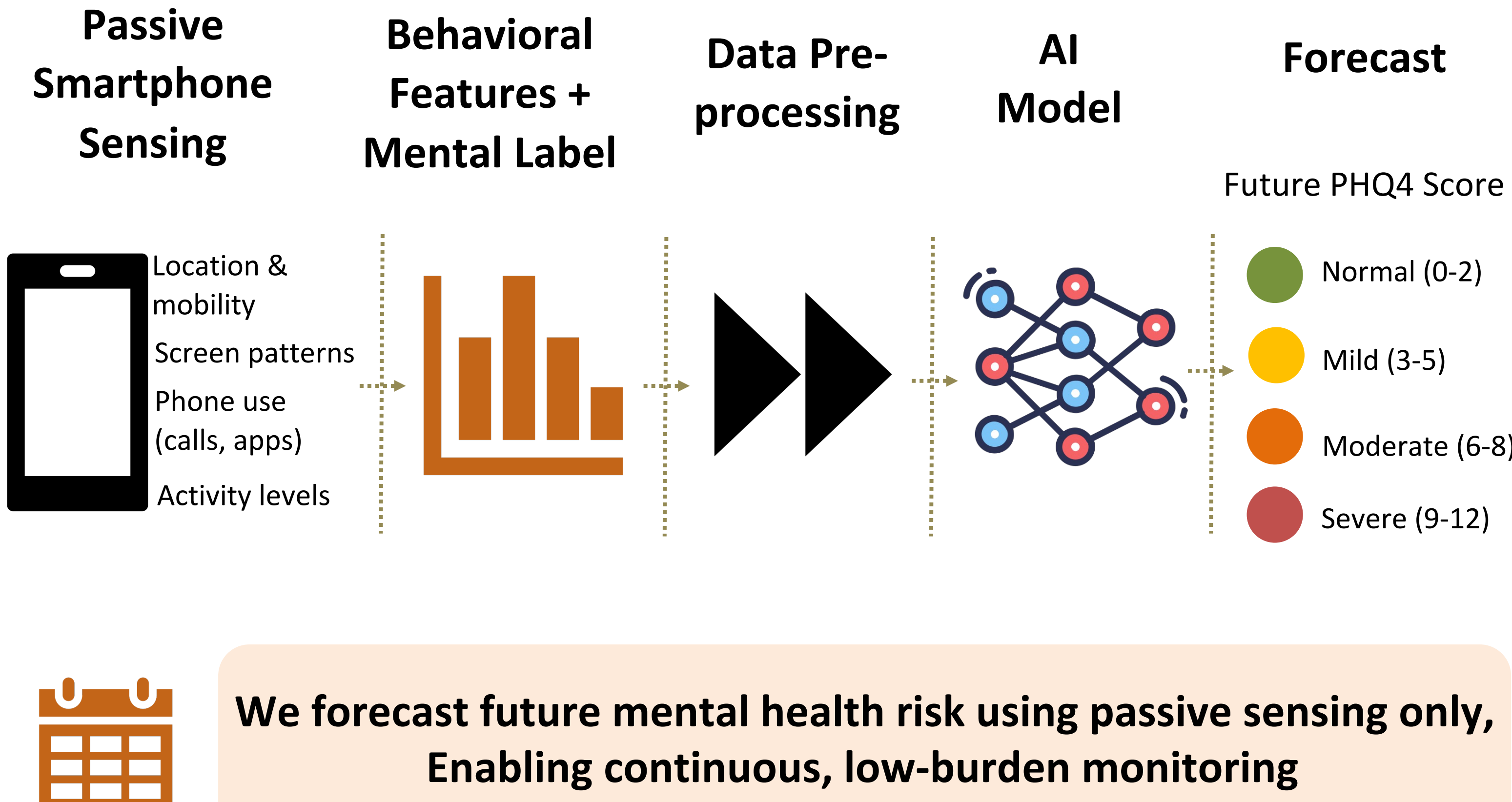
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1. Why It Matters for Warfighters

- Warfighter mental health directly impacts medical readiness, resilience, and mission effectiveness.
- Current monitoring is largely reactive; problems recognized after performance has already declined.
- Early identification of emerging risk before functional degradation occurs is critical for maintaining readiness.
- Passive smartphone sensing + AI provides a scalable, low-burden pathway for continuous monitoring.
- However, the design of deployable, proactive forecasting systems remains insufficiently understood.



2. Our Approach – AI Forecasting Pipeline



3. Study Design – Key Deployment Questions

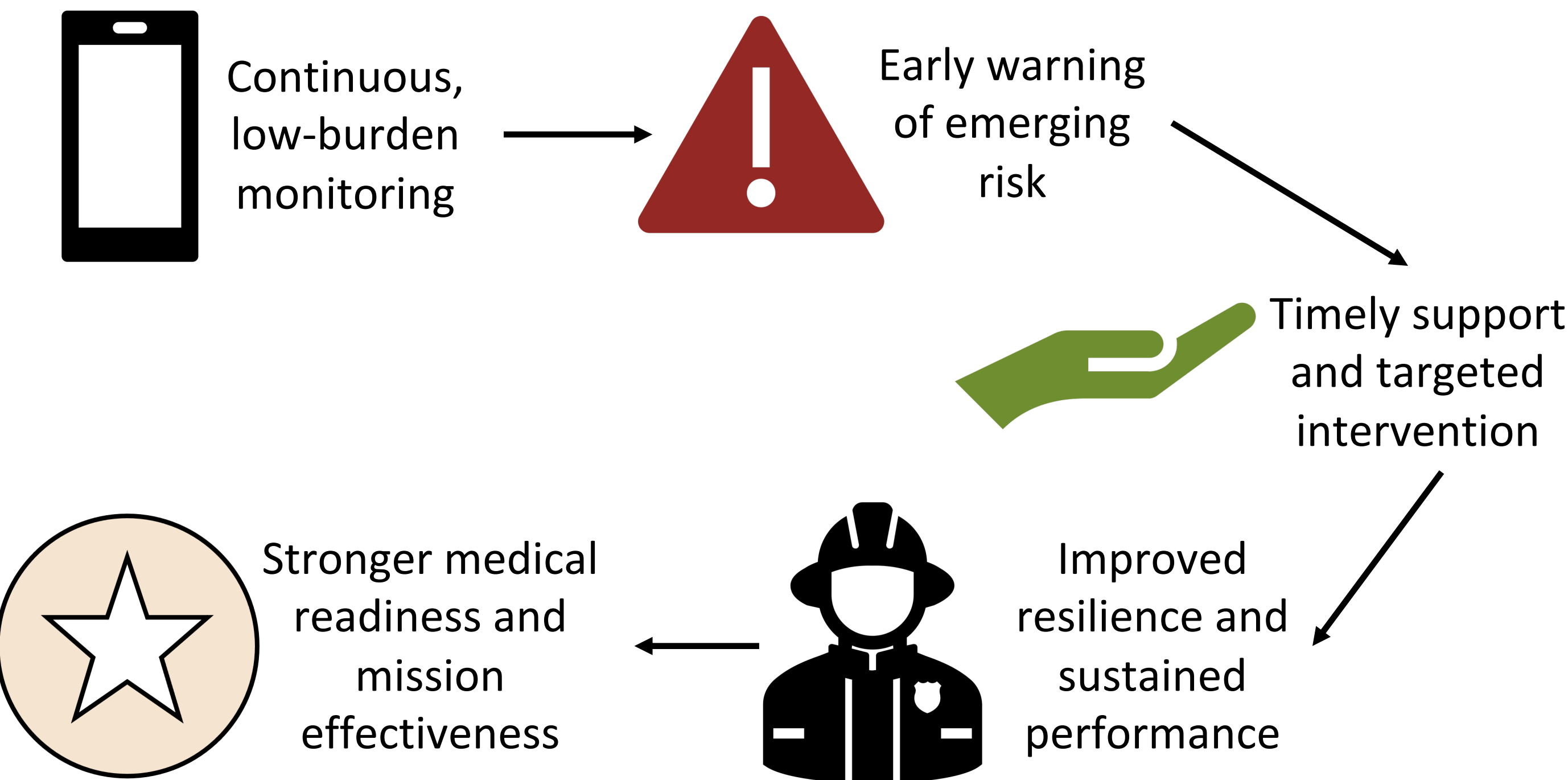
Dataset: College Experience Study (CES)

- 215 participants, multi-year longitudinal study (2017 – 2022)
- Weekly PHQ4 assessments (4 questions: 2 anxiety + 2 depression)
- Passive smartphone sensing
- Five-fold cross validation

Three Deployment-Relevant Questions

- Can we forecast using only one person's data?
 - Privacy-preserving
 - Data-scarce deployment
- What model granularity works best?
 - Population vs. Similarity-based vs. Personalized (fine-tuned)
- Should forecasting use one-stage or two-stage AI?
 - Which architecture delivers best final risk prediction?

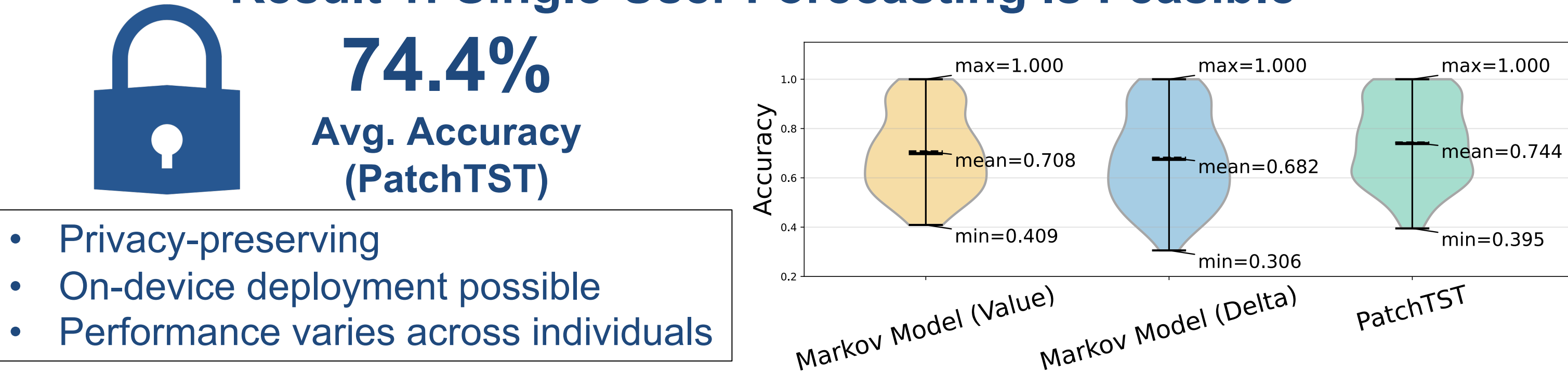
5. Implications for Warfighter Readiness



AI-enabled passive sensing can forecast future mental health risk before functional degradation occurs, providing a scalable, privacy-preserving foundation for proactive behavioral health monitoring that supports warfighter readiness & mission success.

4. Evaluation Results

Result 1: Single-User Forecasting Is Feasible



Result 2: Population Models Generalize Best

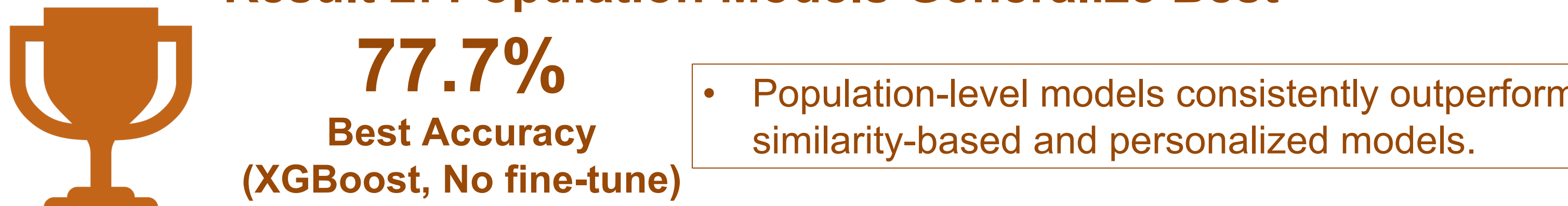
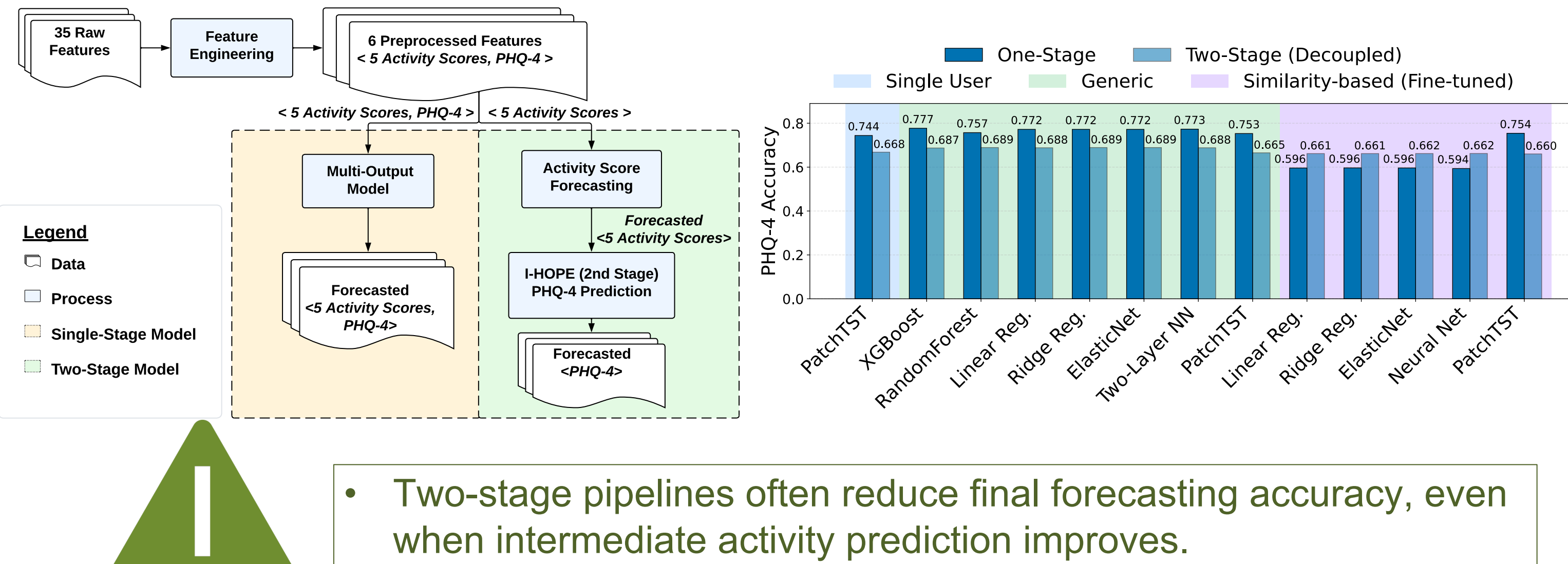


TABLE II: Forecasting Results at Different Model Granularity. Overall accuracy (Acc.) is reported per model, while precision (P), recall (R), and F1 are reported per PHQ-4 category (RQ₂, §III-B).

Initialization	Model	No Fine-tune on Target User's Data												Finetuned on Target User's Data (Personalized Model)													
		Normal			Mild			Moderate			Severe			Normal			Mild			Moderate			Severe				
		Acc.	P	R	F1	P	R	F1	P	R	F1	P	R	F1	Acc.	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Generic Model	Linear Reg.	0.772	0.888	0.872	0.880	0.602	0.678	0.638	0.440	0.421	0.430	0.700	0.344	0.457	0.732	0.722	0.813	0.758	0.458	0.384	0.401	0.183	0.112	0.129	0.113	0.083	0.089
	Ridge Reg.	0.772	0.888	0.872	0.880	0.602	0.678	0.638	0.440	0.421	0.430	0.700	0.342	0.456	0.732	0.722	0.813	0.758	0.458	0.384	0.401	0.182	0.112	0.128	0.113	0.083	0.089
	ElasticNet	0.772	0.888	0.872	0.880	0.600	0.688	0.641	0.441	0.417	0.429	0.709	0.334	0.450	0.734	0.711	0.848	0.768	0.427	0.332	0.356	0.153	0.100	0.089	0.055	0.064	0.064
	Neural Network	0.773	0.876	0.893	0.885	0.621	0.624	0.622	0.418	0.379	0.397	0.580	0.461	0.508	0.728	0.809	0.931	0.865	0.593	0.465	0.519	0.417	0.287	0.335	0.552	0.303	0.369
	RandomForest	0.757	0.881	0.871	0.876	0.590	0.660	0.623	0.385	0.398	0.390	0.639	0.182	0.275	-	-	-	-	-	-	-	-	-	-	-	-	-
	XGBoost	0.777	0.879	0.889	0.884	0.616	0.662	0.638	0.449	0.405	0.425	0.720	0.322	0.434	-	-	-	-	-	-	-	-	-	-	-	-	-
	PatchTST	0.753	0.737	0.814	0.772	0.455	0.403	0.416	0.144	0.125	0.124	0.068	0.034	0.042	0.752	0.748	0.787	0.765	0.461	0.434	0.439	0.168	0.143	0.145	0.084	0.050	0.060
Similarity-based Model	Linear Reg.	0.591	0.597	0.967	0.686	0.062	0.025	0.029	0.016	0.004	0.005	0.014	0.004	0.005	0.596	0.597	0.975	0.691	0.061	0.022	0.026	0.023	0.011	0.009	0.026	0.004	0.006
	Ridge Reg.	0.591	0.597	0.969	0.687	0.062	0.023	0.028	0.016	0.011	0.006	0.014	0.002	0.003	0.596	0.597	0.976	0.691	0.060	0.021	0.026	0.021	0.007	0.006	0.026	0.003	0.004
	ElasticNet	0.596	0.596	0.990	0.694	0.010	0.001	0.002	0.008	0.000	0.000	0.008	0.000	0.000	0.596	0.596	0.990	0.694	0.013	0.002	0.002	0.000	0.000	0.000	0.017	0.000	0.000
	Neural Network	0.511	0.667	0.620	0.546	0.309	0.326	0.252	0.089	0.098	0.048	0.025	0.024	0.014	0.594	0.690	0.609	0.617	0.333	0.372	0.332	0.092	0.152	0.103	0.063	0.047	0.046
	RandomForest	0.594	0.679	0.710	0.623	0.316	0.385	0.288	0.044	0.058	0.041	0.017	0.013	0.014	-	-	-	-	-	-	-	-	-	-	-	-	-
	XGBoost	0.579	0.666	0.696	0.618	0.330	0.384	0.291	0.073	0.046	0.037	0.016	0.007	0.008	-	-	-	-	-	-	-	-	-	-	-	-	-
	PatchTST	0.753	0.760	0.788	0.772	0.463	0.439	0.439	0.156	0.139	0.135	0.082	0.046	0.056	0.754	0.759	0.800	0.777	0.465	0.427	0.435	0.169	0.145	0.146	0.088	0.046	0.057

Result 3: Mode Complex AI Is Not Necessarily Better



Key Takeaways

- Single-user forecasting is achievable using only a person's data, enabling privacy-preserving, on-device solutions.
- Population-level models provide the most reliable risk forecasts across individuals.
- Mode complex, two-stage AI does not necessarily improve final prediction and can even reduce accuracy.
- Performance varies across individuals; models must be validated and monitored continuously.
- Simplicity, robustness, and privacy are key for deployable solutions.