From Video Games to Real-life ”Games”: The Emergence of Real-life Expertise in (Serious) Video Games

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Something about me

- I am originally Italian (Milan)
- I have lived in the Netherlands for almost 8 years
- I have a background in philosophy, neuroscience, and AI
- I have recently obtained a PhD in cognitive science and artificial intelligence
- My project dealt with the complex decision making and behavioural transfer between real life and serious games (In collaboration with the Port of Rotterdam)
- I focused on non-invasive technology to track physiological variations

Chapter 1: Introduction

- Problem Statement:

  To what extent can in-game choices and blinks-related behavior be used to predict expertise in digital games?

- Main Goals:

- Investigate behavioural and physiological aspects that specific to experts
- Introduce new non-invasive scalable technology to track physiological variations
- Evaluate the use of serious games for real-life purposes in port environments

Chapter 2: Exploring the Relationship between Domain-General Skills and Planning Capabilities

Research Question: *Are domain-general skills such as numeracy and fluid intelligence significant predictors of the scores obtained in video games focusing on planning?*

Aims and Background

- Investigate the effect of domain-general skills (fluid intelligence, and numeracy) on planning capabilities
- Planning capabilities are relevant for the development of expertise in different fields
- Introduce a new game to measure planning capabilities

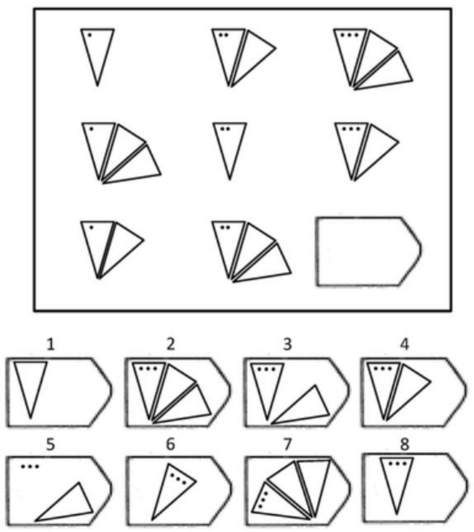
Sample and Experimental Procedure

- 78 participants recruited at Tilburg University
- Study was run completely online
- Introduce a new game to measure planning capabilities

Test Batteries

Example Raven Progressive Matrices

A



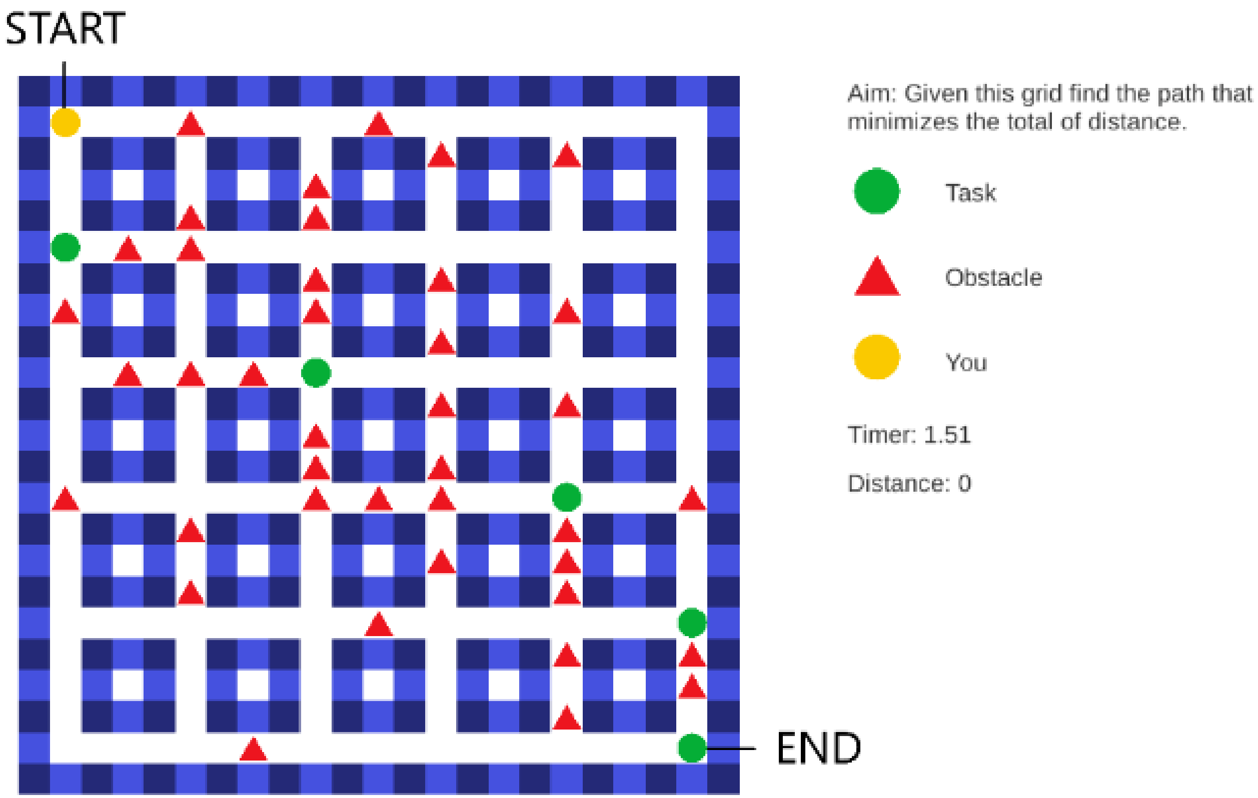
Example Berlin Numeracy Test

1. Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3, or 5)?

   _____________ out of 50 throws.

- Raven Progressive Matrices for fluid intelligence administered as a speed test (20 seconds per matrix)
- Berlin Numeracy Test (5 minutes to complete) and Subjective Numeracy Scale for numeracy
- Scores obtained in *The Planning Game*

The Planning Game



- *The Planning Game*: Inspired by maze-based cognitive paradigms
- Six mazes to solve
- Two domains: Distance Domain, Obstacles Domain
- Participants have either to minimize the distance or the number of obstacles walked on (red triangles) while collecting the tasks (the green dots) or the number of obstacles walked on (red triangles)
- The lower the distance and the number of triangles walked on the higher the score
- The final score is obtained summing the normalized score of the Distance Domain and Obstacles Domain

Results

- Male participants have higher score in the subjective Numeracy scale ($M = 35.8$, $SD = 5.27$) compared to females ($M = 33.02$, $SD = 5.27$; $t(36.01) = 2.37$, $p = .02$)
- Fluid Intelligence is a significant predictor of the score obtained in the game in a Multiple Linear Regression model explainining 23 % of the variance ($p = .01$)
- None of the participants found the optimal path in both the domains

	B	**SD**	β	**U**	**L**	t	p
Biological Sex (Ref. Female)	-0.04	0.08	-0.06	0.27	-0.46	-0.52	.603
Age	0.08	0.08	0.13	0.23	-0.07	1.13	.263
Years of Education	-0.04	0.07	-0.06	0.10	-0.18	-0.51	.615
Fluid Intelligence	-0.24	0.08	-0.38	-0.09	-0.40	-3.10	.003**
Objective Numeracy	-0.04	0.08	-0.06	0.12	-0.19	-0.49	.627
Subjective Numeracy	-0.06	0.08	-0.15	0.07	-0.26	-1.14	.256
Subjective Numeracy x Biological Sex	0.07	0.09	0.10	0.57	-0.26	0.75	.458

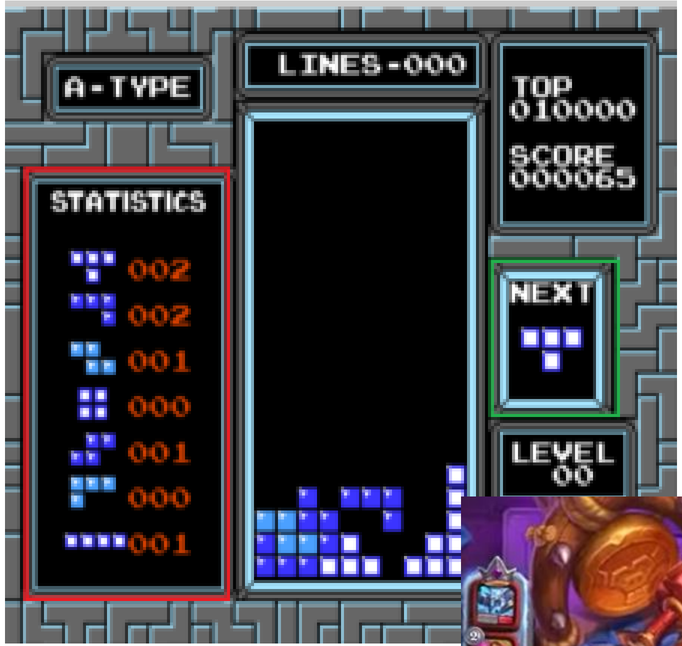
Discussions

- Fluid intelligence was the only significant predictor in our model
- The relevance of fluid intelligence may be explained with its connection with planning capanilities both in real life tasks and video games
- The results obtained suggest the potential effectiveness of cognitive paradigms-based games to measure domain-general skill
- The methods used for this study can be combined with other non-invasive methods to collect in-game behaviours and physiological variations

Chapter 3: Identify Expert Video Games Players Using Blinks

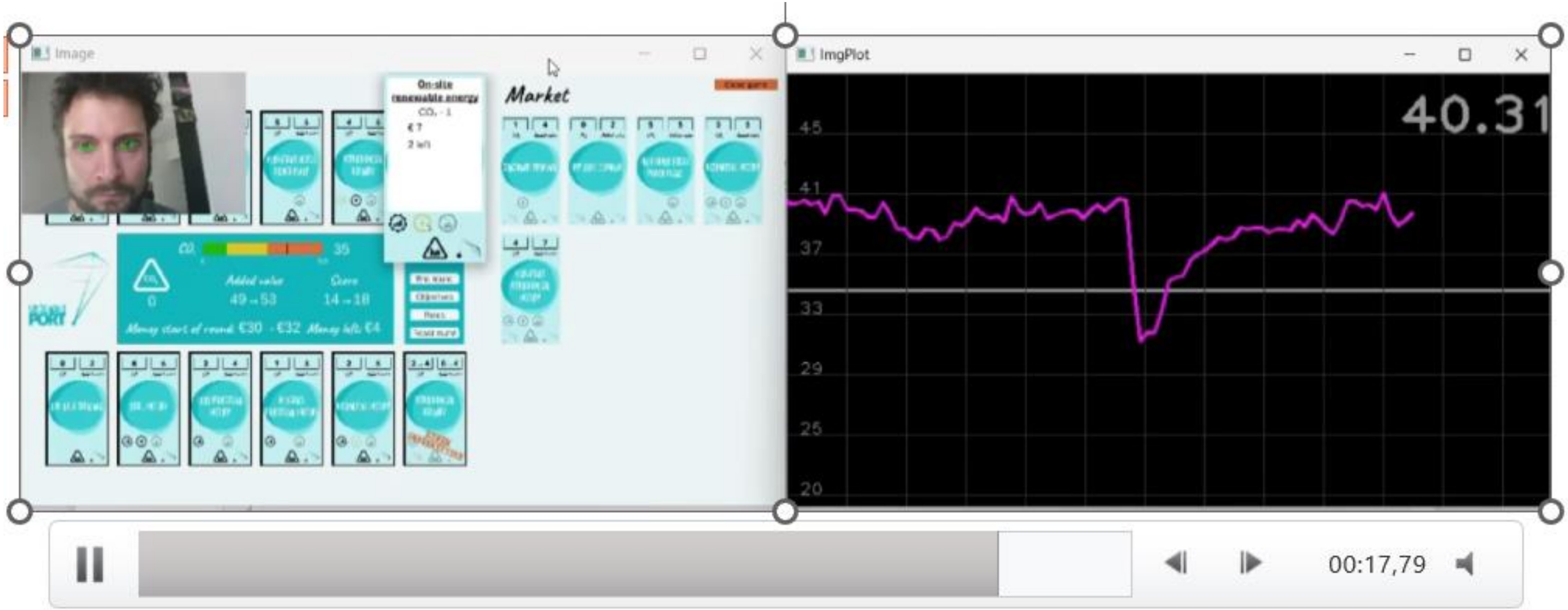
Research Question: *To what extent can blink frequency(blinks/m) be used to identify players having a different level of expertise during a video game session?*

Aims and Background



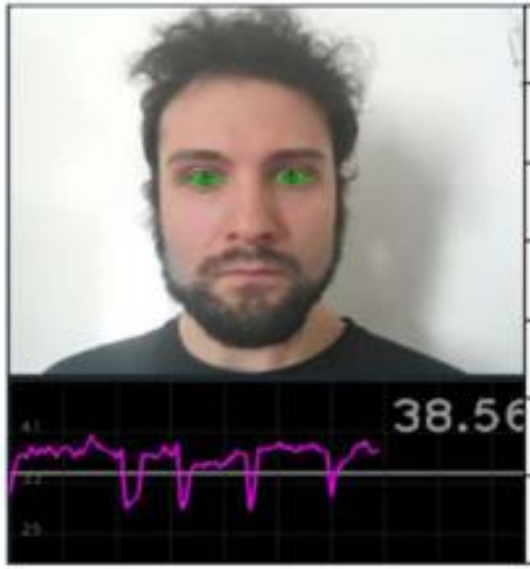
- Introduce a new validated method to extract blinks-related information from commonly available webcams
- Investigate the relationship between expertise in recreative video games (Tetris, Hearthstone) and variations in eyeblinks between baseline and game session
- This chapted in based on previous studies where eye-blinks have been connected with expertise and performance in real-life
- Variations in blinks are connected to brain activity in the striatum, prefrontal cortex, and ventral tegmental area. Such areas are relevant for attention, reward, and goal directed behaviour

EAR-based blinks extraction



EAR-based blinks extraction

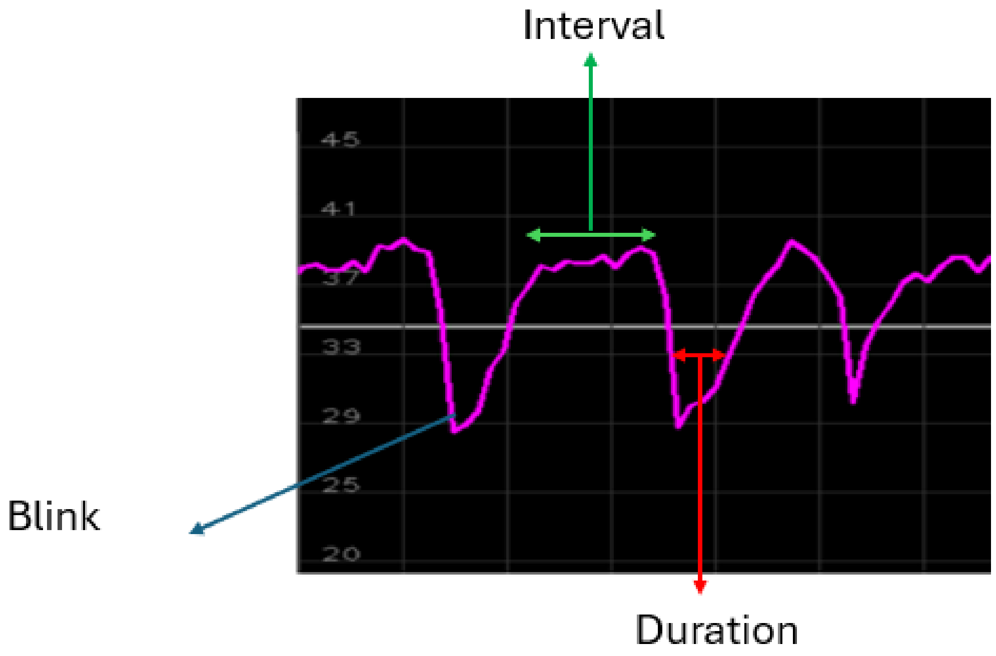
- Implemented using the CV2 library
- Tracks eyelid distance using FaceMeshDetector (EAR)



Points	Left eye	Right eye
P1	243	385
P2	22	252
P3	24	254
P4	130	463
P5	160	387
P6	158	359

$$\mathrm{EAR} = \frac{\|P_2 - P_6\| + \|P_3 - P_5\|}{2 \cdot \|P_1 - P_4\|}$$

EAR-based blinks extraction: extractable Info

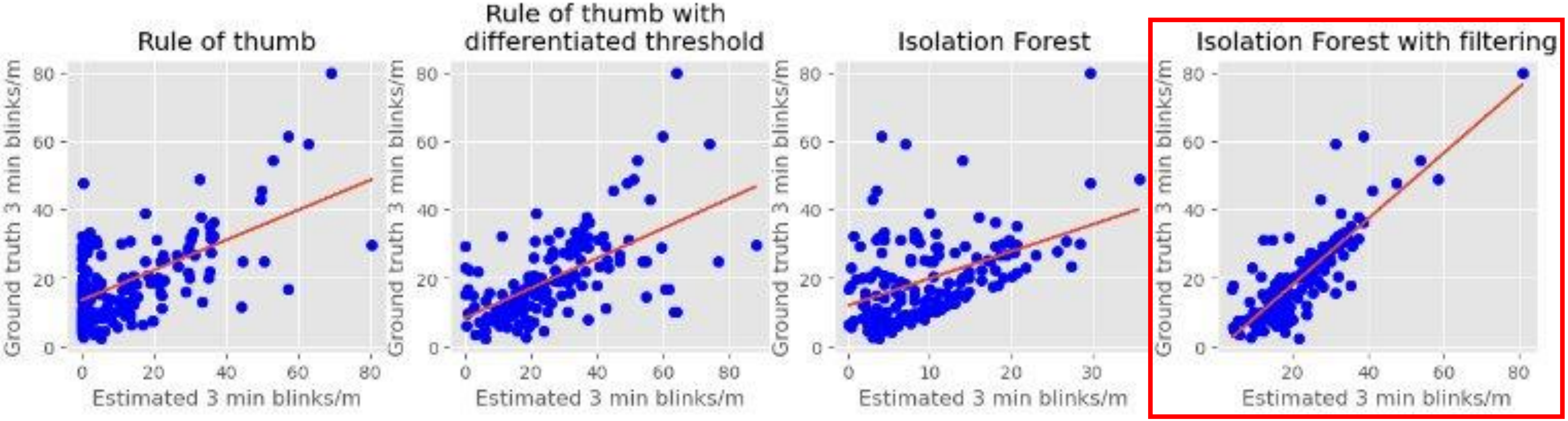


ML process for blinks extraction

- First step: EAR collection
- Second step: anomaly detection using an Isolation Forest: potential outliers frames are detected with a length between 2 and 15 frames (signal collected at 30 fps).
- Third step: filtering function to detect missing frames belonging to blinks based on expected blinks intervals (4 frames minimum = 120 ms)
- Forth step: final frames clustered in blinks (2 to 15 frames = 66 ms to 500 ms), longer clusters are discarded.
- Fifth step: the algorithm excludes frames not beloning to blinks and cluster them to define intervals-based information.

EAR-based blinks extraction: validation

- Validated on 160 participants



EAR-based blinks extraction: validation

TABLE I
COMPARISON WITH FOUR METHODS WITH CORRELATION COEFFICIENT (PEARSON'S R) AND MAPE

	r	MAPE (%)	Blinks/m of 3 min (M, SD)	U	p
Ground truth			19.66 (12.17)		
Rule of Thumb [21]	0.58	60.91	14.02 (16.01)	17343	$p < .001$
Rule of Thumb with diff. thres. [16]	0.61	70.90	25.98 (17.00)	9877	$p < .001$
Isolation Forest [22]	0.50	45.58	9.65 (7.02)	19911	$p < .001$
Isolation Forest with filtering	<u>0.88</u>	<u>27.98</u>	19.76 (10.56)	12278.5	<u>$p = .53$</u>

Sample and Expertise Definition: Hearthstone

- Collected during a tournament
- 16 participants (all males)
- 146 videos across all the participants
- Expertise was defined with a K-means using the number of hours per week spent playing the game and the self assessed expertise.
- 3 clusters were detected and named Novices, Intermediates, and Experts
- Blinks/m analyzed extracted directly from tournament's videos

	Novices	Intermediates	Experts
Hours per week	1.75 ($SD = 1.30$)	8.28 ($SD = 2.37$)	19.75 ($SD = 3.90$)
Self-assessed Hearthstone experience	1.5 ($SD = 0.5$)	3.78 ($SD = 0.41$)	4.75 ($SD = 0.43$)

Sample and Expertise Definition: Tetris

- Collected during a Tetris session
- 80 participants (39 males, 40 females, 1 nd)
- Expertise was defined with a K-means using the number of matches played 13 minutes and the average score obtained
- 3 clusters were detected and named Novices, Intermediates, and Experts
- Blinks/m analyzed extracted performing a baseline correction (blinks/m during baseline – blinks/m during the task)

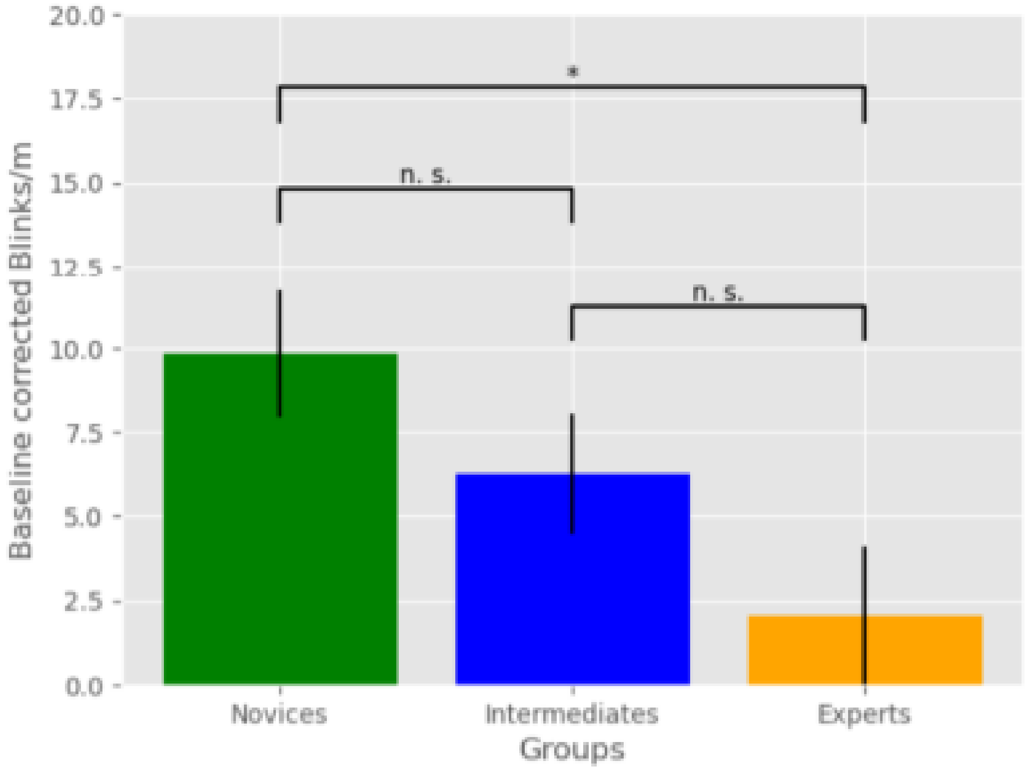
	Novices	Intermediates	Experts
Matches Played	5.22 ($SD = 1.41$)	2.32 ($SD = 0.86$)	1.1 ($SD = 0.30$)
Average Score	305.69 ($SD = 147.07$)	1483.26 ($SD = 971.14$)	14013.45 ($SD = 7556.00$)
Tetris Experience	1.73 ($SD = 0.69$)	2.21 ($SD = 0.87$)	2.80 ($SD = 0.75$)

Results Hearthstone

- A Mixed Linear Model with Experts being the reference group with the model's intercept being at 26.51 (95% CI [18.56 34.47], $t = 6.59$, $p < .001$) showed significant results
- The level of expertise had a negative effect on both Intermediates ($B = -11.11$, 95% CI [-20.81, -1.41], $t = -2.26$, $p = 0.042$; $\beta = -1.12$) and Novices ($B = -15.67$, 95% CI [-27.07, -4.26], $t = -2.72$, $p = 0.017$; $\beta = -1.57$).
- In simple words: experts show higher blinks/m across the matches they played during the tournament.

	B	SD	t	p
Experts-Intermediates	11.11	4.91	2.67	.10
Experts-Novices	15.67	5.77	2.71	.04*
Intermediates-Novices	4.55	5.00	0.91	.64

Results Tetris



- Anova analyses show that expert players have a lower variations in blinks/m between baseline and task (baseline corrected blinks/m) both during the first minute of game play when all players were playing at level 0 ($F(2,74) = 3.17$, $p = .048$) and across the entire game session ($F(2,74)= 4.89$, $p = .03$).

Results Tetris

- Expert Tetris and Hearthstone players tend to have higher blinks/m compared to their less experience counterpart.
- Such results are in line with what found in studies conveying the relationship between blinks, expertise, and performance.
- In Tetris, the same results emerged after one minute of gameplay (during level 0). This is in line with previous behavioural studies focusing on zoids positioning

Chapter 4: Identify Expert Tetris Players using Early Keystrokes behavior

Research Question: *Can in-game decisions, made in the early phases of a game session, be used to identify players with different levels of expertise?*

Aims and background

- Expert players can show specific behaviours early in a game session
- Previous studies show that experts can be detected early in a game session by looking at how they position the zoids
- Evaluation of most relevant keystrokes to detect experts during level 0
- Evalute how many seconds can be used to identify players with different levels of expertise in Tetris
- Identify main decisions that characterize experts (keys pressed)

Sample and methods

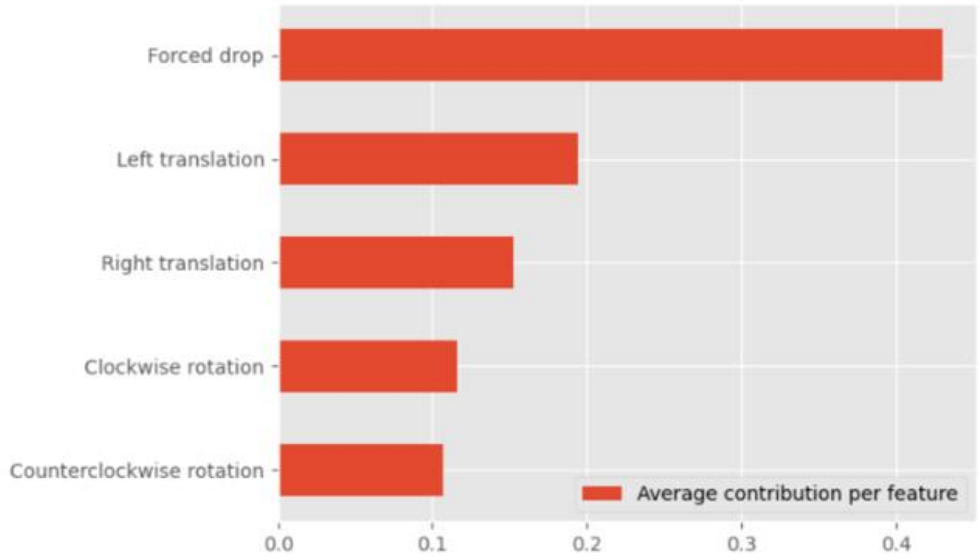
- 80 participants collected during a Tetris session
- Machine Learning task (Random Forest)
- Tetris players divided in three groups (Novices, Intermediates, Experts)
- Decisions made in the gameplay corresponds to extracted key pressed
- 5 potential actions: Left/Right translation, Clockwise/Counterclockwise Rotations, Forced Drop
- Metrics used: ROC AUC, F1, Accuracy

Results with five keys

- Baseline Scores: ROC AUC = 0.70, F1 = 0.25, Accuracy = 0.48

	Accuracy	ROC AUC	F1
45 seconds	0.66 ($SD = 0.10$)	0.81 ($SD = 0.05$)	0.64 ($SD = 0.09$)
40 seconds	0.62 ($SD = 0.11$)	0.76 ($SD = 0.05$)	0.61 ($SD = 0.08$)
35 seconds	0.59 ($SD = 0.14$)	0.77 ($SD = 0.07$)	0.59 ($SD = 0.12$)
30 seconds	0.59 ($SD = 0.11$)	0.77 ($SD = 0.08$)	0.58 ($SD = 0.11$)
25 seconds	0.57 ($SD = 0.11$)	0.76 ($SD = 0.09$)	0.53 ($SD = 0.14$)
20 seconds	0.60 ($SD = 0.12$)	0.77 ($SD = 0.08$)	0.58 ($SD = 0.11$)
15 seconds	0.54 ($SD = 0.14$)	0.72 ($SD = 0.07$)	0.51 ($SD = 0.14$)
10 seconds	0.51 ($SD = 0.09$)	**0.69** ($SD = 0.08$)	0.47 ($SD = 0.08$)
5 seconds	0.49 ($SD = 0.11$)	**0.65** ($SD = 0.09$)	0.39 ($SD = 0.11$)

Scores variations across 45 seconds



Features contribution

Results with two most revant keys

	Accuracy	**ROC AUC**	**F1**
45 seconds	0.65 ($SD = 0.08$)	0.83 ($SD = 0.07$)	0.63 ($SD = 0.08$)
40 seconds	0.61 ($SD = 0.15$)	0.79 ($SD = 0.06$)	0.57 ($SD = 0.15$)
35 seconds	0.60 (SD = 0.13)	0.79 (SD = 0.05)	0.55 ($SD = 0.17$)
30 seconds	0.63 ($SD = 0.12$)	0.78 ($SD = 0.06$)	0.57 ($SD = 0.16$)
25 seconds	0.55 ($SD = 0.10$)	**0.69** ($SD = 0.07$)	0.51 ($SD = 0.08$)
20 seconds	0.65 ($SD = 0.12$)	0.77 ($SD = 0.09$)	0.63 ($SD = 0.10$)
15 seconds	0.50 ($SD = 0.11$)	0.73 ($SD = 0.09$)	0.47 ($SD = 0.11$)
10 seconds	0.52 ($SD = 0.13$)	0.72 ($SD = 0.09$)	0.48 ($SD = 0.14$)
5 seconds	**0.46** ($SD = 0.13$)	**0.64** ($SD = 0.14$)	0.39 ($SD = 0.11$)

Scores variations across 45 seconds (left translation and forced drop)

Discussions

- Players can be correctly identify after 10/15 seconds they started the gameplay
- Left translation and forced drop are the most relevant decisions
- Expert players used forced drop to increase their score quicker and tend to accumulate their zoids more on the left. This is dued to more possibilities given by the left side of the screen
- Specific action may suffice to detect experts players during early phase of the game
- These insights can be used by game designers to make games more engaging and during tournaments select participants

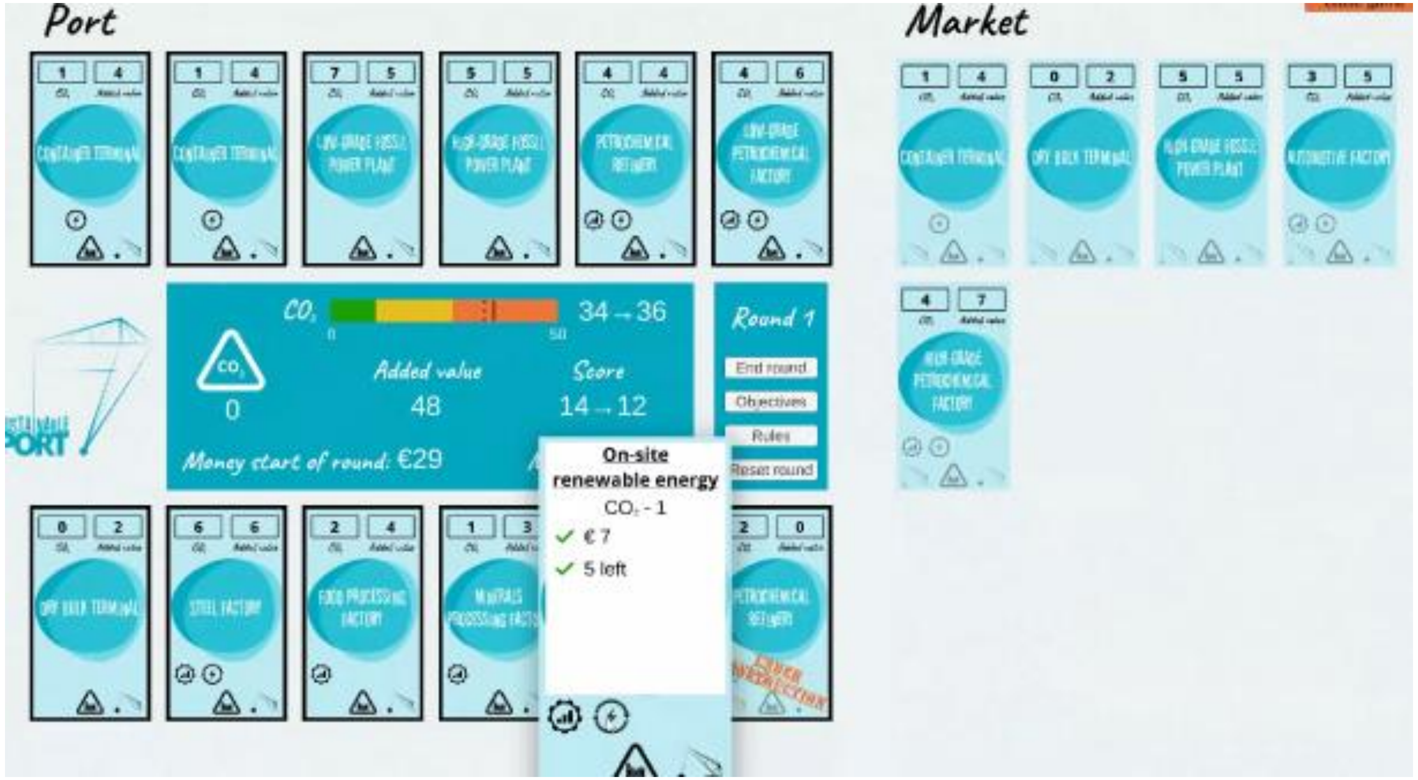
Chapter 5: Introducing The Sustainable Port: a Serious Game to Study Port Decision-Making

Research Question: *R4a) Can The SustainablePort simulate the dynamics occurring at the Port of Rotterdam? RQ4b: Do employees working for the Port Authority of the Port of Rotterdam (experts)obtain higher scores than students (novices) in The Sustainable Port?*

Aims and background

- Behaviour displayed in real-life may be transfered to simulated environments like serious games
- Serious games provide safe environment where experiment with agency and learn new skills
- Serious games can be used to train new employess and for hiring purposes

The Sustainable Port



- Originally developed as board game by The Barn (Delft, NL)
- The game tries to capture real-life development of the Port of Rotterdam
- This was a digitalized version made by our team at Tilburg University
- The game presents uncertainty when making decisions
- The player has to constantly re-evaluate her strategy
- Crucial to balance CO2 emissions, and revenues considering a limited budget
- Single player game

Sample and methods

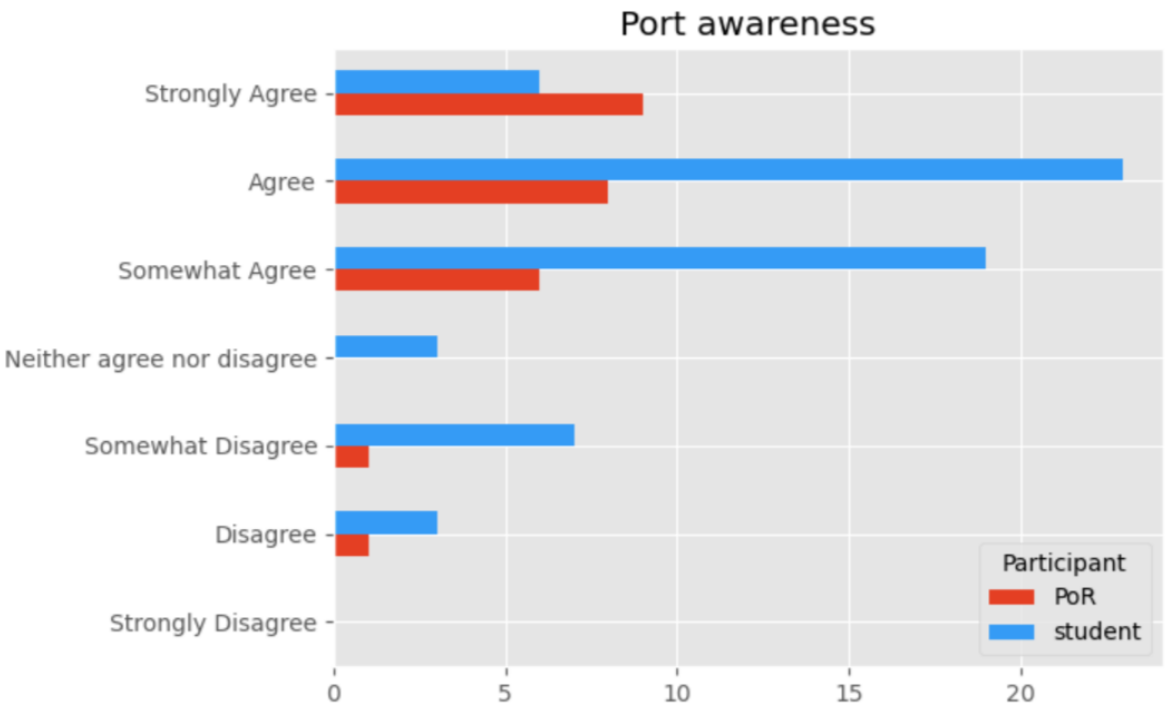
- 109 Participants: 75 students and 34 PoR employees (experts) involved in strategic departments
- Evaluation of score obtained in the game (multiple linear regression)
- Evaluation of board games habits and digital games habits on the score (on a Likert scale between 1 and 5)
- Evaluation of subjective experience with the game (on a Likert scale between 1 and 7):

  - Perception of effectiveness to use the game to raise awareness about complexity characterizing port environments

  - Evaluation of use of the game to simulate dinamycs occuring at the Port of Rotterdam (only for PoR employees)

  - Evaluation of the use of in real-life-obtained expertise to play *The Sustainable Port* (only for PoR employees)

Subjective experience with the game



- 80.73 % of the participants who play The Sustainable Port suggest that the game can be used to raise awareness about the complexity characterizing port environments
- 88.23 % of the PoR employees affirmed that The Sustainable Port can be used to simulate dynamics occuring at the Port of Rotterdam
- 72.73 % of the PoR employees affirmed they used their expertise acquired at the Port of Rotterdam to play this game

The word of the experts

Question:

- Do you think this game may be an effective tool to start a discussion about future decisions concerning the Port of Rotterdam's development? In which way?

Answers:

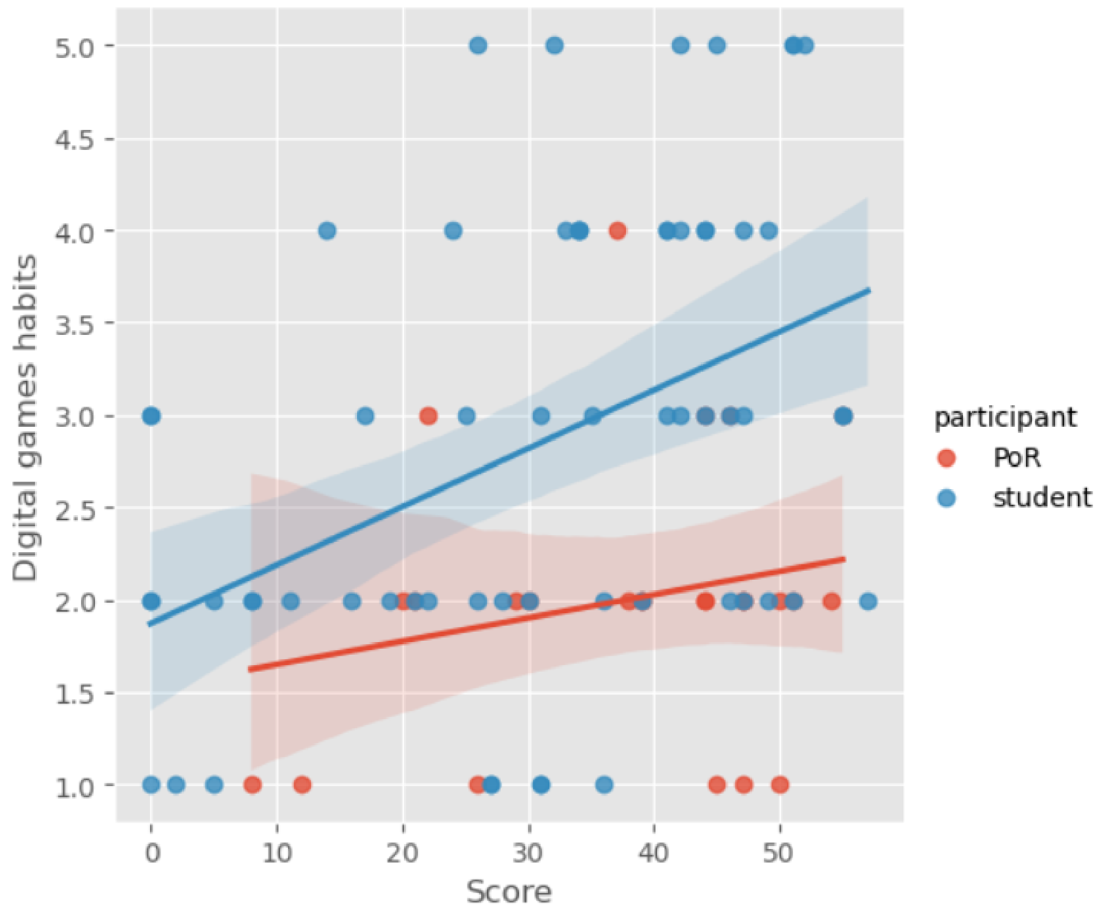
- *“Yes, I think it helps with the dilemma's we're facing. Personally, I believe we should put even more weight on CO_2 vs added value, since the societal aspects of CO_2 are not priced effeciently currently. So, the climate cost of current activities are higher than paid by polluters.”*
- *“Definitely, might be mandatory for everyone to play at least once to understand the transition our Port is aiming for!”*
- *“Not in details but certainly on a conceptual level, or as to introduce new staff or stakeholders to the complex decision processes that PoR is in”*
- *“helps to create awareness and understanding. It is a big challenge we are facing”*
- *“Perhaps this could be useful to simulate on whether or not a decision will contribute to reaching the strategic goals as set out by the POR.”*
- *“I think it really would…It would also help to visualize what would actually happen. I therefore think it is important that we as the PoR try to quantify as much as we can, so we can use comparisons as is done in this game.”*

Score: PoR employees vs students

- The multiple linear regression model proposed explains 24% of the variance ($p < .001$)
- Being a PoR employees and Video games habits are the only significant predictors in the model

	B	SD	U	L	t	p
Age	-0.30	0.23	0.16	-0.77	-1.29	.20
Biological sex (Ref. Male)	-6.90	3.52	0.10	-13.91	-1.96	.053
Digital Games Habits	4.14	1.50	7.12	1.17	2.77	.007**
Board Games Habits	3.33	2.76	0.23	-2.15	1.21	.23
Participants (ref. students)	13.33	5.41	24.10	2.56	2.46	.016*

Video games habits



- Further analysis show that there is a significant correlation between the score obtained and the digital games habits in the students' group ($r = 0.42$, $p < .001$) but not in the PoR employees' group ($r = 0.22$, $p = .30$)
- This suggests that PoR employees may play the game better independently from their video games habits

Discussions

- PoR employees performed significantly better than students on this game
- There is a significant correlation between digital games habits and score obtained in the game but just in the students group
- Both the groups suggest that this game may be used to simulate situations occuring at the Port of Rotterdam
- The results may suggest differences in strategies adopted in the game by the two groups and differences in their physiological reactions as well (blinks, eye-gaze)

Chapter 6: Detecting PoR Employees using Blinks-related Features

Research Question: *To what extent can blinks-related features be used to identify experts and novices playing The Sustainable Port?*

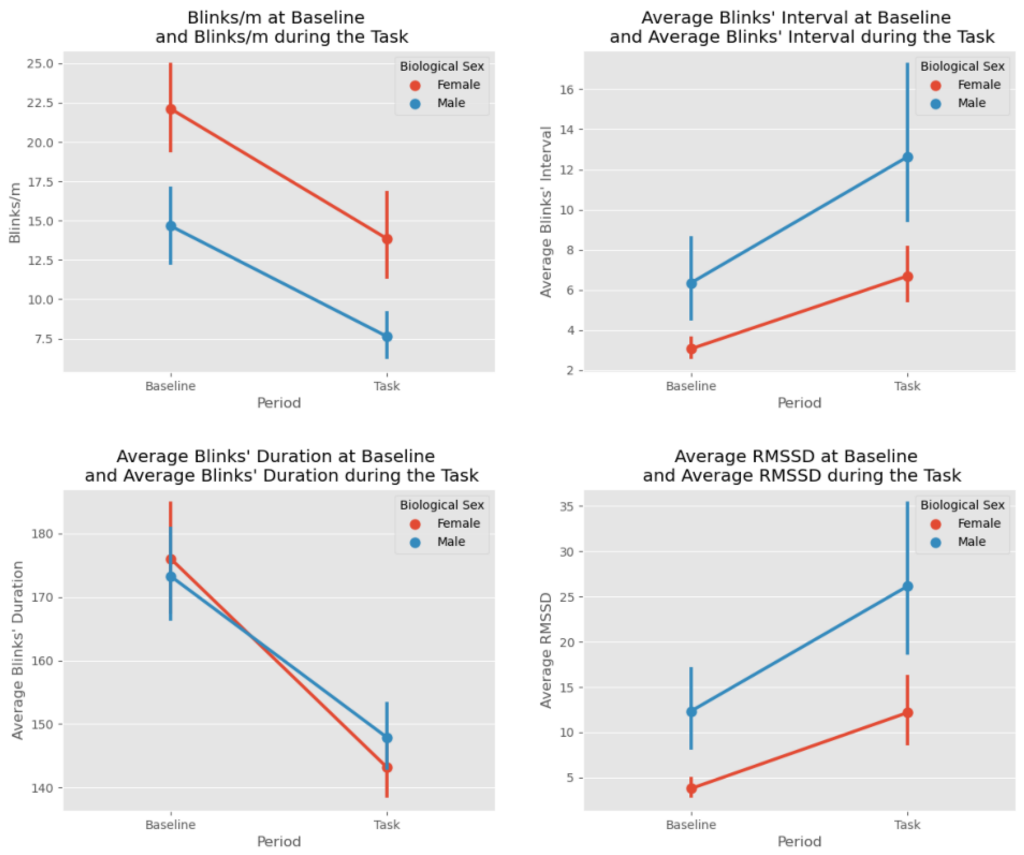
Aims and background

- Evaluation of physiological differences between PoR employees and students playing The Sustainable Port
- Introducing a robust methodology to evaluate blinks studies
- Evalutation of relationship between performance, expertise acquired in real life, and blinks-related information.
- Introducing further blinks-related information to evaluate differences between the two groups

Sample and Methods

- Same sample as in Chapter 5
- Use of baseline corrected blinks/m, average blinks' duration, average blinks' interval and RMSSD.
- Machine Learning task (Logistic Regression) to identify students and PoR employees
- Evaluate of relevant information to detect PoR employees and students (logistic regression to fit the data)
- Metrics: ROC AUC, F1, PR AUC, Pseudo-R2

Results: baseline-correction robustness



	Biological Sex	Age	Duration of the Recording	Age x Biological Sex
Blinks/m	$F = 0.52$ $p = .47$	$F = 0.27$ $p = .60$	$F = 0.30$ $p = .58$	$F = 2.19$ $p = .14$
Average Blinks' Duration	$F = 1.09$ $p = .30$	$F = 0.08$ $p = .78$	$F = 0.01$ $p = .93$	$F = 0.03$ $p = .86$
Average Blinks' Interval	$F = 1.08$ $p = .30$	$F = 0.60$ $p = .81$	$F = 0.17$ $p = .68$	$F = 0.41$ $p = .52$
Average RMSSD	$F = 0.83$ $p = .37$	$F = 0.11$ $p = .74$	$F = 0.13$ $p = .72$	$F = 0.16$ $p = .69$

Results: logistic regression

	ROC AUC	PR AUC	F1
Logistic Regression	0.70 (SD = 0.11)	0.64 (SD = 0.17)	0.62 (SD = 0.05)
Dummy Classifier (baseline)	0.50 (SD = 0.00)	0.46 (SD = 0.14)	0.46 (SD = 0.02)

	B	**SD**	**U**	**L**	***t***	***p***
Blinks/m	-0.087	0.041	0.033	-0.167	-2.133	.03*
Baseline-corrected Average Blinks' Duration	-0.022	0.009	-0.015	-0.022	-0.253	.80
Baseline-corrected Average Blinks' Interval	0.165	0.087	0.335	-0.006	1.895	.06
Baseline-corrected Average RMSSD	-0.083	0.033	-0.019	-0.146	-2.528	.01*

Discussions

- Significant variations occur between periods at rest and the gameplay
- Blinks/m and RMSSD are the most relevant blinks-related information to identify PoR employees and students
- Similar to the results in Tetris, PoR employees undergo a lower decrease in blinks/m when compared to baseline
- PoR employees had an higher RMSSD which may suggest a better adaptability to the task
- This means to the results obtained in Tetris and Hearthstone generalized to this serious game. This may represent a more foundamental connection between blinks/m and performance on screen based tasks.

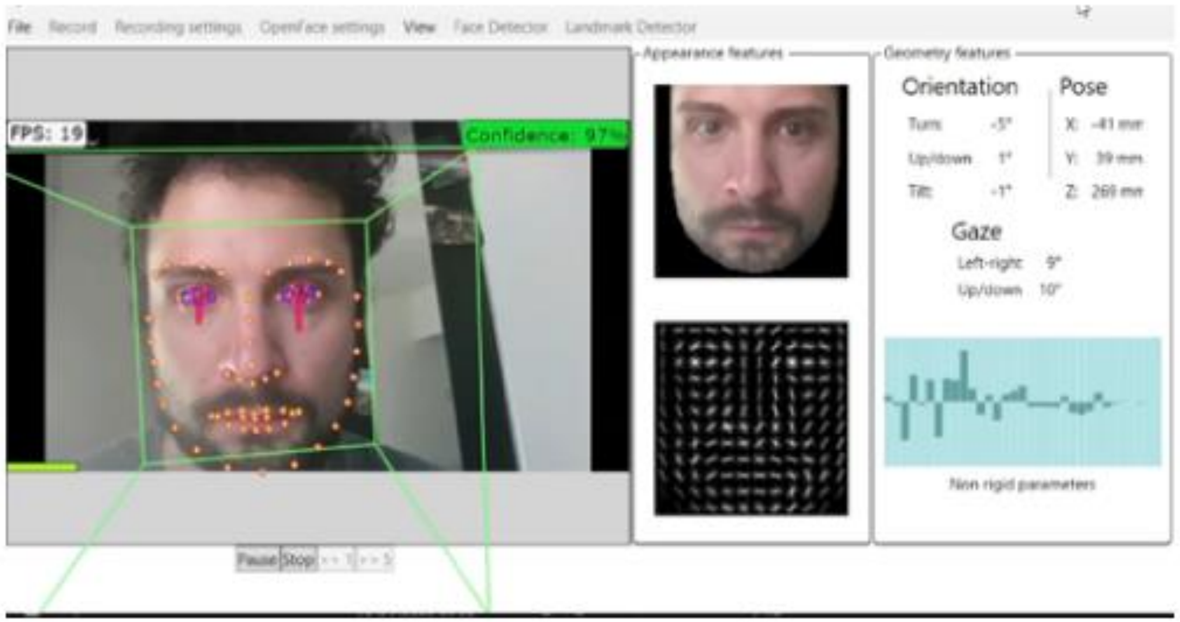
Chapter 7: Detecting PoR Employees using Gaze Direction

Research Question: *Can experts be automatically discriminated from novices by looking at their gaze direction while playing TheSustainable Port?*

Aims and background

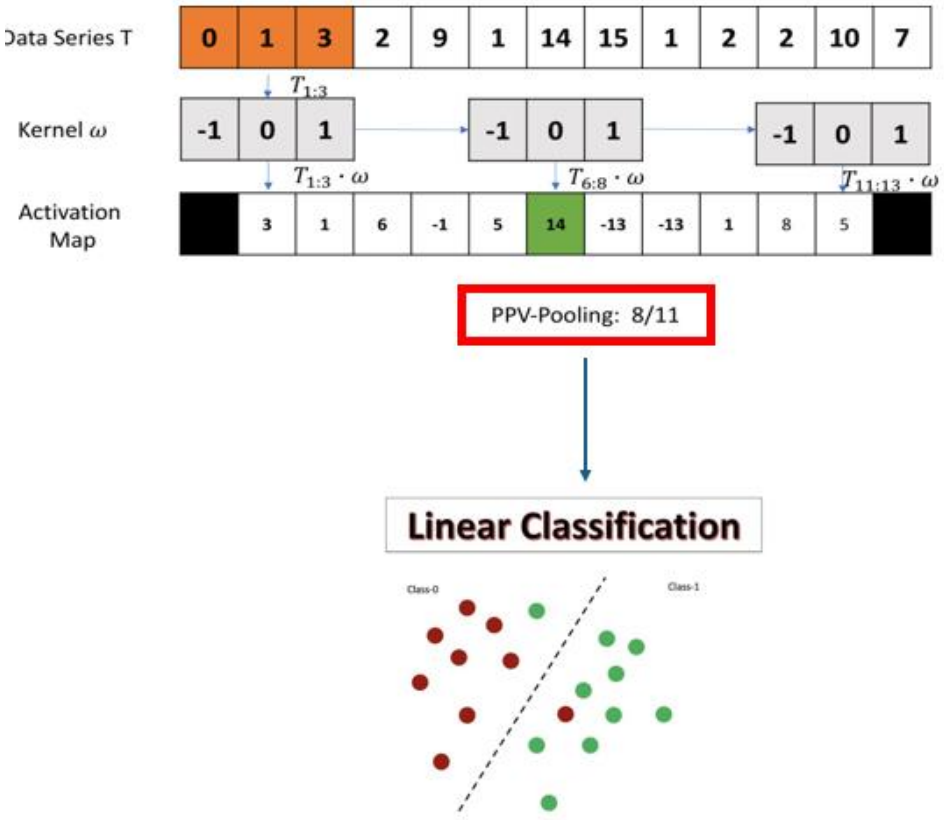
- Expert show different eye movements compared to novices in different fields
- Evaluate if it is possible to identify PoR employees playing The Sustainable Port just by looking at their eye movements extracted non-invasevely
- Show results obtained with scalable and non-invasive methods to detect expertise in simulation (like serious games) but also on screen presented tasks

Sample and Methods



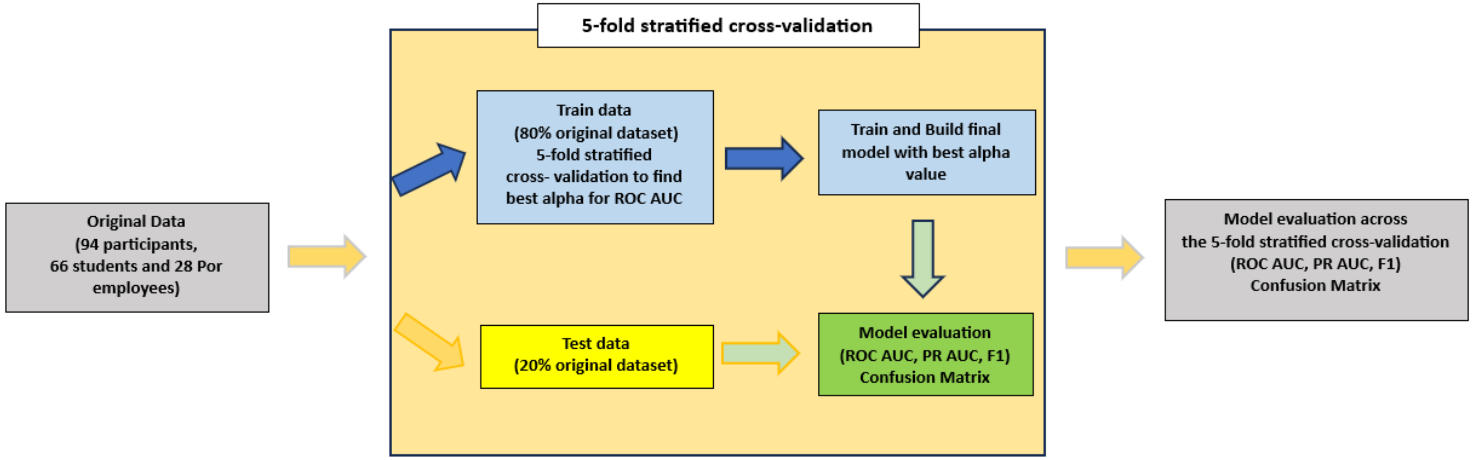
- Expert show different eye movements compared to novices in different fields
- Evaluate if it is possible to identify PoR employees playing The Sustainable Port just by looking at their eye movements extracted non-invasevely
- Eye movements extracted using Openface (gaze_angle_x, gaze_angle_y)
- Time series classification using MiniRocket a scalable time series classifier
- Metrics: ROC AUC, F1, PR AUC

MiniRocket time-series classifier



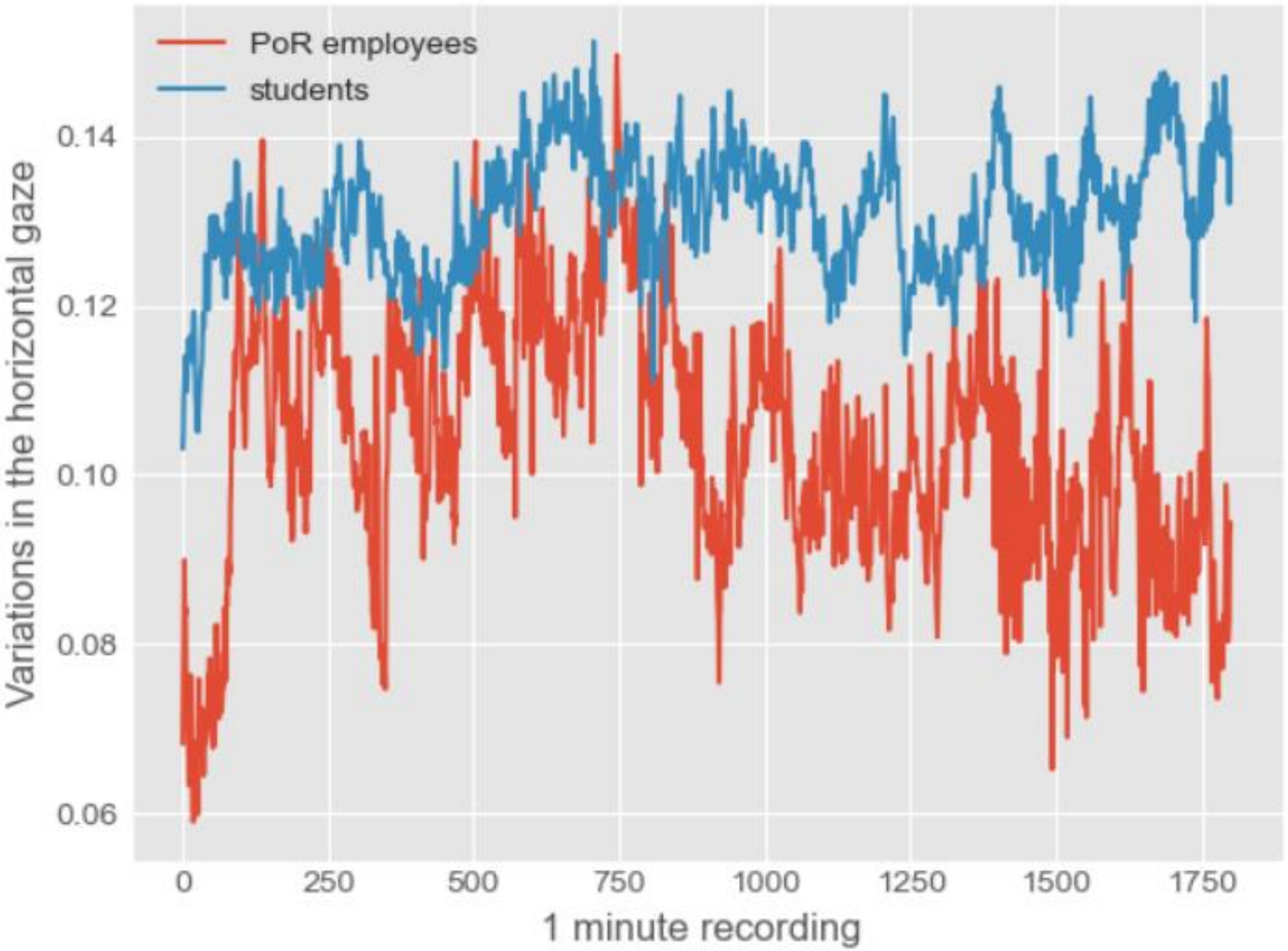
- Fast and effective timeseries classifiers reaching near state-of-the-art performance
- Leverage up-sides of a CNN and a linear classifiers: kenel used to generate activation maps and linear classifiers for classification purposes.

Pipeline and Results



	F1	ROC AUC	PR AUC
MiniRocket	0.75 (SD = 0.07)	0.75 (SD = 0.14)	0.73 (SD = 0.14)
Dummy Classifier	0.46 (SD = 0.03)	0.70 (SD = 0.00)	0.45 (SD = 0.13)

Discussions



- PoR employees and students can be detected when looking at their eye movements
- MiniRocket combined with eye movements, may be an effective solution to detect experts using scalable e non-invasive methods
- Differences in eye movements between the two groups may be connected to decisions performed in the game
- The method here presented may be effective in detecting expertise in other screen presented tasks

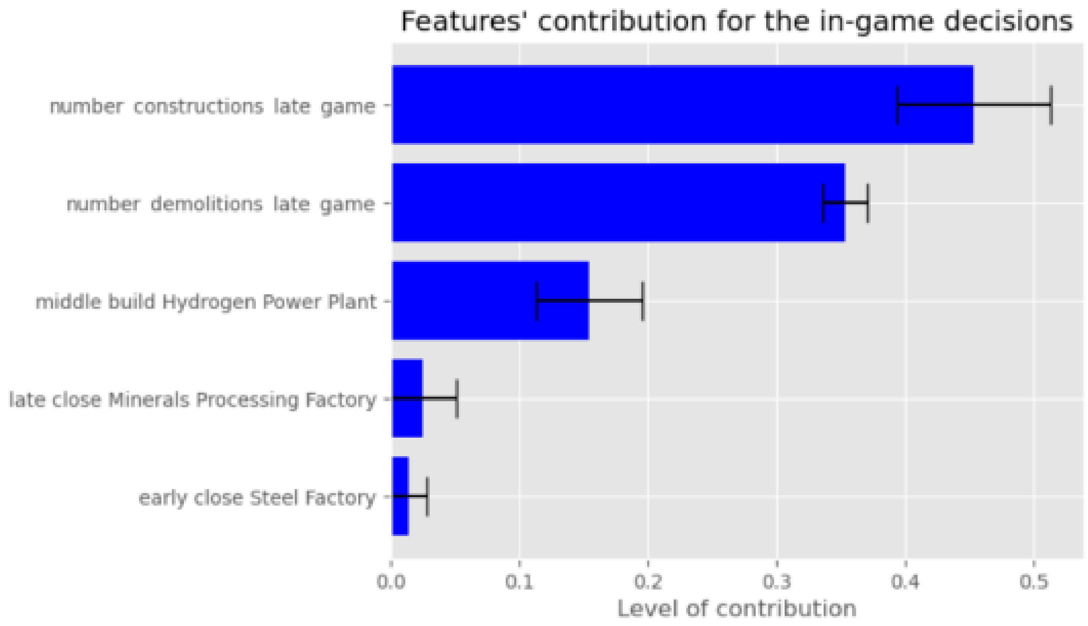
Chapter 8: Detecting PoR Employees Using In-game Decisions and Port Facilities

Research Question: *What differences in decision-making make experts distinguishable from novices playing The Sustainable Port?*

Sample and Methods

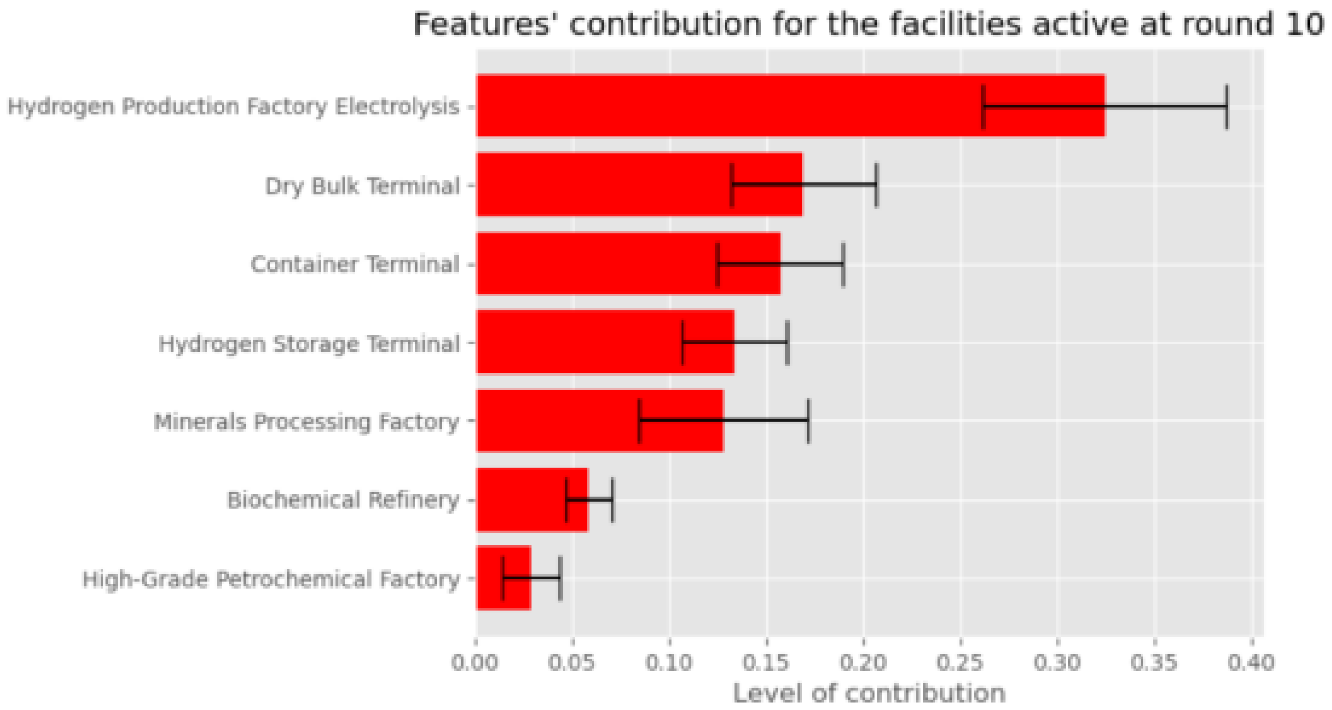
- 109 original participants + 49 collected online (38 students, 11 PoR employees)
- 116 decision performed across the game (Early game, middle game, late game), 16 facilities present at the end of the game
- Machine Learning task (Random Forest)
- Feature Selection on part of the dataset to detect most relevant features (40% of the original data)
- Evaluation if these relevant information applies also on the unseen data (60% of the original data)
- Metrics used: ROC AUC, F1, PR AUC

Results: decisions across the game



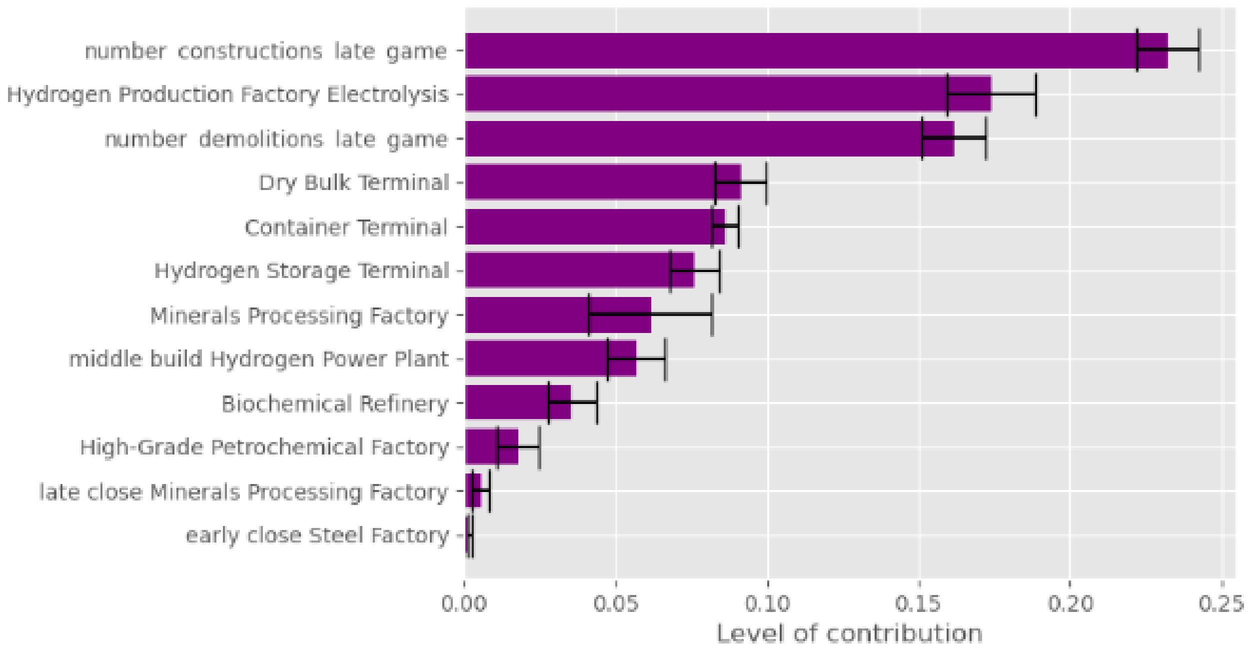
	F1	**ROC AUC**	**PR AUC**
Random Forest Classifier	0.66 $(SD = 0.10)$	0.76 $(SD = 0.13)$	0.81 $(SD = 0.09)$
Dummy Classifier	0.45 $(SD = 0.04)$	0.70 $(SD = 0.00)$	0.35 $(SD = 0.02)$

Results: facilities at the end of the game



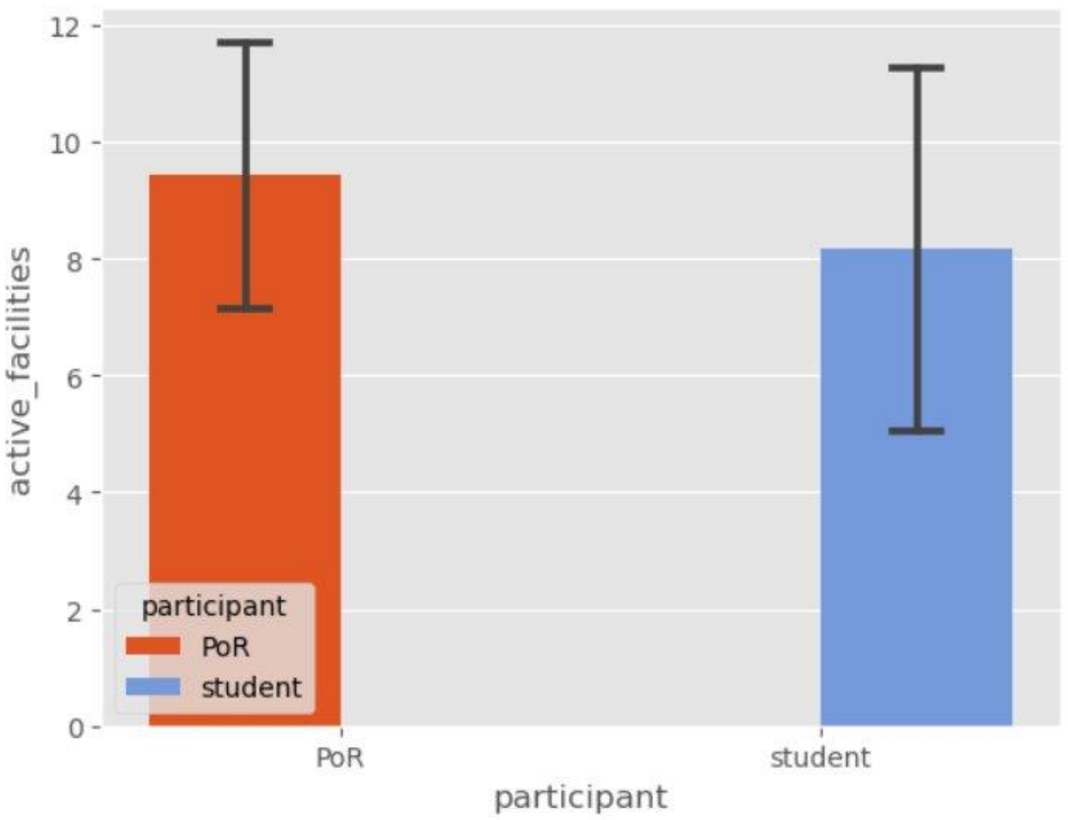
	F1	**ROC AUC**	**PR AUC**
Random Forest Classifier	0.67 ($SD = 0.05$)	0.73 ($SD = 0.16$)	0.72 ($SD = 0.17$)
Dummy Classifier	0.45 ($SD = 0.04$)	0.70 ($SD = 0.00$)	0.35 ($SD = 0.02$)

Results: decisions and facilities



	F1	**ROC AUC**	**PR AUC**
Random Forest Classifier	0.83 ($SD = 0.04$)	0.73 ($SD = 0.10$)	0.80 ($SD = 0.17$)
Dummy Classifier	0.45 ($SD = 0.04$)	0.70 ($SD = 0.00$)	0.35 ($SD = 0.02$)

Discussions



- Specific hydrogen facilities characterize PoR employees gameplay. This is probably connected to the key role of these facilities in the future of the Port of Rotterdam
- PoR employees tend to have more facilities at the end of the game, this is related to the importance of not having empty space in the real port
- PoR employees tend to adopt a more strategic behaviour compared to the more exploratory of the students.
- Specific decisions relevant In real-life may emerge during serious games as well

Chapter 9:

General Discussions

General discussions and future directions

Picture taken at Rotterdam Port Authority

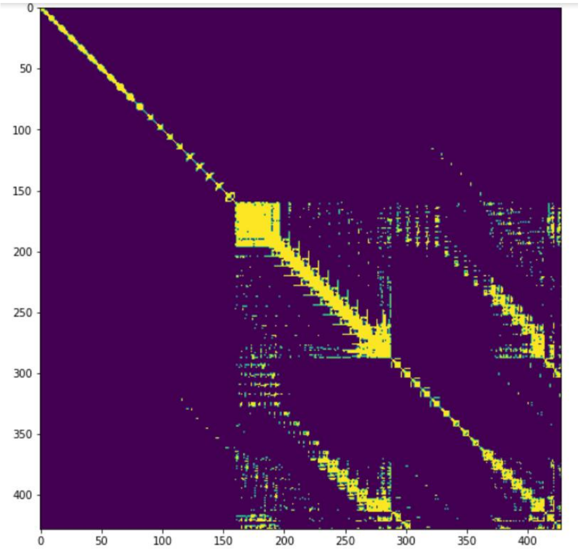
- All the research run during the PhD project was applied and developed in collaboration with the Port of Rotterdam
- The methodology introduce appears to be robust to detect experts in entertainment games and real life experts playing serious games
- The non-invasive methods introduced here (blinks and eye movements) can be applied to other screen presented task beyond digital games offering scalable solutions for business purposes.

Current Research

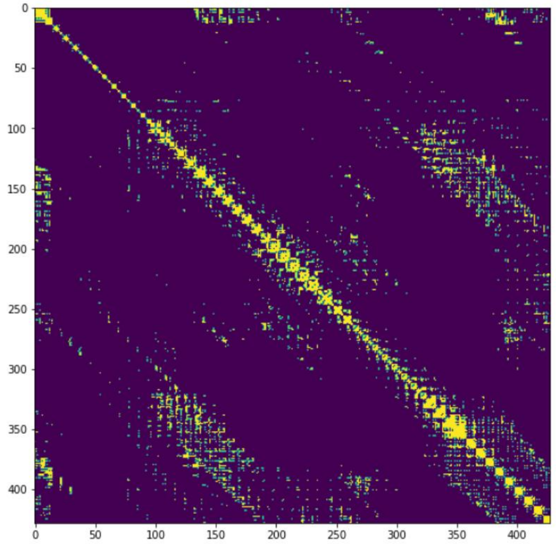
General Discussions

Complex systems and expertise

- This work is about to be submitted for peer review
- Evaluation of complex dynamics occurring in Tetris players using Recurrence Quantification Analysis
- Evaluation of relationship between action performed in the game and complex measures (entropy for example)
- Further step in establishing EAR as an effective signal to track task-depending physiological variations



Novice



Expert

Tetris: expertise and pattern mining

- These results were recently published at the IDA 2025 conference
- Classification and pattern mining in Tetris using non-invasive data
- Comparison of time series classifiers

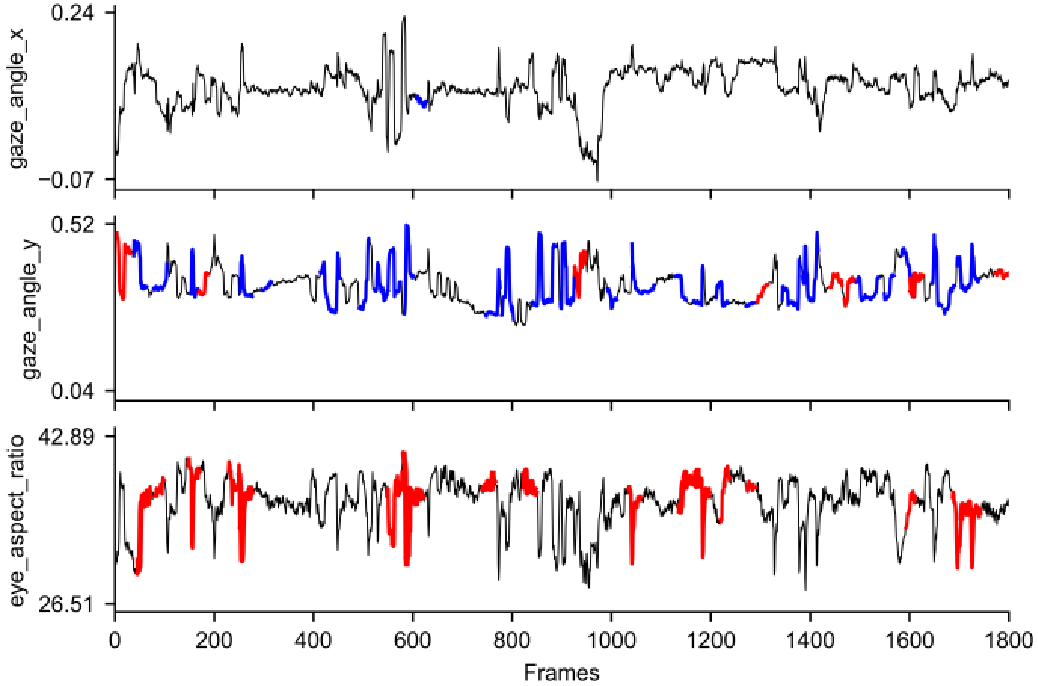


Table 1. Classification results on 13 minutes of game-play

	Accuracy	Weighted accuracy	Weighted F1	AUROC
Majority class	0.468	0.333	0.299	0.487
1-NN DTW	0.443	0.449	0.445	0.584
Hive-Cote 2.0	0.519	0.478	0.508	0.692
MiniRocket	0.532	0.501	0.526	0.621
Mr-Petsc	**0.633**	**0.662**	**0.630**	**0.775**

Cognitive workload prediction in games

- A work is in the pipeline
- High cognitive workload prediction
- Based on features extracted from facial action units
- Machine Learning task using tabular data

Health Research: VVR Prediction

- A work is in the writing phase.
- Focused on predicting vasovagal reaction before micro-invasive medical procedure
- EAR Time series classification using MiniRocket, LearningShapelts, and other transformer
- 30/40 seconds signal before undergoing procedure
- Results show performance above baseline

Thank you and let’s connect!