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A new approach to artificial intelligence for decision support

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ABSTRACT

This research aimed to investigate whether a new approach to AI for decision support, called BAIT, has potential to serve as a novel IDSS in the medical sector. By examining the usefulness of BAIT at the Neonatal Intensive Care Unit (NICU) of the University Medical Centre of Groningen (UMCG). BAIT is utilised for the recommendation of the UMCG physicians on whether to provide parents with advice against or in favour of surgery on a premature baby diagnosed with Necrotizing Enterocolitis (NEC), given the indication that surgery is required to sustain life. BAIT utilises discrete choice modelling (DCM) to codify the domain expertise of experts' to provide introspection on their decisions and support future judgments. By examining the usefulness and potential of BAIT in this case study, this research found that BAIT has a legitimate potential to serve as a novel IDSS in the medical sector. Nonetheless, before a new type of CDSS is implemented in an institutional environment, such as a hospital, it must also comply with many regulations and be approved by an ethical committee. Accordingly, for the successful implementation of BAIT, further research must be conducted on the legal requirements of CDSSs in health care.

1. Introduction

For decades researchers deliberated and continue to debate on how to support and assist humans in decision-making. This resulted in the development of Intelligent Decisions Support Systems (IDSSs). An IDSSs is an application of artificial intelligence (AI) that desires to enhance and support decision-making by enabling tasks to be performed by a computer while mimicking human capabilities (Yilmaz & Tolk, 2008). The two most generally classified types of IDSSs are knowledge-based and non-knowledge based systems (Abbasi & Kashiyarndi, 2010). A knowledge-based system, also called an Expert system, directly translates domain knowledge into a set of rules or cases to support decisions (Hopgood, 2005). In contrast, non-knowledge based IDSSs apply the rapidly growing branch of AI known as machine learning (ML) for decision support. An ML model is trained by using labelled data that provides examples of desired input-output behaviour. This training data is, hence, labelled with the behaviour that the model should conduct on its own (Burrell, 2016).

Recently, a company called Councyl, in collaboration with the TU Delft, developed a new approach to AI that has the potential to constitute a novel type of IDSS for judgement purposes. The new approach to AI is called BAIT (Behavioural artificial intelligence technology). BAIT utilises discrete choice modelling (DCM) to codify the domain expertise of experts' in order to provide introspection on their decisions and support future judgments. BAIT utilises choice modelling by asking a group of experts to conduct a choice experiment. The choice experiment reflects a decision that domain experts face in their line of work—for example, the choice of a surgeon to perform surgery. In the choice experiment, the domain experts face multiple hypothetical choice scenarios for that specific decision. The choice alternatives captured in a choice set each contain a set of attributes. The attributes that construct a choice scenario reflect decision variables that experts consider when making their decision. By estimating a choice model, from the observed choices, the weights that decision makers attach to different attributes can be determined (Louviere, Flynn, & Carson, 2010). These weights provide introspection on their choice behaviour. Furthermore, the encoded decision rules captured by the choice model can be utilised for decision support and to possibly automate decisions (Van Wijnen, 2019).

As BAIT is a new IDDS approach it requires testing in different settings to gain insight into the usefulness and effectiveness of this new method.

To explore the potential of BAIT, this research will employ BAIT at the Neonatal Intensive Care Unit (NICU) of the University Medical Centre of Groningen (UMCG). It will utilise BAIT for the choice task of UMCG physicians on whether to provide parents with a recommendation against or in favour of surgery on a premature baby diagnosed with Necrotizing Enterocolitis (NEC), given the indication that surgery is required to sustain life. NEC is a severe intestinal disease that affects premature neonates.

This study desires to interpret the lessons learned in this case study to discuss the potential of BAIT as a novel IDSS in the medical sector. Therefore, this study aims to answer the following research question:
Does BAIT have potential to serve as a novel type of IDSS in the medical sector?

The article is organised in five sections. After this introduction, the second section describes the method of BAIT to provide decision support. Thenceforth, the third section presents the results of this study to provide introspection on the choice behaviour of the UMCG physicians. Finally, conclusions are drawn by answering the research question followed by a discussion and reflection of this research.

2. Method of BAIT

As mentioned in the introduction, BAIT utilises discrete choice modelling (DCM) to codify the domain expertise of experts in order to provide introspection on experts decisions and support their future judgments.

2.1 First procedure step of BAIT: Choice experiment design

Through an appropriately designed choice experiment, the method can elicit individual preferences by asking them to state their choice over different choice sets. The choice alternatives captured in a choice set each contain a set of attributes. By estimating a choice model, from the observed choices, the weights that decision-makers attach to different attributes can be determined (Abdullah, Markandya, & Nunes, 2011).

This study designed a choice experiment consisting out of 35 choice scenario. Every choice scenario included two choice options; either provide a recommendation against or in favour of surgery. The attributes that construct a choice scenario reflect variables that UMCG physicians take into account when deciding what treatment is the best option for a child. The recommendations provided by the UMCG physicians on the choice scenarios entail what treatment an individual physician would prefer to recommend to the parents of the new-born based on his or her own professional and medical expertise.

The attributes and attribute ranges are drafted in collaboration with several UMCG physicians. The final selection of attributes and levels were established through iterative modifications. A condition for framing the attribute ranges was that the minimum and maximum range still forced the UMCG physicians to make trade-offs between other attributes. Therefore, this research avoided incorporating attribute levels that would constitute a definite “yes” or “no” for surgery. Moreover, it is universally acknowledged that the more the hypothetical scenarios simulate real-world decisions, the higher the validity of the observed choices (Molin, 2010). As the UMCG physicians base their medical recommendation on surgery by trading off multiple decision variables, this research includes a relatively extensive list of attributes compared to the number of attributes commonly incorporated in choice experiments. The list of attributes and their ranges can be found in Table 1 of the Appendix.

First, a pilot survey is designed incorporating 25 choice scenarios. Three UMCG physicians executed this pilot survey. From the observed choices in that study, a Binary Logit model was estimated to determine priors for the final survey design. A D-efficient design is used to design the final survey.

Figure 1 presents an example of a choice scenario incorporated in the choice experiment.

Attribute	Level 1	Level 2	Level 3	Level 4
Gender	Boy	Girl		
Gestational age	24 weeks	26 weeks	28 weeks	30 weeks
Birth weight	500 grams	650 grams	800 grams	1500 grams
Perinatal asphyxia	Yes	Dubious	No	
Congenital comorbidity	Present with high impact	Present with minor impact	Absent	
Progress since birth before a diagnosis of NEC	Serious complications	Minor complications	No complications	
Age since birth	0 – 7 days	7 – 14 days	14 - 21 days	
Growth since birth	Weak	Intermediate	Good	
Ultrasound of the brain	Bad prognosis	Intermediate prognosis	Good prognosis	
Lung function	Weak	Intermediate	Good	
Hemodynamic	Instable despite maximal support	Stable with support	Stable without support	
Cerebral oxygenation	40	60	80	
Wish of parents	In favour of comfort care	Doubtful about surgery	In favour of surgery	
The carrying capacity of parents	Weak	Intermediate	Good	

Table 1: Attributes and levels

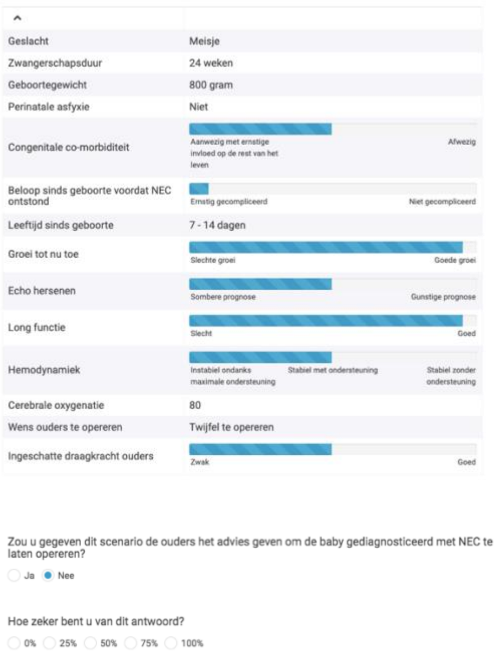

Figure 1: Example choice scenario

2.2 Data collection and sample

15 UMCG physicians conducted the choice experiment. These physicians are the sample group of this study. The physicians are either neonatologists or child surgeons. The UMCG is known to be the only Dutch hospital that is recognised by the Ministry of Public Health as an NEC specialist ("Kinderchirurgie," n.d.). The UMCG physicians are, therefore, known experts in this field. This research desires to provide the UMCG neonatologists and neonatal surgeons with introspection on their recommendations. It does not aim to generalise the results for other neonatologists or child surgeons around the world. Therefore, this research does not require to test the estimates for statistical significance. The group of 15 UMCG physicians executed the choice experiment between Friday the 26th of June and Friday the 17th of July 2020.

2.3 Second procedure step of BAITL: model estimation procedure

This section discusses the model estimation procedure applied for the choice experiment.

This study applies a Random Utility Maximization (RUM) model by assuming that the decision making of the UMCG physicians aligns with the conventional utility maximisation process. It, thereby, assumes that each UMCG physician chooses the alternative that provides them with the highest overall utility. The overall utility consists of a systematic utility and a random utility. For every attribute that is part of the systematic utility function, a parameter (β) will be estimated by the model. By accumulating the parameter with the attribute value, it results in a contribution to the utility function. The systematic utility concerns the sum of all utilities of the attributes in an alternative. The random utility also called the error term is considered as "noise" and cannot be predicted by the model.

Equation 1 provides the linear additive utility function utilised in this research:

(1)

$$U_i = V_i + \epsilon_i = \sum_m \beta_m x_{im} + \epsilon_i$$

Where U_i is the utility associated with alternative i, V_i, is the systematic utility of alternative i, and represent the random utility of alternative i.

This research applies a Binary Logit model to predict the choice probability for a recommendation in favour of surgery. As it is a binary choice task the probability for a recommendation against surgery is equal to 100% minus the probability of a recommendation in favour of surgery.

The Binary Logit model is estimated by using IBM SPSS Statistics 25. The utility function specification is presented in the Appendix. Table 1 presents the estimated parameters.

Variable	Level	Parameter	Standard error	P-value
Gender	Boy			
	Girl	0.020	0.392	0.960
Gestational age	24 weeks			
	26 weeks	1.656	0.431	0.000
	28 weeks	1.851	0.368	0.000
	30 weeks	2.859	0.549	0.000
Birth weight	500 grams			
	650 grams	1.238	0.411	0.003
	800 grams	1.835	0.394	0.000
	1500 gram	2.507	0.731	0.001
Perinatal asphyxia		0.452	0.233	0.053
Congenital co-morbidity	Present with high impact			
	Present with minor impact	0.944	0.336	0.007
	Absent	1.752	0.651	0.006
Progress since birth before a diagnosis of NEC		0.230	0.201	0.252
Age since birth		0.250	0.231	0.279
Growth since birth		0.183	0.200	0.359
Ultrasound of the brain	Bad prognosis			
	Intermediate prognosis	1.798	0.332	0.000
	Good prognosis	2.782	0.571	0.000
Lung function		0.204	0.194	0.293
Hemodynamic		0.279	0.191	0.144
Cerebral oxygenation		0.430	0.215	0.046
Wish of parents	In favour of comfort care			
	Doubtful about surgery	1.729	0.308	0.000
	In favour of surgery	2.154	0.440	0.000
The carrying capacity of parents		0.216	0.202	0.284
Constant		-8.830	1.512	0.000

Table 2 : Binary Logit model estimates

3. Results: output of BAIT

By estimating the choice model, this research inferred, the weights that the UMCG physicians attach to different attributes incorporated in the choice experiment. These are illustrated in Table 2. Comparing the weights of the variables to examine the importance of the decision variables on the recommendations of the UMCG physicians is, however, tricky due to the different attribute ranges drafted for each attribute. Therefore, the maximum utility contribution and relative importance per attribute are calculated to provide introspection on the choice behaviour of the UMCG physicians

It must, however, be taken into account that the maximum utility contribution and relative importance per attribute are still established on the range chosen for a variable. This research determined the variable ranges in consultation with the UMCG physicians. The ranges were drafted such that they capture at least 80% of the bulk of observations faced in reality. Therefore, although it must be taken into consideration that the maximum utility contribution and relative importance are established on the attribute ranges, the values comprised in the ranges are the values on which the UMCG physicians base their recommendations on in reality. Accordingly, the relative importance per variable is a relatively good representation of the importance per decision variable on the medical advice for surgery.

Figure 2 presents the maximum utility contribution per attribute, and Figure 3 presents the relative importance of each variable.

Comparing the maximum utility contribution and relative importance of the variables provides introspection on the UMCG physicians choice behaviour. For, example, comparing the maximum utility contribution of the variables cerebral oxygenation and lung function portrays that the step from the lowest level (40) of cerebral oxygenation to the highest level (80) has more than two times the impact on the utility function then the step from a bad to a good lung function.

Moreover, Figure 3 depicts that gestational age, the wish of parents, birth weight, the ultrasound of the brain, and the congenital co-morbidity nearly make up for 75% of the relative importance; hence, the recommendation on surgery is largely determined by these variables. The other nine attributes have considerably less impact on the recommendation on surgery. The variable gender demonstrates to have the least impact on the advice for a preferred treatment and portrays a relative importance of 0.01%.

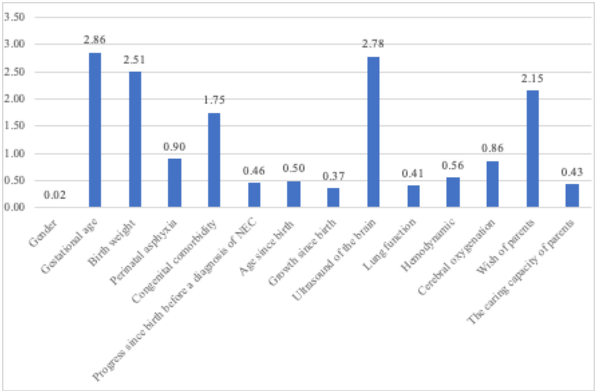

Figure 2: Maximum utility contribution per variable

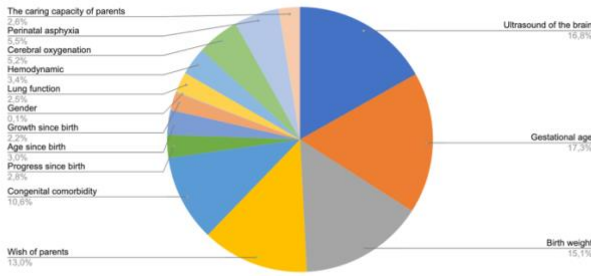

Figure 3: Relative importance per variable

4. Conclusion & Discussion

This study aimed to investigate whether BAIT has potential to serve as a novel IDSS in the medical sector by examining the usefulness of BAIT in this case study.

Firstly, the main focus of this research was codifying the domain expertise of the UMCG physicians through choice modelling to provide introspection on their choice task. The results were presented in a plenary meeting to a large number of the physicians that executed the choice experiment. The results triggered discussions among the medical experts that made them critically reflect their recommendations. Overall, the physicians valued the introspection on their choice behaviour.

Furthermore, the generated choice probabilities by BAIT can also be applied for decision-support. Several UMCG physicians, during the plenary meeting, pronounced that they would accept and appreciate the support of BAIT for future recommendations. This research, however, solely used BAIT to provide introspection on the choice task of the UMCG physicians. Therefore, it cannot declare whether the aid of BAIT will be accepted and appreciated by the experts and, hence, state that the system can be prosperous for decision support.

Moreover, the possible reduction of professional autonomy could also form a potential hurdle for successful implementation of BAIT as decision support in the medical sector. Physicians may worry that a CDSS reduces their professional autonomy as they feel they are expected to act by the judgment provided by a CDSS. A CDSS can, however, also enhance the collective professional autonomy of physicians since if experts have access to a system that enables them to support their judgments to patients and possibly third parties, when questioned about their decision, it can protect their professional autonomy. For his matter is it important that a CDSS provides explainable and transparent decision support, otherwise, the supported judgments can still not be transparently explained to patients or third parties. As BAIT provides explainable decision support, it is able to support the collective professional autonomy of medical experts. Therefore, it illustrates the trade-off between defending collective professional autonomy by limiting individual professional autonomy. The acceptance of a reduction of individual autonomy significantly differs per individual physician and the institutional environment an expert operates in (Armstrong, 2002). Hence, whether physicians are willing to trade off individual autonomy for an enhanced collective autonomy supported by BAIT is, yet, to be determined.

In conclusion, by examining the usefulness and potential of BAIT in this case study, this research found that BAIT has a legitimate potential to serve as a novel IDSS in the medical sector. Nonetheless, before a new type of CDSS is implemented in an institutional environment, such as a hospital, it must also comply with many regulations and be approved by an ethical committee. These strict regulations help to prevent harm from arising to the patients impacted by a new CDSS as well as the physicians utilising the system and, hence, ensures that the principles for trustworthy and ethical AI are protected. Accordingly, for the successful implementation of BAIT, further research must be conducted on the legal requirements of CDSSs in health care.

5. Further research

Firstly, this study solely investigated the choice behaviour of the UMCG physicians, but it is also insightful to study the choice behaviour of physicians in other hospitals on the same choice task to explore the differences and similarities. Therefore, this study recommends executing the same research in different hospitals in the Netherland or outside the Netherland.

Finally, this research only included the wish of the parents as a factor influencing the UMCG physicians recommendations. Therefore, it did not include an analysis of what parents find important when voicing their preferred treatment. For future research applying BAIT to investigate the importance of factors that determine whether parents favour surgery or comfort care might be insightful. Primarily, because research shows that to improve the decision-making process of such ethical and difficult decisions, shared decision making between physicians and parents on the appropriate treatment procedure gained a lot of interest and popularity. Research shows that approximately 80% of the parents highly value shared or active decision-making and experience less regret with the enforced treatment when shared decision making is applied (Soltys, Philpott-Streiff, Fuzzell, & Politi, 2020). An improved understanding of which factors parents find most important while deliberating their wish on the preferred treatment for their child may support shared decision making and is, thus, interesting to investigates.

In conclusion as BAIT is a new IDDS approach, it requires testing in different settings to gain insight into the usefulness and effectiveness of this method. To further investigate the potential of BAIT in the medical sector, this study advises conducting more case studies to further investigate the potential and effectiveness of BAIT in the medical sector.

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Appendix

$$V_{Recommendationinfavorofsurgery} = \beta_{Gender} * Gender + \beta_{Gestationalage1} * Gestationalage1 + \beta_{Gestationalage2} * Gestationalage2 + \beta_{Gestationalage3} * Gestationalage3 + \beta_{Birthweight1} * Birthweight1 + \beta_{Birthweight2} * Birthweight2 + \beta_{Birthweight3} * Birthweight3 + \beta_{Perinatalasphyxia} * Perinatalasphyxia + \beta_{Congenitalcomorbidity1} * Congenitalcomorbidity1 + \beta_{Congenitalcomorbidity2} * Congenitalcomorbidity2 + \beta_{Progresssincebirthbefore\,NEC} * ProgresssincebirthbeforeNEC + \beta_{Agesincebirth} * Agesincebirth + \beta_{Growthsincebirth} * Growthsincebirth + \beta_{Ultrasoundbrain1} * Ultrasoundbrain1 + \beta_{Ultrasoundbrain2} * Ultrasoundbrain2 + \beta_{Lungfunction} * Lungfunction + \beta_{Hemodynamic} * Hemodynamic + Hemodynamic + \beta_{Cerebraloxygenation} * Cerebraloxygenation + \beta_{Wishofparents1} * Wishofparents1 + \beta_{Wishofparents1} * Wishofparents1 + \beta_{Caringcapacityparents} * Caringcapacity$$

Equation 2 Systematic utility function