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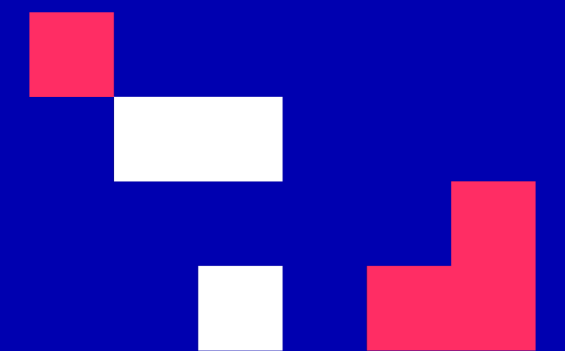
Master programmes in Artificial
Intelligence 4 Careers in Europe

University of Cyprus

HUMAN-CENTERED INTELLIGENT USER INTERFACES - MAI648

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2022



LAB 2

Eye Tracking Research and its Applications in IUI

CONTENTS

- Introduction to Eye Tracking
- An Eye-tracking Multifactorial Model for Eliciting Human Cognitive Factors
- Cognitive-centered User Modelling in Graphical Passwords
- Real-time Eye Gaze-driven Prediction of Human Cognitive Factors during Graphical Password Composition

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Eye Tracking

- *Eye tracking is the process of measuring either the point of gaze (where one is looking) or the motion of an eye relative to the head. An eye tracker is a device for measuring eye positions and eye movement – Wikipedia*

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Eye Tracking

- Where can eye trackers be used?

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Eye Tracking

- Where can eye trackers be used?
- Research in visual systems
- HCI
- Psychology
- Marketing
- Product design

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Pupil-Labs

Open source eye
tracking platform.

The core research building block.



<https://pupil-labs.com/>
https://www.youtube.com/watch?v=_0zXfxxbeXg

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Tobii

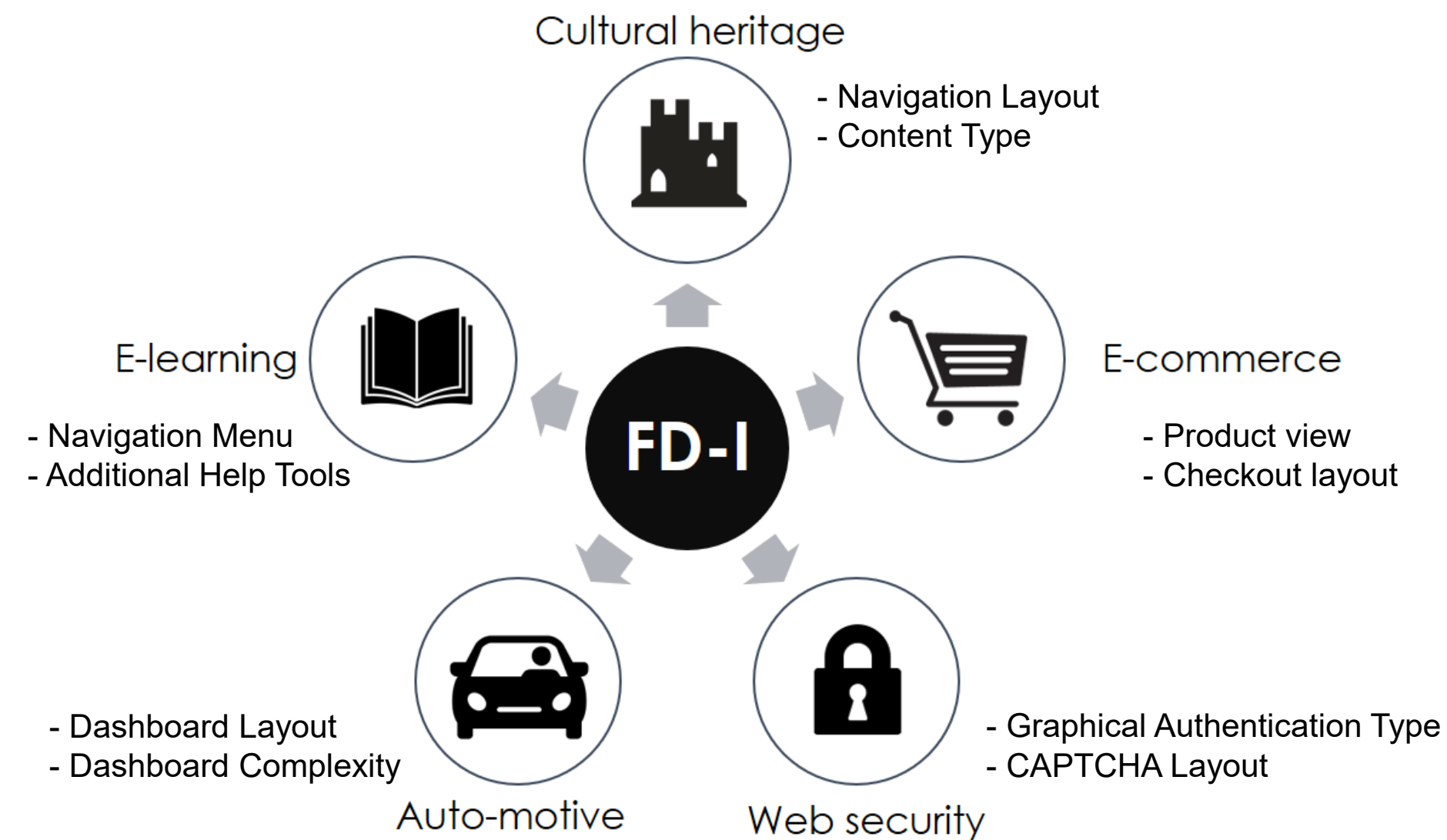


<https://www.tobii.com/>
<https://www.youtube.com/watch?v=3hcQYN0t-VM>

Case Studies

- Raptis, R., Katsini, C., Belk, M., Fidas, C., Samaras, G. Avouris, N., (2017). Using Eye Gaze Data and Visual Activities to Infer Human Cognitive Strategies: Method and Feasibility Studies. In Proceedings of ACM UMAP Conference (ACM UMAP 2017), ACM Press, 8 pages
- Katsini, C., Fidas, C., Raptis, G., Belk, M., Samaras, G., Avouris, N. (2018). Eye gaze-driven prediction of cognitive differences during graphical password composition. ACM SIGCHI Intelligent User Interfaces (IUI 2018), ACM Press, 147-152

Human Cognition Effects in Various Application Domains



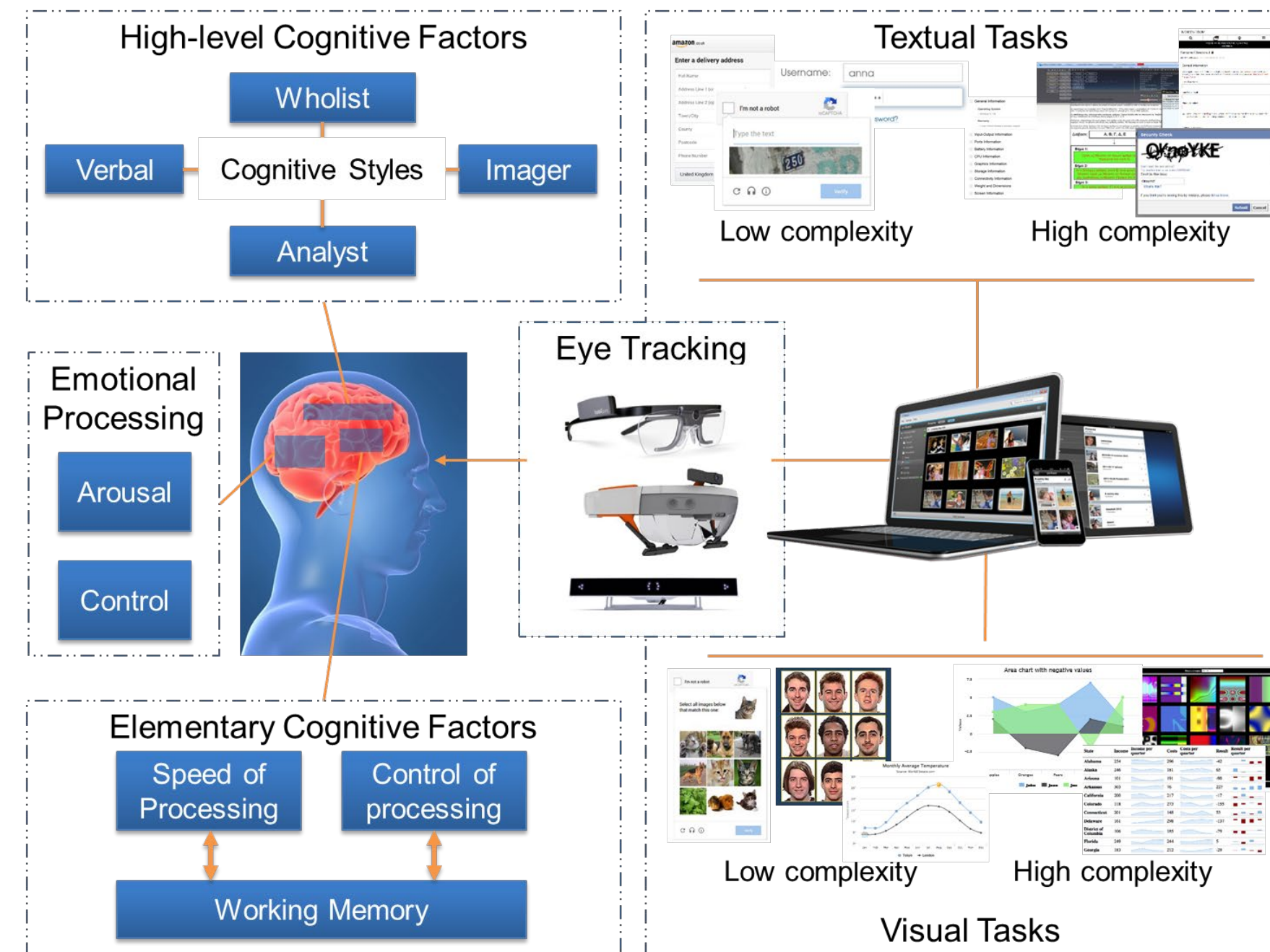
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Challenges

- **The main limitation of cognitive style research is the explicit and non-real-time elicitation of the users' cognitive styles**
 - Traditional in-lab techniques, e.g., “paper-and-pencil” and questionnaires
 - Time-consuming, e.g., 15-20 mins
 - Human intervention
-
- **Compromising real-time integration of human cognitive factors, and negatively affecting user acceptance**

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Implicit Elicitation through Eye-tracking



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On Implicit and Real-time Elicitation of Human Cognitive Styles

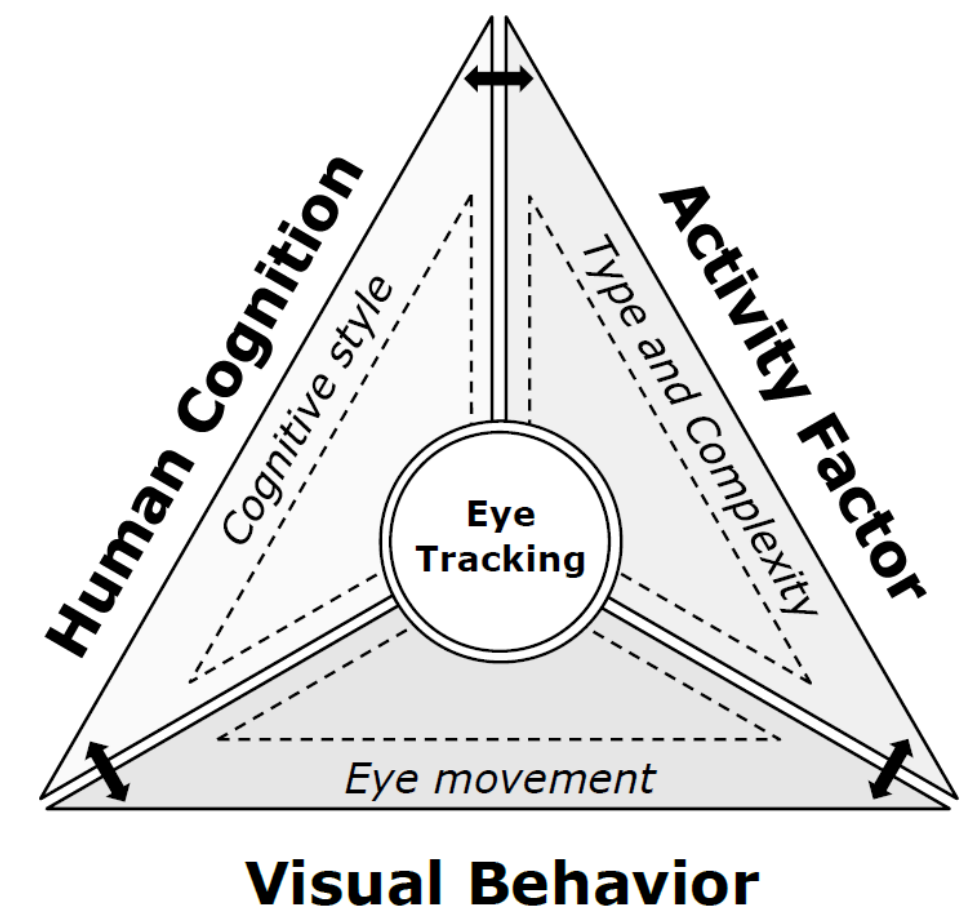
- Build an implicit and real-time elicitation framework of human cognitive styles, based on an eye-tracking multifactorial model
- The model could provide appropriate data for any interactive system to know the users, and adapt to the users' cognitive needs and preferences, to better assist them, so they can benefit from adaptation interventions

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A Multifactorial Model for Implicit Elicitation of Human Cognitive Factors

When humans explore a visual scene

- Humans perform varying **visual activities** which incorporate information processing to some extent, depending on the nature of the **activity**, and thus they involve **human cognition**
- Research has shown that there are inter-dependencies among human cognition, visual behavior, and activity factors



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Method: Implicit Elicitation through Eye-tracking

Eye-tracking

- Use eye gaze data to leverage the interplay among the model factors

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Implicit Elicitation Method

- **Step 1: Data collection**
 - Raw eye gaze data, which is captured through eye-tracking
- **Step 2: Two-phase Data Processing**
 - Decide which eye-tracking measure is the most suitable to perform user classification
 - Transform the data to the corresponding measure.
 - The selection of the most suitable measures depends on the activity and the cognitive style
- **Step 3: Classification**
 - When the transformed eye-tracking measures are provided in the model, it classifies the corresponding individuals on their cognitive style

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Feasibility Studies

- Conducted two studies, with individuals performing different types of visual activity
 - a visual search activity
 - a visual decision-making activity
- Having FD-I as the independent cognitive style variable



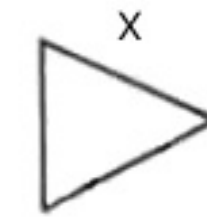
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Feasibility Studies

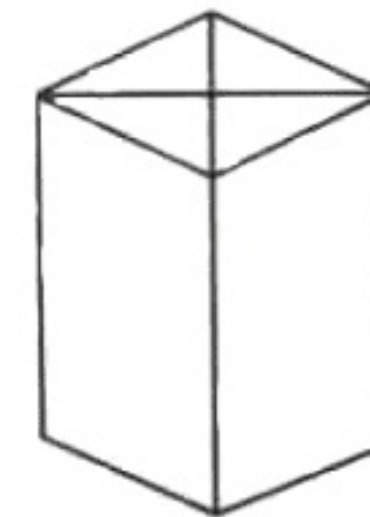
- **Feasibility study I: Visual Search Activity**
 - Used the traditional “paper-and-pencil” FD-I elicitation tool as it is a ground-truth tool for FD-I classification
 - A classic pattern recognition task

- **Feasibility study II: Visual Decision-Making Activity**
 - Graphical user authentication is a representative visual decision-making activity, as the users create their graphical keys by visually scanning, processing, and deciding on the available options

Here is a simple form which we have labeled "X":



This simple form, named "X", is hidden within the more complex figure below:



Feasibility Study I: Method of Study

Hypothesis: *there is a significant difference between FDs and FIs in terms of visual behavior throughout visual pattern recognition tasks of varying difficulty*

- FIs were expected to follow a more oriented and organized approach, while FDs a more disoriented one
- **Participants:** 67 participants (29 females), ranging in age from 20 to 47

Metric: Gaze Transition Entropy

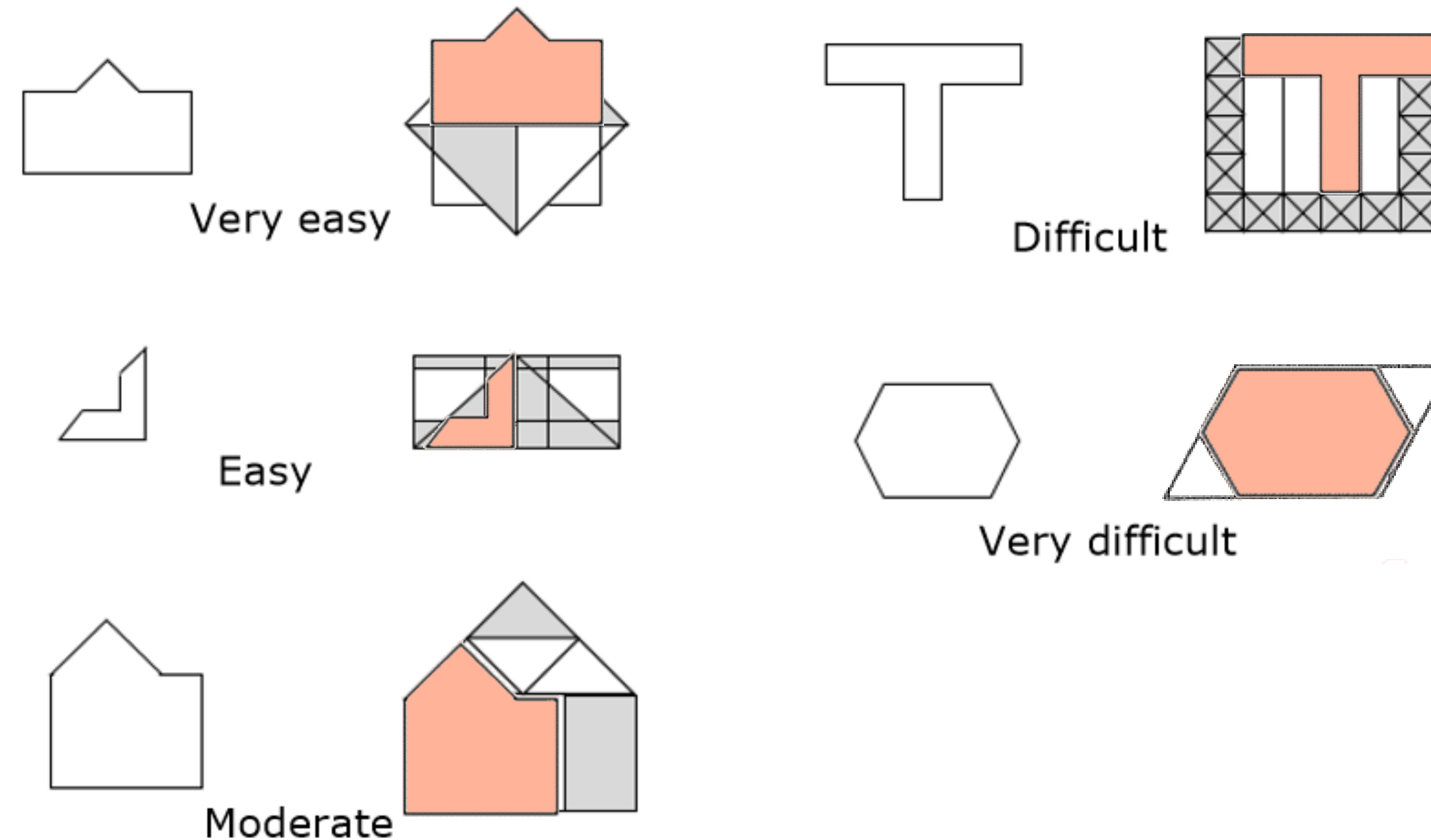
- Entropy measures the lack of order or predictability (*i.e.*, the higher the entropy, the more disordered a system is)
- The gaze transitions made through specific areas of interest of a stimuli, and the stationary distribution of eye-movements over the stimuli, have an impact on visual search behavior
- **Transition entropy H_t**
 - Lower values of H_t indicate more careful viewing of areas of interest, while greater H_t values indicate more randomness and more frequent switching between areas of interest
- **Stationary entropy H_s**
 - Lower values of H_s are obtained when fixations tend to be concentrated on certain areas of interest, while greater H_s indicates that visual attention is distributed more equally among areas of interest

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Feasibility Study I: Visual Search Activity through the GEFT

GEFT

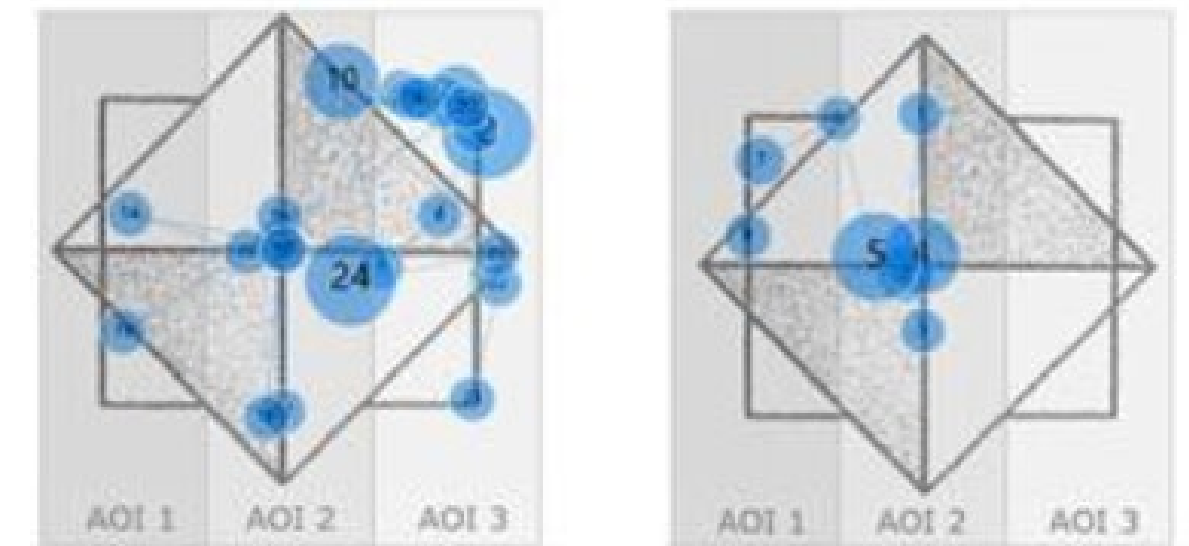
- 18 tasks
- 5 levels of complexity



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Feasibility Study I: Areas of Interest (AOI)

- AOIs: 3 vertical areas
- Scan-paths are transformed in transition matrixes, displaying the probability to perform a gaze transition across the AOIs
 - These matrixes are then transformed into transition entropy values
- Visual behavior metric: **gaze-transition entropy** (Krejtz et al., 2015)
 - Transition entropy measures how random transition are among AOIs



Scan-paths in three vertical AOIs

	AOI 1	AOI 2	AOI 3
AOI 1	67%	22%	11%
AOI 2	10%	70%	20%
AOI 3	25%	50%	25%

	AOI 1	AOI 2	AOI 3
AOI 1	50%	50%	0%
AOI 2	100%	0%	0%
AOI 3	0%	100%	0%

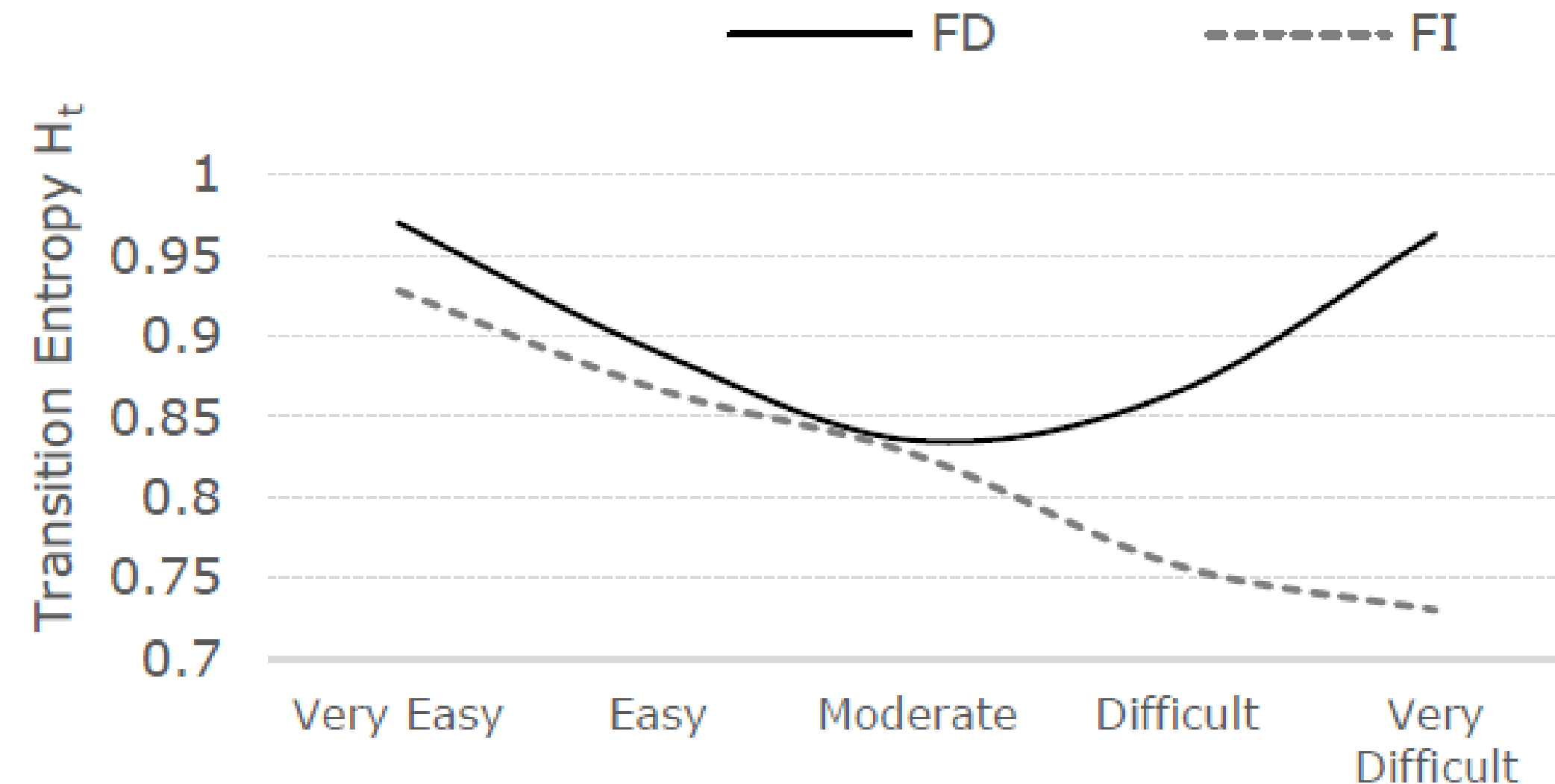
Transition Matrixes: displaying the probability to perform a gaze transition across three vertical AOIs
e.g., the probability to move from AOI1 to AOI2 is 22%

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Feasibility Study I: Results

Gaze transitions

- As the task complexity increases, FDs have higher values of transition entropy H_t than FIs
- This indicates more randomness regarding their eye movements, rather than a systematic approach

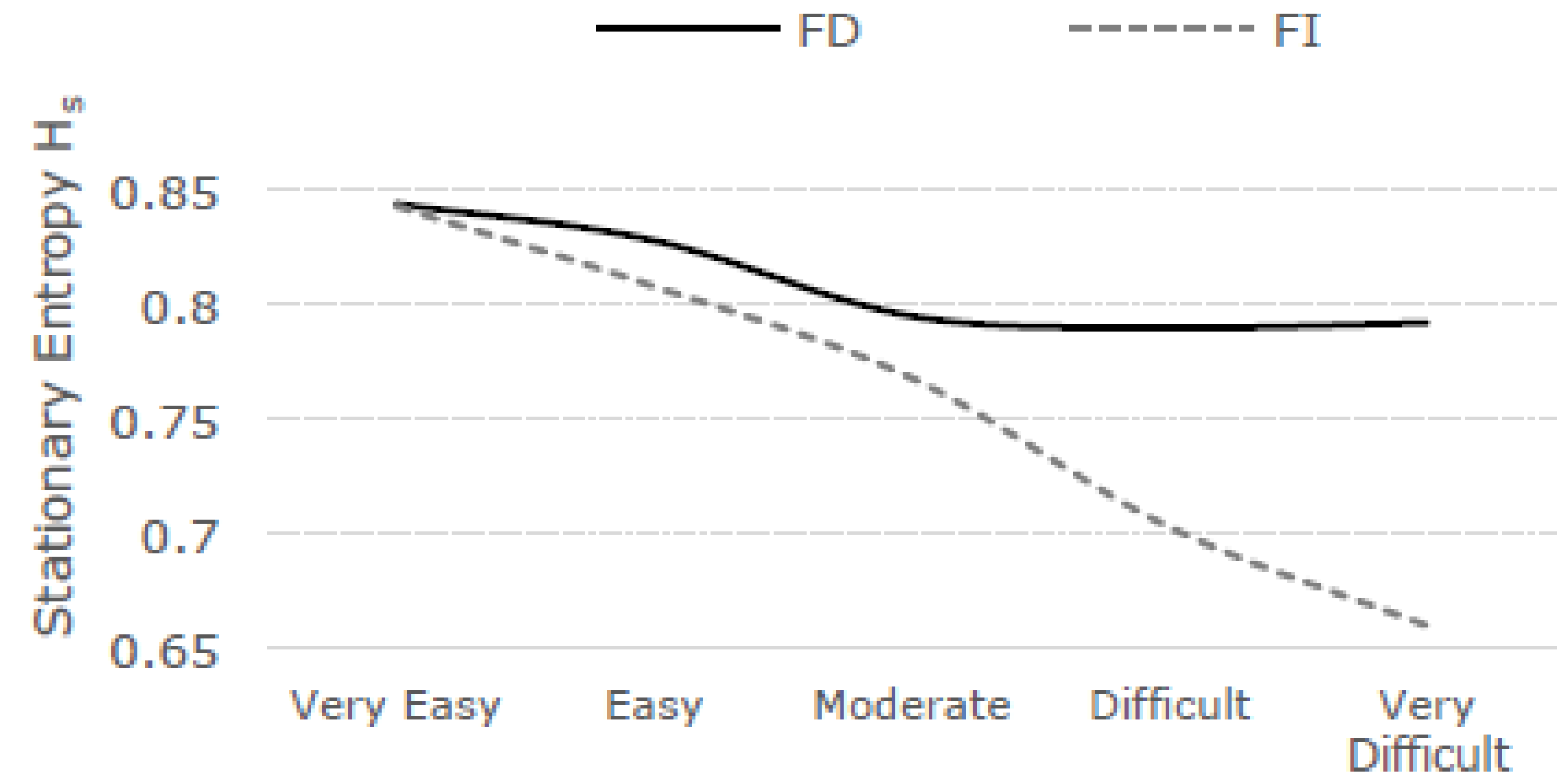


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Feasibility Study I: Results

Visual attention distribution

- As the task complexity increases, **FIs** have lower levels of *H_s* than FDs
- Higher *H_s* values mean that subjects distribute their visual attention more equally among areas of interest; lower ones show that their fixations are concentrated on certain areas of interest



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Feasibility Study I: Classification Experiments

Training phase

- Formed the model training set, based on the extracted classification metrics (i.e., transition and stationary entropies)
- Tested Classifier types
 - Logistic Regression, Naive Bayes, k-Nearest Neighbors, Classification and Regression Trees, and Support Vector Machines

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Feasibility Study I: Classification Experiments

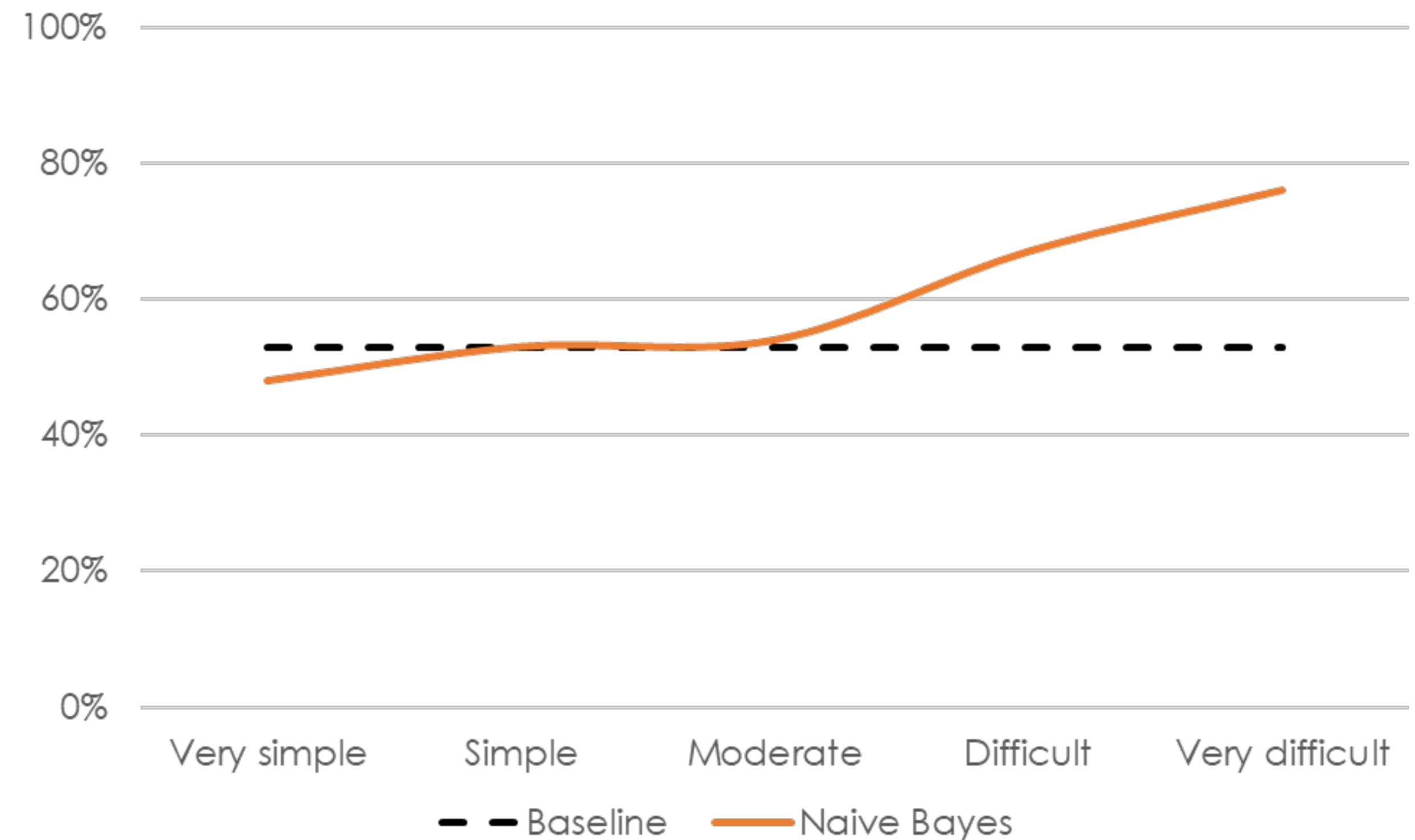
Testing phase

- Recruited 21 individuals (9 females), aged between 25 and 41
- **Naive Bayes** classified correctly 81% of users
 - 9/10 FDs
 - 8/11 FIs
- The prediction certainty of Naive Bayes classifier was $82.22\% \pm 16.67\%$ for FDs, and $79.86\% \pm 19.88\%$ for FIs
- False predictions were made on relatively low certainty rates (60.4% for the misclassified FD, and 50.6%, 61.3%, and 65.4% for the misclassified FIs)

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Classification Results

- Only in the “very difficult” task: 76% - (30-90 seconds)
- Combined difficult and very difficult: 81% - (50-120 seconds)



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Feasibility Study II: Method of Study

- **Hypothesis:** *there is a significant difference between FDs and FIs in terms of visual behavior throughout visual decision making tasks of specific sequence*
- **Participants:** 51 individuals (16 females), aged between 18 and 40
- **Metrics:** Participants selected 5 images as their graphical password. Prior selection, the following were measured for each image:
 - **Fixation duration:** how long (in seconds) the user focused on each image
 - **Fixation count:** on how many images did the user focus

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Feasibility Study II : Visual Decision Making and AOs

- Visual behavior metric: **Number of fixations on AOs**
- AOs: **Each image**

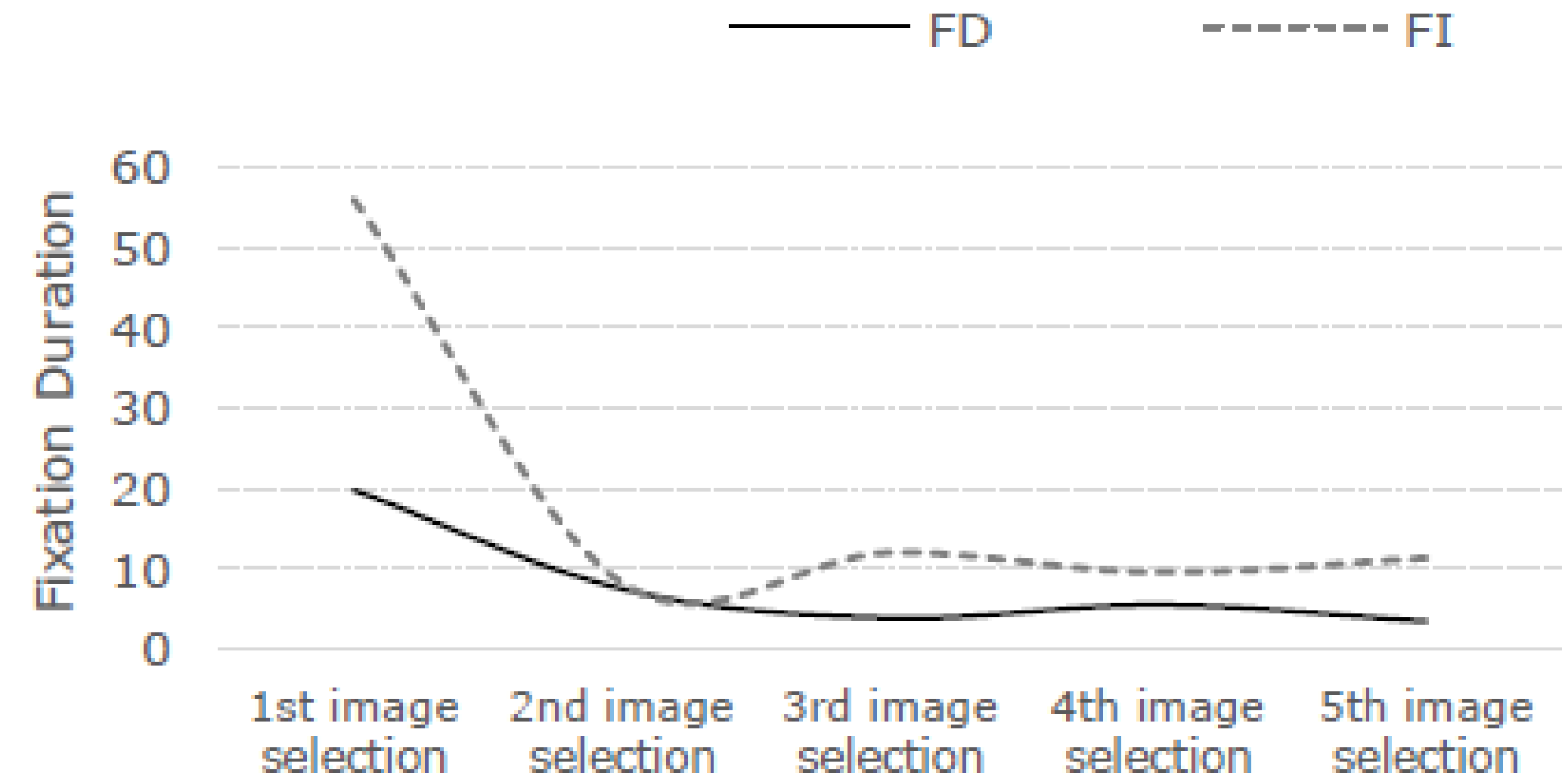


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Feasibility Study II: Results

Fixation duration (sec) for each image selection

- The fixation duration of **FIs** (54.30 ± 32.12 sec) was **significantly longer** than **FDs'** (19.78 ± 18.80 sec), from load until the **selection of the first image**

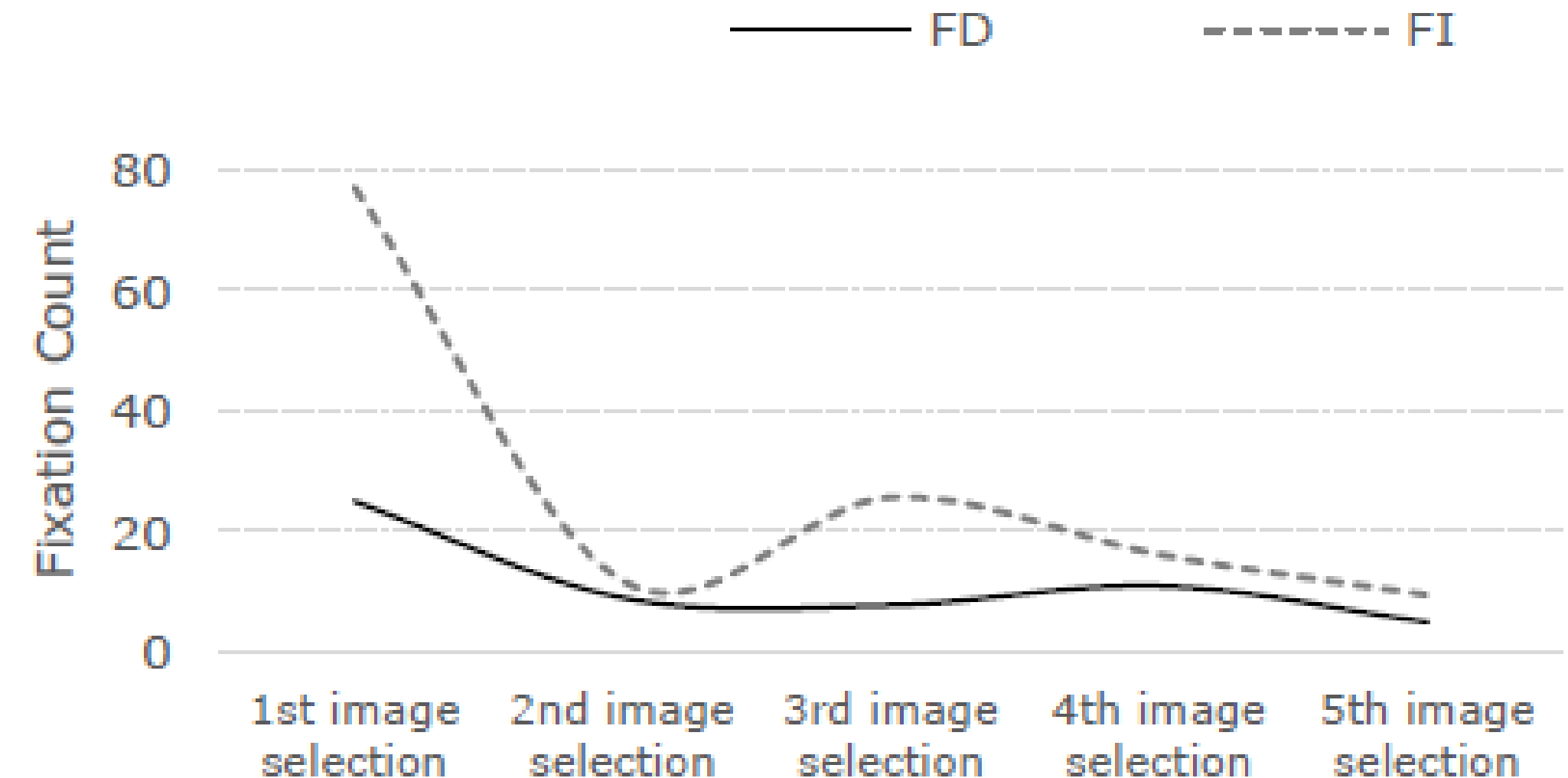


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Feasibility Study II: Results

Fixation count for each image selection

- The fixations made on areas of interest by **FIs** (76.01 ± 51.11) were **significantly more** than the ones made by **FDs** (24.89 ± 20.09), from load until the **selection of the first image**



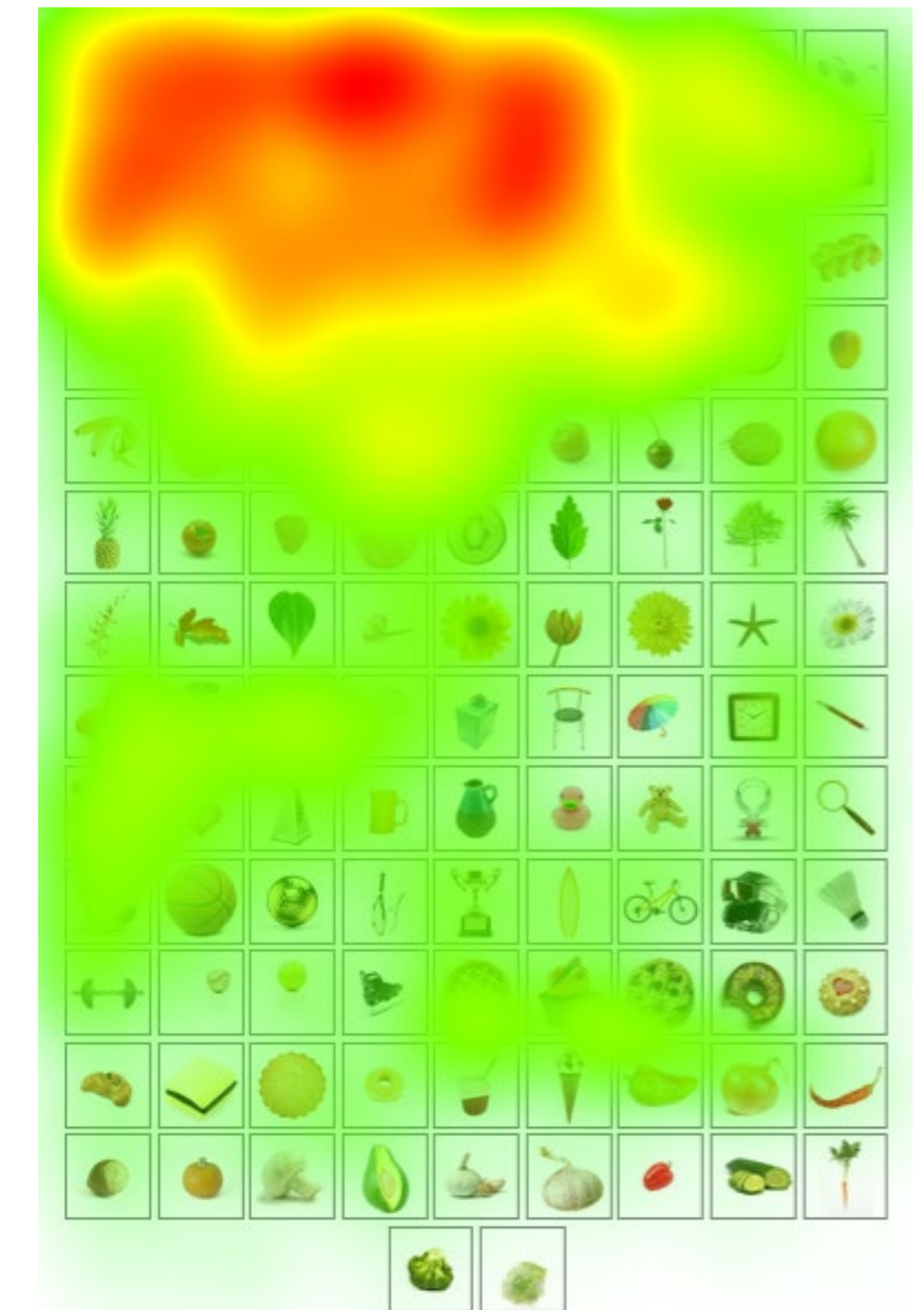
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Heat Maps based on Fixations

- Heat map data further indicate that FI individuals scanned a larger part of the image grid, and fixated on a larger number of images than FDs



Field dependent



Field independent

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Feasibility Study II: Classification Experiments

Training phase

- Formed the model training set, based on the extracted classification metrics (i.e., fixation duration and count)
- Tested Classifier types
 - Logistic Regression, Naive Bayes, k-Nearest Neighbors, Classification and Regression Trees, and Support Vector Machines

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Feasibility Study II: Classification Experiments

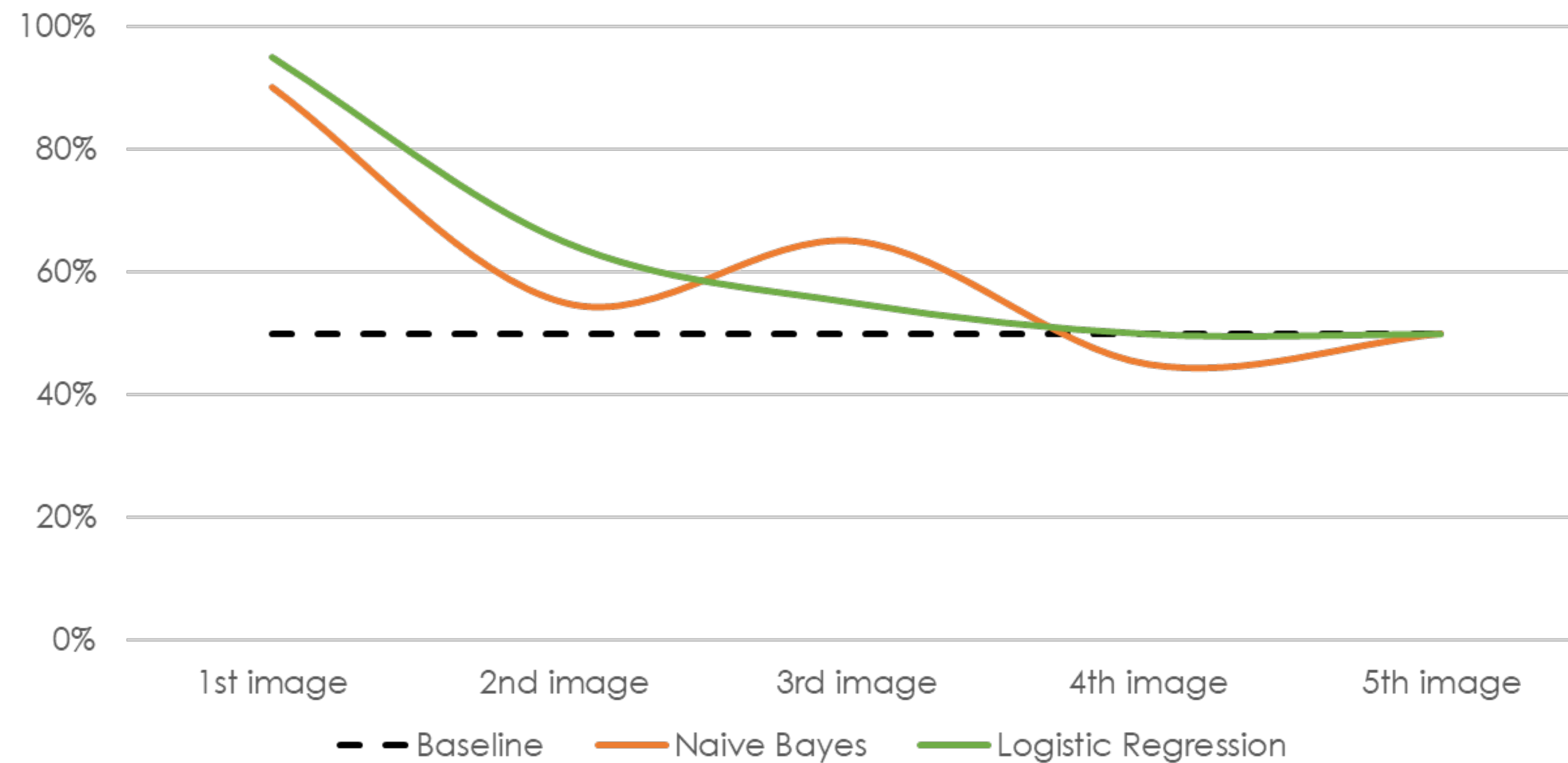
Testing phase

- Recruited 20 individuals (9 females), aged between 25 and 38
- **Naïve Bayes** classified correctly 90% of users
 - All FDs were correctly identified
 - 8/10 of FIs were correctly identified
- **Logistic Regression** classified correctly 95% of users
 - All FDs were correctly identified
 - 9/10 of FIs were correctly identified

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Classification Results

- Only 1st image:
 - NB: 90%
 - LR: 95%



Summary of Findings

Visual Search Tasks

- **FIs** follow a more organized and oriented visual search strategy when performing visual search tasks of increased difficulty while **FDs** followed a more disoriented approach
- Naive Bayes classifier performed best
 - Correctly identified 81% of users when considering high difficulty types

Summary of Findings

Visual Decision-making Activities

- **FIs** produced **more and longer fixations** on the first of the tasks required (sequence dependent activity)
- Naive Bayes and Logistic Regression classifiers performed best
 - 90% accuracy rate for Naive Bayes
 - 95% accuracy rate for Logistic Regression

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Summary of Findings

FD-I style was correctly identified for:

- **17/21 (81%)** participants in less than **2** minutes for **visual search** activity
- **19/20 (95%)** participants in less than **1** minute for **visual decision making** activity

based only on eye-tracking data

LAB 2**Real-time elicitation of the users' cognitive styles is feasible via his/hers visual behavior**

- Cognitive-centered User Modelling in Graphical Passwords
 - Real-time Eye Gaze-driven Prediction of Human Cognitive Factors during Graphical Password Composition

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Recall-based Graphical Authentication

- Users draw gestures on a background image to login
 - Combination of tabs, circles, straight lines

Set up your gestures

Draw three gestures on your picture. You can use any combination of circles, straight lines, and taps.

Remember, the size, position, and direction of your gestures — and the order in which you make them — become part of your picture password.

1 2 3

Start over

Cancel



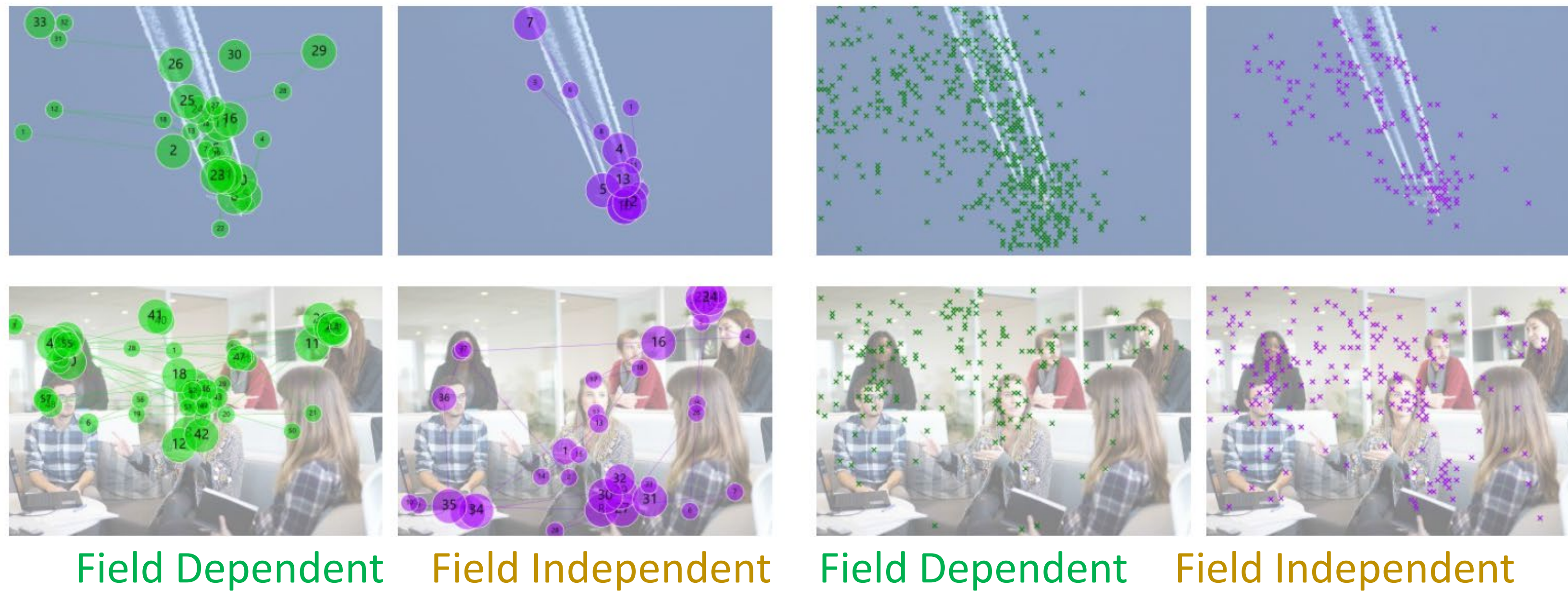
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Influences of Human Cognition and Visual Behavior on Password Strength

- Visual attention, search, processing and comprehension are important cognitive tasks during a graphical password composition activity
- Is it feasible to use real-time eye-gaze data to elicit the FD-I style when users are engaged in a graphical password composition task?

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Gaze and Scatter Plots of a typical FD vs. FI individual



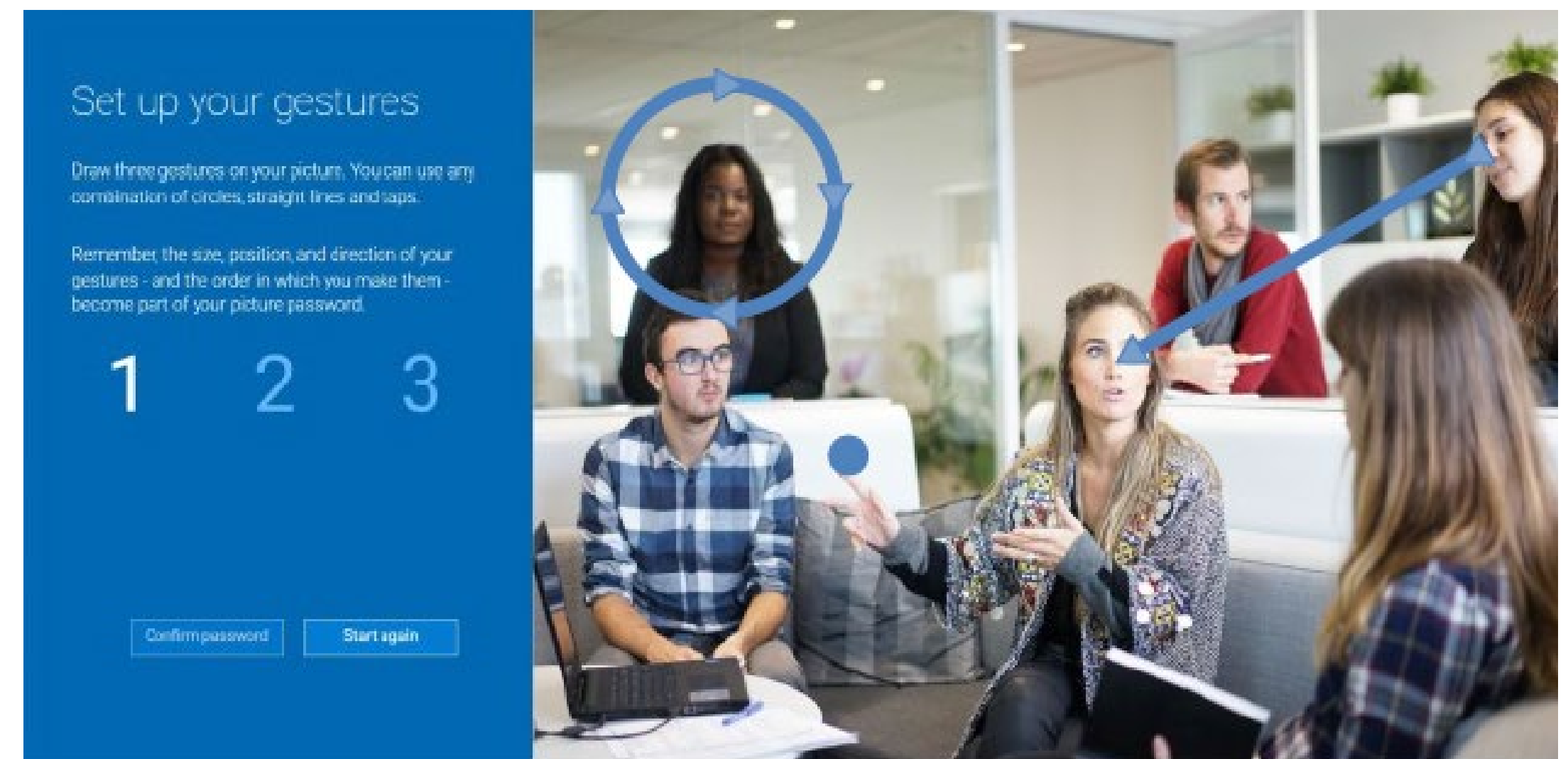
Procedure

- **Users interacted with a GUA in a real-life task in which their eye-gaze data was measured and further used a validated cognitive elicitation tool (GEFT) as ground truth**

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Graphical User Authentication Scheme

- Used Windows™ Picture Gesture Authentication
- Draw a combination of tabs, circles, straight lines to login
- To store gestures, a grid is created on the image by dividing the longest dimension of the image into 100 segments and then dividing the shortest dimension by the same scale



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Equipment

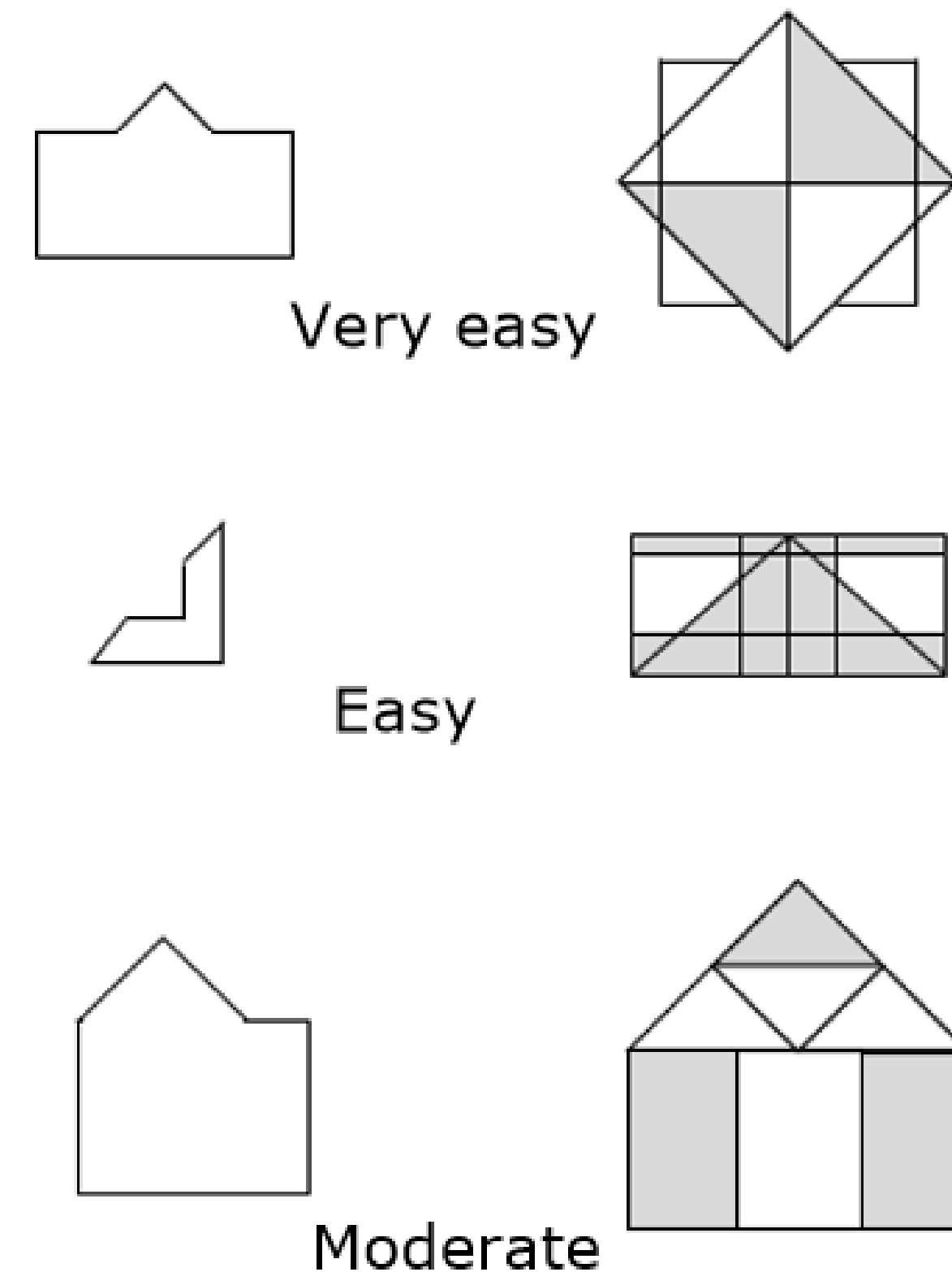
- Tobii Pro Glasses 2
- Fixations were extracted using a velocity threshold identification (I-VT) algorithm by Tobii



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Cognitive Style Elicitation Test

- Group Embedded Figures Test (GEFT)
- Consists of 18 pattern-recognition tasks
- Identify a given pattern within a complex context
- The higher the score, the more field independent you are



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Eye-Gaze Metrics

- **Fixation duration:** total duration of fixations of an individual within an area of interest (AOI), considering visits and revisits to the AOI
 - sum, mean, max, and std.
- **Fixation count:** total number of fixations of an individual within each AOI, considering visits and revisits to the AOI
- **Saccade length:** distance between rapid eye movements from one fixation to another
 - sum, mean, max, and std.

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Classification Experiment

- Performed a classification on the sample
- **Divided the activity time in time-slots of 1 second**
 - **Starting as soon the user was engaged with the task**
 - Users were classified either as FD or FI
 - Accuracy rate in relation to the ground-truth GEFT classification
- Compared the classification results with a baseline model (ZeroR classifier)
- Tested several classifiers (Logistic Regression, Naïve Bayes, k-Nearest Neighbors, Classification and Regression Trees, and Support Vector Machines)
- **Logistic Regression (LR) provided the best results**

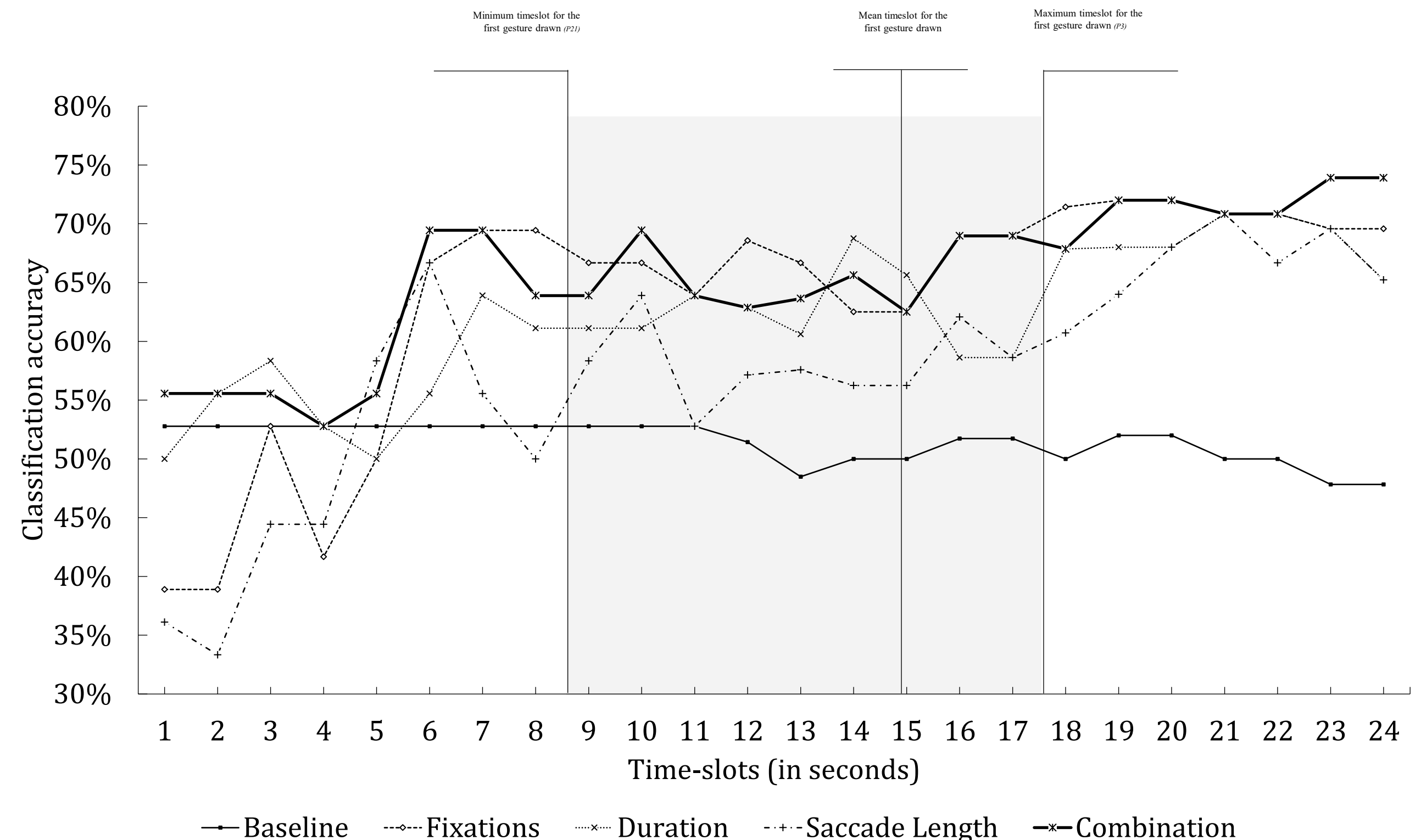
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Results

Peak accuracy of 72% and an upward trend of the combined model after the 4th sec

Early predictions

- LR achieved maximum accuracies (over 63%) between the 6th and 10th time-slot
- LR performed better than the baseline in all time-slots (apart from the 4th)



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Results

Different metrics performed best for classifying FDs and FIs in terms of F-measure

- **FD:** the most effective metric was the saccade length ($F=.795$)
- **FI:** the most effective metric was the fixation count ($F=.767$)

- This could be attributed to the visual behavior differences between FD and FI
 - FDs tend to produce more fixations than FIs
 - FDs search in a more unarticulated and disoriented way, visually scanning different areas, producing saccades of larger length

Summary

- **Real-time (around 6 seconds) elicitation of the users' cognitive styles is feasible by via his/hers visual behavior during graphical password composition task**

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Sources

- Raptis, R., Katsini, C., Belk, M., Fidas, C., Samaras, G. Avouris, N., (2017). Using Eye Gaze Data and Visual Activities to Infer Human Cognitive Strategies: Method and Feasibility Studies. In Proceedings of ACM UMAP Conference (ACM UMAP 2017), ACM Press, 8 pages
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Thank you.