Supplementary Information

Behavioural Artificial Intelligence Technology for COVID-19 Intensivist Triage Decisions: Making the Implicit Explicit

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Background information

Though there are many areas in which medical experts make choices that have a major impact (e.g., admit patients to the ICU, perform surgery, prescribe medication), the currently available resources for decision support, mainly rule-based systems and machine learning, are often inadequate.

Rule-based systems require experts to explicate their knowledge into hard rules, which behavioural research has shown to be difficult. In addition, these systems are not very well suited to decisions that are not based on rigid criteria or that need to deal with exceptions and contradictions, such as ICU eligibility. In addition, these systems often become very complex and hard to maintain.

Though machine learning offers the prospect of leveraging routinely collected data, for some domains data is neither readily available nor free of bias. Especially data pertaining ICU admission often lack (correctly labelled) decisions or sufficient numbers of those decisions. In addition, complex machine learning algorithms are difficult to interpret without resorting to specialised tools.

In this manuscript we suggest another approach. By having experts make choices in the context of hypothetical scenarios, a so-called discrete choice experiment, it is possible to make the implicit assessments of experts explicit. Using efficient experimental design techniques [1], scenarios are constructed such that each choice generates a maximum amount of information, guaranteeing a reliable estimation of factors (e.g., criteria that play a role in the decision of ICU eligibility). This involves generating scenarios that present to the participant a difficult trade-off between factors. To enable such an efficient design, some form of prior knowledge is needed for the factor weights. This can be obtained during the design phase of the experiment by asking a selection of experts, for each factor, if it is critically important, moderately important, or less important (‘nice to have’). Given this information, using experimental design software, it is possible to assess for each potential scenario, if it presents the decision-maker with a real trade-off to be made. The most promising scenarios (in terms of their potential to minimize entropy associated with the expected parameter estimates) will be kept, while ‘easy’ scenarios will be discarded.
As a result, with a relatively low number of choices (25-30) from 10-15 experts, it is possible to model (codify) the decision of this group of experts [2].

Since the model reflects the considerations and trade-offs of the participating experts, the model could have added value in supporting individual intensivists in their daily practice when considering ICU eligibility. The availability of the predicted decision of the group and the factors that play a role for that decision at the bedside may aid the intensivist making these hard decisions.

**eMethods**

**Factor selection**

Factors, i.e. criteria that presumably played a role in the evaluation of eligibility for ICU treatment and/or initiation of mechanical ventilation, were determined in a series of brainstorm sessions with experts, consisting of a small group of intensivists of hospital A. Since the modelling process took place during the COVID-19 pandemic, and ICU capacity influences are known to influence ICU admission policies, ICU capacity of the hospital and regional/national hospitals were used, in addition to clinical condition (Table S1). The co-morbidity factors used subjective 3-point scales with levels ranging from ‘no impairment’ to ‘severe impairment’.

**Discrete choice experiment design**

Before generating the scenarios, constraints were specified to preclude combinations of factor-scores (such as severe comorbidity in a patient with low frailty score) that are impossible or highly unlikely to occur in real life. After selecting the factors, the experiment was designed using specialized software (Ngene 1.2.1, ChoiceMetrics Pty Ltd, Sydney, Australia). The 25 most informative scenarios were used for the experiment.

The participants, consultant intensivists and fellows in intensive care medicine, were asked if they would find a patient eligible for ICU admission and the initiation of mechanical ventilation given a scenario. The decisions were entered directly by the participants in a web application at their convenience. The observed choices were used to estimate the importance weights (parameters) of all factors including their signs (positive or negative) and any non-linear
curvatures (e.g. concavity of convexity), using maximum likelihood techniques. This process
starts with predicting probabilities for the choices made by experts in the choice experiment,
based on the choice model including a set of starting values for the parameters. These
predictions are then compared to the actual choices made by the experts. By iteratively
adjusting the parameter values, increasingly accurate choice probability predictions are
generated to match the observed choices, until no further improvements can be made.

Discussion

Our approach allowed us to gain insight into the triage decision of two urban hospitals in the
Netherlands. The intubation models showed higher McFadden’s $\rho^2$, compared to the admission
models, suggesting that there is higher agreement between intensive care clinicians to admit
patients that require mechanical ventilation, than for the general question to admit patients. A
relatively low $\rho^2$ value for these readmission models, however, should not be interpreted as a
poor model. Since the choice scenarios were actually designed to force experts to make hard
trade-offs, a low $\rho^2$ in this context shows the inherent difficulty and therefore differences
between groups of physicians making decisions. Additionally, the importance of factors differs
between our two hospitals, which of course prevents ‘generalizability’ of a model. Nevertheless,
since ICU admission policies differ between regions and cultures, the goal of a discrete choice
model should not be to develop a generalizable model, but to create insight into these often
subtle implicit differences.

After retrograde and antegrade validation, and obtaining CE marking for medical devices for
clinical use, the model will be made available to clinicians using a web based application.
Individual patient data (i.e. age and BMI) would be filled out in the application and the values of
factors on organ dysfunction could be set using a slider, varying between ‘no impairment’ and
‘severe impairment’. After entering the choice the clinician would make (whether or not to admit
the patient to the ICU and/or initiate mechanical ventilation), the model would provide the
percentage of peers that would have made the same choice as the clinician based on the model
including the factors determining this decision. In future studies, we will investigate if and how
such a model influences decisions at the bedside.
References

1. Hensher DA, Rose JM, Greene WH (2015) Applied Choice Analysis, 2nd ed. Cambridge University Press, Cambridge

2. ten Broeke A, Hulscher J, Heyning N, et al (2021) BAIT: A New Medical Decision Support Technology Based on Discrete Choice Theory. Med Decis Making 0272989X211001320. https://doi.org/10.1177/0272989X211001320
Figure S1

Screenshot of web-based hypothetical scenario case with patient characteristics and ICU capacity information. Participants were requested to enter their triage decision: ‘would not admit to the ICU’, ‘would admit without mechanical ventilation’, or ‘would admit for invasive mechanical ventilation’. Every hypothetical scenario was created by varying the values of the factors shown in Table S1.

| Scenario 4 / 25 |
|----------------|
| **Relocation to regional/national hospitals** | Available |
| **ICU capacity** | None (stabilise and relocate) |
| **Acute patient condition** | Severely hypoxaemic; supplemental O2 requirements expected to be >15L/min in the next hours |
| **Age (approx.)** | 50 years |
| **Comorbidity: Cognitive functioning** | No impairment | Severe impairment |
| **Comorbidity: Cardiovascular** | No impairment | Severe impairment |
| **Comorbidity: Pulmonary** | No impairment | Severe impairment |
| **Comorbidity: Renal** | No impairment | Severe impairment |
| **Comorbidity: Liver** | No impairment | Severe impairment |
| **Comorbidity: Immunity** | No impairment | Severe impairment |
| **COVID pneumonia disease course** | Progressive |
| **Body mass index (kg/m2)** | <20 |
| **Frailty (Clinical Frailty Score)** | 5 |
| **Patient decision** | Perform invasive mechanical ventilation |

Choose an option...
- ✔ Would not admit to the ICU
- Would admit to the ICU without invasive mechanical ventilation
- Would admit to the ICU for invasive mechanical ventilation
Table S1

Factors presented to participants of hypothetical patients, the question to be answered and the possible answer categories

| Factor                                      | Category 1                                      | Category 2                                      | Category 3                                      |
|---------------------------------------------|------------------------------------------------|------------------------------------------------|------------------------------------------------|
| Relocation to regional/national hospitals   | Not available                                   | Available                                       |                                                |
| ICU capacity                                | None (stabilise and relocate)                  | Limited (1-2 beds)                              | Ample (>2 beds)                                 |
| Acute patient condition                     | Acute respiratory failure: urgent intubation required | Severely hypoxaemic: supplemental O2 requirements expected to be >15L/min in the next hours | COVID-19 patient without severe hypoxemia, expected to deteriorate |
| Age (approx.)                               | 30 years                                       | 50 years                                       | 70 years                                       |
| Comorbidity: Cognitive functioning          | No impairment                                  | Mild impairment                                | Severe impairment                               |
| Comorbidity: Cardiovascular                 | No impairment                                  | Mild impairment                                | Severe impairment                               |
| Comorbidity: Pulmonary                      | No impairment                                  | Mild impairment                                | Severe impairment                               |
| Comorbidity: Renal                          | No impairment                                  | Mild impairment                                | Severe impairment                               |
| Comorbidity: Liver                          | No impairment                                  | Mild impairment                                | Severe impairment                               |
| Comorbidity: Immunity                       | No impairment                                  | Mild impairment                                | Severe impairment                               |
| COVID pneumonia disease course              | COVID-19 with complications                    | Progressive                                    |                                                |
| Body mass index (kg/m²)                     | <20                                            | 20-40                                         | >40                                            |
| Frailty (Clinical Frailty Score)            | 5                                              | 3 and 4                                       | 1 and 2                                        |
| Patient decision                            | Do not perform invasive mechanical ventilation | Perform invasive mechanical ventilation         |                                                |
| Question                                    | Would you admit a COVID-19 patient with above mentioned criteria to the ICU? | Would admit to the ICU without invasive mechanical ventilation | Would admit to the ICU for invasive mechanical ventilation |
| Answer categories                           | Would not admit to the ICU                     | Would admit to the ICU without invasive mechanical ventilation | Would admit to the ICU for invasive mechanical ventilation |
**Table S2**

Performance of the ICU admission and intubation models for both hospitals, individually and combined.

| Model                                        | Performance ($\rho^2$) |
|----------------------------------------------|------------------------|
| ICU admission hospital A                     | 0.26                   |
| ICU admission hospital B                     | 0.16                   |
| ICU admission combined hospitals A+B         | 0.18                   |
| Intubation hospital A                        | 0.40                   |
| Intubation hospital B                        | 0.49                   |
| Intubation combined hospitals A+B            | 0.41                   |