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IJCCI 2018

10th International Joint Conference on Computational Intelligence

Adapted Psychological Profiling Verses the Right to an Explainable Decision

Keynote Lecture at the 10th International Joint Conference on Computational Intelligence

Dr Keeley Crockett Leader - Computational Intelligence Lab – Manchester Metropolitan University)

With special thanks to

Prof. Dr. Tina Krügel, LL.M – Leibniz University Hannover

Dipl.Jur. Jonathan Stoklas – Leibniz University Hannover

Dr James O'Shea and Dr Wasiq Khan – Manchester Metropolitan University

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Leibniz Universität Hannover

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Who Am I ?

- Reader in Computational Intelligence
  - Fuzzy trees, forests and ensembles
  - Genetic algorithms and AIS for optimisation
  - Neural networks
  - More decision trees
  - Semantic similarly
  - Intelligent tutoring Systems
  - Fuzzy natural language processing
- Leader of the Computational intelligence Lab
- Qualified Coach and Mentor
- IEEE Volunteer, IEEE Coach and Mentor
- STEM Volunteer

Intelligent Systems Group

fhi360 THE SCIENCE OF IMPROVING LIVES

ServicePower

AccessPay

Silent Talker INTELLIGENT SYSTEMS

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Overview

- Adaptive psychological **profiling** and **non-verbal** behavior
- **Silent Talker** - Automated Deception Detection
- Case Study: Intelligent Border Control in the European Union
- Case Study: Profiling ***comprehension***
    - Measuring Comprehension of Individuals During a Mock Medical Informed Consent Trial Using **FATHOM**
    - **Hendrix** – a near real time conversational intelligent tutoring system adaptive to comprehension
- **Ethical considerations …** and the **General Data Protection Register**

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Psychological Profiling with Artificial intelligence

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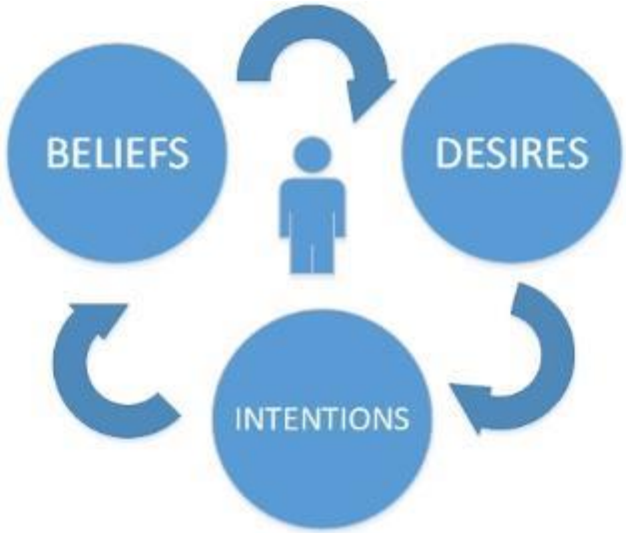
What is Physiological Profiling ?

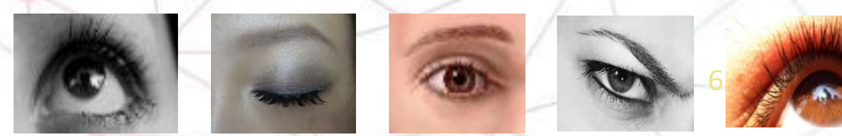
- The detailed and intricate **analyses** of the **non-verbal behaviour** of a person, often in an interview situation to **detect their mental state**
- Non-verbal messages are continuous and are, at least in part, involuntary and unintended.
- **Complex** - requiring simultaneous conjecture of many non-verbal signals.



Nonverbal Behaviour

- Measure of a mental, behavioural and/or physical state
  - (e.g. stress, deception, tiredness).
- Gestures - ambiguous/controllable
- Expressions (normal, micro, squelched)
  - ambiguous/controllable (especially normal expressions, research focus is on extreme expressions)
- Microgestures - less likely to be controlled, large number, complex
- Overall behaviour is MULTICHANNEL
  - faking unlikely due to lack of congruence

Source: Designed by Rawpixel.com - Freepik.com



The Science of Lying

- “On any given day we're lied to from 10 to 200 times” - Pamela Meyer, author of Lie spotting
- 6 Ways to Detect a Liar in Just Seconds – Psychology Today
- The act of deceiving changes behaviour
- Exposing Liars through Science



Source:The Lying Game: The Crimes That Fooled Britain – Shine, ITV, 2014

Detecting Deception

- Polygraph
- Voice Stress Analysis
- Human Based Detection
- Automated Deception Detection

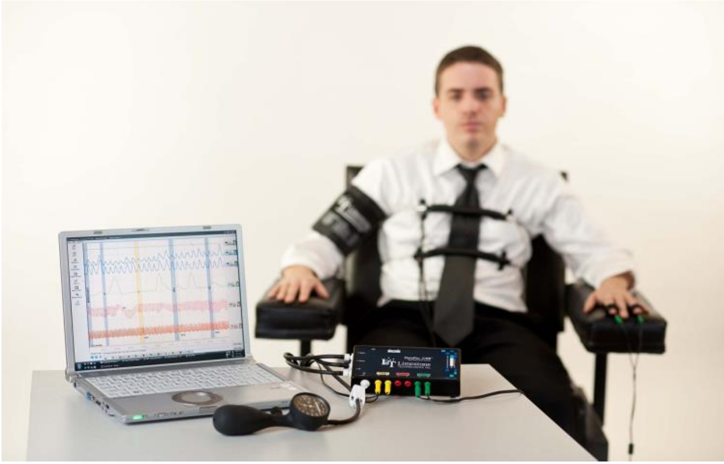
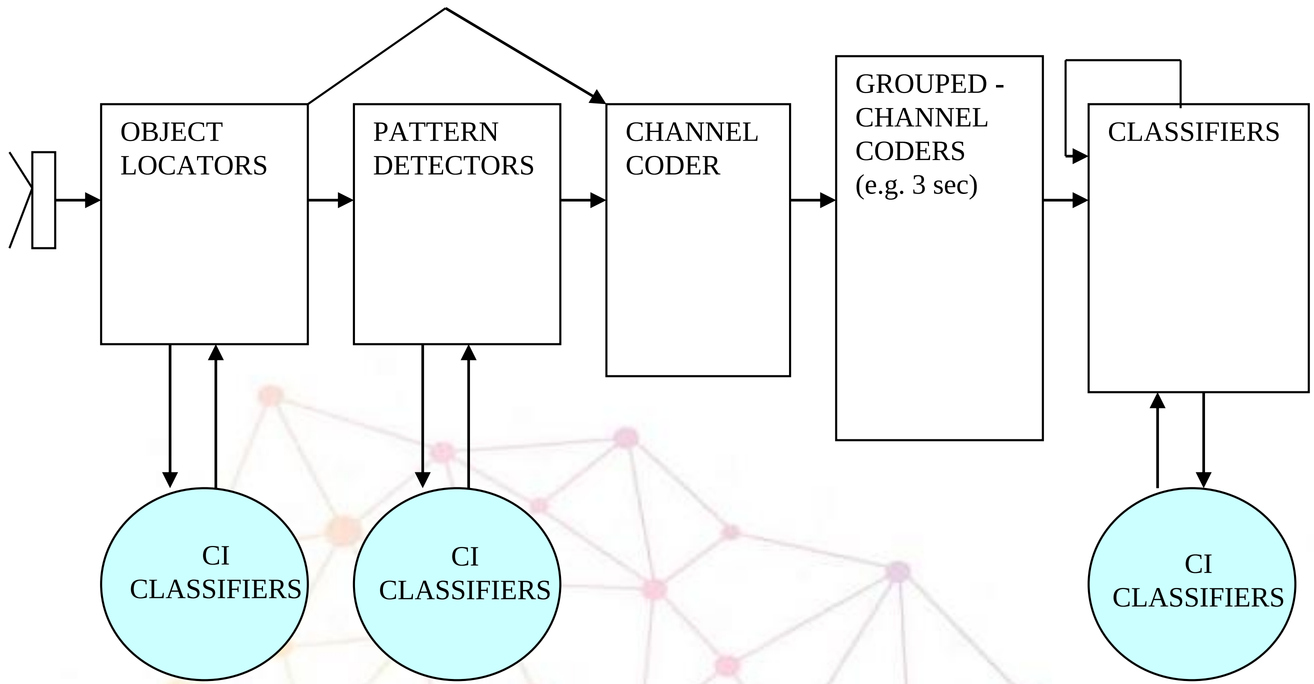


Image Source: Prof Nick Bowring, MMU.

Automated Lie Detection : Silent Talker

- Extraction and Analysis of Multi-channels of Non-verbal Behaviour using CI Classifiers
- Nonverbal Behaviour - All the signs and signals - visual, audio, tactile and chemical (93%) used by human beings to express themselves apart from speech and manual sign language (7%)
- Multi-channels – A large number of fine-grained nonverbal gestures are monitored to make the classification
- ST patent covers a wide range of CI and statistical techniques, but heavy use is made of Artificial Neural Networks (Bandar, J., McLean, D., O'Shea, J. and Rothwell, J. ANALYSIS OF THE BEHAVIOUR OF A SUBJECT WO02087443).

Silent Talker Architecture



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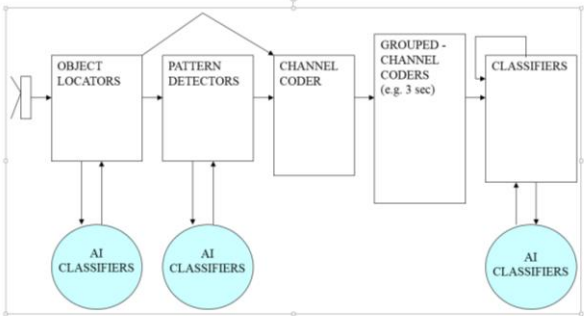
Multichannels



- The total nonverbal behaviour is multichannel (e.g. 1 – 3 seconds gives channel data)
- Each channel monitors a specific microgesture (representing a single aspect of the overall behaviour exhibited by the subject)
  - e.g. a small head movement, pupil contraction, mouth corner twitch or one eyebrow raised momentarily
- Channel processing requires a combination of CI and image processing techniques
  - Location of the interviewee
  - Location of the features being measured
  - Detection of the status of the features

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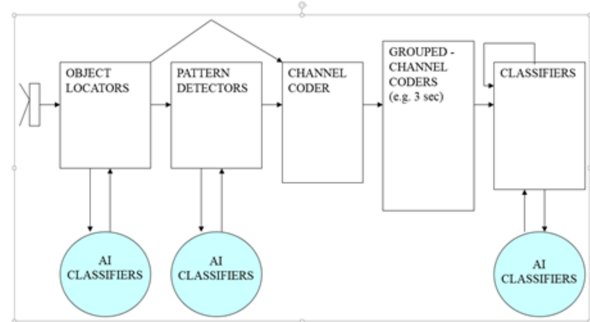
CI classifiers



- Typically the final classifier is a type of artificial neural network trained by supervised learning
- This requires creation of training / validation / testing data……
- This requires careful experimental design to eliminate confounding factors etc.
- Is a generic deception detector possible? We believe so, based on psychological / philosophical work by John Searle on beliefs, desires and intentions.

BIAS

How does Silent Talker work?

- Not objectively - ST is a collection of black box technologies.
- Underlying conceptual model that certain factors influence NVB during deception
- **Stress** (measured by other lie detectors)
- **Cognitive load** (George A. Miller - Magical Number 7 +/- 2)
- **Behaviour Control** – Steven Lawrence Suspects
  - http://youtu.be/XvZuX9hq-Is 3-4,6,9 minutes
  - Arousal (Guilty Knowledge*, Duping Delight)

- Can you train people to reproduce ST's capabilities?
  - No – we replaced our final classifier with a trained decision tree, thousands of decision nodes beyond the capability of a human mind to learn and apply

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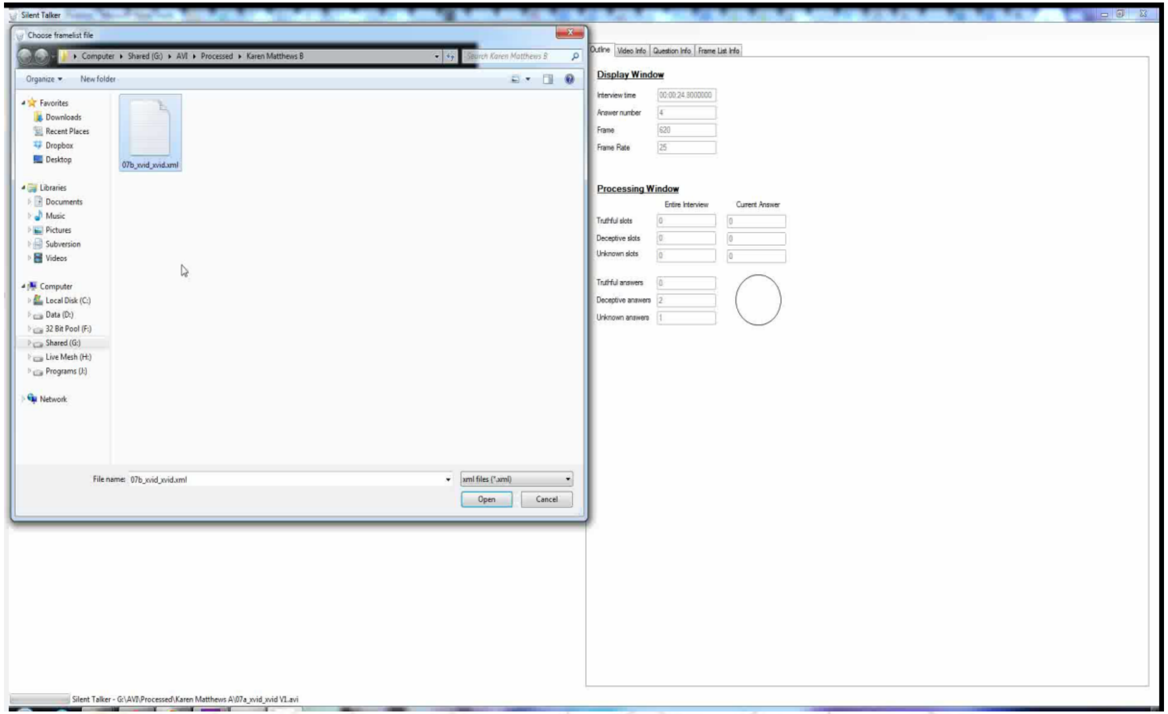
Silent Talker Demonstration



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The Lying Game: The Crimes That Fooled Britain – Shine, ITV, 2014
Silent Talker in operation, (42m 20s)
https://youtube/zkUAFwQzD3g

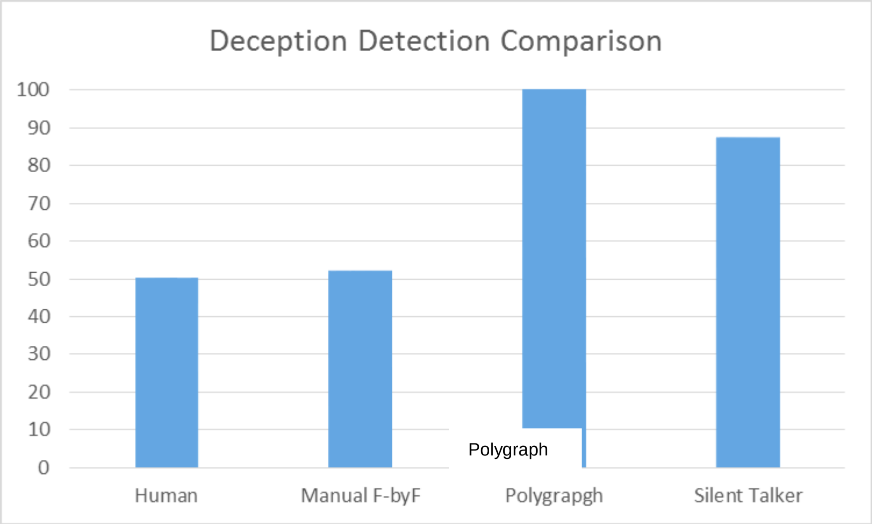
Original Silent Talker Results Comparison

- **Humans** do no better than chance, but individuals may do better in a specialised field over a limited time.

- **Manual Frame-by-Frame**, manual processing of video taped interviews. Subjective judgement of an individual expert. Expensive. Error-prone.

- **Polygraph** Accuracy depends on whose opinion you take - 0 to 100% quoted

- **Silent Talker**: non invasive, many channels, cheap, unbiased………..



Potential Applications*

- Security interviews
  - Smuggling at ports / airports
  - Border control, illegal immigration
  - “Shoplifting”, retail employee theft
  - Rogue Traders, city investment banks
  - Paedophiles, parole process
  - Tiredness, Long distance drivers
  - Drunkenness/ Intoxication, aircraft boarding
  - Witness credibility

- Counter Infiltration Employee screening
  - Shooting into crowds
  - Counter-infiltration
  - Improvised explosive devices
  - Sentry / Checkpoint protection

* Many of these potential applications have been proposed by domain practitioners during demonstrations

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Ethical Dimensions – the GDPR

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Robots 'could take 4m UK private sector jobs within 10 years'

Royal Society of Arts survey suggests technology could phase out mundane roles, raise productivity and bolster wages

Ban on killer robots urgently needed, say scientists

Technology now exists to create autonomous weapons that can select and kill human targets without supervision as UN urged to outlaw them

Image and Story Credits:

1. https://spectrum.ieee.org/

2. https://spectrum.ieee.org/the-human-os/biomedical/devices/selfdriving-wheelchairs-debut-in-hospitals-and-airports

3. https://www.theguardian.com/science/2017/nov/13/ban-on-killer-robots-urgently-needed-say-scientists

Profiling and Automated Decision-making

Profiling → Decision

Profiling: gathering information about an individual and analysing his/her behaviour patterns in order to place them into a certain category or group, and/or to make predictions or assessments

Decision: the ability to make decisions based on certain information, including personal information such as profiles without human interaction

Automated decision-making under the GDPR

- General Data Protection Regulation (GDPR) (Regulation (EU) 2016/679, 2016): **25 May 2018**.
- Art. 22 (1) GDPR states an **automated decision** is a decision based solely on automated processing, including **profiling**, which produces **legal effects** concerning him or her or similarly **significantly affects** him or her.

Image Source: https://www.forescout.com/wp-content/uploads/2018/03/three-reasons-GDPR-good.png

Safeguards and information obligations

- Article 22 is "***The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her***"
- the individual has the right to ask for human intervention and provide an explanation of how the machine based decision has been reached through disclosure of "***the logic involved***"
- Recital 71 states that the **data controller should use appropriate mathematical and statistical procedures for profiling and that data should be accurate in order to minimize the risk of errors.**

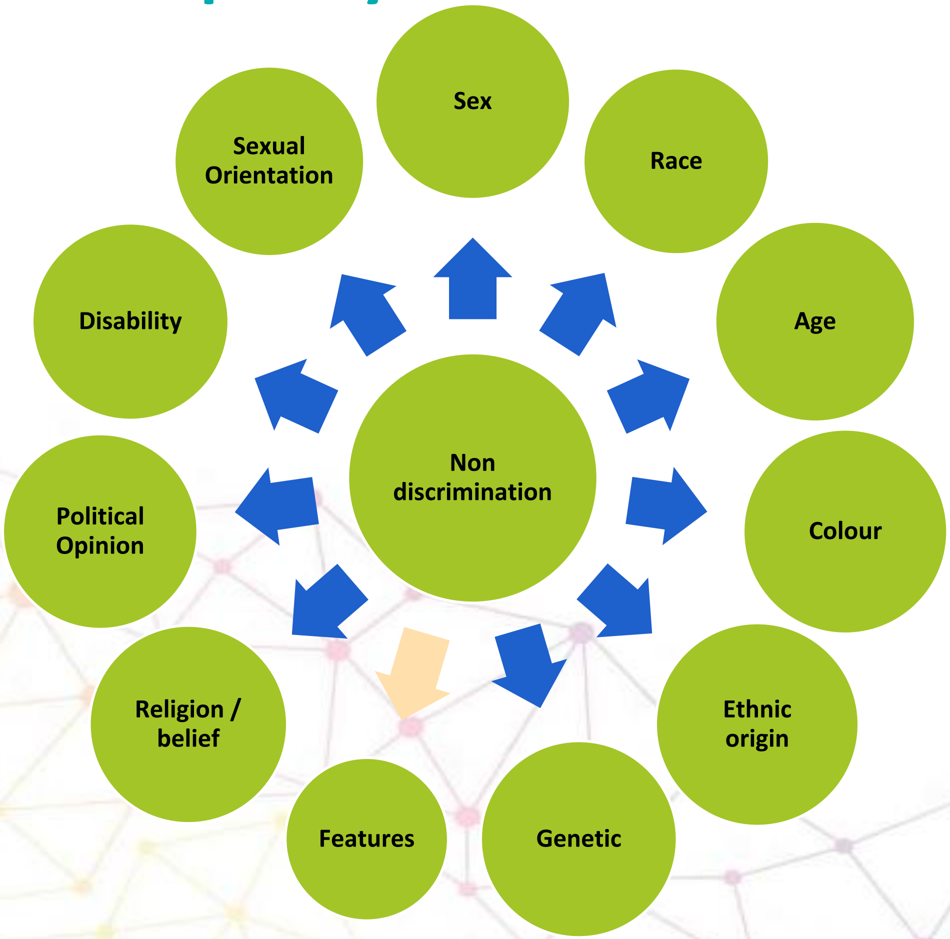
The right to receive an explanation

- Individuals will now have the right, "***not to be subject to a decision…which is based solely on automated processing and which provides legal effects (on the subject).***"
- How easy is this ?
  - Decision trees Verses artificial neural networks
  - Is the language friendly to the public ?
- Dinsmore [8] argues that the requirement may force data scientists to stop using techniques such as deep learning where decisions are more difficult to explain and interpret

Challenges for the technical community

- How to properly assess the legal situation regarding automated decision-making and on how to apply proper safeguards?
- How to explain an algorithm without leaking trade secrets?
- How can algorithms based on computational intelligence be explained?
- Can the information on how an algorithm learns be sufficient to understand it’s functioning and decision-making?
- Can self-learning algorithms also explain their decision-making, and could this be updated frequently for every user?

CI and the principle of equality and non-discrimination



The Risk of False Positives and Negatives

Individual	Society
Discrimination	Security
Equality	Humans are not perfect either…
Burden of proof	Better overall results (?)

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Case Study: IBorderCtrl

H2020 Project Grant Agreement No. 700626

Grant: 4.5 M Euro

Start: 1 Sep 2016 (M1)
End: 31 Aug 2019 (M36)

13 Partners, 9 Countries

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 700626.

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i BORDER Ctrl
Intelligent Portable Control System
i BorderCtrl mission
To provide a **unified solution** in a **two-stage-procedure** with aim to **speed up the land border crossings** and at the same time **enhance security** by bringing together many **state of the art technologies**.
i BorderCtrl system
follows the principles of the Entry/ Exit (EES) and the European Travel Information and Authorisation (ETIAS) Systems
paves the way towards the Interoperability of EU systems for security, border and migration management
i BorderCtrl modules
Storage/ Applications
Document Authenticity Analytics Tool
Biometrics Module - Palm Vein
Biometrics Module - Fingerprints
External Legacy and Social interfaces
Border Control Analytics Tool
RISK
Risked Based Assessment Tool
Hidden Human Detection Tool
Automatic Deception Detection System and Avatar
Face Matching Tool

i BorderCtrl innovations

- **Introducing a Pre-Registration Phase:** Travellers -before arriving at the borders- register through their mobile phone, tablet or computer, submit their travel documents and participate in an interview by a virtual border agent.
- **Empowering border guards at Border Crossing:** Key technologies are provided to the border guards, both integrated to existing static installations as well as in a portable hardware unit.
- **Conducting a Risk Based Assessment:** Takes advantage of the checks outcomes and classifies travelers in terms of risk, supporting the decision-making of the border guard.
- **Introducing Analytics in the Border Control context:** Analysis of data to identify new patterns and knowledge in order to increase the accuracy at the individual crossing level.
- **Speeding up the border crossing** for valid and bona-fide travelers while highlighting those that must be further checked by agents.
- **Going beyond Biometrics:** Collects data onto biomarkers stemming from the virtual border agent interview, indicating the probability of deceit.
- **Cross-checking traveler's information from legacy systems and social media,** such as VIS, SIS II and Twitter providing the necessary interoperability interfaces.
- **Enhancing the User Experience through three Applications/Interfaces:** Traveler User Application, Border Guard User Application for the border checks and Border Manager User Application for the superiors responsible for resources management.

iBorderCtrl technologies

Traveller and Border Guard Applications

Consortium

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 700626.

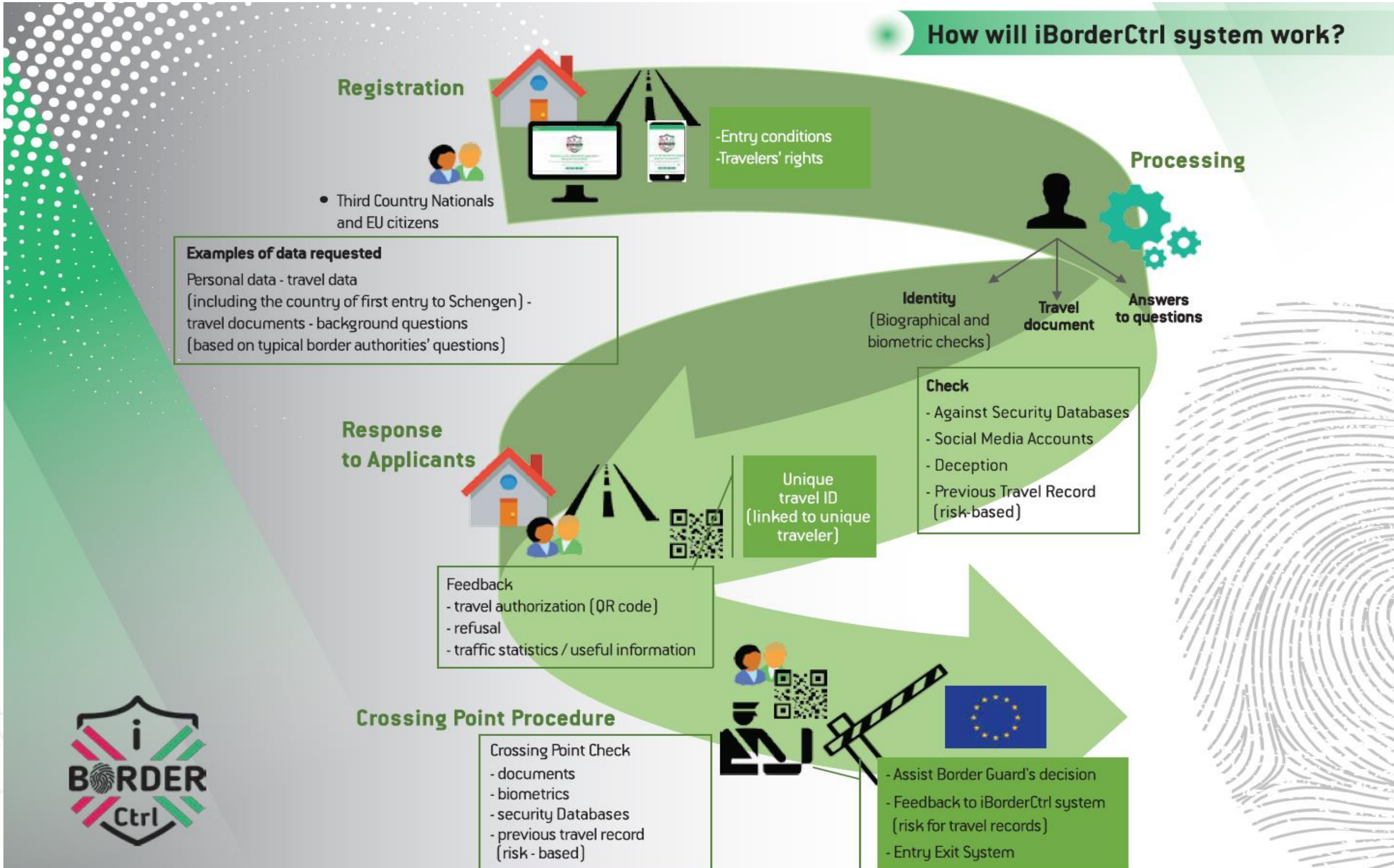
European Commission

www.iborderctrl.eu

@iBorderCtrl

iBorderCtrl

Scan here to visit the iBorderCtrl website:


How will iBorderCtrl system work?
Registration
-Entry conditions
-Travelers' rights
Third Country Nationals and EU citizens
Examples of data requested
Personal data - travel data
(including the country of first entry to Schengen) - travel documents - background questions
(based on typical border authorities' questions)
Processing
Identity (Biographical and biometric checks)
Travel document
Answers to questions
Check
- Against Security Databases
- Social Media Accounts
- Deception
- Previous Travel Record (risk-based)
Response to Applicants
Unique travel ID (linked to unique traveler)
Feedback
- travel authorization (QR code)
- refusal
- traffic statistics / useful information
Crossing Point Procedure
Crossing Point Check
- documents
- biometrics
- security Databases
- previous travel record (risk - based)
- Assist Border Guard's decision
- Feedback to iBorderCtrl system (risk for travel records)
- Entry Exit System
i BORDER Ctrl

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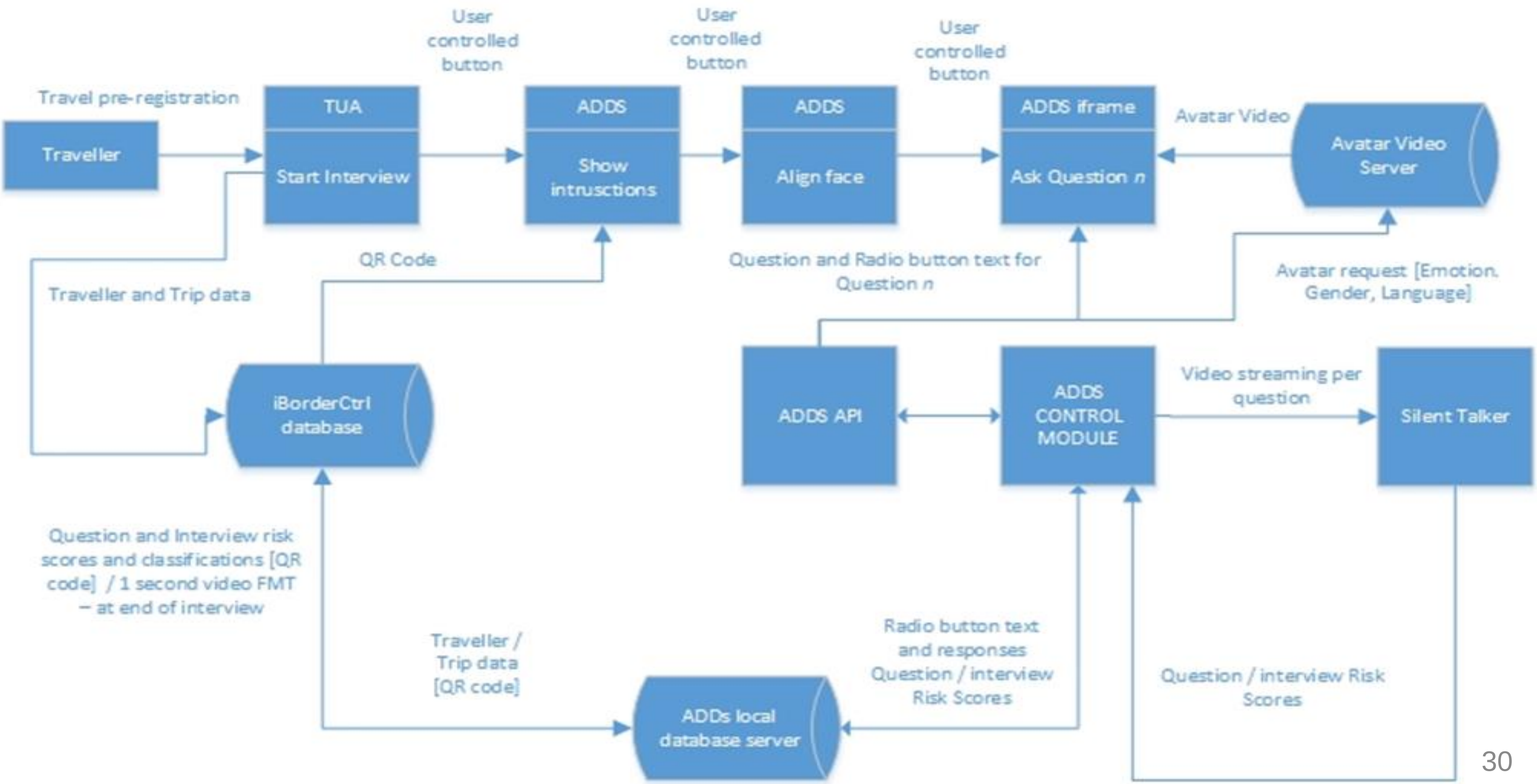
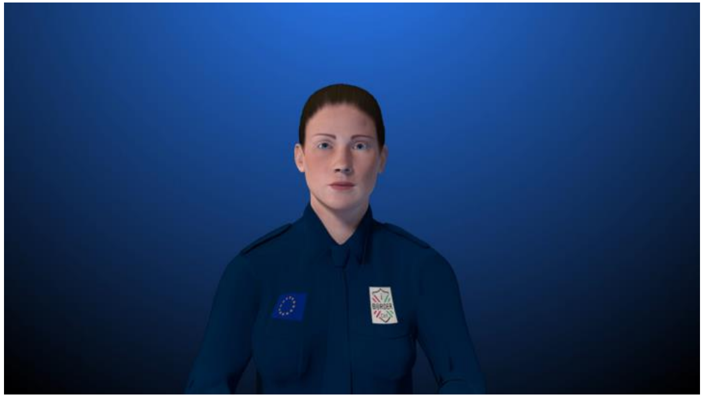
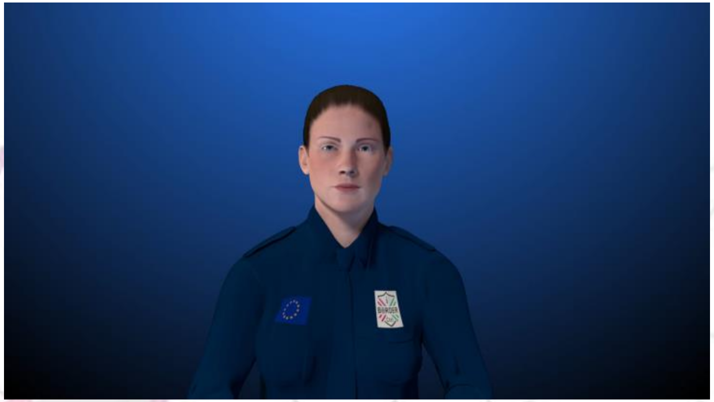
Automated Deception Detection System

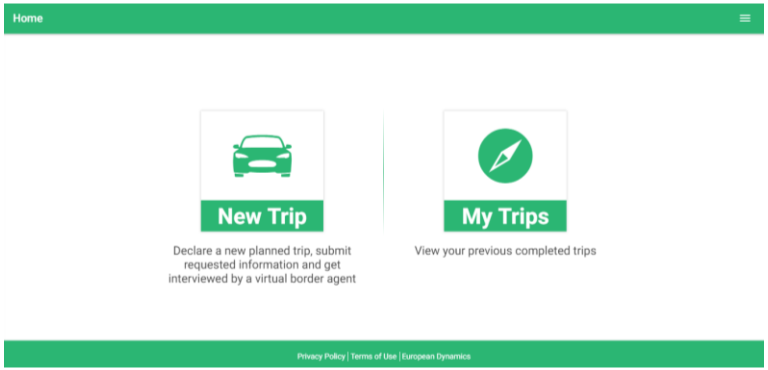


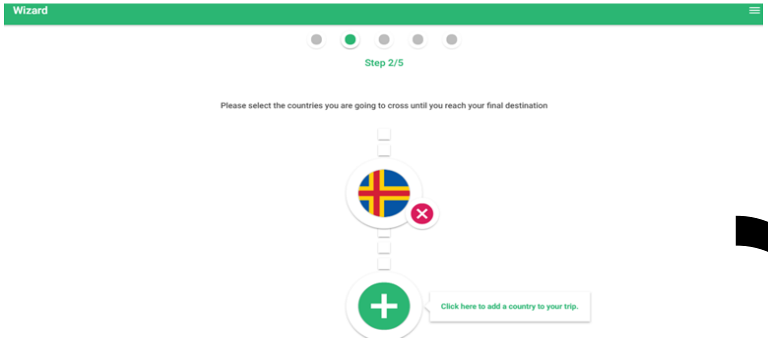
Adaptive Avatars (Neutral, Sceptical, Positive)

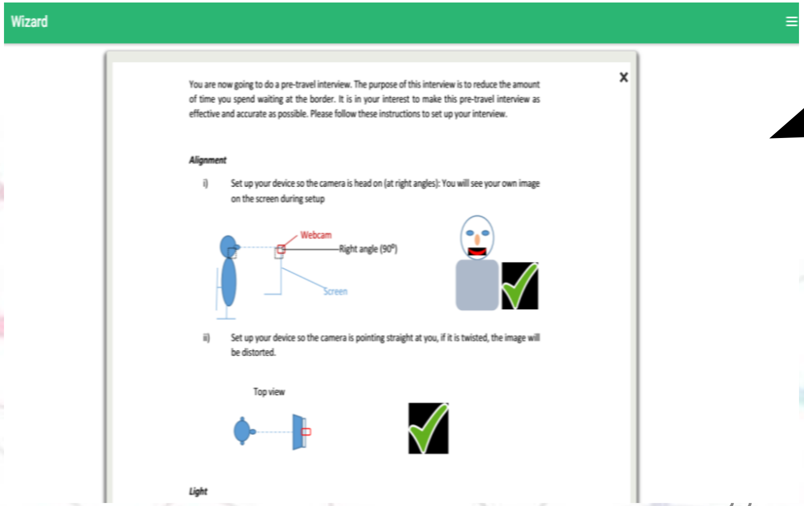


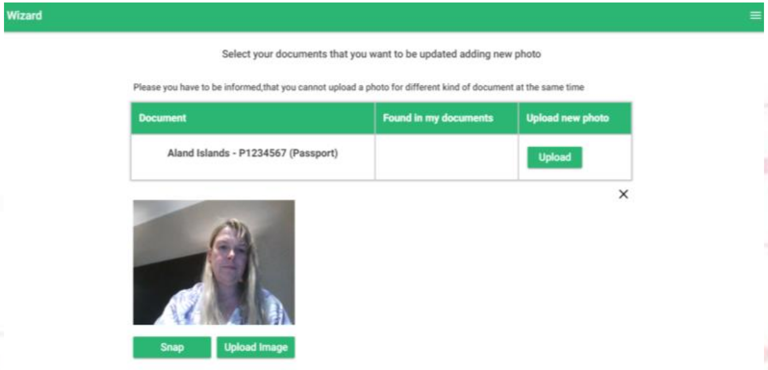


Integration: Automatic Deception Detection Prototype









Integration: Automatic Deception Detection Prototype

Wizard

Step 4/5

Repeat | Confirm Answer

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Experiments

S1: SCENARIO TRUTHFUL

- All participants will use their true identities as recorded in their identification documents.
- All participants will answer questions about a real relative or friend who is an EU / UK citizen (equivalent of a Sponsor in border questions asked by EU border guards).
- All participants will pack a suitcase with harmless items typical of going on a holiday
- Participants will answer questions about identity, sponsor and suitcase contents.
- All answers to questions can be answered truthfully.

DECEPTIVE SCENARIOS

- Fake identities
- S2: Simulated biohazard infectious disease in test tube with informational video about weaponization
- S3: Simulated biohazard infectious disease in test tube without informational video
- S4: Simulated Drug package (soap powder in clear packet)
- S5: Simulated Forbidden agriculture/ food product i.e. seeds.

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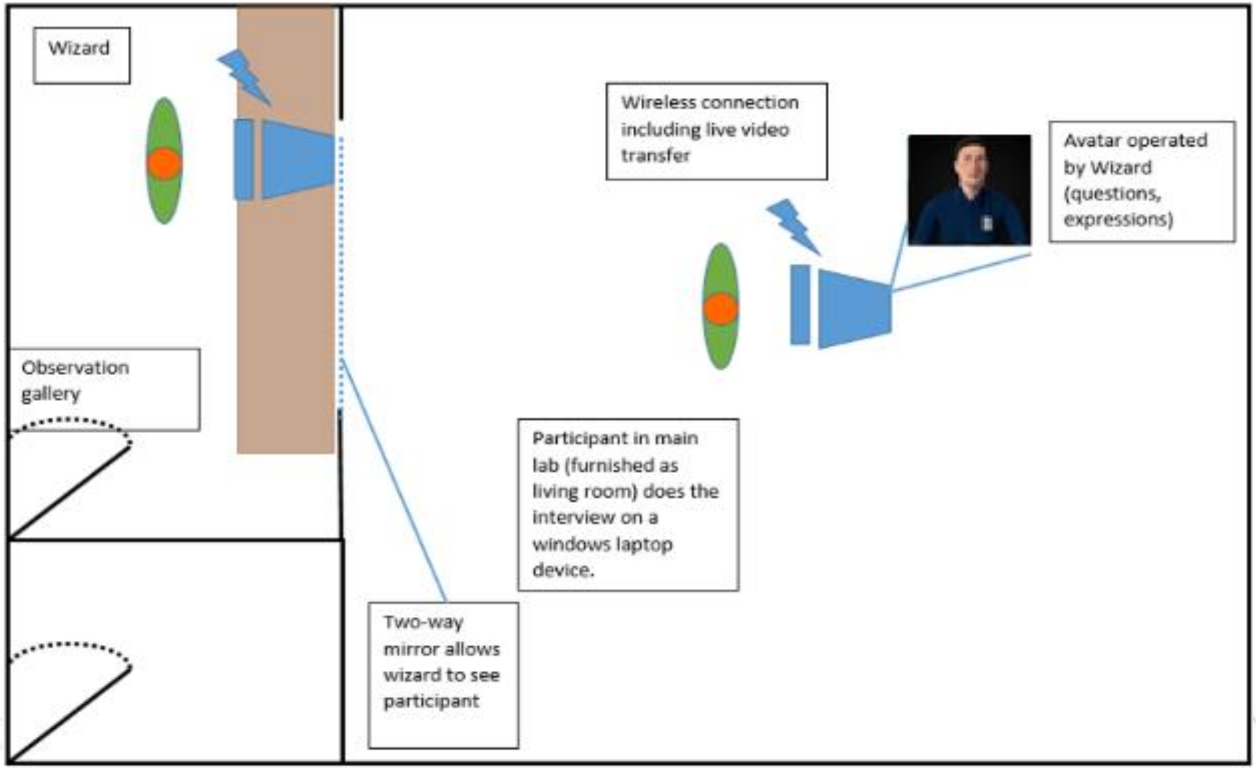
Experimental Set Up (Task + Interview)



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Poster sample from the Department of Transportation and Communications-Office of Transportation Security, The Philippines)

Deception Risk Score

- . The deception risk score, Dq, of each question was defined as

$$D_q = \frac{\sum_{s=1}^{n} d_s}{n}$$

- Where *ds* is the deception score of slot *s* and *n* is the total number of slots for the current question.
- Classification thresholds

IF Question_risk (D_q) *<= x THEN*

Image vector class = truthful

ELSE IF Question_risk (D_q) *>= y THEN*

Image vector class = deceptive

ELSE

Indicates not classified

END IF

Where x = -0.05 and y = +0.05

Phase 1: Experimental Dataset

No. of Question per Interview	13
Total Participants	32 (17 Deceptive, 15 Truthful)
Total number of video files	448
Deceptive participants	Male (10) , Female (7), Asian/Arabic (4), EU White (13)
Truthful Participants	Male (12), Female (3) , Asian/Arabic (6), EU White (9)
No of non-verbal channels analyzed	38
Total number of truthful vectors in dataset	43051
Total number of deceptive vectors in the dataset	43535

Results using 10 Fold Cross Validation

No. of Hidden Layer Neurons	Accuracy (%)					
	Training		Validation		Test	
	T	D	T	D	T	D
11	94.13	95.04	93.68	94.41	94.30	93.69
12	94.45	95.63	93.75	94.74	93.62	94.96
13	94.92	95.77	94.41	95.14	94.31	95.15
14	94.85	96.26	94.29	95.67	94.23	95.46
15	96.19	96.19	95.40	95.50	95.50	95.41
16	96.16	96.40	95.58	95.80	95.45	95.91
17	96.56	96.98	95.90	96.32	95.75	96.22
18	96.81	97.17	96.14	96.52	95.91	96.28
19	97.23	97.11	96.48	96.48	**96.67**	96.45
20	97.28	97.50	96.53	96.81	96.55	**96.78**

Classification Outcomes using Unseen Participants

Test No	Participant				Accuracy (%)	
	Truthful		Deceptive		Truthful	Deceptive
	Gender	Ethnicity	Gender	Ethnicity		
1	M	EU	M	A/A	100	57
2	M	A/A	F	EU	50	36
3	M	A/A	F	EU	50	100
4	M	EU	F	EU	90	100
5	M	A/A	M	EU	100	10
6	M	EU	M	EU	72	100
7	M	A/A	F	EU	100	100
8	F	EU	F	A/A	38	100
9	M	EU	M	EU	80	60
Overall Accuracy (%)					**75.55**	**73.66**

O'Shea, J. Crockett, K. Khan, Kindynis, P. Antoniades, A. Intelligent Deception Detection through Machine Based Interviewing, IEEE WCCI 2018, July 2018, in press

Are Profiling Decisions Explainable ?

- ***Hypothesis*** *to be tested*
  - *H0: A decision made by an automated deception profiling system can be explained using decision tree models*
  - *H1: A decision made by an automated deception profiling system cannot be explained using decision tree models*

- Methodology used 10 Fold cross validation

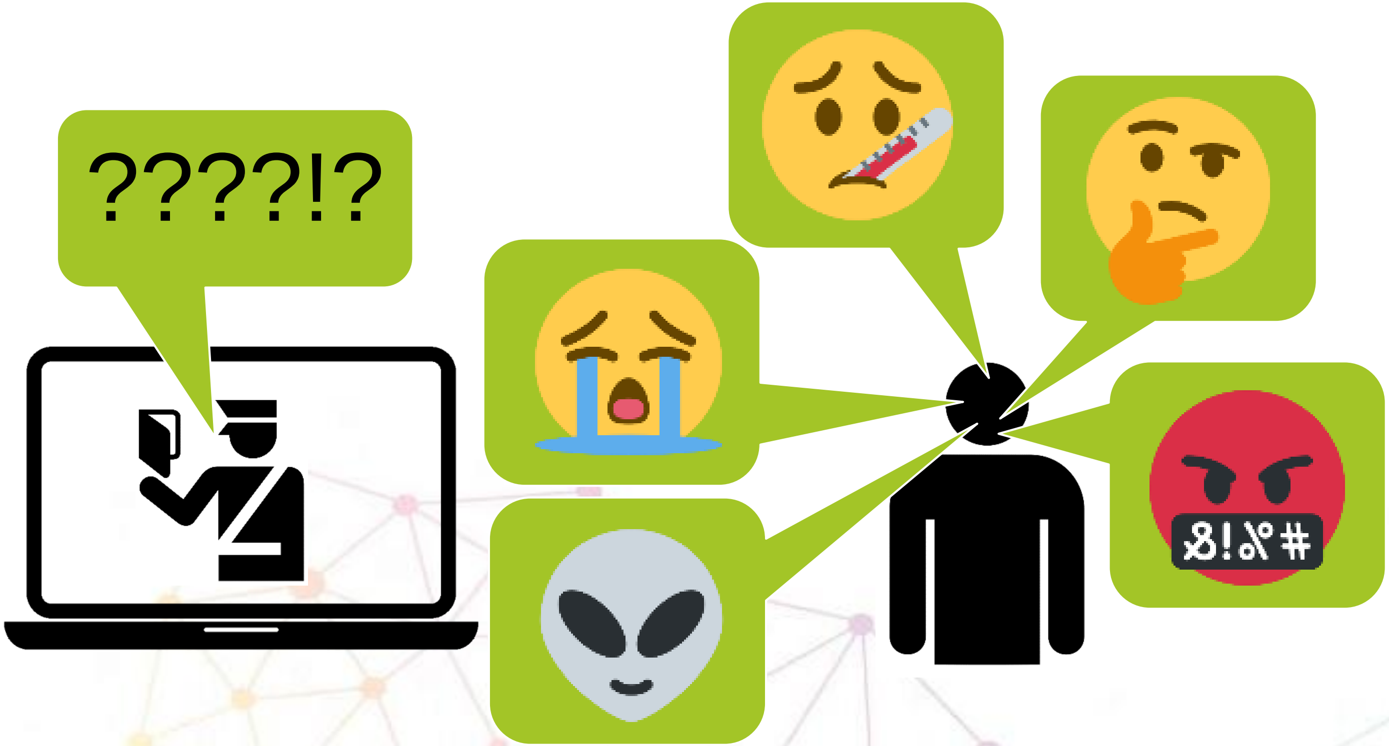
Results

- ADDS-ANN - 96.8%
- ADDS-DT - 96.8%

```
lhleft <= -0.407407
|   lright <= 0.777778
|   |   fmuor <= 0.072831
|   |   |   rhright <= -0.809524
|   |   |   |   fbla <= -0.07892
|   |   |   |   |   fblu <= -0.773891
|   |   |   |   |   |   rleft <= 0.793103
|   |   |   |   |   |   |   rright <= 0.310345
|   |   |   |   |   |   |   |   rhclosed <= -0.933333
|   |   |   |   |   |   |   |   |   fhs <= -0.888889
|   |   |   |   |   |   |   |   |   |   fmuor <= 0.028317
|   |   |   |   |   |   |   |   |   |   |   lright <= -1
|   |   |   |   |   |   |   |   |   |   |   |   rleft <= -1
|   |   |   |   |   |   |   |   |   |   |   |   |   fbla <= -0.997762
|   |   |   |   |   |   |   |   |   |   |   |   |   |   fblu <= -0.963101
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   fmc <= -0.942354: TRUTH (10.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   fmc > -0.942354: DECEPTION (9.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   fblu > -0.963101
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   lhleft <= -1: DECEPTION (180.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   lhleft > -1
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   Ethnicity <= -1: TRUTH (10.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   Ethnicity > -1: DECEPTION (27.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   fbla > -0.997762
|   |   |   |   |   |   |   |   |   |   |   |   |   |   Ethnicity <= -1
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   fmuor <= -0.030638
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   fhs <= -1: DECEPTION (59.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   fhs > -1: TRUTH (18.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   fmuor > -0.030638
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   lclosed <= -0.034483: TRUTH (140.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   lclosed > -0.034483
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   flm <= -0.9: TRUTH (29.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   flm > -0.9: DECEPTION (6.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   Ethnicity > -1: DECEPTION (29.0)
|   |   |   |   |   |   |   |   |   |   |   |   rleft > -1: DECEPTION (127.0)
|   |   |   |   |   |   |   |   |   |   |   lright > -1: DECEPTION (521.0/2.0)
|   |   |   |   |   |   |   |   |   |   fmuor > 0.028317
|   |   |   |   |   |   |   |   |   |   |   Gender <= -1: DECEPTION (17.0)
|   |   |   |   |   |   |   |   |   |   |   Gender > -1
|   |   |   |   |   |   |   |   |   |   |   |   lright <= -1
```

IF lhleft < -0.407407 AND lright <= 0.777778 AND fmuor <=0.072831 AND rhright <= 0.310345 AND rhclosed <=-0.93333 AND fhs <= -0.888889 AND fmour <=0.028317 and lright <=-1 and rleft <=-1 and fbla <=-0.997762 and fblu <=-0.963101 and fmc > -0.942354 THEN CLASS DECEPTION.

Ethical Dilemmas



Case Study:

Adaptive Psychological Profiling: Comprehension

FATHOM

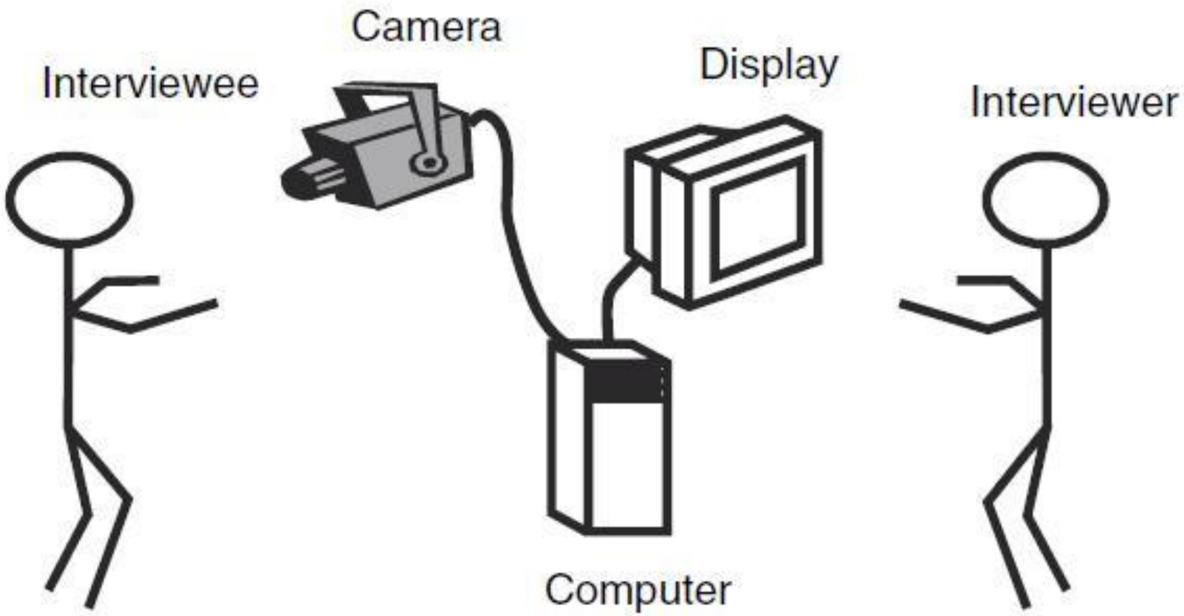
- What would be the impact if it could be possible to detect **low comprehension** of an individual undergoing the **informed consent** process ?

- **Fathom** - computerized, **non-invasive** psychological profiling system which detects human comprehension through the monitoring of multiple channels of **facial nonverbal** behaviour using **Artificial Intelligence**

Research Context

- HIV/AIDS
  - Preventable
- UNAIDS Report on Global AIDS epidemic
  - Sub-Saharan Africa
    - 22.5 million with HIV
    - HIV more prevalent in women
- Clinical trials
  - Informed consent
    - Comprehension vital element

FATHOM – Set Up



[8]

Field Study Background

- International Ethics
- 80 participants
  - Female
  - 18-35 years old
- Videoed interview
  - Learning task topics
  - Questions about topics

Interview Design

TASK A

- Easy topic
  - Condom usage
  - High comprehension
- Easy topic questions
  - 10 x closed-ended
  - 10 x open-ended

TASK B

- Difficult topic
  - HIV recombination
  - Low comprehension
- Difficult topic questions
  - 10 x closed-ended
  - 10 x open-ended

Can FATHOM's Comprehension Classifier reliably distinguish between the *easy and hard learning tasks?*

Comprehension/ Noncomprehension	Training Classification Accuracy	Validation Classification Accuracy	Testing Classification Accuracy
Both	89.56%	88.19%	88.40%
Comprehension	89.82%	88.32%	88.60%
Noncomprehension	89.29%	88.06%	88.20%

Data sets from learning tasks
Task A = easy = comprehension = +1
Task B = difficult = non-comprehension = -1

Data Set Size: 241,954 vectors
45% comprehension
55% non-comprehension

Can FATHOM's Comprehension Classifier reliably distinguish between human comprehension and non-comprehension within the easy and hard learning tasks?

Comprehension/ Noncomprehension	Training Classification Accuracy	Validation Classification Accuracy	Testing Classification Accuracy
Both	89.35%	84.95%	85.52%
Comprehension	89.50%	86.19%	86.66%
Noncomprehension	89.20%	83.70%	84.37%

Data Set Size: 71,787 vectors
63.5% comprehension
36.5% non-comprehension

Open-ended questions mapped to learning task sentences

- IF answer = correct THEN comprehension = +1
- IF answer = wrong THEN noncomprehension = -1

What is the Impact of FATHOM ?

- **For Informed Consent………**
  - Detection of low comprehension of the informed consent process at an early stage implies it would be possible to adapt the briefing stage to correct this and comply effectively with legal and ethical implications.

- **For Education………**
  - A online learning system that can adapt and provide personalized learning based on comprehension levels.

Adaptive Psychological Profiling: Comprehension in Intelligent Tutoring

- **COMPASS:** a novel real-time comprehension assessment and scoring system, developed for use in e-learning platforms.
- **Hendrix 2:** Conversational Intelligent tutoring system with COMPASS (2017)

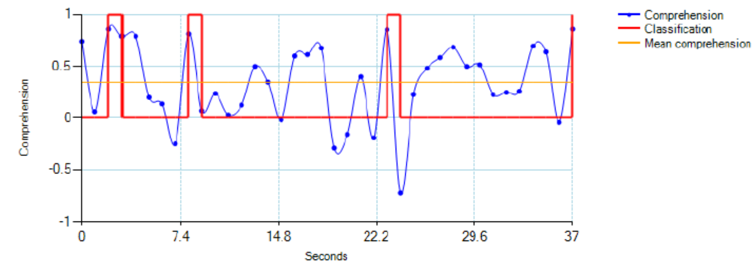


Fig. 3. COMPASS time-series for a correct answer period

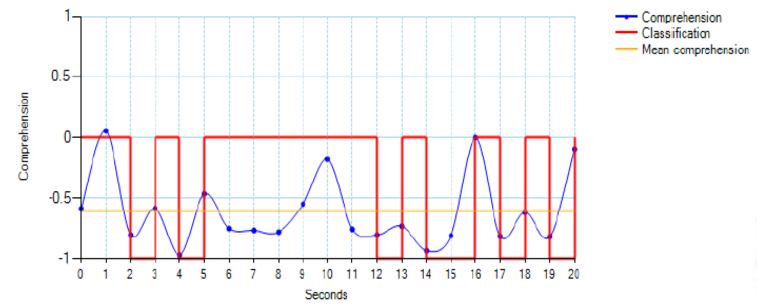
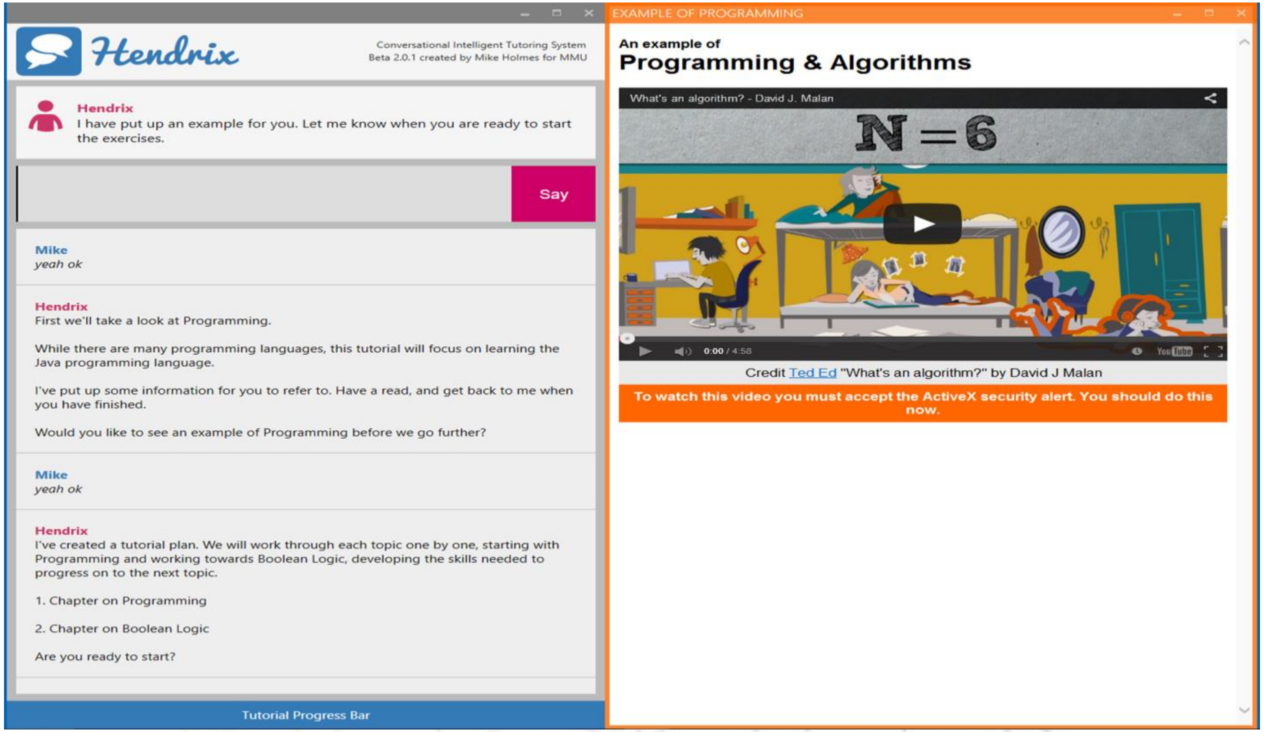


Fig. 4. COMPASS time-series for an incorrect answer period

Holmes, M. Latham, A. Crockett, K, O'Shea, J. Near real-time comprehension classification with artificial neural networks: decoding e-Learner non-verbal behaviour, IEEE Transactions on Learning Technologies, Year: 2017, Volume: PP, Issue: 99, DOI: 10.1109/TLT.2017.2754497

Hendrix Conversational intelligent Tutoring System



Technologies for better human learning and teaching

Manchester Metropolitan University

Conclusions

School of
Computing, Mathematics and Digital Technology

Challenges: Developing Physiological Profiling systems

- The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems
    - **Task Force on Ethical and Social Implications of Computational Intelligence**
- "Human-in-the-loop" philosophy
- **Article 22 of the GDPR** concerns the rights of an individual when interacting with systems that may automatically make a decision or profile them in any way that they have not given consent to.
- **Bias** - Systems approach – suitable training for humans using CI components
- Experimental design to respect rights of participants

Guidance: Developing Physiological Profiling systems

- **IEEE Ethically aligned design document** V2.
- Close collaboration of both the legal and technical community.
- **Ethics** takes time.
- Adopt a **privacy by design** approach at the start of the research project and build in privacy and data protection to the research proposal or any knowledge transfer partnerships with industry.

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