Development of a Brief MENTAL HEALTH SCREENING CHECKLIST

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Aviation personnel are responsible for the safe carriage of thousands of people each day and need to be physically and mentally fit to perform the job. It is important to regularly evaluate their mental health due to the stressors they face that can increase the risk of developing a mental health disorder.

Performing extensive psychiatric evaluations as a regular part of aeromedical assessments can be overwhelming in terms of cost-effectiveness. It is still recommended that AeMCs and AMEs pay attention to common mental health disorders (CMDs) as well as life stressors that can affect flight performance and safety.

The use of minimally intrusive, easy-to-use mental health checklists may help AeMCs and AMEs in the decision making process.

AIM OF THE PRESENT RESEARCH

AIM 1: Develop a Mental Health Screening Checklist (MHSC) to be used by AeMCs and AMEs as a screening tool. We decided to make the checklist:

- short (few minutes to complete), yet exhaustive in the coverage of CMDs and life stressors;
- simple and direct to reduce misunderstandings, and increase accountability of responses;
- with a limited number of response options to decrease the cognitive burden of respondents' decision making.

CHECKLIST AREA	ITEMS
Fatigue, stress	2
Maladaptive Personality	4
Life Concerns	4
Relevant events, conditions	5
NRG Drinks, Alcohol, Tobacco, Drugs	5
Perceived Psychological Well-Being	1

AIM 2: Devise a computationally efficient automated strategy to identify individuals who required professional help from mental health experts.

SAMPLE AND METHODS

The research sample consisted of 240 participants, 126 pilots, 37 cabin crew members and 77 pilot applicants. 213 were males, and 27 females. Age spanned from 18 to over 60, with a modal range of 18-30.

Within a cross-sectional design, we administered our checklist to the research sample. We then implemented an automated *multi-step outlier detection pipe* in order to identify outlier profiles that significantly departed from the majority of the other ones. In other words:

- outlier profiles contained responses that fell outside the typical range;
- individuals with an outlier profile would be referred to a mental health specialist.

Looking at **FIGURE 1**, we can see our *multi-step outlier detection pipe*, built upon 5 detection strategies:

- **3 RBS Rule-Based Systems**: (**A**) to verify missing items, (**B**) to spot positively answered sentinel items such as *aggressiveness towards others or self*, (**C**) to identify profiles with unique/rare response patterns. A rule-based system is a ML algorithm that makes decisions based on a set of explicitly defined rules. These rules are typically devised by human experts;
- **2 Isolation Forests**: (**D**) to assess the degree of *outlierness* of the MHSC responses and (**E**) to assess the degree of *outlierness* of the aggregated scores. An isolation forest is a ML algorithm that works by recursively partitioning a dataset into subsets and isolating outliers with fewer partitioning steps than normal data points.

Finally, the dataset was projected onto a 2D surface via a dimensionality reduction technique (i.e., Truncated Single Value Decomposition) to visualise how extensively the *outlier detection pipe* tracked down anomalous MHSC profiles.

Results

As can be seen in **FIGURE 2**, the *outlier detection pipe* identified 82% profiles with no evidence of anomalous responses, and about 18% of profiles that required additional scrutiny for mental health risk potential. Such profiles showed various degrees of *outlierness*, from moderate to extreme.

As depicted in **FIGURE 3**, the 2D projections of the dataset confirmed that the *outlier detection pipe* correctly marked as strong/extreme outliers the MHSC profiles in the peripheral regions of the representative space. Due to its multi-step nature, the pipeline further identified potentially problematic profiles that traditional measures of pure *outlierness* might have overlooked.

CONCLUSIONS

The MHSC was a fast, easy, and unobtrusive way to screen aviation workers for mental health issues; the users perceived MHSC quite well, as it is a "cultural device" proximal to the aviation industry mental toolset.

The *outlier detection pipe* was a valuable tool for automatically flagging individuals who were candidates for an in-depth clinical interview.

LIMITATIONS AND FUTURE DIRECTIONS

- The *outlier detection pipe* needs be trained on a sample representative of the assessed population before being able to make predictions;
- in those cultures where mental health conditions are considered a social stigma, under-reporting phenomena may be an issue as the MHSC is fakeable;
- an MSHC profile not flagged as outlier doesn't rule out the presence of a mental health condition;
- in future versions of the *outlier detection pipe*, more sophisticated ML algorithms (e.g., semantic reasoner models) could be implemented.

FIGURE 1

MHSC multi-step outlier detection pipeline

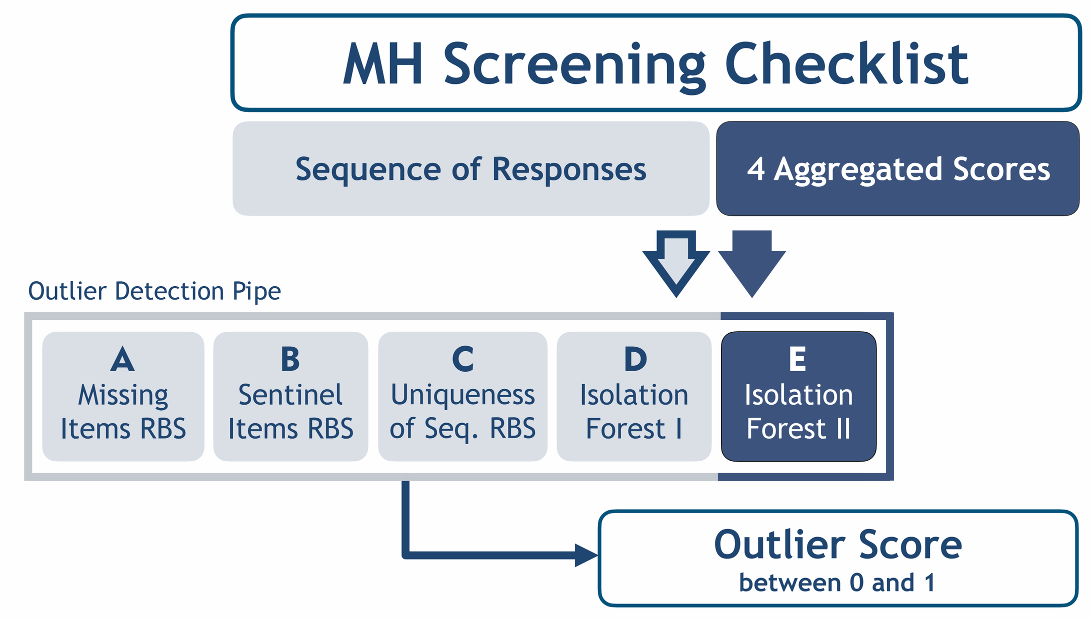


FIGURE 2

MHSC outlier percentages in research sample

82% No outliers

5% P C A — **Moderate** outliers

10% P C A — **Strong** outliers

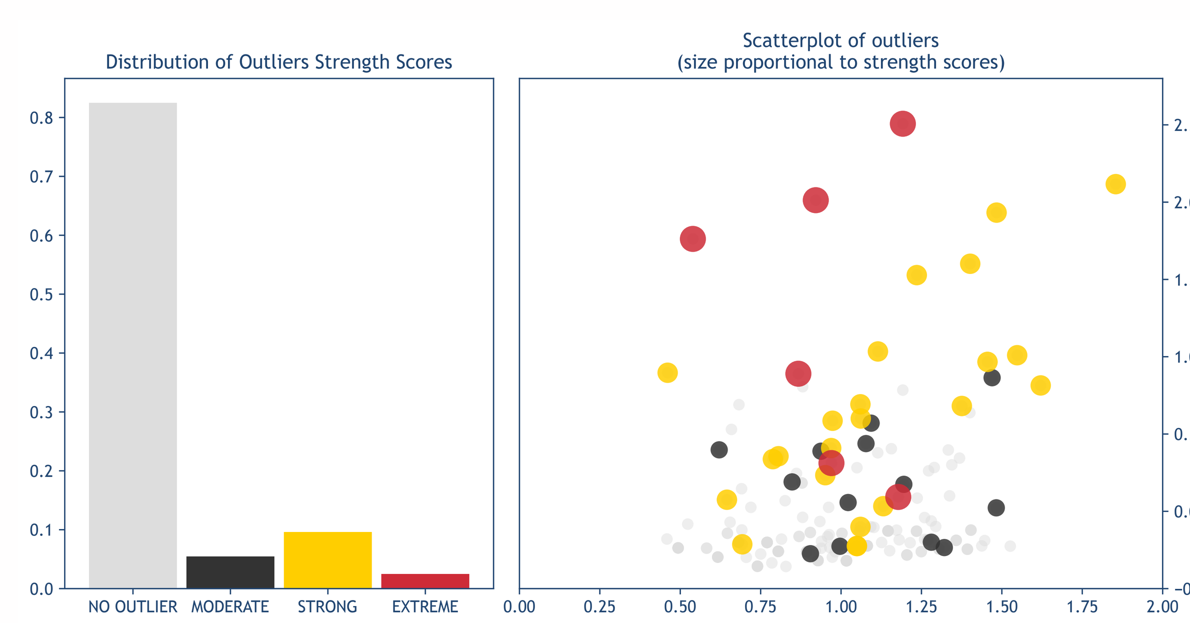
3% P C A — **Extreme** outliers

P = Pilots · **C** = Cabin Crew · **A** = Applicants

MIND THE **COLORS**

FIGURE 3

Visualisation of MHSC outliers on a 2D space



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poster and checklist

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