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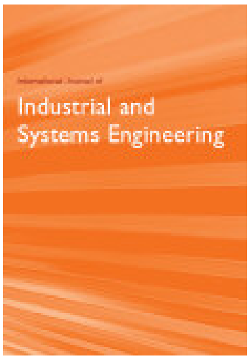

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A decision support system for selecting augmentative and alternative communication devices

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Abstract: The goal of this research is to improve access to services for patients in need of augmentative and alternative communication (AAC). The specific aim of this paper is to develop a decision-making model that evaluates an exhaustive list of AAC devices and recommends the best alternative(s) for the patient. The model maximises a best-fit function that considers the patient's disability profile and the capabilities of each device. Currently, there are multiple private and government companies that offer a large variety of devices targeting patients in need of AAC. However, the decision-making process of what device to try on the patient is largely based on the health professional's experience and familiarity with specific companies. The proposed decision-model has the capability of improving patient experience of care by reducing the assessment time required to find the best device.

Keywords: decision making; augmented and alternative communication; AAC; healthcare; medical devices.

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1 Introduction

The World Health Organisation (WHO) estimates that more than one billion people are in need of at least one type of assistive technology (AT); however, only one in ten people have access to AT services (WHO, 2016a). Individuals requiring AT often need to attend multiple appointments at different locations and with different health professionals to obtain a complete assessment of their condition (Sajan-Varguse et al., 2019). The availability of AT services can vary greatly by geographic region and access is limited for patients living outside urban areas in the USA (Upasani et al., 2019). In addition, multiple appointments are needed to find the device that best matches the individual's disability profile. AT selection is difficult because it requires the patient to test equipment from a large number of options, often placing a lot of stress on the patient.

As a global commitment to improve access to AT, WHO established the Global Cooperation on Assistive Technology (GATE), which specifies a list of 50 AT devices carefully selected based on population needs and potential impact (WHO, 2016b). A significant portion of this list is dedicated to devices that help individuals with acquired or degenerative communication disorders. Augmentative and alternative communications (AAC) are AT devices used to support individuals with complex communication needs. There is a wide range of congenital and acquired health conditions that require the use of AAC. These conditions include but are not limited to autism, cerebral palsy, dual sensory impairments, genetic syndromes, intellectual disability, multiple disabilities, hearing impairment, disease, stroke, and head injury (ASLH, 2016). The process of selecting and fitting an AAC device proves to be particularly challenging when patients have decreased memory, distractibility, and lack of insight. To improve access to AT, the GATE initiative hopes to develop innovative models of service provision that would enable individuals to access AT for all their functional needs from a single healthcare infrastructure.

Models that seek to improve the service provision in healthcare applications are common (Walker et al., 2015; Pérez et al., 2017; Reese et al., 2017; Pérez and Dzubay, 2021; Jiang and Yuan, 2020). However, no existing research have considered the use of optimisation techniques to find the best AAC device fit for patients suffering from conditions associated with neurological disorders. This research builds on existing research exploring the application of the International Classification of Functioning, Disability and Health (ICF) model in AT selection (Steel et al., 2011). A couple of surveys of AT models and instruments have suggested the need for evidence-based tools for the selection of AT devices that increase patient satisfaction and device usability (Bernd et al., 2009; Friederich et al., 2010). The noticeable gap in the literature between theories and practice suggests the need for better decision-making methods for AT selection.

The *goal* of this research is to improve the access to services for patients in need of AAC. The *research objective* is to develop a decision-making model that can help in recommending the best group of AAC devices to consider for a patient. The research methodology applies the complete ICF framework in a decision-making model that considers the patient's disability profile and the capabilities of AAC devices. The model is designed for use by the various practitioners involved in AAC selection. As stated earlier, a large pool of devices is offered from multiple companies, however, the decision-making process of what device or devices to consider is largely based on the health practitioner's experience. The proposed model and algorithm try to minimise patient discomfort by recommending a limited list of devices that are likely to provide the best fit based on the patient's disability profile. A short list of devices will reduce patient assessment time which at the end minimises patient discomfort.

The rest of the paper is organised as follows. Section 2 presents a literature review. Section 3 presents the research methodology. The application and experimental designs are discussed in Section 4. The computational results are presented in Section 5. Section 6 ends the paper with concluding remarks and directions for future research.

2 Literature review

Prior to this study, the research focusing on the *AAC-patient matching problem* has been very limited. To the best of our knowledge, the work presented in this paper is the first attempt to develop a practical decision-making model for AAC selection that uses the complete structure of the ICF and the power of its interaction between components. Several authors have examined the application of the ICF model in the selection of AT devices and have proposed conceptual models to guide practitioners (Arthanat and Lenker, 2008; Fuhrer et al., 2003; Jutai et al., 2005; Scherer et al., 2007). However, the resulting models and instruments have incorporated only some of the ICF components and most of the proposed models rely on the practitioner's interpretation to make decisions. For example, Arthanat and Lenker (2008) consider only five of the ICF components for AT selection, and Scherer et al. (2007) incorporated only environmental and personal factors from the ICF.

In terms of decision-making models, no other research has considered application of mathematical models to solve the *AAC-patient matching problem*. Therefore, the focus of this literature review is on problems that are similar to the AAC-patient matching problem. The problem list includes the *surgeon-patient matching* problem (Jiang and Yuan, 2020; Abdelghany and Eltawil, 2017), the *patient-organ donation* matching problem (Su and Zenios, 2005), the *suppliers-organisations matching* problem (Bafrooei et al., 2014; Hatefi and Razmi, 2013), and the *product-storage location matching problem* (Hale et al., 2015; Karam et al., 2016).

The *surgeon-patient matching* problem seeks to select the right surgeon for a patient and arrange an appropriate surgery for the surgeon. Abdelghany and Eltawil (2017) consider linking approaches for healthcare systems planning and discusses advantages and disadvantages of different simulation methods. Yang et al. (2019) introduced the two-sided matching theory into the problem of setting appointments between experts and patients and applied a balanced matching model considering the fairness of both types of agents. Jiang and Yuan (2020) presents a new approach to obtain the surgeon-patient matching scheme with the pairwise comparison information while still maintaining the original preference information. Like the *AAC-patient matching problem*, in the *surgeon-patient matching* problem the patient status is considered at the time of making decisions. However, in the surgeon-patient donation matching problem the decisions (i.e., matching) are mostly based on the preferences of the doctor and the patient (e.g., time and date of surgery) and solution methods do not require a multidimensional fit between the agents.

Given the enduring scarcity of donated organs for transplantation, several allocation models and data mining techniques have been developed to identify patterns that are critical to assign an organ to a patient (Wang et al., 2019; Karami et al., 2019; Gentry et al., 2020). For instance, Su and Zenios (2005) present a kidney allocation framework that captures the imbalance between patient choice and social welfare. The authors present a model in which candidates form different queues based on the type of kidney needed by the patient. The problem is solved using a subjective partition policy by dividing the organ supply among the different queues to maximise social welfare. The patient-organ donation matching problem is challenging because the demand is hefty, and the supply is limited due to the scarcity of organs. In contrast, in the *AAC-patient matching problem*, the demand is limited, (i.e., a single patient) and the supply (i.e., availability of AAC devices) is high.

The *suppliers-organisations matching problem* and the *product-storage location matching problem* feature a supply and demand relationship similar to the *AAC-patient matching problem*. In the *suppliers-organisations matching problem* a list of suppliers is evaluated, based on performance, with the goal of finding the best match for a list of projects. For instance, Cao and Wang (2007) formulated a combinatorial two-stage optimisation model to help clients find the best vendor match for outsourced projects. Similarly, Ebrahim et al. (2009) formulated a multi-objective mixed integer program (IP) to find the match between multiple projects and suppliers. The problem of assigning stock-keeping units (SKU) to storage locations is similar to the suppliers-organisations matching problem (Tompkins et al., 2010). In the *product-storage location matching problem*, a list of SKUs is evaluated, based on demand, with the goal of finding the best storage location. In addition, the problem considers multiple products and multiple storage locations. For instance, Pang and Chan (2017) developed an algorithm for *product-storage location matching problem* that minimises the manual labour in the warehouse operations. In general, models addressing the *suppliers-organisations matching problem* and *product-storage location matching problem* consider the matching of many entities in the supply with many entities in the demand. In contrast, in the AAC-patient matching problem, the demand is limited to a single entity (i.e., a single patient).

Table 1 Comparison of similar problems and applications

Attributes	*Surgeon-patient matching*	*Patient-organ donation matching*	*Suppliers-organisations and product-storage matching*	*AAC-patient matching (this research)*
Multidimensional comparison of supply and demand				X
Multiple suppliers	X		X	X
Multiple demand	X	X	X	
Single supply		X		
Single demand				X

The models and applications discussed in this literature review do not meet the needs of the AAC selection problem as described in Table 1. This study presents a decision-making model that can help in recommending the best group of devices to consider for a patient based on a disability profile. The decision-making model allows for the selection of a device or devices while considering practical constraints associated with the problem. Specifically, the model considers patients suffering from conditions associated with neurological disorders and build their profiles using the ICF framework (WHO, 2014). The key challenge is to decide which device or devices to consider based on patient limitations (i.e., number of devices that can be fitted on the patient, to make a final decision, before the patient gets tired). The model developed in this study can help decision-makers address multiple key issues simultaneously while recommending the best group of devices to satisfy the patient needs.

3 Methodology

The decision-making model proposed here takes the form of an IP, constructed to work in conjunction with the ICF framework (WHO, 2014) that is designed to capture individual disability progression. The *AAC-patient matching problem* considers a patient with a specific disability profile and a group of AAC devices that could address one or more areas of the patient disability profile. It is assumed that the number of devices available is significant. For instance, the Texas Technology Access Program has about 100 AAC devices listed on their website (TTA-Program, 2019). The goal of the decision-making model is to provide a systematic method to find the best match between the patient and the list of AAC devices available.

In this study, two set of parameters are required to build and solve the decision-making model. The first set of parameters defines the patient disability profile. The patient disability profile is defined according to the eleven assessments of the ICF framework listed in Table 2. A score is assigned to each assessment based on the patient ability of meeting the expected thresholds. The second set of parameters defines the assessment information for each AAC device considered as an option for the patient. Each device is also evaluated according to how well they meet the eleven assessments of the ICF framework listed in Table 2.

Table 2 ICF framework assessments with descriptions

Assessments	*Description*
Sensory and motor status	The sensory and motor status assessment includes vision test, sensation status and the integrated sensory system ability. Vision test mainly focuses on the ability of the patient to see the symbols or orthography on the AAC device. Sensation assessments include light touch and pressure test, proprioception test, temperature test and pain test. The integrated sensory assessment tests the patient's ability to regulate and ready the body for communication.
Hearing screening	A pure-tone test is the most common hearing screening. It is an assessment to see how well the patient hears different sounds. Failing a hearing screening does not mean that the patient has a hearing loss. If the patient fails, he/she requires a complete hearing test by an audiologist to determine the degree of hearing loss.
Speech-sound	Speech-sound assessment of a patient can help in the identification of factors that contribute to the speech-sound disorder and description of the characteristics and severity of the disorder. The severity of the patient case is often defined along a continuum from mild to profound.
Spoken language	Standardised language screening is used to identify the broad characteristics of language functioning. A literacy assessment is included in the comprehensive assessment for language disorders because of the well-established connection between spoken and written language.
Written language	Assessments of reading and writing skills must be linguistically appropriate, culturally relevant and functional. Screening can result in the determination of premorbid and current literacy level of the patient with complex communication needs.
Social communication	Social communication screening includes the use of competency-based tools such as interviews and observations and self-report questionnaires. The assessment helps to identify underlying strengths and weaknesses in communication and communication-related areas and limitations in activity and participation, including functional communication and interpersonal interactions
Cognitive communication	Cognitive-communication deficits result from underlying cognitive or thinking difficulties in attention, memory, organisation, reasoning, executive functions, self-regulation, or decreased information processing. Cognitive communication screening helps in identifying cognitive and communication demands of relevant real-world contexts.
Symbol assessment	Symbol assessment process involves the screening of patients in the identification and recognition of the type of symbols, symbol size, field size and organisation of display.
Feature matching	Feature matching is a collaborative process which involves using criterion-based assessment strategies to gather relevant information about a client's communication and sensorimotor abilities. Feature matching allows identification of the most appropriate applications available in the AAC devices.
Identification of contextual facilitators and barriers	Facilitator screening identifies the ability and willingness of the patient to use AAC systems, family support and the patient's motivation to communicate. The barriers during the assessments include cognitive deficits, visual and motor impairments, lack of acceptance of disability and/or AAC use, limitations of AAC system, seating and positioning limitations across environments.
Case history	Medical status and history, education, occupation, and cultural and linguistic backgrounds are considered a part of the patient's case history. Prognosis and the potential for disease progression are also deliberated in determining the best-suited device for the patient.

The ICF framework is a qualitative assessment. In this study, the qualitative results are transformed into quantitative amounts by discretising them using a deterministic selection score. An evaluation score set $E = \{1, 2, 3, 4\}$ is defined, where 1 = 'poor', 2 = 'fair', 3 = 'average', and 4 = 'good'. For the device data, the scores are used to characterise the competency of available devices to meet each component of the ICF framework. Each device $i \in I$ is evaluated using a set of relevant assessments $j \in J$ from the ICF framework. The patient scores for each ICF assessment $j \in J$ are denoted by $s_j \in E$. The device evaluation scores for each device i and each ICF assessment j is denoted by $d_{ij} \in E$. The device evaluation score represents the minimum level of usability of the device for the specific assessment. For example, $d_{11} = 2$ states that the score for device 1 on assessment 1 is 'fair'. Therefore, the device will be a good fit for a patient only if the patient scores 2 'fair', 3 'average', or 4 'good' in this assessment. If the patient scores a 1 'poor' in the assessment, then device 1 will not meet the patient needs for this portion of the assessment.

3.1 Decision-making model for the AAC-patient matching problem

The decision-making model takes the form of an IP. This IP is the first decision-making model developed to solve the *AAC-patient matching problem*. The model represents the first attempt to integrate the ICF framework as part of a formal decision process. This is the novelty of the model that differentiates it from other health-related allocation models in literature. The model has two binary decision variables. Decision variable y_{ij} determines whether device i satisfies patient assessment j. Decision variable x_i determines whether device i is selected as a good fit for the patient. The objective function maximises a best-fit function that considers the patient's disability profile and the ability of each device to meet the patient's needs. The best-fit function equals the sum of number of evaluations satisfied by each device (y_{ij}) multiplied by a weight (w_j) parameter that denotes the importance of each evaluation for a specific patient. The output of the model provides a group of devices that are selected as the most suitable for the patient's disability profile.

Table 3 lists the sets, parameters, and decision variables used to formulate the model. The model constraints are defined in equations (1) to (7). Equation (2) checks that the patient assessment score for assessment $j(s_j)$ is greater than or equal to device i score (d_{ij}). Equation (3) verifies if device i meets the minimum number of ICF assessments that must be passed for the device to be considered suitable for the patient. Equation (4) limits the number of devices to be selected to no more than n. Equation (5) is a selection constraint. Finally, equations (6) and (7) limit the decision variables to binary values. The IP model is solved using IMB CPLEX (Lima, 2010).

$$\max z = \sum_{i \in I} \sum_{j \in J} w_j y_{ij} \tag{1}$$

Subject to:

$$s_j y_{ij} - d_{ij} y_{ij} \geq 0, \quad \forall i \in I, \forall j \in J \tag{2}$$

$$\sum_{j \in J} \frac{1}{|J|} y_{ij} \geq \beta x_i, \quad \forall i \in I \tag{3}$$

$$\sum_{i \in I} x_i \leq n, \tag{4}$$

$$y_{ij} - x_i \leq 0, \quad \forall i \in I, \forall j \in J \tag{5}$$

$$x_i \in \{0, 1\}, \quad \forall i \in I \tag{6}$$

$$y_{ij} \in \{0, 1\}, \quad \forall i \in I, \forall j \in J \tag{7}$$

Table 3 IP model sets, parameters, and variables

	Sets
I	Set of AAC devices, indexed $i \in I$
J	Set of ICF assessments, indexed $j \in J$
E	Set of evaluation scores for each ICF, $E = \{1, 2, 3, 4\}$.
	Parameters
d_{ij}	Device i evaluation score for ICF assessment j, $d_{ij} \subset E$.
s_j	Patient evaluation scores for ICF assessment j, $s_j \subset E$.
β	A percentage that is used to establish the minimum total number of ICF assessments that the device must pass to be considered appropriate for the patient.
n	Number of AAC devices to be recommended by the decision maker.
w_j	Weight used to denote the importance of assessment j. High w_j's identifies patient priorities in terms of their disabilities as measured by the ICF assessments.
	Decision variables
x_i	A binary variable that determines the devices selected for the patient. $x_i = 1$, if device i is recommended for the patient and 0 otherwise.
y_{ij}	A binary variable that determines if device i satisfies patient assessment j. $y_{ij} = 1$, if device i passes assessment j and 0 otherwise.

The following lemma establishes that for a given set of devices, say I, the group of n devices with the maximum best-fit function $C_{\max}$ is found by sequencing the devices in I in non-increasing order of the ratio $g_i = \sum_j ((d_{ij} w_j) / s_j)$. Therefore, the proposed problem is solvable in polynomial time.

Lemma 1. Let I be the set of devices available ordered so that:

$$g_1 \geq g_2 \geq g_3 \geq \ldots \geq g_n \geq g_{n+1} \geq \ldots \geq g_k,$$

And k be the number of devices in I, then the *best-fit function* $C_{\max} = \sum_{i=1}^{n} g_i$ is optimal.

Proof. Let I' be as set I but with the devices in positions n and $n + 1$ exchanged.

The best-fit function $C_{\max}$ for I is:

$$C_{\max} = g_1 + g_2 + g_3 + \ldots + g_n.$$

The best-fit function $C'_{\max}$ for I' is:

$$C'_{\max} = g_1 + g_2 + g_3 + \ldots + g_{n+1}.$$

It is supposed, by contradiction, that $C_{\max} < C'_{\max}$, then:

$g_n < g_{n+1}$

which cannot be true given

$g_n \geq g_{n+1}$.

It must be concluded that $C_{\max} \geq C'_{\max}$.

Q.E.D.

3.2 Augmentative and alternative communication selection (AACS) algorithm

A heuristic algorithm is developed to solve the IP model presented in Section 3.1. The heuristic algorithm uses *Lemma 1* to solve the problem to optimality. The additional benefit of the AACS algorithm is that it provides a way for healthcare professionals to use the methodology without investing in a commercial optimisation solver. The algorithm was coded using PHP (hypertext pre-processor) language and the database is managed using MySQL. The software tool phpMyAdmin was used to administer the algorithm over the Web.

The algorithm applies some of the parameters defined for the optimisation model and listed in Table 3. New parameters are also required for the algorithm and are defined as follows. Parameter k defines the total number of assessments and parameter 'counter' keeps track of the number of assessments satisfied by device j. Parameter m defines the total number of devices and g_i is the *patient-device fit score*. Let V be a set that includes the devices i designated as good-fit for the patient and let H be a set that is used to include the *patient-device fit score* for devices in V. In addition, ← is used to denote assignment. Figure 1 present the pseudocode for the *AACS algorithm*.

Figure 1 Pseudocode for AACS

***AACS* algorithm**

```
V ← {∅}, counter = 0,
for i = 1 to m do
    for j = 1 to k do
        if d_ij / s_j ≤ 1
            counter++
        if counter / |J| ≥ β
            i ∪ V
            break
while V ≠ {∅} do
    g_i = Σ_j (d_ij w_j / s_j)
    g_i ∪ H
sort g_i in H in non-increasing order
select n devices with the higher g_i scores in H
```

Line 1 initialises the parameters. Lines 2 to 5 determine, for each device i, the number of assessments j that meets patient profile s_j. In line 5, parameter 'counter' is increased by one if device i covers the patient needs for assessment j as defined by profile s_j. Line 6 checks if device j meets β. If device j meets β, a *patient-device fit score* is computed in lines 9 to 11. Line 12 sorts all scores in H in non-decreasing order and line 13 selects the n devices with the higher score in H.

4 Application and experimental design

In this section, an experimental study is designed to study the AAC-patient matching problem and the performance of the methods discussed in Sections 3.1 and 3.2. Specifically, this section defines the input parameters values to be considered in the experiments. A general factorial design was selected to conduct a total of 81 runs without replications. The experiments consider four input factors with three levels. The output response is the 'patient-device fit score' for each device recommended for the patient. The four input factors include 'patient condition', 'number of devices available', 'assessment weight distribution' and 'minimum level of assessment satisfaction'.

Table 4 Experimental factors and corresponding levels

Factors	*Level*		
	Low (L)	*Medium (M)*	*High (H)*
Patient condition	Minor	Moderate	Severe
Number of devices available	20	50	100
Assessment weight distribution	Equally weighted	Highly weighted on needs	Randomly weighted
Minimum level of assessment satisfaction	70%	80%	90%

Table 4 lists the input factor and corresponding levels. The input factor 'patient condition' considers patients with three different disability profiles (i.e., *minor*, *moderate*, and *severe*). The disability profile is determined using the ICF framework scores. The attainable disability scores span from 1 to 4, ranging from the lowest to the highest possible score as discussed in Section 3. A patient with a *severe* disability profile typically scores between 1 and 2 for most assessments. A patient with a *moderate* level disability often scores between 1 and 3 and a patient with a minor level disability typically scores between 1 and 4. Disability profiles were defined in consultation with experts in the field of communication disorders with the goal of representing the majority of cases observed in practice. The 'number of devices available' considers the number of devices available to evaluate the patient. The number of devices available varies depending on the professional in charge of conducting the assessments. Some practices have access to more devices than others. For example, the Texas Technology Access Program has 52 devices available to loan to patients requiring AAC (TTA-Program, 2019) and the Augmentative Communication Consultants group has 85 devices available (AC-Consultants, 2019). The three levels considered for the factor 'number of devices available' are 20 devices, 50 devices and 100 devices.

The ‘assessment weight distribution’ factor is used to prioritise assessments according to the patient disability profile. There are three experimental levels for the ‘assessment weight distribution’ factor. The low (L) level distributes the weights equally among the assessments. The medium (M) level focuses on patient needs and assigns an 80% of the weight to three of the eleven assessments and 20% of the weight to the rest of them. Finally, the high *(H*) level assigns weights to assessments randomly which represents a patient disability profile that is unique.

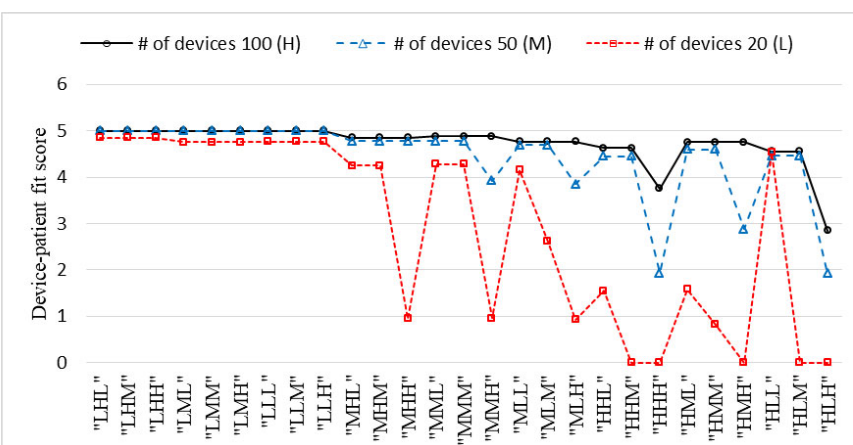
The factor ‘minimum level of assessment satisfaction’ is a ratio used to establish the minimum number of patient assessments, from the ICF framework, that each device must satisfy to be considered a good fit for the patient. The following ratios were selected for levels low (*L*), medium (*M*), and high (*H*) respectively: 70%, 80% and 90%. For example, for the eleven assessments in Table 1, a 70% ‘minimum level of assessment satisfaction’ indicates that eight out of the eleven ICF framework assessments must be satisfied for the device to be considered a good fit for the patient.

5 Computational results

The goal of the computational study is to analyse the performance of the IP decision-making model and associated solution algorithm, (i.e., AACS algorithm) in solving the *AAC-patient matching problem*. The computational study results provide insights about the effects of the experimental factors on the output response ‘patient-device fit score’.

The computational study considers multiple patient disability profiles as defined in Section 4. For which the maximum *number of AAC devices to be recommended* equals five (i.e., n = 5). Tables 5, 6 and 7 show the results for the general factorial design described in Table 4. The computational results are separated by the experimental factor ‘number of devices available’. Table 5 lists the results for 100 devices [i.e., high (*H*)]. Table 6 shows the results for 50 devices [i.e., medium (*M*)] and Table 7 shows the results for the third group where the experimental factor ‘number of devices available’ is at level low (*L*) or 20 devices. Figure 2 summarises the results in a single plot.

Figure 2 Device-patient fit scores by factor ‘number of devices’ (see online version for colours)



The level for each experimental factor is listed in the second, third, and fourth columns of Tables 4–6. For instance, the combination 'HML' indicates the following: 'patient condition' (*H*), 'assessment weight distribution' (*M*), and 'minimum level of assessment satisfaction' (*L*). The fifth and sixth columns list the devices selected by the optimisation model and the AACS algorithm respectively. Finally, the seventh column indicates the 'patient-device fit score' for $n = 5$, which is the experimental response. As stated earlier, the AACS algorithm solves the IP decision model to optimality. Therefore, only one column is used to display the optimal values for the 'patient-device fit score'.

Table 5 Computational results for factor 'number of devices available' fixed at level high (*H*)

#	*Patient condition*	*Assessment weight distribution*	*Minimum level of assessment satisfaction*	*Optimisation model solution*	*AACS algorithm solution*	*Patient-device fit score*
1	L	H	L	72, 75, 88, 91, 92	6, 10, 31, 33, 40	5.00
2	L	H	M	48, 75, 88, 91, 92	6, 10, 31, 33, 40	5.00
3	L	H	H	31, 33, 40, 72, 75	6, 10, 31, 33, 40	5.00
4	L	M	L	48, 50, 72, 75, 88	6, 10, 31, 33, 40	5.00
5	L	M	M	6, 50, 88, 91, 92	6, 10, 31, 33, 40	5.00
6	L	M	H	50, 75, 88, 91, 92	6, 10, 31, 33, 40	5.00
7	L	L	L	72, 75, 88, 91, 92	6, 10, 31, 33, 40	5.00
8	L	L	M	10, 75, 88, 91, 92	6, 10, 31, 33, 40	5.00
9	L	L	H	31, 33, 40, 42, 72	6, 10, 31, 33, 40	5.00
10	M	H	L	33, 48, 53,75, 77	33, 48, 77, 18, 52	4.85
11	M	H	M	33, 48, 52, 53, 87	33, 48, 77, 18, 52	4.85
12	M	H	H	33, 48, 52, 53, 77	33, 48, 77, 18, 52	4.85
13	M	M	L	18, 33, 48, 50, 75	33, 48, 18, 50, 75	4.88
14	M	M	M	18, 33, 48, 50, 75	33, 48, 18, 50, 75	4.88
15	M	M	H	18, 33, 48, 50, 75	33, 48, 18, 50, 75	4.88
16	M	L	L	33, 48, 75, 76, 92	33, 48, 18, 50, 52	4.77
17	M	L	M	33, 48, 52, 53, 92	33, 48, 18, 50, 52	4.77
18	M	L	H	18, 33, 48, 87, 92	33, 48, 18, 50, 52	4.77
19	H	H	L	33, 48, 51, 75, 87	33, 48, 87, 51, 49	4.63
20	H	H	M	33, 48, 51, 75, 87	33, 48, 87, 51, 49	4.63
21	H	H	H	33, 48, 51, 87	33, 48, 87, 51	3.75
22	H	M	L	33, 48, 73, 74, 87	33, 48, 87, 49, 73	4.76
23	H	M	M	33, 48, 49, 75, 87	33, 48, 87, 49, 73	4.76
24	H	M	H	33, 48, 49, 75, 87	33, 48, 87, 49, 73	4.76
25	H	L	L	33, 48, 73, 87, 89	33, 48, 87, 28, 29	4.56
26	H	L	M	28, 29, 33, 48, 87	33, 48, 87, 28, 29	4.56
27	H	L	H	33, 48, 87	33, 48, 87	2.85

Table 5 shows that when the 'patient condition' factor is set at level low (*L*) (i.e., patient disability is classified as minor) the decision-making model is able to recommend five devices that perfectly meet the patient's needs (i.e., 'patient-device fit score' = 5). However, when the 'patient condition' factor is set at level medium (*M*) (i.e., patient disability is classified as moderate) the decision-making model is not able to recommend five devices that perfectly meet the needs of the patient. When 'patient condition' factor is set at level medium (*M*), the 'patient-device fit score' response values range between 4.77 and 4.88. The 4.77 scores are observed when the 'assessment weight distribution' is set to level low *(L)* (i.e., ICF components are equally weighted). This result shows that it is difficult to find a group of devices that meets patients' needs when all assessments of the ICF framework are equally important. Finally, when the 'patient condition' factor is set at level high (*H*) (i.e., patient disability is classified as severe), the 'patient-device fit score' response values range between 2.85 and 4.76. The 2.85 score is observed when the 'assessment weight distribution' is set to level low (*L*) (i.e., ICF components are equally weighted) and the 'minimum level of assessment satisfaction' is set to level high (*H*) (i.e., 90%). This result shows that is not possible to find a group of five devices that meets the needs of the patient when all assessments of the ICF framework are equally important and the 'minimum level of assessment satisfaction' is very high.

Table 6 Computational results for factor 'number of devices available' fixed at level medium (*M*)

#	*Patient condition*	*Assessment weight distribution*	*Minimum level of assessment satisfaction*	*Optimisation model solution*	*AACS algorithm solution*	*Patient-device fit score*
1	L	H	L	33, 40, 42, 48, 50	6, 10, 31, 33, 40	5.00
2	L	H	M	31, 40, 42, 48, 50	6, 10, 31, 33, 40	5.00
3	L	H	H	6, 31, 42, 48, 50	6, 10, 31, 33, 40	5.00
4	L	M	L	33, 40, 42, 48, 50	6, 10, 31, 33, 40	5.00
5	L	M	M	31, 40, 42, 48, 50	6, 10, 31, 33, 40	5.00
6	L	M	H	6, 33, 40, 48, 50	6, 10, 31, 33, 40	5.00
7	L	L	L	33, 40, 42, 48, 50	6, 10, 31, 33, 40	5.00
8	L	L	M	33, 40, 42, 48, 50	6, 10, 31, 33, 40	5.00
9	L	L	H	6, 10, 31, 42, 48	6, 10, 31, 33, 40	5.00
10	M	H	L	18, 33, 48, 49, 50	33, 48, 18, 50, 21	4.78
11	M	H	M	18, 33, 48, 49, 50	33, 48, 18, 50, 21	4.78
12	M	H	H	18, 33, 48, 49, 50	33, 48, 18, 50, 21	4.78
13	M	M	L	18, 33, 48, 49, 50	33, 48, 18, 50, 4	4.78
14	M	M	M	18, 33, 48, 49, 50	33, 48, 18, 50, 4	4.78
15	M	M	H	18, 33, 48, 50	33, 48, 18, 50	3.92
16	M	L	L	18, 33, 48, 49, 50	33, 48, 18, 50, 4	4.69
17	M	L	M	18, 33, 48, 49, 50	33, 48, 18, 50, 4	4.69
18	M	L	H	18, 33, 48, 50	33, 48, 18, 50	3.85
19	H	H	L	29, 33, 48, 49, 50	33, 48, 49, 28, 29	4.45
20	H	H	M	29, 33, 48, 49, 50	33, 48, 49, 28, 29	4.45
21	H	H	H	33, 48	33, 48	1.93
22	H	M	L	29, 33, 48, 49, 50	33, 48, 49, 28, 29	4.60
23	H	M	M	29, 33, 48, 49, 50	33, 48, 49, 28, 29	4.60
24	H	M	H	33, 48, 49	33, 48, 49	2.88
25	H	L	L	29, 33, 48, 49, 50	33, 48, 28, 29, 49	4.46
26	H	L	M	29, 33, 48, 49, 50	33, 48, 28, 29, 49	4.46
27	H	L	H	33, 48	33, 48	1.92

Table 6 reports the performance of the decision-making model when the factor 'number of devices available' is fixed at level medium (*M*) (i.e., 50 devices). Table 6 shows that when the 'patient condition' factor is set at level low (*L*) (i.e., patient disability is classified as minor) the decision-making model is able to recommend five devices that perfectly meet the needs of the patient (i.e., 'patient-device fit score' = 5). However, when the 'patient condition' factor is set at level medium (*M*) (i.e., patient disability is classified as moderate) the decision-making model is not able to recommend five devices that perfectly meet the needs of the patient. When 'patient condition' factor is set at level medium (*M*), the 'patient-device fit score' response values range between 3.85 and 4.78. The 3.85 score is observed when the 'assessment weight distribution' is set to level low (*L*) (i.e., ICF components are equally weighted) and the 'minimum level of assessment satisfaction' is set to level high (i.e., 90%). This result shows that is not possible to find a group of five devices that meets the needs of the patient when all assessments of the ICF framework are equally important and the 'minimum level of assessment satisfaction' is very high. Finally, when the 'patient condition' factor is set at level high (*H*), (i.e., patient disability is classified as severe), the 'patient-device fit score' response values range between 1.92 and 4.60. The 1.92 score is observed when the 'assessment weight distribution' is set to level low (*L*), (i.e., ICF components are equally weighted) and the 'minimum level of assessment satisfaction' is set to level high (H) (i.e., 90%). This result shows that the decision-making model is not able to recommend a group of five devices that meets the needs of the patient when all assessments of the ICF framework are equally important and the 'minimum level of assessment satisfaction' is very high.

Table 7 reports the performance of the decision-making model when the factor 'number of devices available' is fixed at level low (*L*) (i.e., 20 devices). Table 7 shows that when the 'patient condition' factor is set at level low (*L*) (i.e., patient disability is classified as minor) the decision-making model is no longer able to recommend five devices that perfectly meet the needs of the patient. When 'patient condition' factor is set at level low (*L*), the 'patient-device fit score' response values range between 4.77 and 4.85. The 4.77 scores are observed when the 'assessment weight distribution' factor is set to level low (*L*) (i.e., ICF components are equally weighted). This finding shows that is more difficult to find a group of devices that meets patients' needs when all assessments of the ICF framework are equally important. When 'patient condition' factor is set at level medium (*M*), the 'patient-device fit score' response values range between 0.92 and 4.28. The 0.92 score is observed when the 'assessment weight distribution' is set to level low (*L*), (i.e., ICF components are equally weighted) and the 'minimum level of assessment satisfaction' is set to level high (i.e., 90%). This result shows that is not possible to find a group of five devices that meets patients' needs when all assessments of the ICF framework are equally important and the 'minimum level of assessment satisfaction' is very high. Finally, when the 'patient condition' factor is set at level high (*H*), (i.e., patient disability is classified as severe), the 'patient-device fit score' response values range between 0.00 and 1.58. One of the 0.00 scores is observed when the 'assessment weight distribution' is set to level low (*L*), (i.e., ICF components are equally weighted) and the 'minimum level of assessment satisfaction' is set to level high (*H*) (i.e., 90%). This result shows that the decision-making model cannot recommend a group of devices that meets patients' needs when all assessments of the ICF framework are equally important and the 'minimum level of assessment satisfaction' is very high.

Table 7 Computational results for factor 'number of devices available' fixed at level low (*L*)

#	*Patient condition*	*Assessment weight distribution*	*Minimum level of assessment satisfaction*	*Optimisation model solution*	*AACS algorithm solution*	*Patient-device fit score*
1	L	H	L	6, 10, 11, 12, 13	6, 10, 9, 11, 12	4.85
2	L	H	M	6, 10, 11, 12, 13	6, 10, 9, 11, 12	4.85
3	L	H	H	6, 10, 11, 12, 13	6, 10, 9, 11, 12	4.85
4	L	M	L	5, 6, 10, 17, 18	6, 10, 5, 8, 9	4.78
5	L	M	M	5, 6, 10, 17, 18	6, 10, 5, 8, 9	4.78
6	L	M	H	5, 6, 8, 10, 11	6, 10, 5, 8, 9	4.78
7	L	L	L	6, 8, 10, 11,12	6, 10, 5, 8, 9	4.77
8	L	L	M	5, 6, 8, 9, 10	6, 10, 5, 8, 9	4.77
9	L	L	H	5, 6, 10, 17, 18	6, 10, 5, 8, 9	4.77
10	M	H	L	9, 11, 13, 17, 18	18, 9, 13, 17, 4	4.25
11	M	H	M	9, 11, 13, 17, 18	18, 9, 13, 17, 4	4.25
12	M	H	H	18	18	0.95
13	M	M	L	4, 10, 13, 17, 18	18, 4, 10, 13, 17	4.28
14	M	M	M	4, 10, 13, 17, 18	18, 4, 10, 13, 17	4.28
15	M	M	H	18	18	0.96
16	M	L	L	4, 9, 12, 13, 18	18, 4, 9, 10, 11	4.15
17	M	L	M	4, 9, 18	18, 4, 9	2.62
18	M	L	H	18	18	0.92
19	H	H	L	9, 12	9, 12	1.55
20	H	H	M	0	0	0.00
21	H	H	H	0	0	0.00
22	H	M	L	9, 12	12, 9	1.58
23	H	M	M	12	12	0.82
24	H	M	H	0	0	0.00
25	H	L	L	9, 12	9, 12	1.54
26	H	L	M	0	0	0.00
27	H	L	H	0	0	0.00

The results show that multiple optimal solutions exist for many of the experiments. This is expected when multiple combinations of devices provide the same 'patient-device fit score'. To illustrate this behaviour, Table 8 compares the devices selected for experiment five in Table 7. In this experiment, two out of the five devices selected by the IP decision-model are different from those selected by the AACS algorithm. The 'patient-device fit score', per device and solution method, is depicted in Table 8. It is observed that the AACS algorithm selected devices 8 and 9 instead of devices 17 and 18 because they have the same 'patient-device fit score', (i.e., 0.9) and at the end the optimal solution resulted in the same aggregated 'patient-device fit score'.

Table 8 Device selection comparison for experiment 5 in Table 7

			Optimisation model			
Devices selected	*5*	*6*	*10*	*17*	*18*	*Total score*
Patient-device fit score	0.96	1	1	0.9	0.9	4.76
			AACS algorithm			
Devices selected	*6*	*10*	*5*	*8*	*9*	*Total score*
Patient-device fit score	1	1	0.96	0.9	0.9	4.76

5.1 Discussion

The factorial analysis of variance conducted compares means across each of the factors to determine which effects (i.e., factors) and interactions are significant. Figure 3 depicts the analysis of variance performed for the general factorial experiment shown in Table 4. A significance level of 0.05 is adopted to assess the experimental results.

Figure 3 ANOVA analysis

General Linear Model: Overall Device Satisfaction Score versus Patient Condition, Number of Devices Available, Assessment Weight Distribution, Minimum Level of Assessment Satisfaction

Analysis of Variance

Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	**P-Value**
Assessment weight distribution	2	0.274	0.137	0.150	0.858
Patient Condition	2	49.780	24.890	27.980	0.000
Minimum level of assessment satisfaction	2	16.006	8.003	9.000	0.000
Number of devices available	2	52.241	26.120	29.360	0.000
Error	72	64.060	0.890		
Total	80	182.361			

Model Summary

S	**R-sq**	**R-sq (adj)**	**R-sq (pred)**
0.94325	64.87%	60.97%	55.54%

The *p*-values shown in the analysis of variance exhibits the strength of evidence for the significance of factors. The factors ‘patient condition’, ‘number of devices available’, and ‘minimum level of assessment satisfaction’ display a *p*-value less than 0.05 which indicates strong evidence of significance on the output model. A *p*-value of 0.849 exhibited by the factor ‘assessment weight distribution’ denotes a very low significance on the overall device satisfaction. This is also validated by the low *F*-value of 0.15 for the same factor which demonstrate that the variability in ‘assessment weight distribution’ factor does not have a high impact on the output response. The high *F*-values shown by the rest of the experimental factors confirm their significant effect on the output response ‘patient-device fit score’.

Figure 4 shows main-effects-plot which shows the impact of each experimental factor on the mean of the output response. The main effect of each experimental factor is independent of all other factors and therefore disregards any possible interactions between the factors. The results show that the mean aggregated ‘patient-device fit score’ increases when the experimental factor ‘number of devices available’ is high (*H*). Therefore, the chances of meeting the patient’s evaluation needs are greater as the number of device options increases. This fact is also evident in Figure 2 where, for all experimental combinations, the best result is obtained when the 'number of devices available' factor is at a high level (*H*).

Figure 4 Main effects plot (see online version for colours)

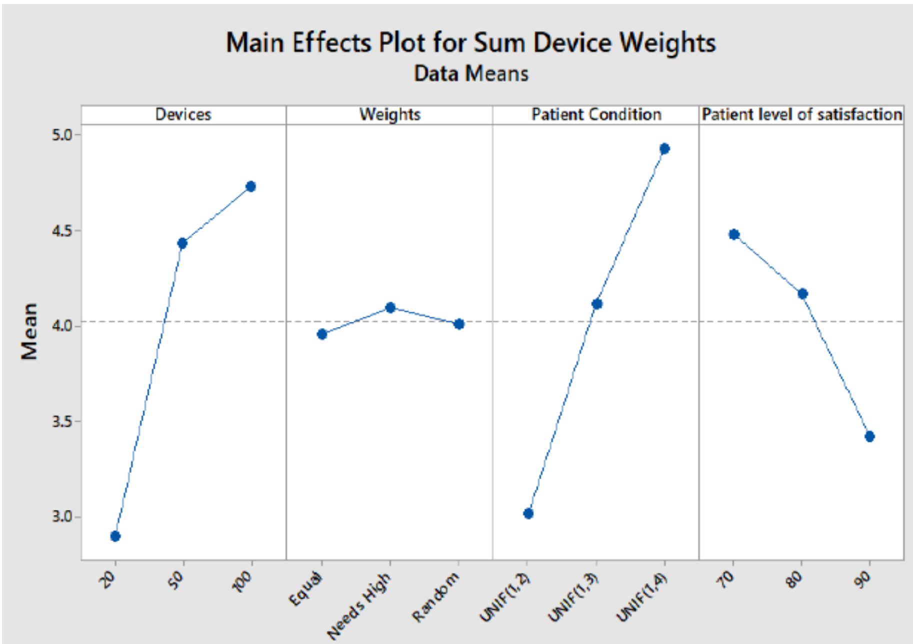
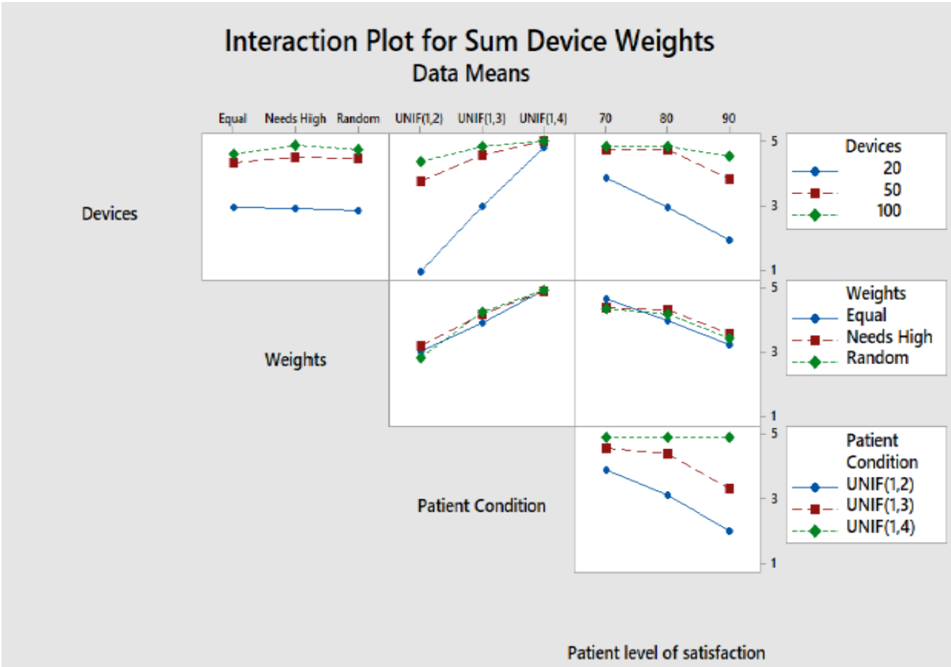


Figure 4 also shows that the mean aggregated 'patient-device fit score' decreases as the 'patient condition' factor spans from *minor* to *severe*. This indicates that the prospect of finding devices that satisfy the needs of a patient with a severe disability profile is lower when compared to a patient with *moderate* or *minor* disability profile. The results show that the aggregated 'patient-device fit score' response decreases as the level for the 'assessment satisfaction' factor increases. As the threshold level increases for the device to be considered a good fit, the pool of devices that satisfy the imposed constraints reduces and hence the aggregated 'patient-device fit score' response decreases. The highest variation in the mean of the aggregated 'patient-device fit score' response occurs for the independent factors 'patient condition' and 'number of devices available'.

Figure 5 analyses possible 2-way-interactions. Figure 5 confirms that the 'patient condition' and 'number of devices available' factors have the major impact on the aggregated 'patient-device fit score' response. In the 'patient condition' versus 'number of devices available' plot, the worst overall performance is observed when the 'patient condition' is severe (i.e., low scores for most assessments) and the 'number of devices available' is low (i.e., 20 devices). The overall performance of the aggregated 'patient-device fit score' response gradually improves as the 'patient condition' improves and the 'number of devices available' increases.

Figure 5 Two-way interaction plot (see online version for colours)



In the ‘patient condition’ versus ‘assessment satisfaction’ plot, the worst overall performance is observed when the ‘patient condition’ is severe, (i.e., low scores for most assessments) and the ‘assessment satisfaction’ is high (i.e., 90%). The overall performance of the aggregated ‘patient-device fit score’ response gradually improves as the ‘assessment satisfaction’ decreases and the ‘patient condition’ improves. Finally, in the ‘number of devices available’ versus ‘assessment satisfaction’ plot, the worst overall performance is observed when the ‘assessment satisfaction’ is high (i.e., 90%) and the ‘number of devices available’ is low (i.e., 20 devices). The overall performance of the aggregated ‘patient-device fit score’ response gradually improves as the ‘assessment satisfaction’ decreases and the ‘number of devices available’ factor increases.

6 Conclusions

The *AAC-patient matching problem* is complex and involves many professionals to effectively serve patients with different disability profiles. In this paper, a decision-making model was developed to recommend the best group of devices to consider based on the patient’s disability profile. In the *AAC-patient matching problem*, there are often a large number of devices available from various companies; however, the decision-making process of which device or devices to consider for a patient is largely based on the experience of the healthcare professional in charge of the case. The proposed decision-making model and solution algorithm attempt to minimise patient discomfort by recommending a limited list of devices that are likely to provide the best fit based on the patient’s disability profile. A short list of devices can reduce the patient assessment time which at the end minimises patient discomfort. Selecting an inappropriate AAC device can lead to treatment abandonment, reducing the likelihood of patients seeking follow-up care. Therefore, it is crucial to match the competencies of the AAC user with a suitable communication device.

The decision-making model and solution algorithm presented in this document improve the mapping of the conformance attributes of the patient's diagnostic profile to the attributes of the AAC devices. The computational study shows that several experimental factors contribute more than others to the aggregated 'patient-device fit score'. The factors with the highest influence on the aggregated 'patient-device fit score' are 'number of devices' and 'patient condition'. The results show that the probability of finding a fitting device for a patient with a severe disability profile is low when compared to a patient with a moderate or minor disability profile. This is especially true when few devices are available as options.

This research aims to bridge the substantial gap between the need for and the provision of AT assessment available around the world. The model and solution algorithm presented in this paper minimises patient discomfort and reduce device assessment time by recommending a limited list of devices that are likely to provide the best fit based on the patient's disability profile. As future research, the authors would like to test the models with real data. In addition, the authors would like to introduce the uncertainty related to the health professional's expertise and experience into the decision-making process.

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