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From Mining Affective States to Mining Facial Keypoint Data: The Quest Towards Personalized Feedback.

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Grand Engineering Challenges of the 21st century: ***Development of Personalized Learning***

[Vest 2008]

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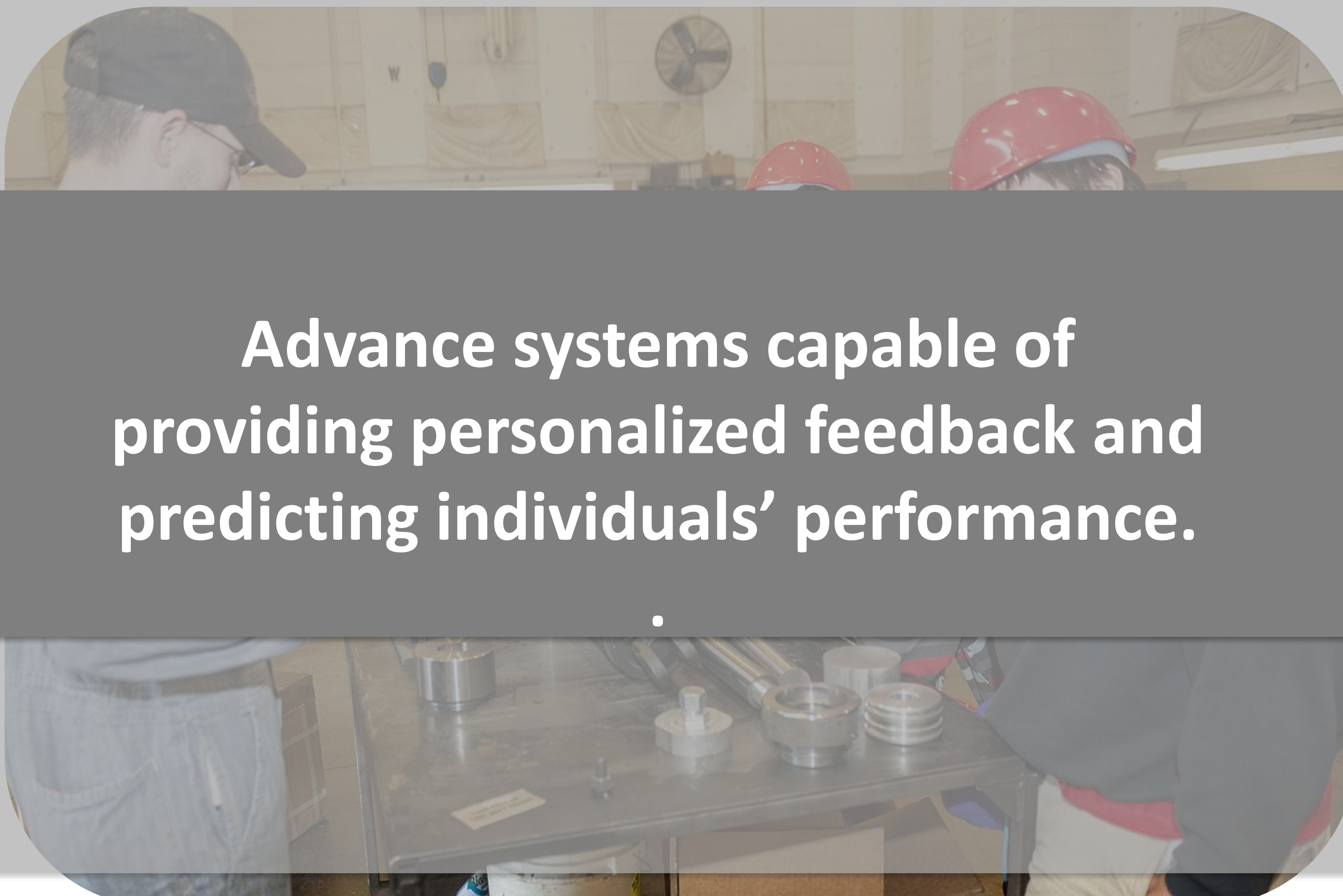

Advance systems capable of providing personalized feedback and predicting individuals' performance.

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Individuals communicate their affective states through verbal and non-verbal cues.

Verbal:
- Content
- Intonation
- Pace

Non-Verbal:
- Facial Expression
- Body Movement
- Gestures

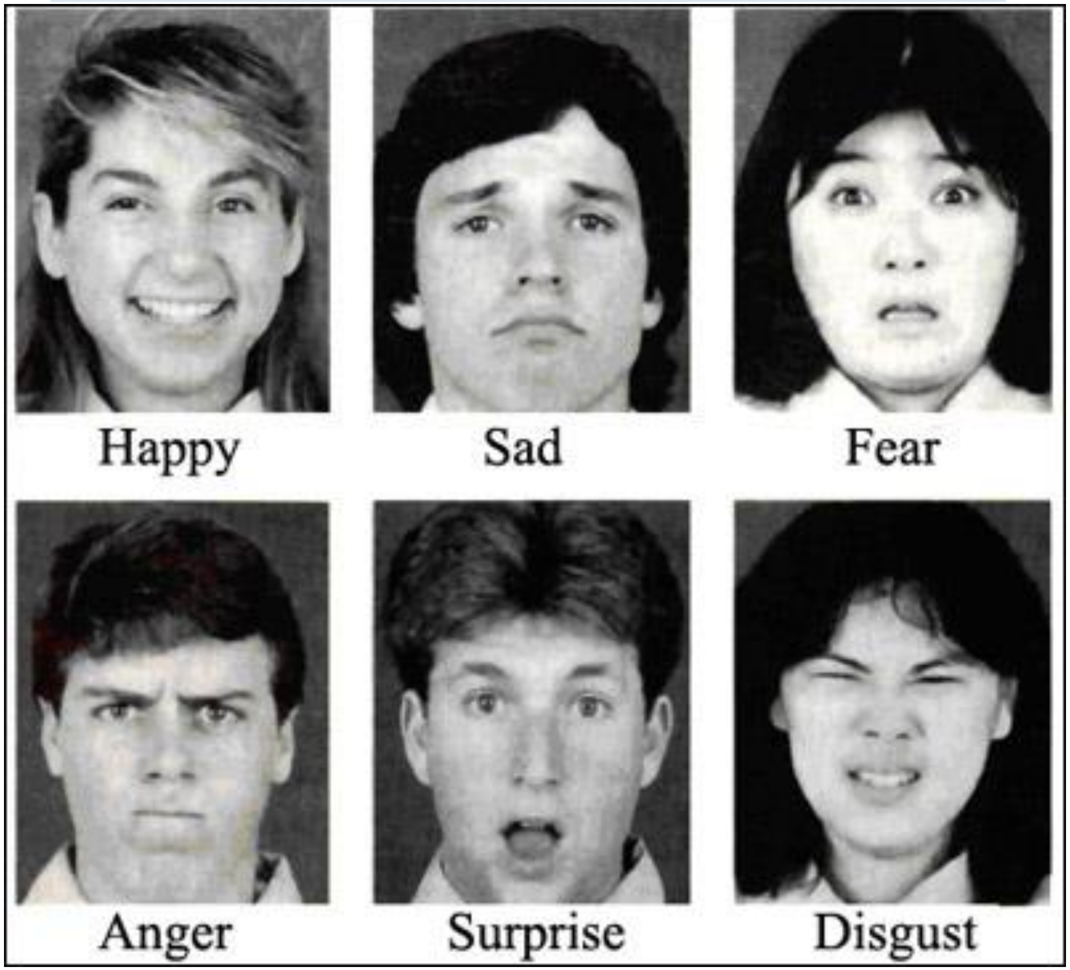
Current methods still have several limitations

	Subjective Method	**Objective Method**	Label Emotion	**Non-Label Emotion**	General Models	**Individual Models**
Sonalkar et al. (2011)	X		X			X
Balters & Steinert (2015)		X	X		X	
Behoora & Tucker (2015)		X	X		X	
Bezawada et al. (2017)		X	X			X

Affect-sensitive systems tend to label an individual's affective states into discrete categories.

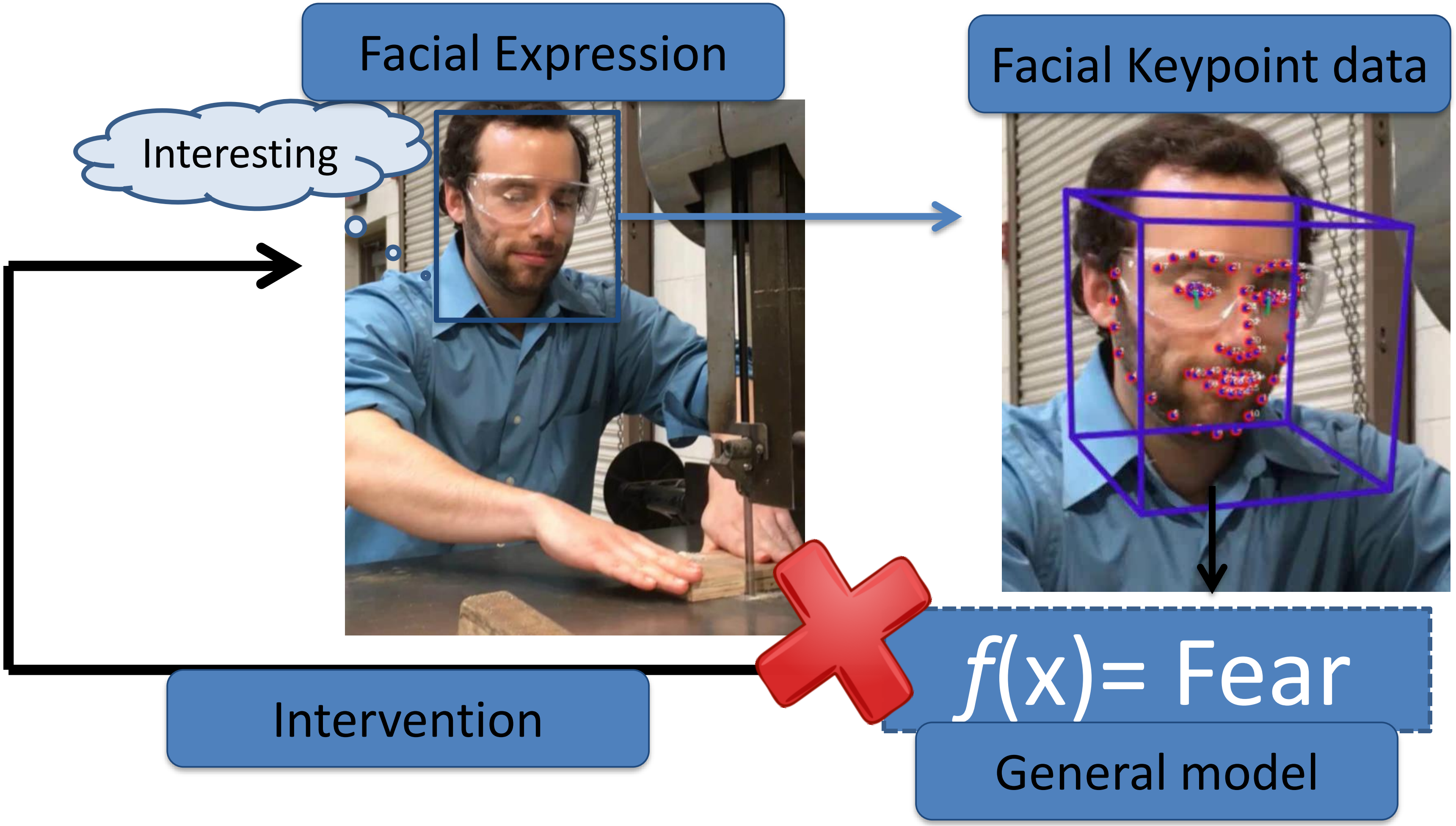
[Calvo & Mello 2010]

Ekman's Basic Emotions



[Ekman &Friesen 1978]

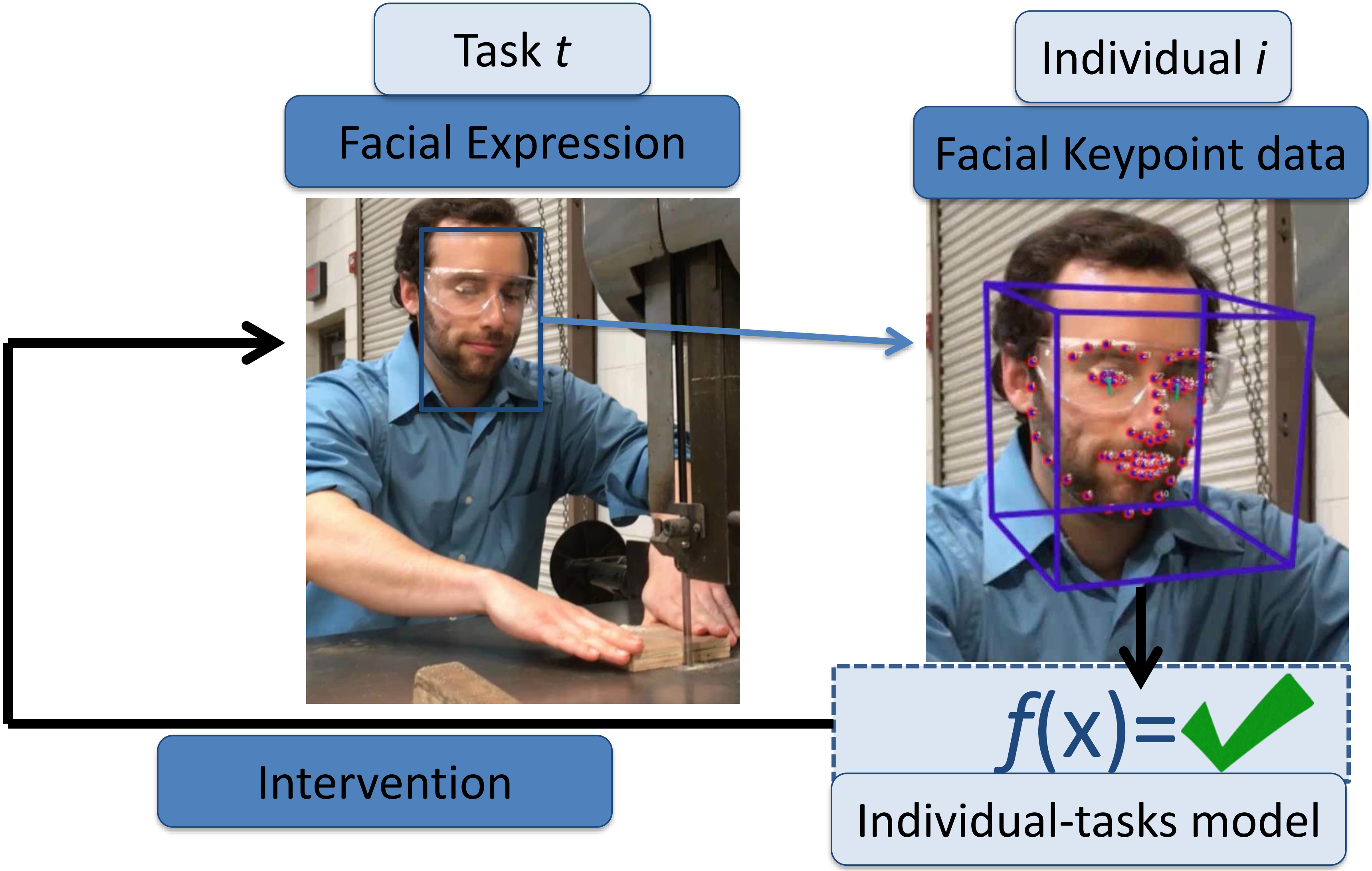
General models limit the capability to provide appropriate and personalized feedback



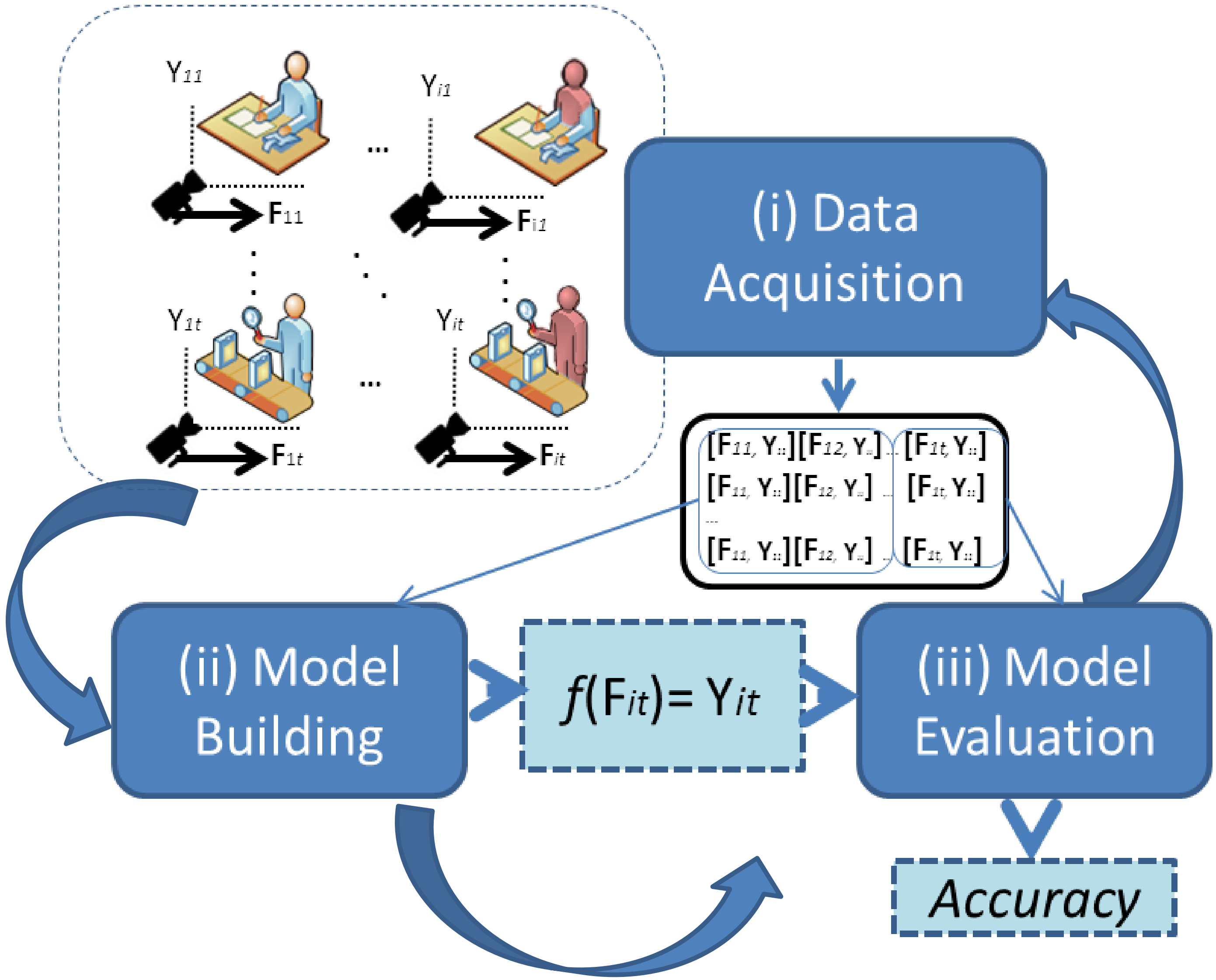
Advance personalized system capable to take into account Task and Individual characteristics

	Subjective Method	**Objective Method**	Label Emotion	**Non-Label Emotion**	General Models	**Individual Models**
Sonalkar et al. (2011)	X		X			X
Balters & Steinert (2015)		X*	X		X	
Behoora & Tucker (2015)		X	X		X	
Bezawada et al. (2017)		X	X			X
This Work		X		X		X

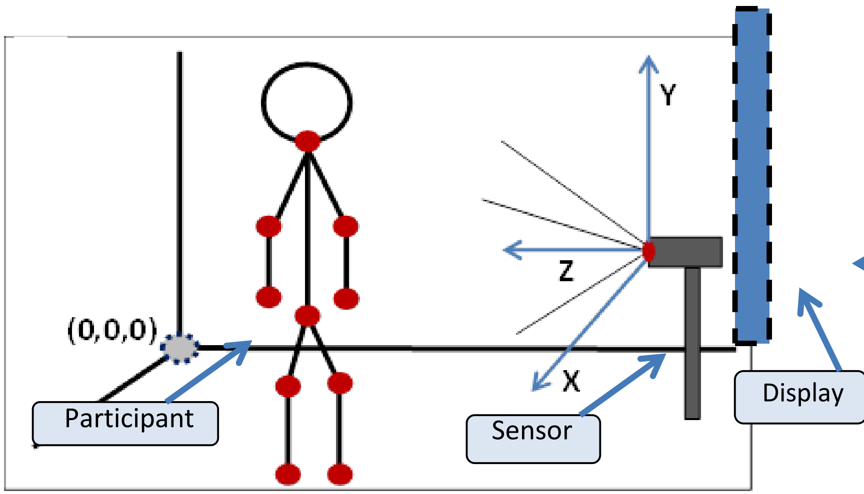
The proposed *individual-task* model takes into consideration tasks and individuals differences.



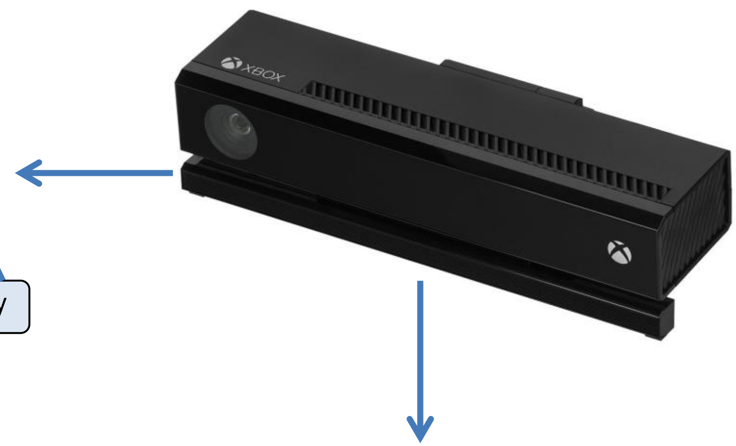
Machine Learning method to predict individuals' performance by using their facial keypoints

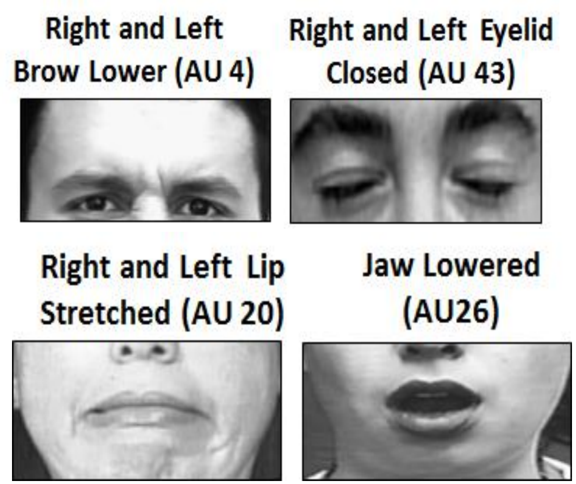


Data Acquisition:
Performance and Facial Keypoint Data



Performance data





Facial Keypoint data

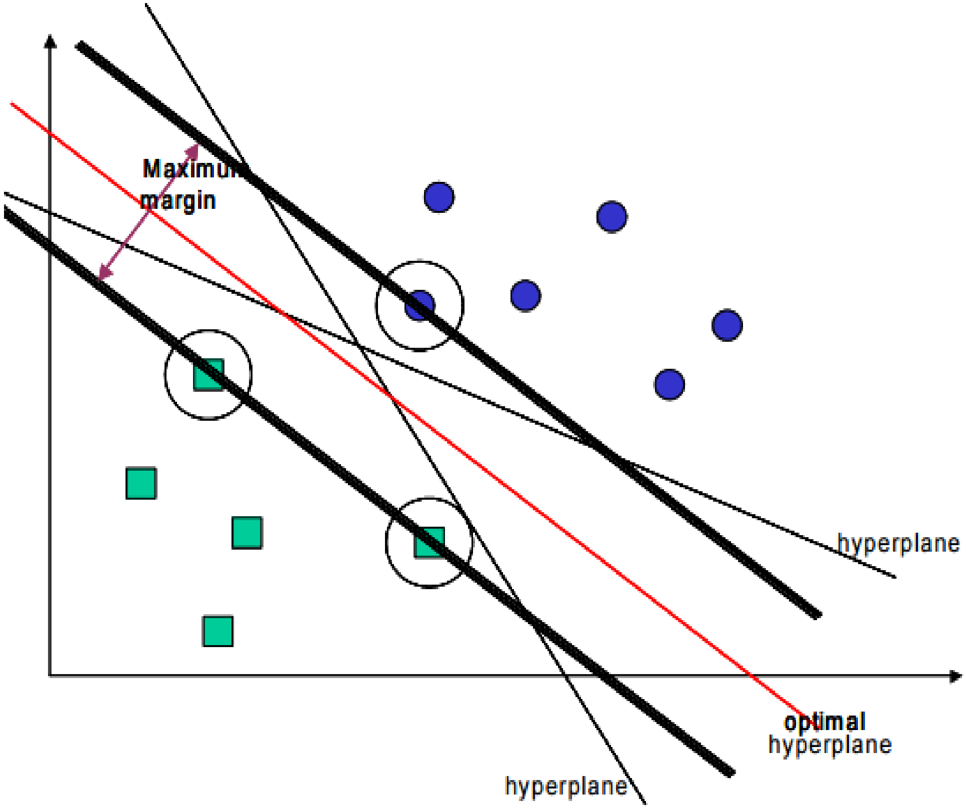
1	*Upper Lip Raise*	6	*Jaw Lower*
2	*Left Lip Stretch*	7	*Right Brow Lower*
3	*Right Lip Stretch*	8	*Left Eyelid Closed*
4	*Left Brow Lower*	9	*Right Eyelid Closed*
5	*Left Lip Corner Depressor*	10	*Right Lip Corner Depressor*

Model Building:
Support Vector Machines (SVM)

Performance of an individual *i* on a given task *t* is assumed to be a binary variable, where:

- Y_{it}= 1, if individual *i* correctly performed a task *t*
- Y_{it}=0, otherwise.

For ,
i ϵ set of individuals {**I**}
t ϵ set of tasks {**T**}



[Kotsiantis 2007]

Model Evaluation:
Leave-one-out Cross Validation

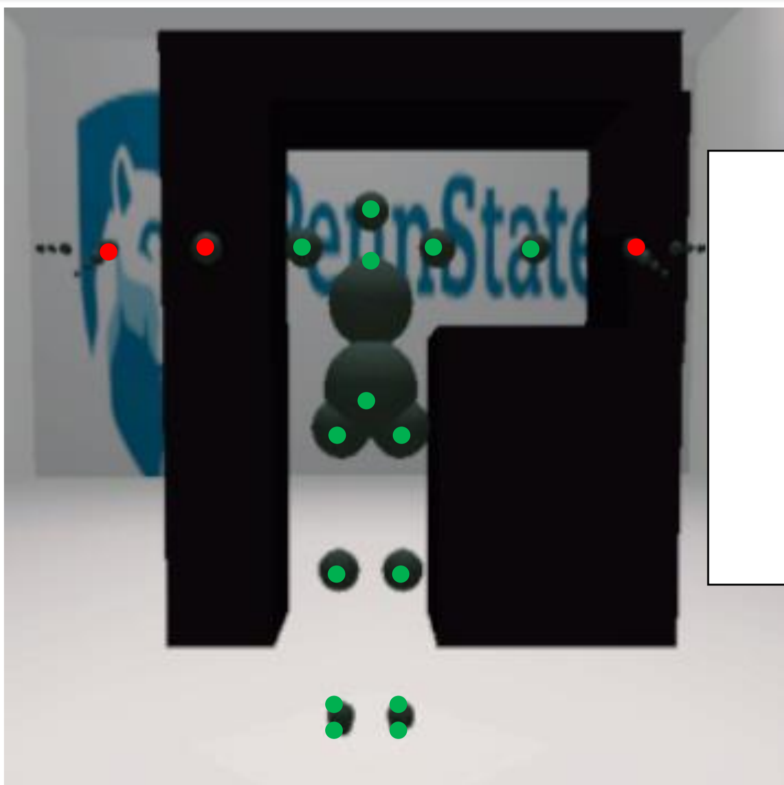
Facial Key point 1	Facial Key point 2	…	Facial Key point 10	Individual *(i)*	Task *(t)*	Y_{it}
0.355	0.574	…	0.355	1	1	0
0.674	0.234	…	0.632	1	2	1
0.365	0.642	…	0.192	1	3	0
…	…	…	…	…	…	…
0.244	0.193	…	0.885	*i*	*t*	*1*

Testing Set

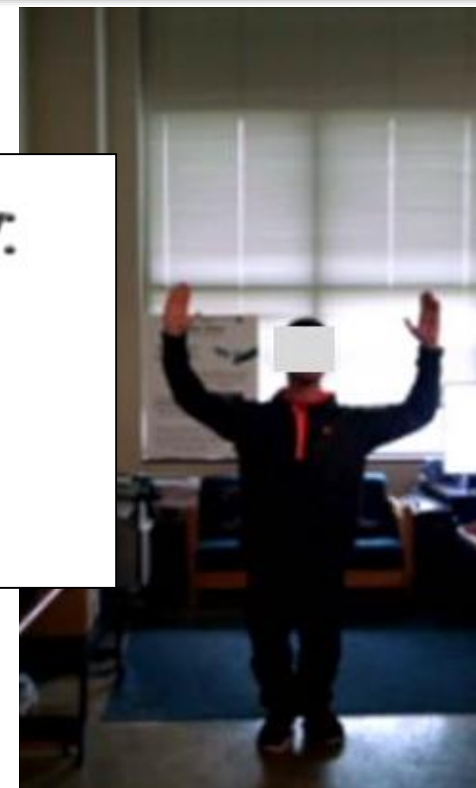
Training Set

Case Study in a Physically-Interactive Application

-31 Participants (μ=19.9 σ=1.2, 18-22 years old)
-12 task
*-372 Data tuples (i.e., 31*12)*



Developed by:
D.A.T.A Lab
at
Penn State

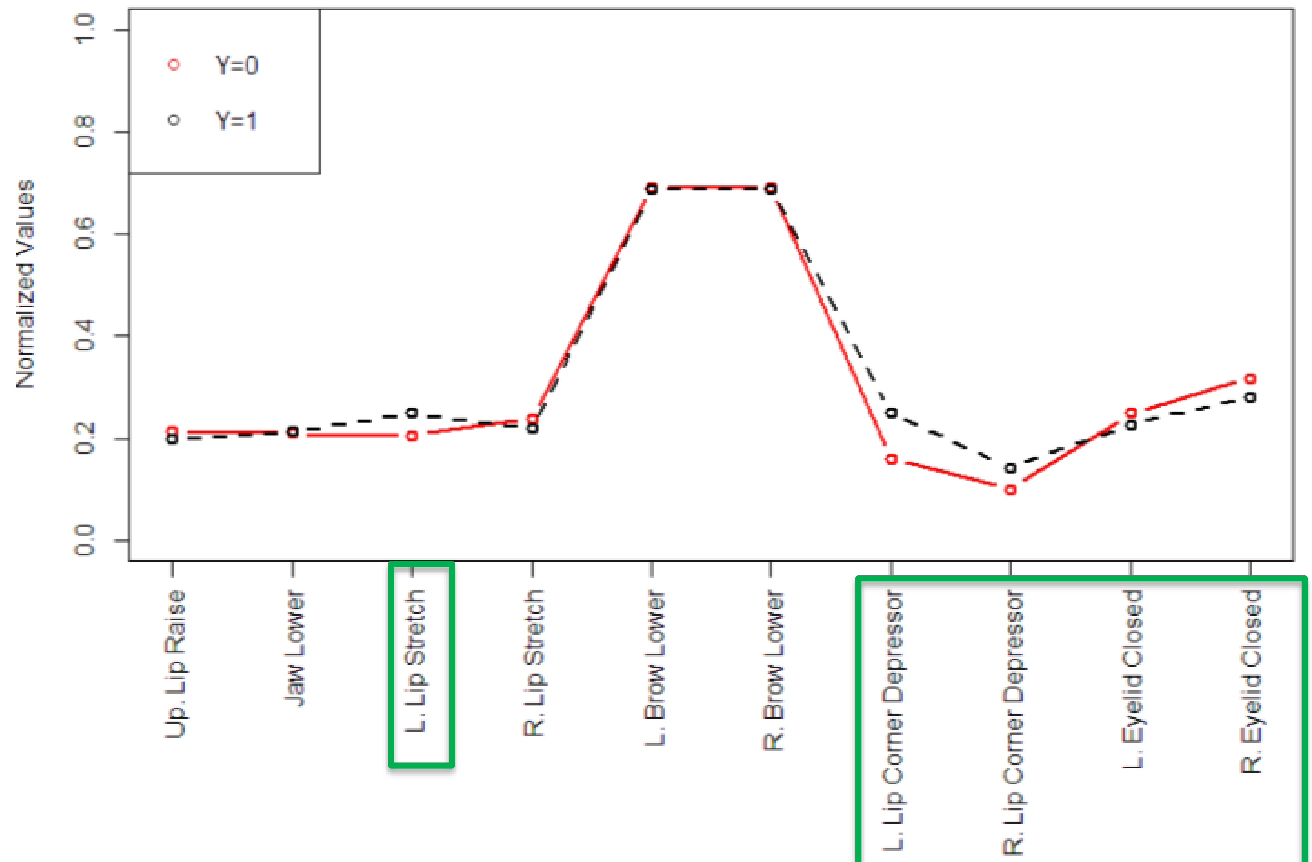


Results and Discussion:
Participants' Facial Keypoints data is significantly different depending on their performance

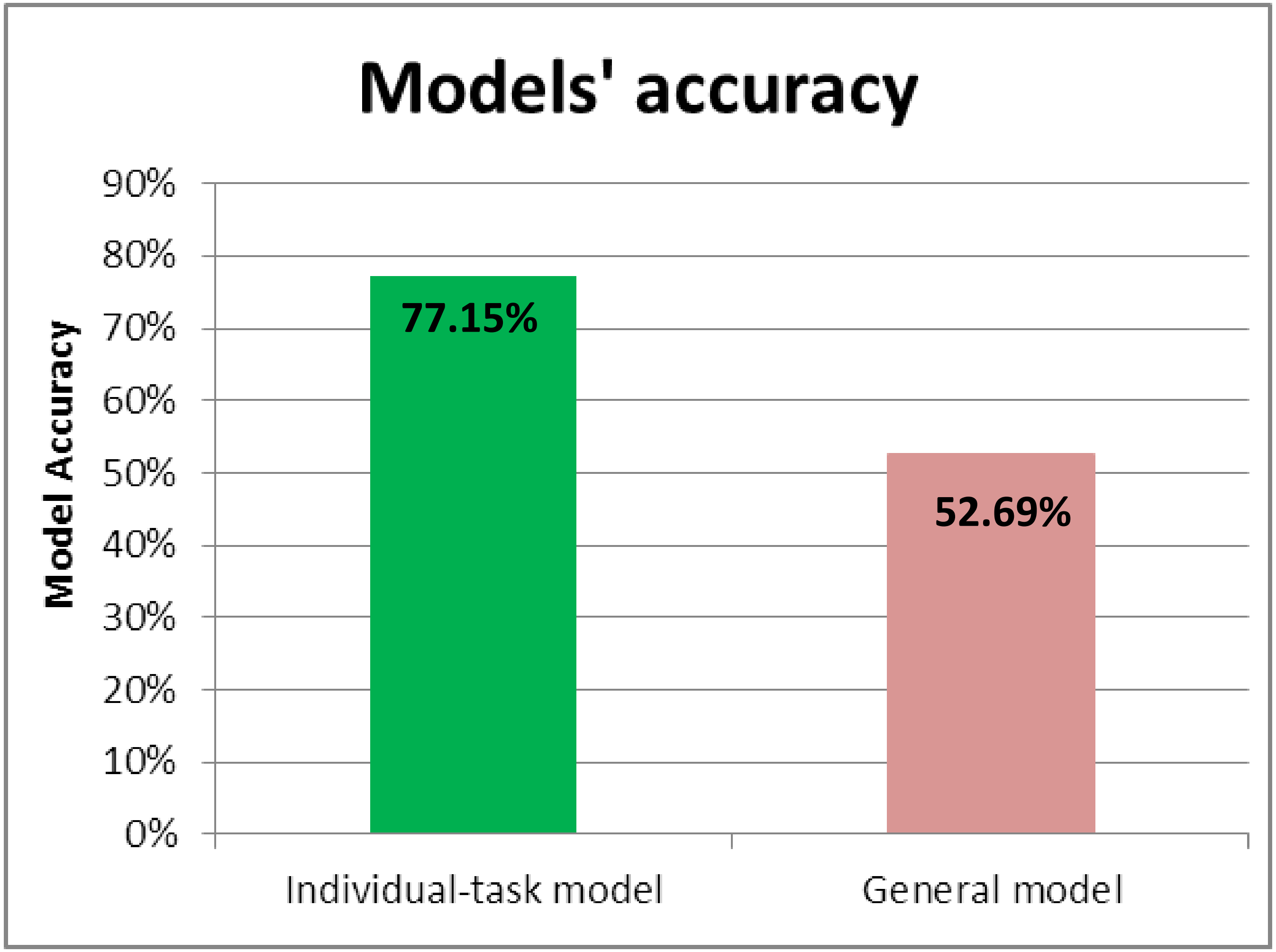
The MANOVA results:

Wilks' Lambda= 0. 9427

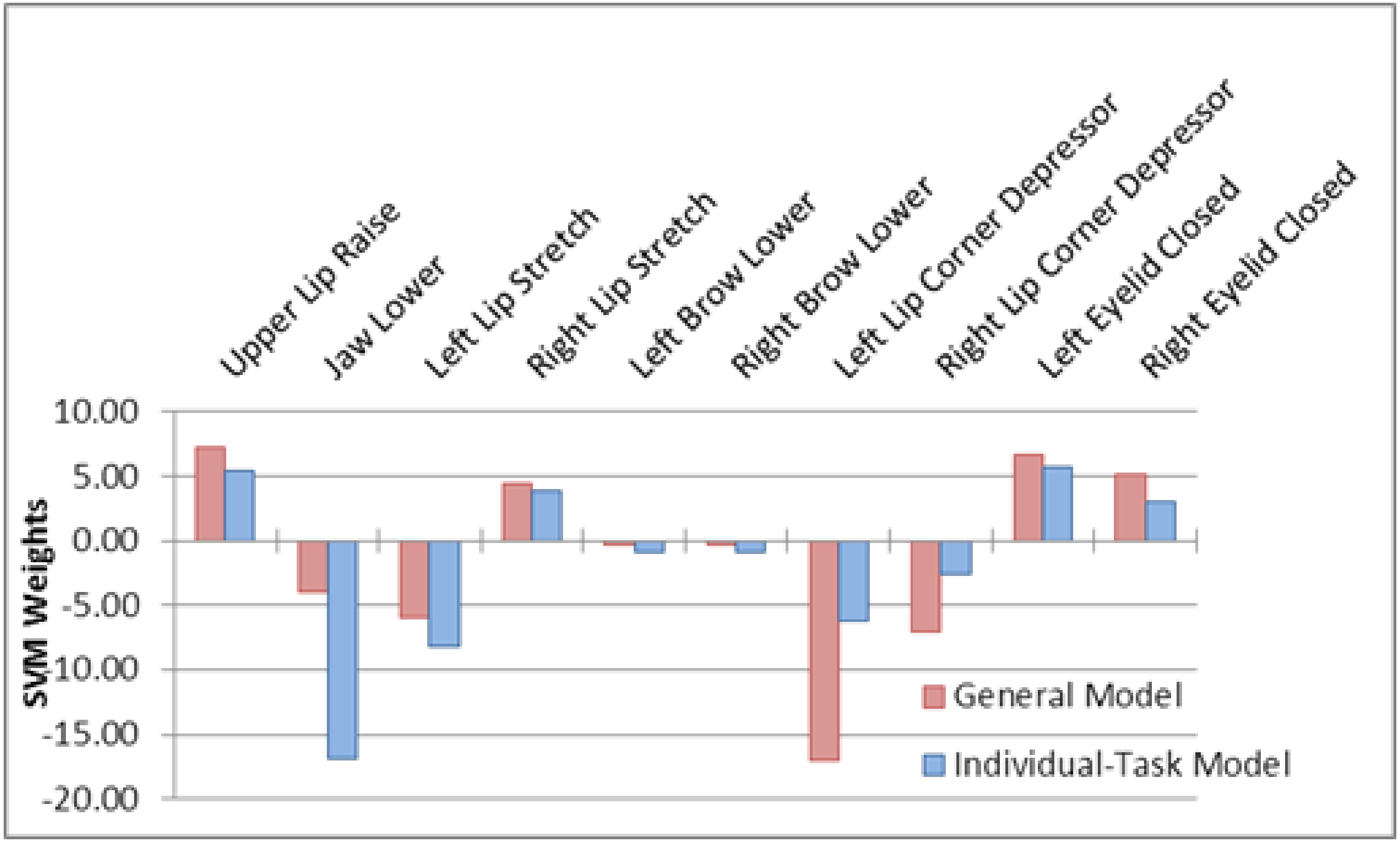
p-value=0.017



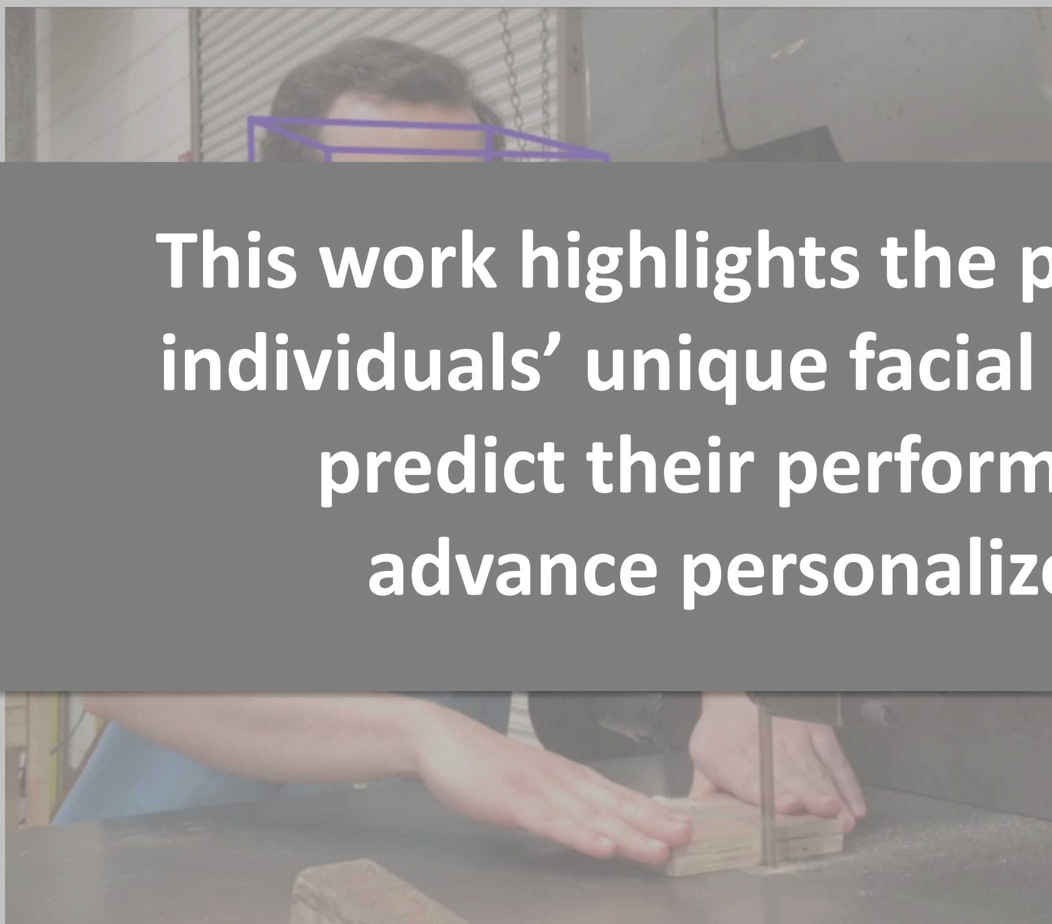
Results and Discussion:
Individual-tasks **model outperform the** ***General*** **model**

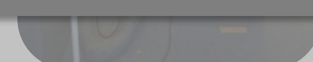


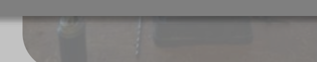
Results and Discussion:
Some Facial Keypoints plays a more central role



Limitation and Future Works:
Time evolution of Facial Keypoints and different tasks.







This work highlights the potential of using individuals’ unique facial keypoint data to predict their performance and to advance personalized systems

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Thank you!

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