University of Michigan – Ann Arbor

Integrated Tech Team (ITT)	Aligned Technology Team (ATT)	Capability Technology Team (CTT)	Technology Domain	Duration
Enterprise Production System Renee Blasiar	Product Standards & Advanced Products Jane Matera	Production System Analysis & Simulation Ben Nimmergut	Materials & Manufacturing Phil Crothers	01/02/24 – 01/31//25

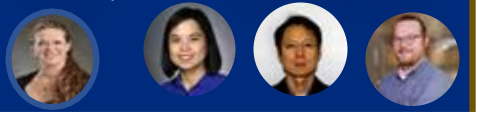
Boeing & UM Innovation Support

Harley Brigman · Megan Elmore · Al Salour · Greg Johnson

Boeing PI Terra Stroup

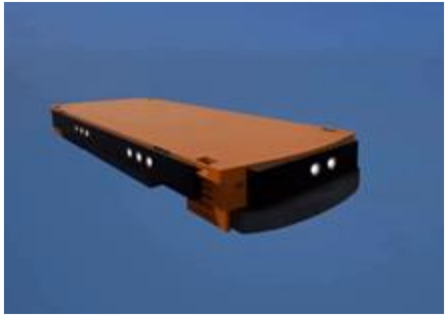
University PIs Jessie Yang · Yili Liu

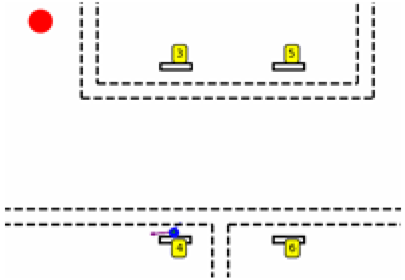
Paul Pridham

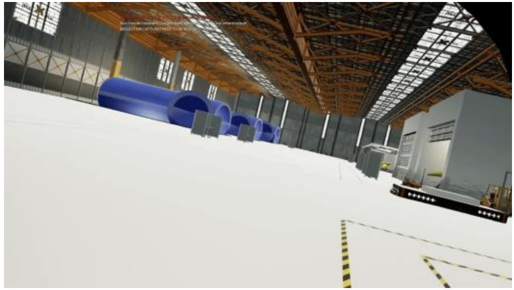


Doowon Han · Shreyas Bhat · Shaoze Yang · Justin Smith

Trustworthy Human-AGV Interaction







Lab photos; external HMI design, and relevant images

Objective Further develop computational models that can be used to predict a worker's behavior in a shared workspace with AGVs in real time and design an external human-machine interface (HMI) to convey the behavior of the AGV. We aim to evaluate these two proposed functions in terms of performance and safety.

Approach The University plans to develop a model that can predict the behavior of the worker and design a method to convey AGV intent to promote safer and efficient manufacturing settings at Boeing. The enhanced autonomous delivery vehicles shall be simulated to deliver equipment and goods along with human participants. The participants shall interact with the AGV in a virtual reality (VR) environment with the headset and omni-directional treadmill..

Benefit This effort will provide Boeing an approach to enhance the current equipment with productive and safer environment considering the human factors constructs in intelligent and adaptive autonomy. The contributing factors include sensing the environment, operator workload assessment, and human factors in planning an optimal action. This research will generate new algorithms and designs to optimize trust, safety, and performance. This technology will contribute to a safer and reliable interaction while in the use of autonomous mobile robots and guided vehicles in the current and future Boeing production systems.

Project goal upon maturity

Enabling trustworthy human-AGV interaction by developing computational models that predict the human worker's state and trajectory and developing AGV adaptive behaviors through external HMI design. This project shall focus on dyadic human-agent teams and extend the methods and algorithms developed into multi-operator-multi-autonomy environments.

SCN owner identified for the project

SCN: BCA – Production Systems

Supporting organization at Boeing & technology need

The approach involves modeling development to predict trust with algorithms that enable an autonomous agent to make optimal decisions by explicitly considering trust in real time. The results will protect against collisions through messaging services that could control the robot motions.

Path toward tech transition including timeline for implementation.

Lab tests at selected Boeing locations will begin during the development for technology validation targeted for late 2026. We will leverage the AGV Technology Capability teams within BCA and BDS sites to identify a location for insertion. The initial Technology transition will be targeted for the Composite Wing Center (CWC) in Everett. Additionally, there will be collaborations with the Safe Path in Factory project with CSIRO on the AGV safety system using Industrial cameras and computer vision technology.

What business unit or product/process can use this technology?

BCA Composite Wing Center and BDS St. Louis sites will be initially targeted. Additionally, there will be collaborations with the Safe Path in Factory project with CSIRO on the AGV safety system using Industrial cameras and computer vision technology. Any site that leverages autonomous vehicles and robots can utilize technology.

Student involvement and potential engagement.

PhD students: Shreyas Bhat & Doo Won Han are the two lead PhD researchers. Shreyas' expertise is human-robot interactions and trust modeling. Doo Won's expertise is human-autonomous vehicle interaction.
Master students: Shaoze Yang and Justin Smith

Ultimate Benefits: Boeing, Industry, Academia, Etc.

Boeing utilizes autonomous guided vehicles and mobile robots in our manufacturing environment. However, we are not to the point to operate such vehicles without human interventions. The current standard is to have a minimum of one operator monitoring a vehicle at all times. UM will develop computational approach to measure human factors constructs in intelligent and adaptive autonomy. The contributing factors include sensing the environment, operator workload assessment, and human factors in planning an optimal action.

Agenda

- Recap
- Predictive Modeling
- Design of External HMI (eHMI) for Adaptive AGV
- Experimental Design in VR & Results
- Future work
  - Synthetic Multi Agents
  - Enhanced eHMI design

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Recap: Motivation

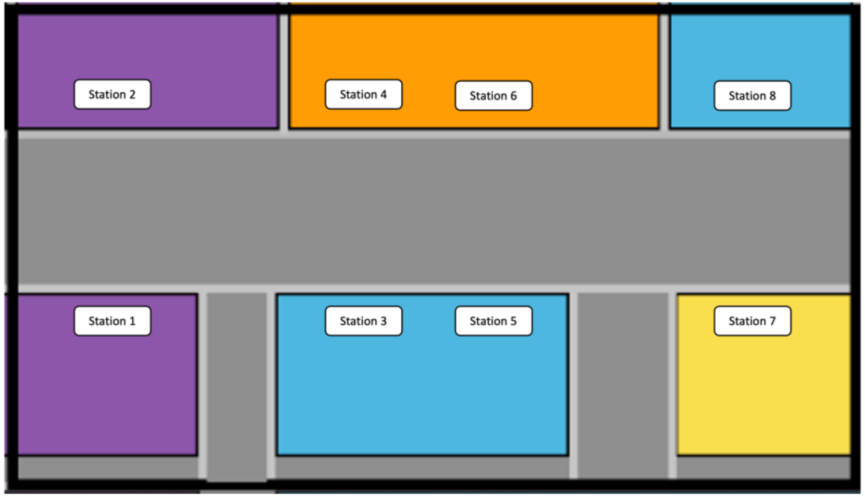
- Industry 4.0 introduced Automated Guided Vehicles (AGVs) that move stuff around in manufacturing plants

- However, most AGVs work in isolation with limited sharing of workspace with humans

- To safely share the same workspace, AGVs need to be able to predict workers' motion and convey its status effectively

Ref: FORI AUTOMATION AGV

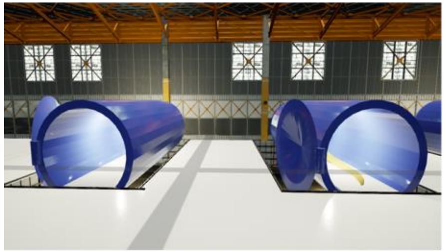
Recap: VR testbed design



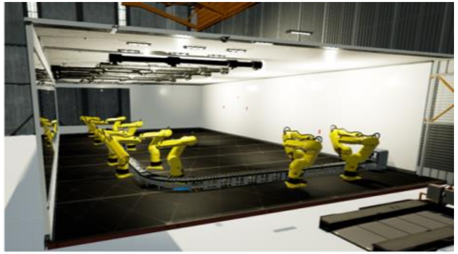
Birds-eye view of the manufacturing plant

Actual AGV Photo

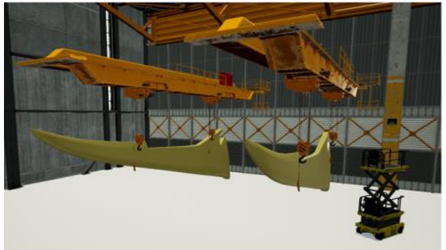
Our Custom-built AGV



Autoclaves



Robot Arms



Wing Parts

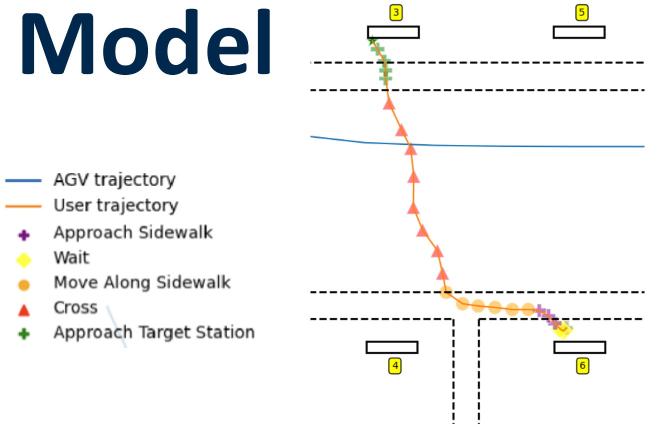
Office Space

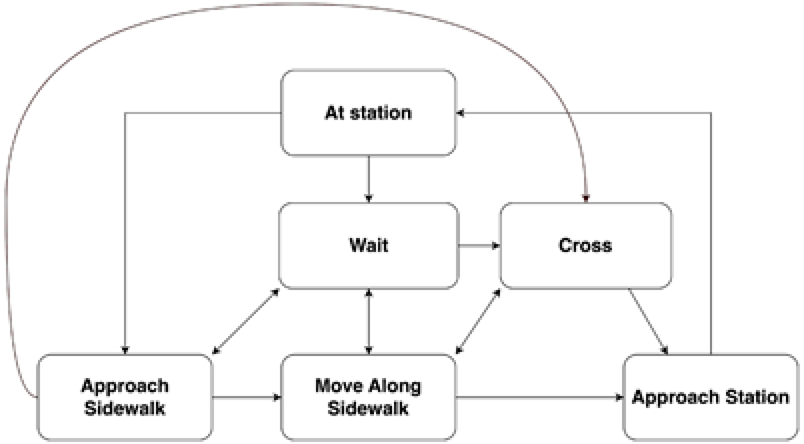
Recap: The Finite Automaton Model

- We used a Finite Automaton Model (FAM) with 6 intuitive states to predict worker walking behavior [1]

- **Limitation:** Only predicts the current state of the worker

- The AGV needs the future state of the worker to reason about their behavior





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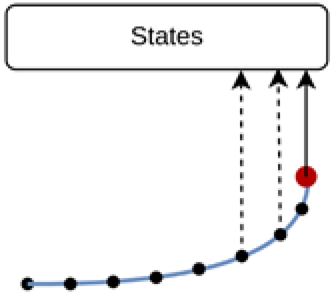
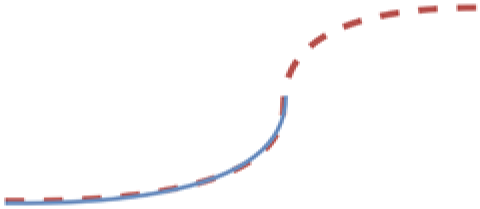
Predictive Modeling

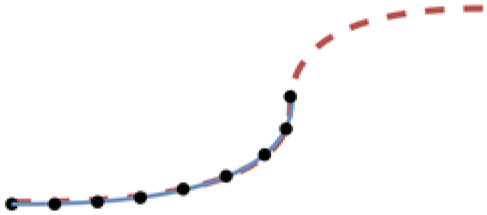
- We added predictive modeling to our basic model
- This allows us to predict the location of the worker in the next 3-4 seconds
- This prediction, along with the FAM, can help the AGV modify its behavior while interacting with the workers



Finite Automaton Model



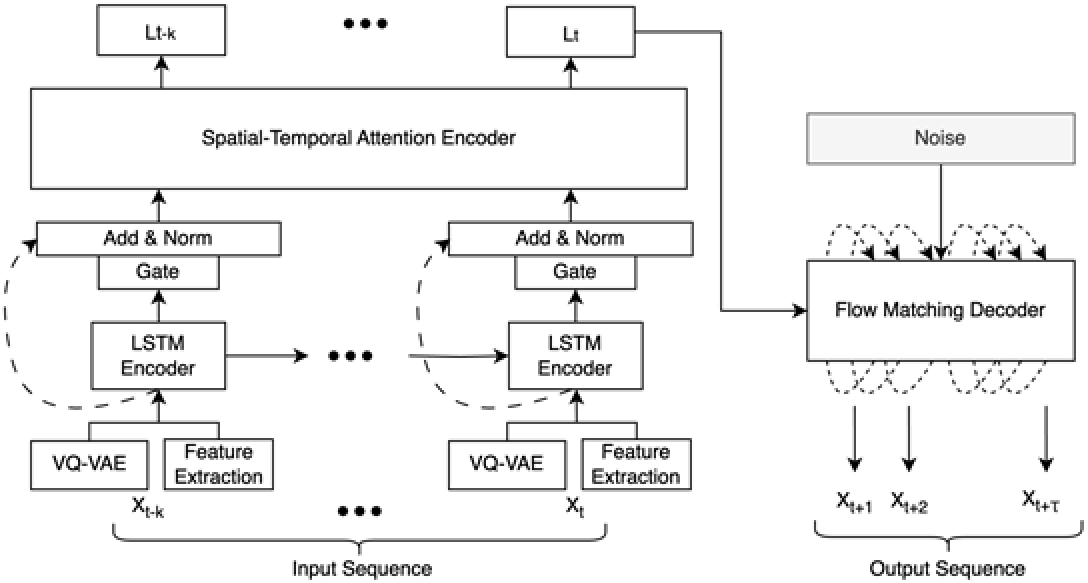
Trajectory Prediction Model



Prediction + FAM

Predictive Modeling

- We took inspiration from recent developments in pedestrian trajectory prediction models [2] to develop a deep learning based model
- **Model Architecture**
    a. **Encoder:** Gated Recurrent Unit [3] + Spatial Temporal Transformer [4]
    b. **Decoder:** Diffusion-based Flow matching [5]
- **Setup**
    a. **Data Frequency:** 10 Hz
    b. **Prediction Window:** [-30, 40]

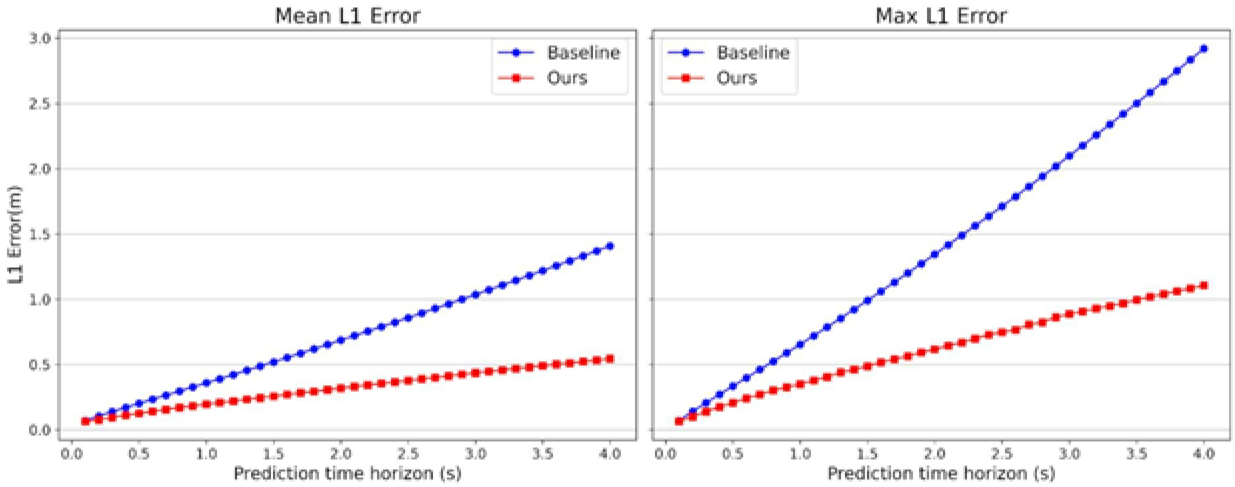


Looking at the previous 30 frames, predict the next 40 frames of data

2. Rudenko et al. (2020) 3. Cho et al. (2014) 4. Cong et al. (2021) 5. Lipman et al. (2023)

Predictive Model Results

- Comparison between our models and baseline model (constant velocity).
- Mean/Max L1 error reduced by **65%**
- Trained and tested using data from last year's VR study



$$L_{1\ \text{mean}} = \frac{1}{T}\sum_{t=1}^{T} L_1^t$$

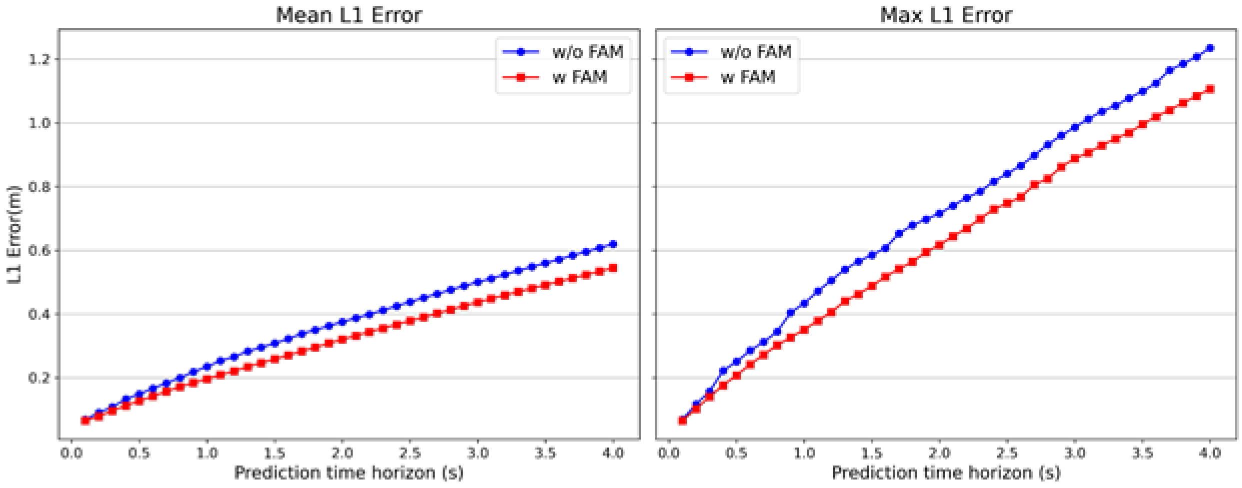
$$L_{1\ \text{max}} = \max_{t\in\{1,2,\ldots,T\}} L_1^t$$

$$L_1^t = \left| Pos_{\text{gt}}^t - Pos_{\text{pred}}^t \right|$$

A measure of the absolute difference between the predicted position and the actual position of the worker

Predictive Model Results

- Comparison between our models with/without the FAM.
- Mean/Max L1 error reduced by **15%**



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$$L_1^t = \left| Pos_{\mathrm{gt}}^t - Pos_{\mathrm{pred}}^t \right|$$

A measure of the absolute difference between the predicted position and the actual position of the worker

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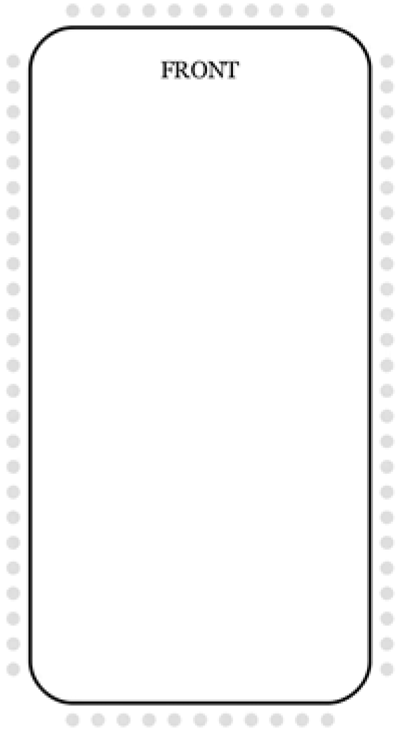
Recap: LED light strips with projections

- We planned on using LED light strips around the AGV to display information to the workers
- The strips are positioned such that the workers can also see the lights reflected from the ground
  - This mitigates any issues if a part of the LED strip gets obstructed



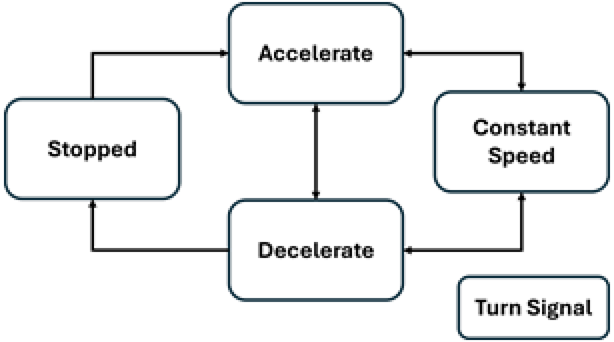
Purpose & Research Questions

- We aim to design an eHMI design using LED light strips around the AGV to display information to the workers

- Research question
  - Which of the 24 design patterns can effectively convey the 5 predetermined AGV's intentions or states?

Design Generation and Selection

- Generated light strip pattern designs to convey AGV behaviors
  - Considered different parameters such as number, pattern, intensity, frequency, direction
  - Came up with **8 different design groups** and generated **24 light strip patterns** in total



AGV Behavior Model

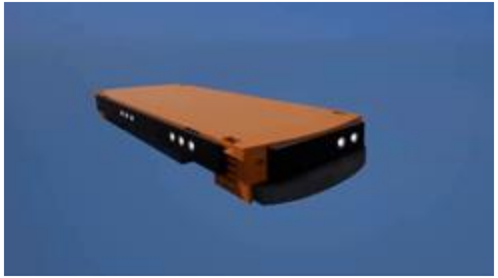


Illustration of Traveling Light eHMI

Design Group	Used Parameters
Static	Number & Pattern
Breathing	Number & Pattern Intensity Frequency
Blinking	Number & Pattern Intensity Frequency
Alternate Blinking	Number & Pattern Intensity Frequency
Traveling Light	Number & Pattern Frequency Direction
No Light	Intensity
Directionally Moving Light	Number & Pattern Frequency Direction
Independent Progress Bars	Number & Pattern Frequency Direction

Online Survey Design

- 97 participants
- 4 blocks of questions
  - Each block contains all 24 designs asking:
    - What does the design pattern mean
    - How confident the participants were with their response
  - Block 1-3 asked to respond based on their quick intuitive judgement
  - Block 4 asked to respond based on their careful and best response
- In all blocks, the presentation order of the designs were randomized for all participants

Design Generation and Selection

- Final selection of eHMI designs
  - We sorted the top 3~5 most frequently selected designs from each behavior
  - Selected one design to represent each AGV behavior through internal evaluation

Constant Speed

Accelerate

Decelerate

Stopped

Turn Signal (R&L)

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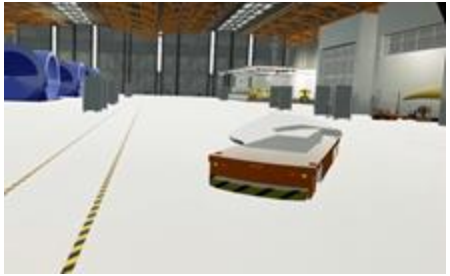
Purpose & Research Questions

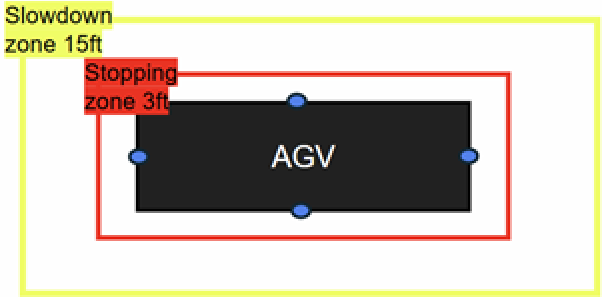
- We aim evaluate the effect of the prediction model and eHMI design in a simulated environment

- Research question
  - Will the prediction and the eHMI design have effect compared to the current AGV used in practice?
  - If so, among these aspects: trust, safety, performance, and understandability, which aspect will the prediction and the eHMI design affect the most in enhancing the AGV?

VR Study Design

- Three conditions for the AGV





Control

- Decelerates to a slower speed when participant is in the slowdown zone
- Maintains a normal operating speed otherwise (accelerating when necessary)

Prediction

- Computes the (predicted) position of the AGV and participant at t=0, 1s, 2s, 3s, 4s.
- If the positions result in the participant being in the slowdown zone AND the participant is not in the "safe" states at t=0, the AGV decelerates to a slower speed
- Maintains normal operating speed otherwise (accelerating when necessary)

Prediction+eHMI

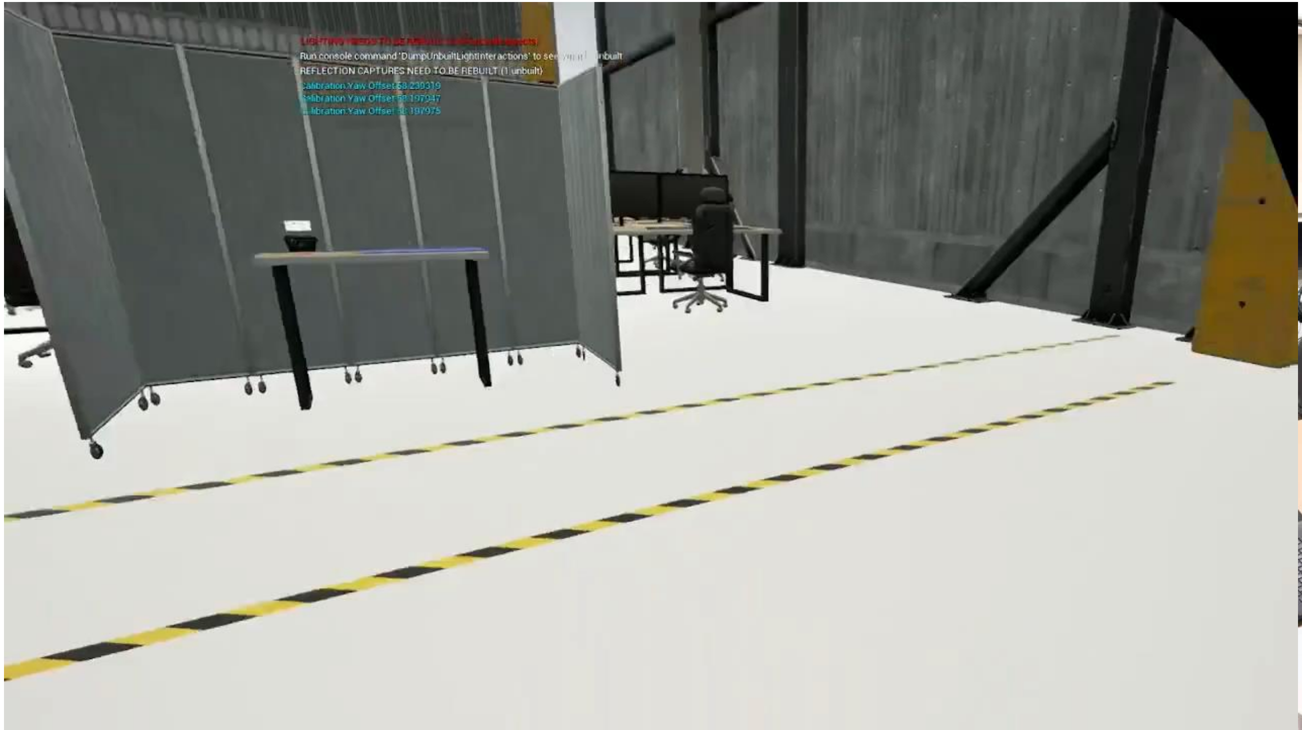
- Same as the prediction condition, but also conveys the intent of the AGV using the eHMI

Safe states:

- At station
- Approaching station

Note: In all conditions, the AGV comes to a complete stop if the participant enters the stopping zone

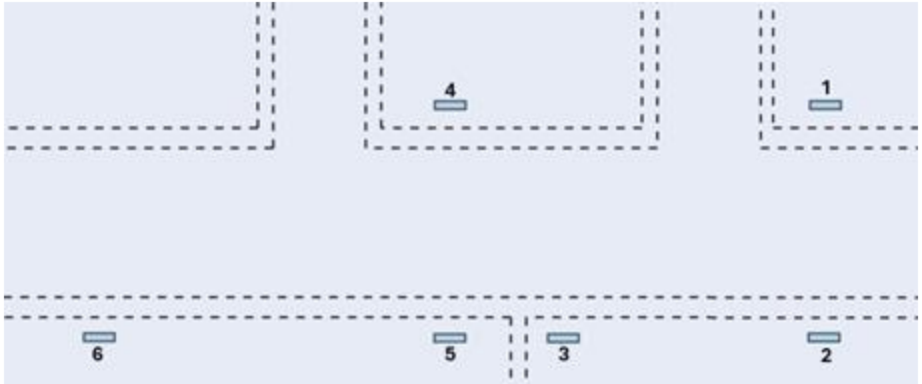
Video Slide for Inside and Outside VR

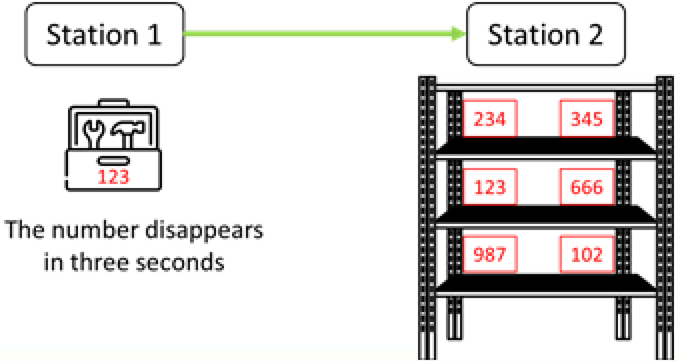


Trajectory & Scenario design:

- We designed trajectories for the AGVs and the participants considering the following metrics
    - Crossing/non-crossing interaction
    - Direction of AGV encounter
    - AGV in closer/further lane

- In total, each participant completed 10 trials of placing toolboxes in a target location for each AGV condition





Data Collection

- 30 participants (22 Male, 8 Female, Age = 25 ± 4.95)

- Each participant completes 10 (AGV trajectories) x 3 (conditions) = 30 trials

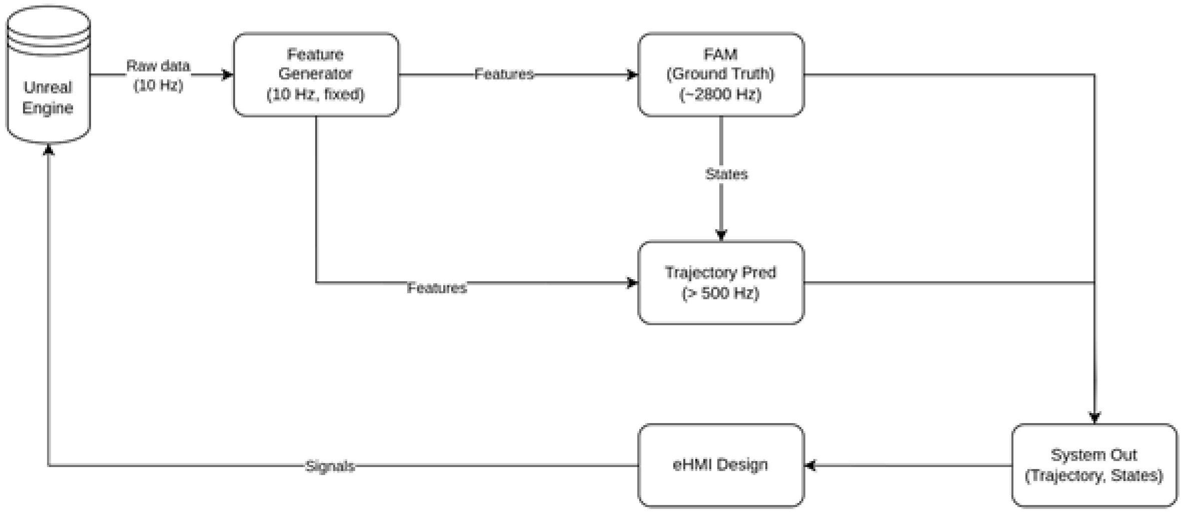
- The testbed records the following at 10 Hz
  - Participant's location, pose, and eye gaze direction
  - AGV's location and pose

- We also collected survey data assessing the participant's trust, perceived safety & performance, and understandability on the AGVs after each trial

Integrate Predictive Model to Sim

Workflow Overview:

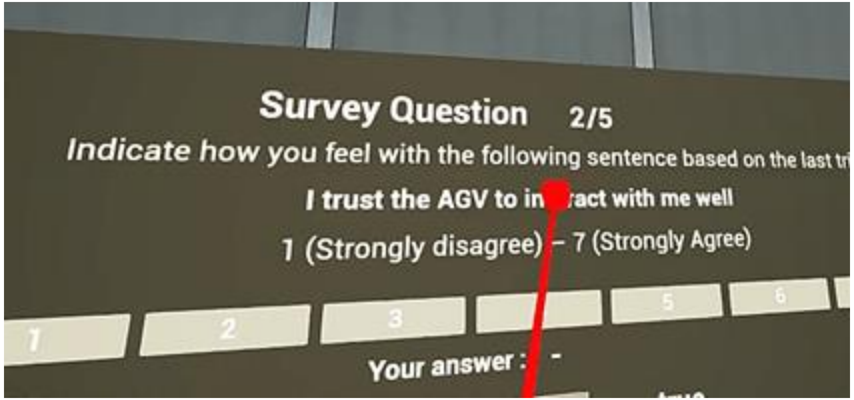
- Build & Train Model
- Export model to ONNX (deployable format)
- Build Infra, translate code to C++ for use in Unreal Engine (FAM, data proc.)
- Run real-time pipeline in Unreal Engine



Framework

Results

- **Prediction Model**
- **Main Trial**
  - **Notice of the AGV - (Yes/No)**
  - Task Performance
  - **Trust**
  - **Perceived Safety**
  - **Perceived Performance**
  - **Understandability**
- **Post-Condition**
  - **Trust**
  - **Perceived Safety**
  - **Perceived Performance**
  - **Understandability**



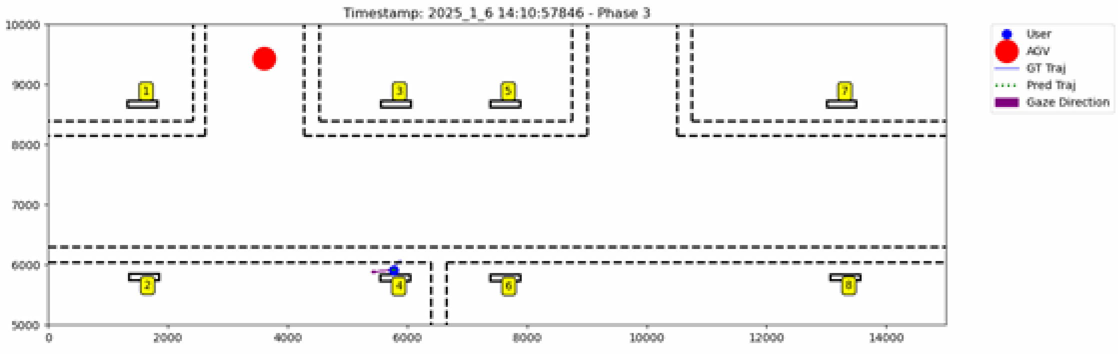
All questionnaires were given in 7-point Likert scale

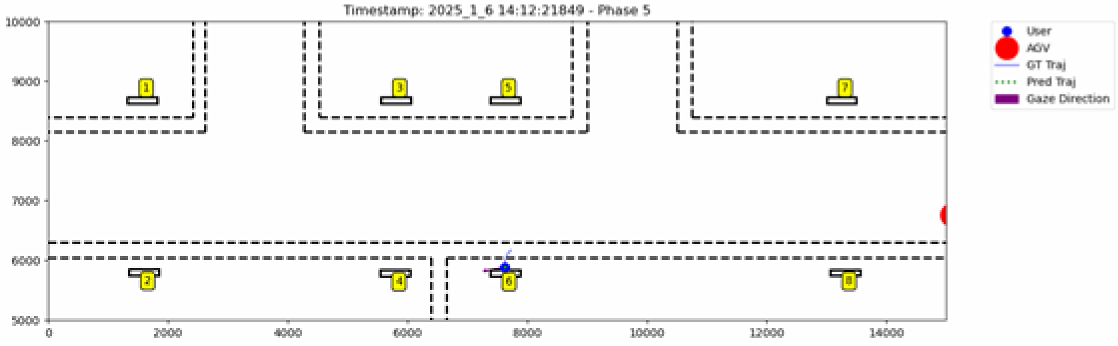
Visualization

Key Strengths of Our Prediction Model:

- Effectively handles edge cases, such as diagonal crossings (compared to an L-shaped crossing where the worker uses the sidewalk)

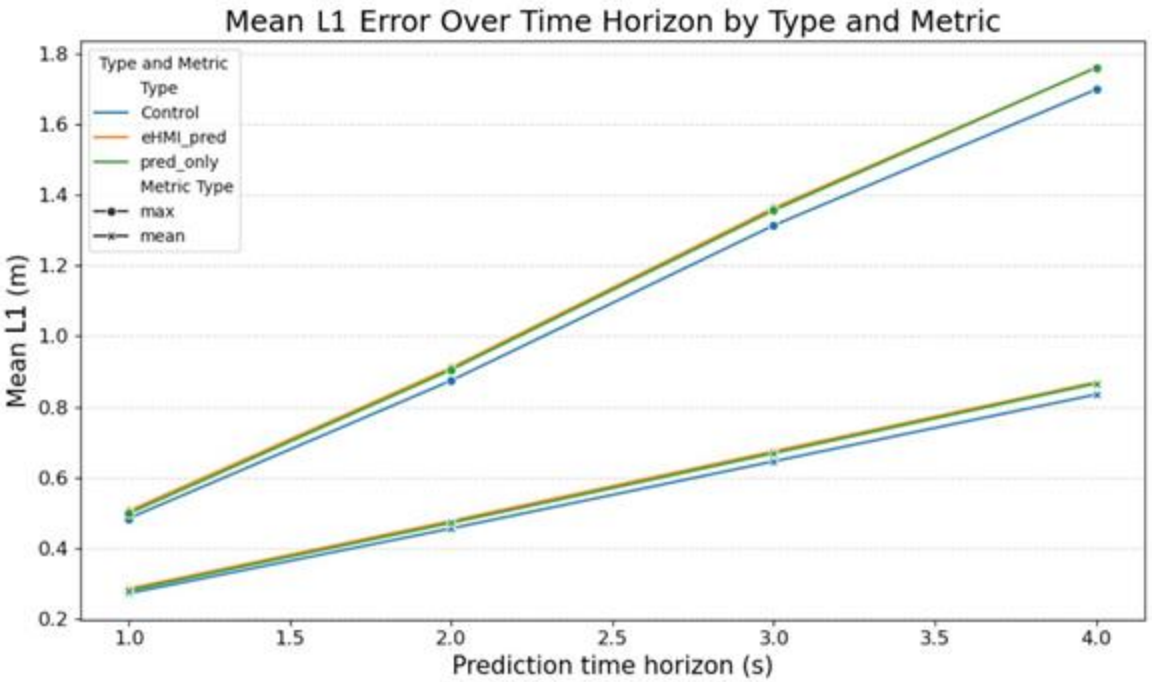
- Accurately predicts across various interaction scenarios, adapting to dynamic scenarios.





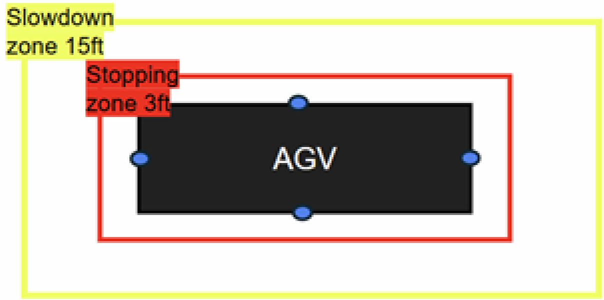
Predictive Model Results

- We trained our model with data from our previous experiment
- And evaluated on the data collected from the current experiment
- We see that our model is robust across all 3 experimental conditions!



Task Performance

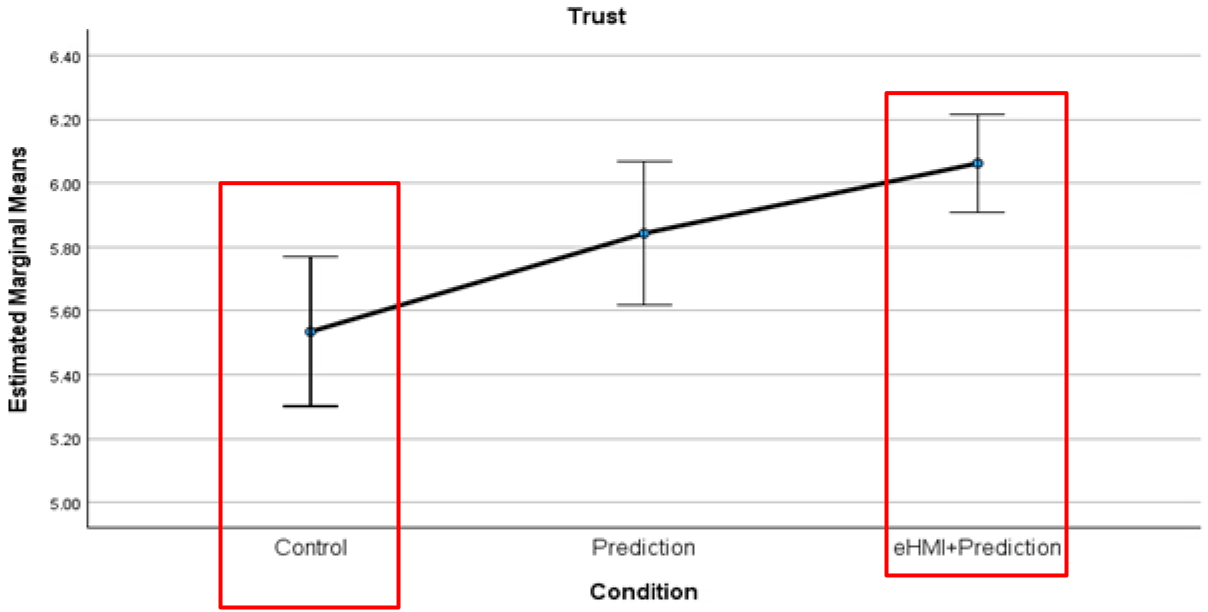
- Total of 12 crashes (entering Stopping/Red zone)
- Total of 139 slow downs (entering Slowdown/Yellow zone)
- Both most frequently happened in the control condition and less frequently in the eHMI+Prediction condition



	Enter Red Zone	Enter Yellow Zone
Control	3.07%	26.53%
Prediction	1.52%	15.59%
eHMI+ Prediction	0.82%	11.84%

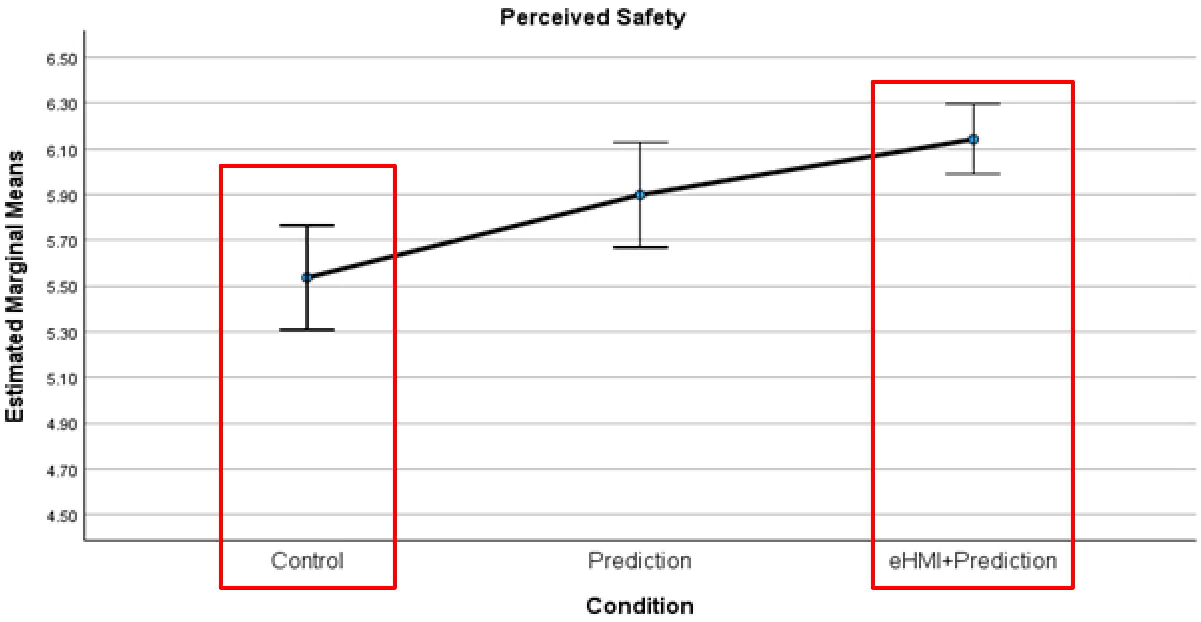
Trust

- I trust the AGV to interact with me well



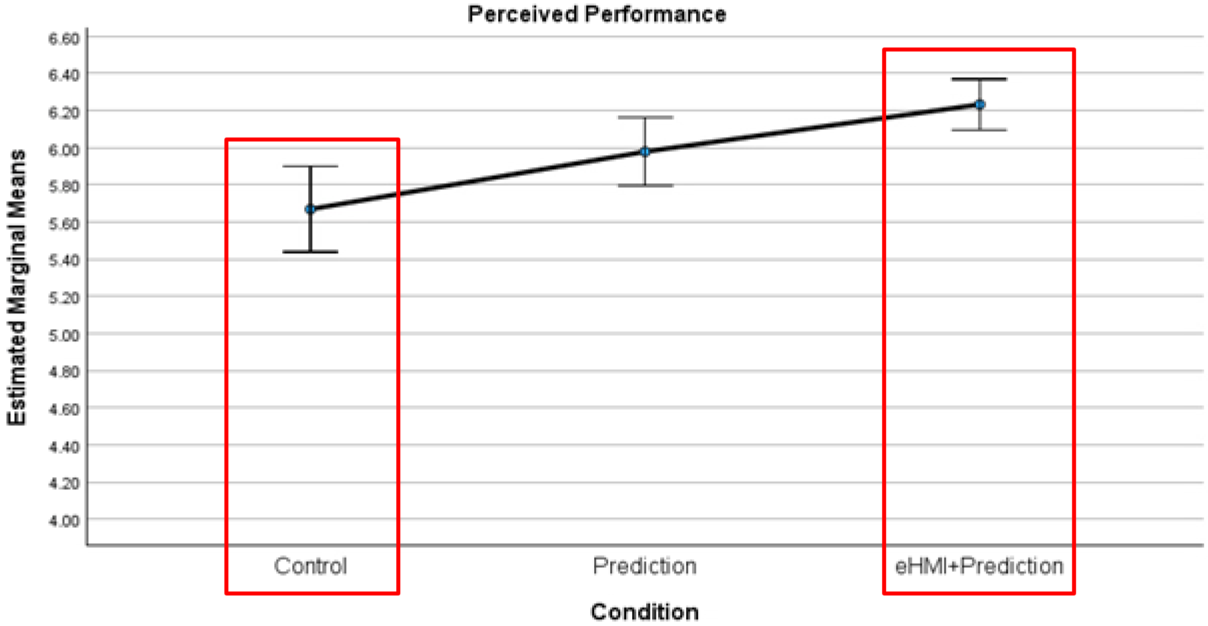
Perceived Safety

- I feel safe sharing the same space with the AGV



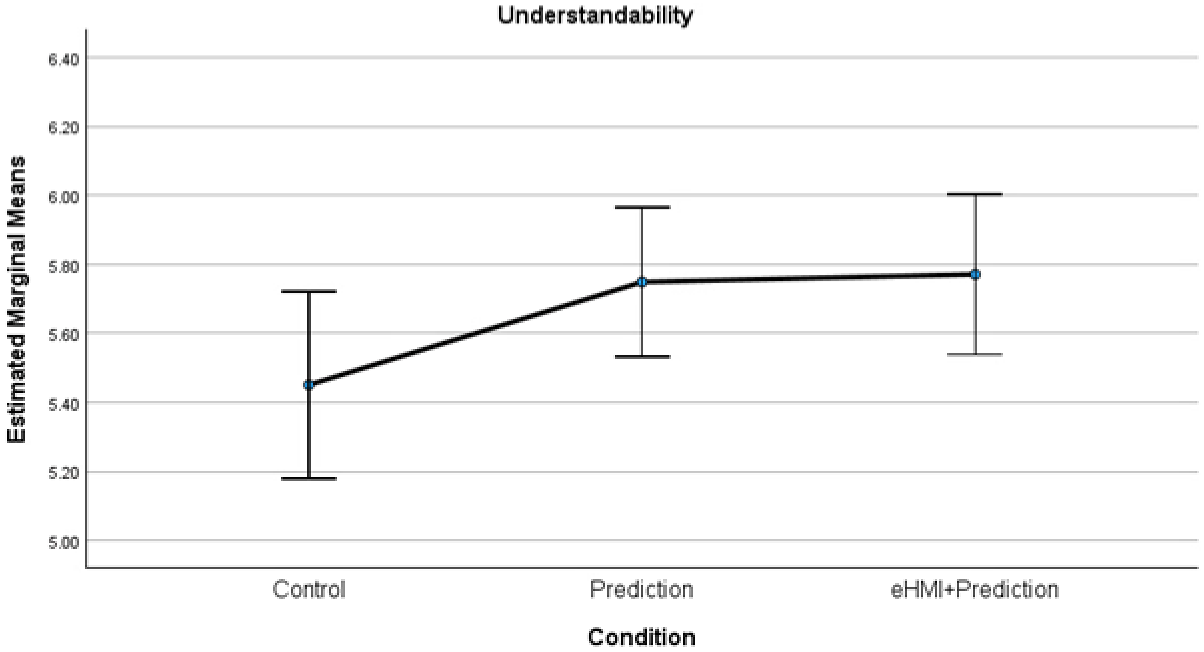
Perceived Performance

- The AGV behaved as I expected during the interaction with me



Understandability

- I understood what the AGV was trying to do during the interaction with me



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Next Steps: Multi-Agents Sim & Modeling

- Currently, our model predicts the trajectory of a single agent. While it has the potential to scale to multiple agents, it lacks explicit modeling of agent interactions.

- To address this limitation, we are developing agent simulators, validated using previously collected dataset, and plan to test our predictive model in a multi-agent simulation setting.

Next Steps: New Design Parameter for eHMI

- Currently, our eHMI design was generated from ideation without color
- Only one type of light strip, a type that goes around the AGV was considered
- To further develop effective eHMI design that integrates color and considers different types of light strips, we plan to further investigate the current AGV used in practice and design recommendations specifically related to color and lighting in the AGV & the manufacturing facility it is used within.


Summary

- We built and trained a predictive model leveraging the Finite Automaton Model and feature generator from our previous study.
  - Our model reaches high-precision and offers robust prediction across different experiment scenarios.

- We have verified that the eHMI design and the prediction promotes higher trust, perceived safety, and perceived performance compared to the current AGV used in practice.

- We would like to take a step further into developing a realistic virtual environment with the following:
  - Multiple agents in the simulation
  - New design parameter for eHMI with colors and considering current AGV’s stacked design

References

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