A Literature Review of MCDM methods in Healthcare

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Summary

Multi-Criteria Decision Making (MCDM) has become an integral part of healthcare decision making. In order to address resource allocation decisions, these methods are used to ensure that bias and decision-making fatigue are avoided, and that fair and equitable treatment is provided to patients regardless of the healthcare facility. The main types of problems that MCDM can help to solve are (1) choice problems to identify the best alternative, (2) ranking problems to identify the rank ordering of alternatives from best to worst, and (3) sorting problems where assignment of the alternatives to pre-defined ordered categories is necessary. During this literature review I examine how different studies utilize MCDM methods in organ allocation, COVID treatment priority, and vaccination priority group designation, as well as ways that these studies could have been improved. As a whole, the use of MCDM techniques comes with its own set of challenges that have the potential to be improved upon in the future. Throughout this literature review, I show that MCDM approaches to decision making are common in the healthcare industry, but not necessarily standardized across different healthcare facilities. Standardization of MCDM methods across different hospitals, companies, states, and countries may be necessary to make results comparable across different bodies and ensure equitable healthcare is provided everywhere

Background

The World Health Organization defines health as “a state of complete physical, mental and social well- being and not merely the absence of disease or infirmity [1].” The healthcare industry and health services aim to maintain and or improve the health of their surrounding populations via the prevention, diagnosis, treatment, recovery, or cure of disease, illness, injury, and other physical and mental impairments in people [2]. The healthcare industry is one of the largest and fastest growing industries in the world. With a global estimated worth of $8.45 trillion in 2018, it is predicted to surpass $10 trillion in spending by 2022. Along with catering billions of jobs to people all across the world, the healthcare industry is pivotal to everyday life in areas where populations have access to it [3]. Amid this massive system of governments, health care providers, and other stakeholders, there are millions of decisions being made on a daily basis which are utilized in order to prioritize human life, minimize human suffering, optimize spending, and minimize losses. Efforts to improve operational efficiency, improve quality, and cut costs have been sought after for decades. Andel et. al. discuss the implications of health care errors and losses in a journal article published in the National Library of Medicine:

“However, based on recent reports, approximately 200,000 Americans die from preventable medical errors including facility-acquired conditions and millions may experience errors. In 2008, medical errors cost the United States $19.5 billion. About 87 percent or $17 billion were directly associated with additional medical costs, including: ancillary services, prescription drug services, and inpatient and outpatient care, according to a study sponsored by the Society for Actuaries and conducted by Milliman in 2010 [4].”

These losses are greatly attributed to the incorrect decisions being made at the incorrect times. In addition to the human error that is costing the United States $1 trillion annually when quality-adjusted life years [4], poorly designed systems which are not designed to help healthcare providers make the right decisions can also be to blame. Andel et. al. go on to say:

"Quality care is less expensive care. It is better, more efficient, and by definition, less wasteful. It is the right care, at the right time, every time. It should mean that far fewer patients are harmed or injured. Obviously, quality care is not being delivered consistently throughout U.S. hospitals. Whatever the measure, poor quality is costing payers and society a great deal [4]."

This idea of quality care being better, more efficient, and less wasteful can be supported by integrating standardized decision-making methods into everyday life. This type of decision making is crucial to any type of health policy or medical practice. Due to the probabilistic nature of health outcomes, most decisions are made when health care uncertainty is present [5]. It is therefore of utmost importance for healthcare facilities like hospitals, to have specific guidelines for decision making when necessary to address resource allocation decisions which are necessary to make every day. This can range from prioritizing certain patients via triage to determine who will receive medical treatment first in an emergency room setting, to deciding which cohorts or classifications of people are eligible to receive a vaccination first. These decisions are pivotal to ensure that bias and decision-making fatigue are avoided, and that fair and equitable treatment is provided to patients regardless of the healthcare facility.

To begin my discussion of the various research articles that I collected, I will first discuss modern approaches to Multi-Criteria Decision Analysis in healthcare decision making in general.

MCDM Framework

A research paper (2019) titled *Multi-Criteria Decision Analysis (MCDA) in Healthcare Decision-Making* published in *the Oxford Research Encyclopedia* in the Economics and Finance section discusses the rise of Multi-Criteria Decision Analysis in decision making [6]. The authors Paul Hansen and Nancy Devlin talk about the different types of decisions that are made on a daily basis in a healthcare setting. One of the most important decisions that are made are choosing which health “technologies” (i.e., drugs, devices, procedures, ect..) to fund which is known as health technology assessment (HTA). Prioritizing diseases for R&D, patients for surgery, and decision about licensing treatments are all other areas in which Multi-Criteria Decision Analysis is applicable.

The authors (2015) of *Making Good Decisions in Healthcare with Multi-Criteria Decision Analysis: The Use, Current Research and Future Development of MCDA* which is published in the *Applied Health Economics and Health Policy* Journal discuss very similar topics in their articles [7]. The purpose of the article is mainly to describe, “the framework of MCDA and illustrates potential areas of application in healthcare.” The authors discuss how common measures used to make decisions in healthcare such as quality-adjusted life-year which are used in cost-effectiveness analyses often show disadvantages and limitations and may even lead to inappropriate decisions in terms of reimbursement and funding decisions [7]. Similar to the previous article, the authors of this article propose that Multi-Criteria Decision Analysis can help to structure complex decision problems in healthcare decision making. The authors go on to discuss how the three main types of decision problems that Multi Criteria Decision analysis can address are (1) choice problems to identify the best alternative, (2) ranking problems to identify the rank ordering of alternatives from best to worst, and (3) sorting problems where assignment of the alternatives to pre-defined ordered categories is necessary. One important aspect that is highlighted in this article is the need for a more systematic approach to decision-making in healthcare which adheres to more standardized and structured guidelines. In modern day healthcare settings, most applications of decision making are based on a weight-sum model, in which criteria weights are explicitly defined. Once these criteria are weighted, each alternative is rated based on these criteria, and each alternative's "performance" on the criteria is aggregated using a linear additive equation to produce a total score. The alternative with the highest total score is selected to be the most optimal one [6].

These weighted sum models are discussed in more detail in this article by the authors, which is the primary focus of the paper. The general steps in the Multi Criteria Decision Analysis Process are as follows: (1) structuring the decision problem, (2) specifying the criteria, (3) measuring alternatives' performances, (4) scoring the alternatives on the criteria, (5) weighting the criteria, (6) applying scores and weights to rank alternatives, and (7) supporting decision making. Steps 1-3 require validation from all stakeholders which may include patients, clinicians, ethics committees, and members of the general population. When scoring the alternatives in step 4, one evaluation criteria should be defined so that comparisons between scores can be made, with the intervention with the highest degree of achievement receiving the highest score.

The next step, weighting of the target criteria, is an important step in this process because it can often determine whether one alternative will eventually be selected over another. Different weighting methods include discrete-choice experiments, best-worst scaling, point allocation, swing weights approach, and the analytic hierarchy process [6,7]. While these methods are all effective and relevant in certain contexts, the analytical hierarchy process is a rather popular method used to both score alternatives on the criteria, and weigh the criteria themselves [6]. For each criterion in scoring alternatives, they are pairwise compared and their intensity of importance relative to each other is expressed on a 1 through 9 ratio scale. A score of 1 means the criteria of each alternative are "equally preferred" while a 9 means "extreme importance" [6]. The scores for each alternative are then calculated from ratios using eigenvalue analysis and normalized to sum across each criterion.

Using the analytical hierarchy process to weight the criteria uses the same method in a slightly different manner. Authors Hansen and Delvin describe the process as "Each level in the hierarchy of criteria and subcriteria (and sub-subcriteria, etc.), as represented in a "value tree," can be analyzed as a separate decision problem (and then combined multiplicatively) " (Hansen 2019). Subsequently, for each level the criteria are pairwise compared, and their "intensity of importance" relative to each other is expressed using the same 1 to 9 ratio scale. The weights are then calculated from the ratios using eigenvalue analysis [6]. An example of these pairwise comparisons (trade-offs) is shown in the figure below [16].

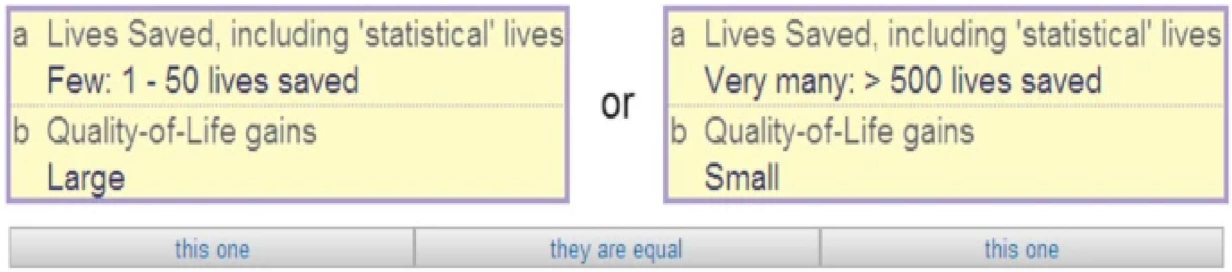


Figure 1: Example of a pairwise-ranking question for determining point values.

Step 6 involves applying the scores and weights to rank the alternatives by multiplying each alternative's scores on the criteria by the weights and summing the weighted scores across the criteria to get each alternative's total score. Step 7 looks to support the decision-making by presenting the results to decision-makers for review. In the context of something like healthcare budgets, it is important to consider their Multi-Criteria Decision analysis score relative to their cost and consider additional factors that are not included in the original analysis [6]. In some instances, Pareto optimality can be used to determine which alternatives are non-inferior. In the case of healthcare budgets, this would mean that no other technologies have both higher cost and lower benefits/value, or else they could simply be eliminated because they would be dominated by other alternatives. An example of this is demonstrated in the figure below, in which authors Hansen and Devlin discuss a "Value of Money" chart (figure 3) that comes from an article written by Golan and Hansen (2012), in the context of a Health Technology Assessment that was performed In Israel [16].

Dimensions	Points (weights)
Lives saved, including ‘statistical’ lives (i.e. cure or reduced risk of death)	
None (or not yet known)	0
Few: 1-50 lives saved	0.091
Some: 51-250 lives saved	0.192
Many: 251-500 lives saved	0.268
Very many: > 500 lives saved	**0.343**
Life-prolongation benefits – in terms of increase in life expectancy and its quality-of-life, and number of patients affected	
None/Very small (or not yet known)	0
Small benefits	0.053
Medium benefits	0.152
Large benefits	**0.244**
Quality-of-life gains – in terms of baseline QoL, size of QoL gains and duration, and number of patients affected	
None/Very small (or not yet known)	0
Small QoL gains	0.051
Medium QoL gains	0.138
Large QoL gains	**0.217**
If this technology were *not* to be funded ...	
Many/most patients **will** be able to pay for it themselves (privately)	0
Many/most patients **will get an alternative** treatment (less effective) already funded by government	0.055
Many/most patients will **not** receive any treatment for condition	**0.108**
Other important social or ethical benefits, e.g. targeted to children/minorities; reduces health gaps, etc	
None/Very small (or not yet known)	0
Yes	**0.087**

Note: The bolded values represent the relative weights of the dimensions overall (i.e. the bolded values sum to unity).

Figure 2: Illustrative points system for the incremental-benefits variable

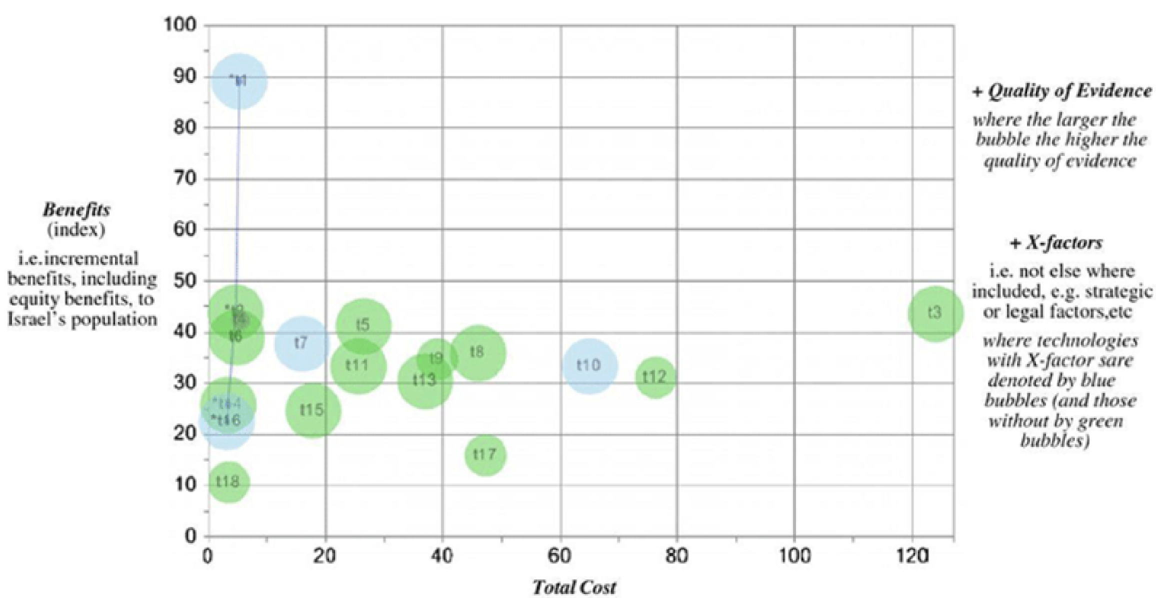


Figure 3: Value for money chart, with 18 illustrative technologies (see Table 2 for their names).

Technology (indication, number of potential patients): t1 = smoking-cessation drugs (smokers, 6,000), t2 = Taxotere (head and neck cancer, 200), t3 = Herceptin (breast cancer—adjuvant treatment, 700), t4 = Elaprase (Hunter syndrome, 3), t5 = Visudyne (age-related macular degeneration, 1,050), t6 = left-ventricular assist devices (terminal heart failure, 12), t7 = statins (hypercholesterolemia, 5,600), t8 = pain relief (neuropathic pain, 14,250), t9 = Revlimid (multiple myeloma—3rd-line treatment, 200), t10 = dental care (children, 20,000), t11 = growth hormone (short-statured children, 3,900), t12 = Avastin [Bevacizumab] (colon cancer, 700), t13 = overactive bladder drugs (urinary urge incontinence, 21,000), t14 = Fuzeon (HIV, 45), t15 = long-acting insulins (diabetes, 10,000), t16 = contraceptives (adolescent girls, 20,000), t17 = Erbitux (colon cancer, KRAS mutation negative, 210), t18 = Humira (psoriatic arthritis, 60).

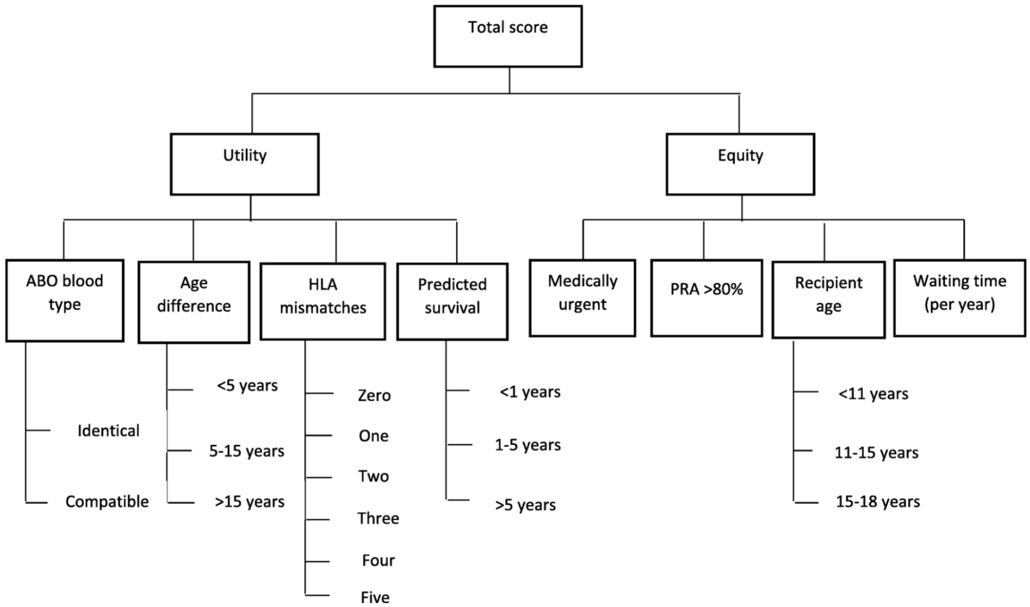
Source: Golan & Hansen (2012, Figure 2).

In this figure, Multi-Criteria Decision Analysis was performed using 18 health technologies for Israel to determine which ones should be funded. These technologies ranged from various cancer treatments to long-acting insulins [16]. In the figure above, the vertical axis of the value for money chart shows each technology's total score. This is a reflection of its incremental benefits, including equity benefits, to Israel's population' by applying a weighting point system to the technologies' ratings seen in figure 2. Coming back to figure 3, the horizontal axis shows each technology's incremental total cost to Israel's health system. The bubble sizes in figure 3 used to represent each technology are in proportion to the 'quality of evidence' (meaning the quality of clinical evidence for a given technology's effectiveness). Finally, the blue bubble indicates 'any additional 'X-factors' not elsewhere included, such as strategic or legal factors. Based on this chart, the authors were able to determine that choosing to fund technologies like smoking cessation drugs and Taxotere (a chemotherapy medication) were the ideal choices by using this model. Overall I think this chart is a really good example of a weight system put into practice to make decisions.

Organ Donation

One aspect that these Multi-Criteria Decision Making methods can be applied to is an area where decision-making training has always been necessary: organ donation and transplantation. According to the *U.S. Government Information on Organ Donation and Transplantation* roughly 39,000 organ transplants were performed in the United States during 2020. An article (2019) published in the *BMC Medical Informatics and Decision Making*, titled *Identification and weighting of kidney allocation criteria: a novel multi-expert fuzzy method,* aims to identify and weigh kidney allocation criteria. In the article, the authors look to use a Fuzzy Delphi Method (FDM) to identify the effective criteria in the kidney allocation algorithm. Subsequently, they use an Intuitionistic Fuzzy Analytic Hierarchy Process (IF-AHP) to determine the weight of the criteria [8]. The Delphi method involves surveying a panel of subject matter experts, which in this case was done via a face-to-face questionnaire. A total of 10 experts answered these questions, who were all decision-makers and policymakers in organ allocation in Iran. The responses from these questionnaires were used to identify the essential factors in kidney allocation. The figure below (figure 4) was used to define the objective, criteria, and sub-criteria, and then build the hierarchy framework.

From: Identification and weighting of kidney allocation criteria: a novel multi-expert fuzzy method



The AHP framework at all levels

Figure 4: The analytical hierarchy framework at all levels

Utilizing the IF-AHP, pairwise comparison matrices were constructed, and the information derived from the Delphi method is fuzzified. After pairwise computations are complete, the numbers are defuzzified and the authors were left with weighted criteria. As stated in the research article, " Of a total of 11 factors gathered from the literature and different allocation systems, eight essential factors were identified, and three factors (location, a prior donation and transplant status) were rejected by the experts " (Taherkhani, 2019). The three factors that were rejected by the experts were done so for several logistical reasons. One of the highest weighted factors reported by the authors was PRA (panel reactive antibodies). The PRA value indicates the "level of sensitivity of a patient to human leukocyte antigens [8]." The chances of finding a match for patients that have very high levels of PRA are very low, and many of these patients may never find a compatible kidney. Prioritization of these patients above those with low PRA values is important to maintain an equitable system [8].

A different research article (2018) titled *Hybrid Multi-criteria Decision-Making Model for Kidney Allocation* uses a similar approach to weighting the effective factors in kidney allocation. The author Nasrin Taherkhani is a co-author of this research paper, as well as the one previously discussed, and a similar approach is used in Iran to weigh the effective factors in kidney allocation [9]. This research paper was written before the one that used IF-AHP, so it seems that this research was a basis that was further improved on using the Fuzzy method. In this research paper, the authors use the Analytical Hierarchy Process to determine the criteria weights by first identifying a list of kidney allocation criteria through the use of a literature review. The criteria are then used to construct a hierarchy, with each factor being separated into two main categories: equity and utility. A questionnaire was designed to be completed by 13 experts who were mainly decision-makers and policymakers in organ allocation in Iran. These questionnaires were subsequently used to make a pairwise comparison, to determine the relative importance of the criteria. From these comparisons, relative weights of the criteria were computed [9].

After these weights were calculated, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a conventional method in Multi-Criteria Decision Making, was used to rank a randomized dataset containing information of 20 patients. Using the TOPSIS, a weighted normalized decision matrix was created, and matrix calculations were performed to determine the relative closeness of each alternative to the ideal solution (1.0). Each alternative was ranked based on this relative closeness to 1.0, and this is how the patient ranking was completed. Figure 5 below is a good visualization of the two-step process that was used in this instance.

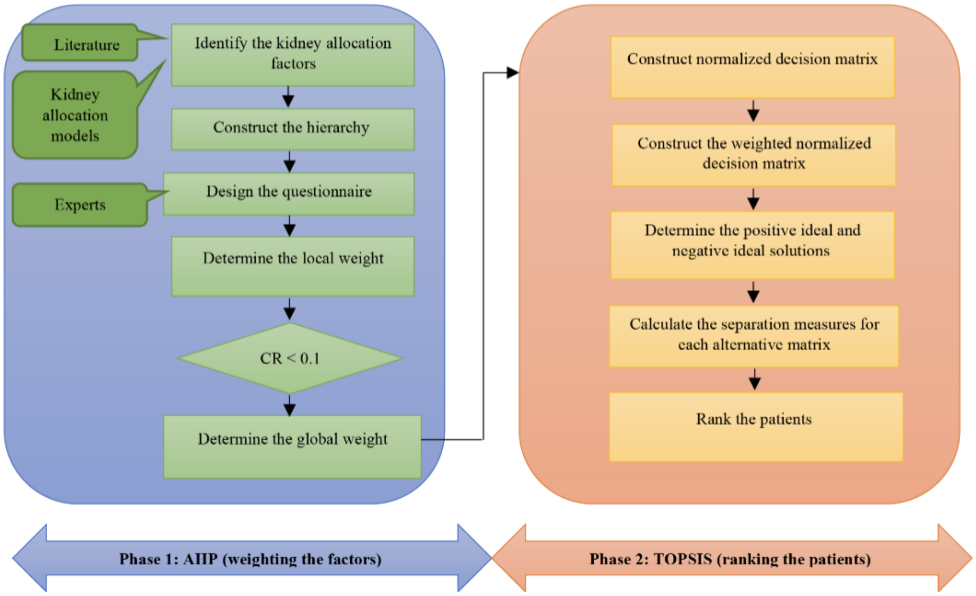


Figure 5: The Proposed Methodology for Developing a Kidney Allocation Model

It is very interesting to see the similarities and differences between this paper, and the previous one that used an IF-AHP approach. One difference is that this article that used an AHP approach also used these calculated weights to rank patients. This was useful to see exactly how these weights are to be utilized once they are calculated. One of the biggest differences between these two research articles is the final sub-criteria that had the largest weight. In the previous paper, the sub-criteria with the highest weight was “PRA,” among others. In this research article, the results showed that “zero HLA mismatches”, “high medical urgency”, and “identical blood type between donor and recipient” had the highest weights, while “PRA” actually had the lowest. These results are shown below in figures 6 and 7 [9].

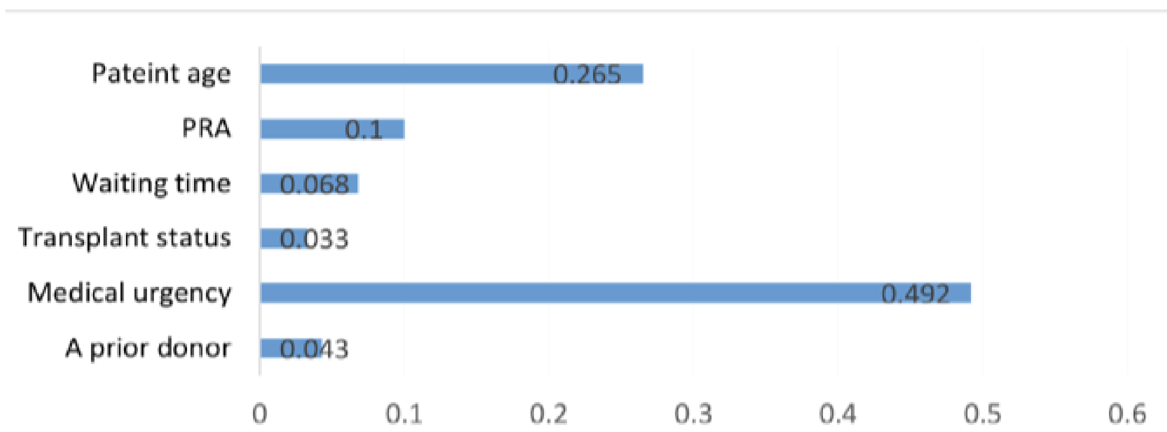


Figure 6: The Weights of Equity Sub-criteria.

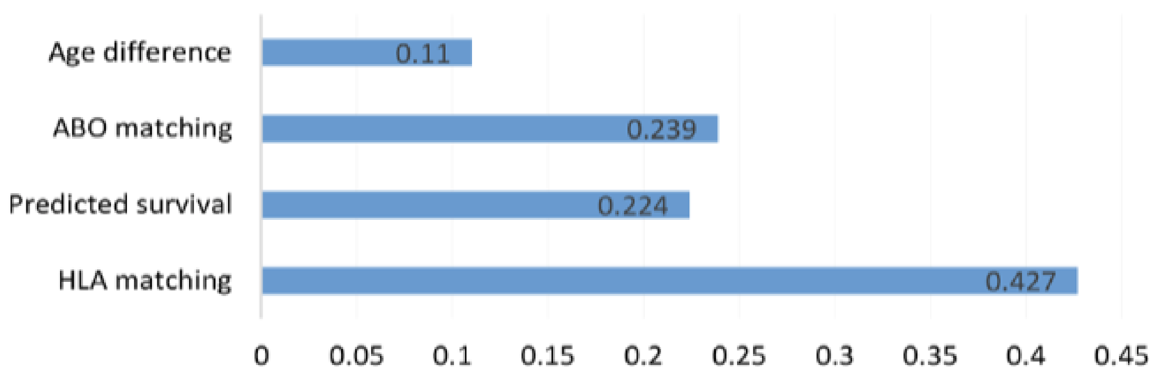


Figure 7: The Weights of Utility Sub-criteria.

Included in these results, from the randomized dataset containing information of 20 patients, the first six priorities based on the TOPSIS were patients 19, 1, 11, 4, 10, and 5 which was validated by 2 experts. The results from this research paper are surely interesting, and it goes to show that the implementation of different models (IF-AHS vs AHS) can lead to far different criteria weights. It would be interesting to see what the IF-AHS model would rank the same randomized list of 20 patients, as I'm sure the results would vary due to drastic differences in weights.

Overall, these are both really good examples of how these methods can be used to develop and identify kidney allocation criteria. Another example that utilizes similar Multi-Criteria Decision Making methods is in the paper (2020) titled: *Prioritizing Factors Affecting Deceased Organ Donation in Malaysia: Is a New Organ Donation System Required?* [9]. In this research paper, the author's objective is to examine human organ transplantation in Malaysia, the factors affecting willingness to donate and to prioritize those factors acting as the pillars of the organ donation system [10]. It is useful to mention that in their research the authors mention that factors affecting willingness to donate are contextual and vary from country to country. This implies that this type of factor analysis could be employed in different countries and regions, leading to different results.

To assign weights to criteria, the Analytical Hierarchy Process was utilized. The authors first created a hierarchy consisting of the goal (selection of best policy), criteria (donor perceptions, socioeconomic status, and demographic factors), subcriteria, and alternatives. This can be seen below in Figure 8. They then administered a questionnaire consisting of bipolar questions to 35 experts who consisted of doctors, hospital medical staff, healthcare professionals, and government policy advisers who deal with organ donation process/policies [10]. When answering these questions, the experts expressed their judgment on a nine-point scale, with 1= "equally important" and 9="extremely important." These preferences were subsequently quantified, and pairwise comparison judgment matrices were constructed. These pairwise comparisons were conducted on three levels depicted in figure 8, which were a selection of the best policy, prioritizing the factors (criteria), and subfactors (subcriteria).

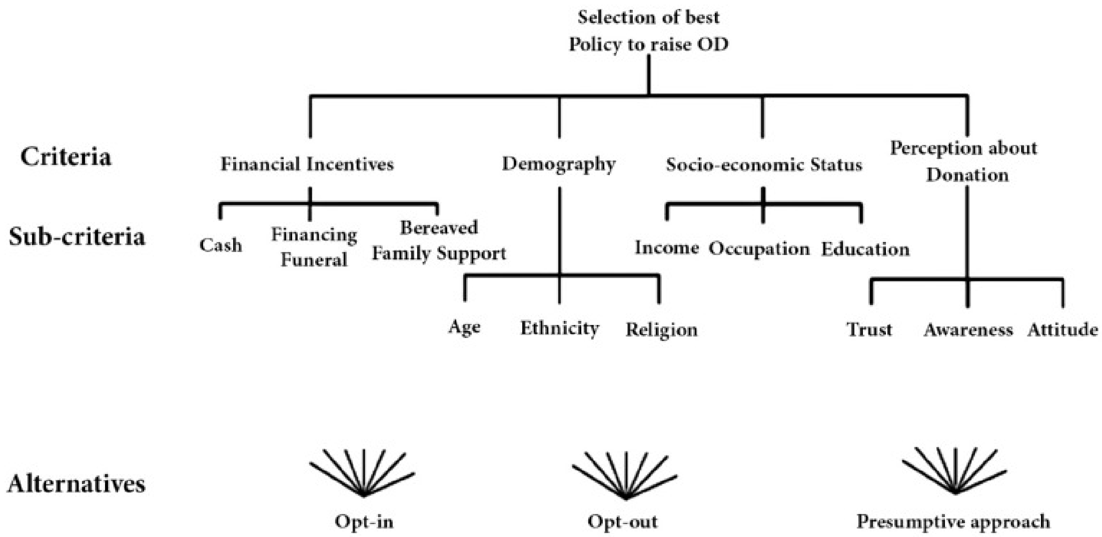


Figure 8: A hierarchical model for policy selection

After completing the AHP, the authors were able to prioritize the factors which influenced the willingness to donate in the Malaysian context and were able to determine the most optimal policy option for raising organ donation rates. They found that four dimensions of socioeconomic status and donation perception—education, awareness, attitude, and trust—main factors affecting willingness to donate. These results demonstrate that organ donation rates can be increased by educating people and promoting altruism [10]. This paper does a good job of explaining the application of the AHP in a slightly different context. This demonstrates that the same method can be used to develop weights for different types of health care problems seamlessly. One aspect where this research lacks is that the authors are unable to implement these changes (increasing education and promoting altruism) in the general Malaysian population, so the best that they can do make a final suggestion based on their results; the recommendation being that that minister focuses on decision-making training nurses to discuss donation with bereaved families and raising public awareness of the benefits of organ donation [11].

COVID

A more recent and novel application of Multi-Criteria Decision Making comes within the context of decision making related to the coronavirus (COVID-19). In March of 2020, COVID was declared a pandemic in the United States, and healthcare workers and providers have been on the frontlines dealing with a staggering number of challenges since. Due to resource limitations, decision-making related to preventative measures, treatment, bed priority, and even vaccination distribution were necessary to examine to ensure equitable outcomes.

Hospitals were hit harder than ever with demands, and national strategies such as "flattening the curve," were partially implemented so that hospitals could manage the quantity of COVID patients. This national strategy consisted of advising the general American population to take part in activities such as social distancing, staying at home, washing hands, and wearing face masks. An article published in the *International Journal of Healthcare Management* titled (2020) *COVID-19: A decision-making approach for prioritization of preventive activities,* uses an analytic hierarchy process-based approach to prioritize certain activities in chronological order based on their effectiveness in preventing the spread of COVID [11].

Similar to the previously discussed AHP applications, the authors in this article created a breakdown of the criteria and sub-criteria hierarchy using available literature as seen below in figure 9. From here, a pairwise comparison matrix was constructed and the weights were calculated. These weights were calculated at the criteria and sub-criteria levels and ranked by highest to lowest weights. The authors discuss how their results are somewhat consistent with the World Health Organization guidelines, as the highest criteria weights were attributed to social distancing, unnecessary touching things, and sharing personal belongings. The highest sub-criteria weights were (1)traveling, (2) touching own face and mouth, (3) shaking hands, and (4) mask-wearing [11].

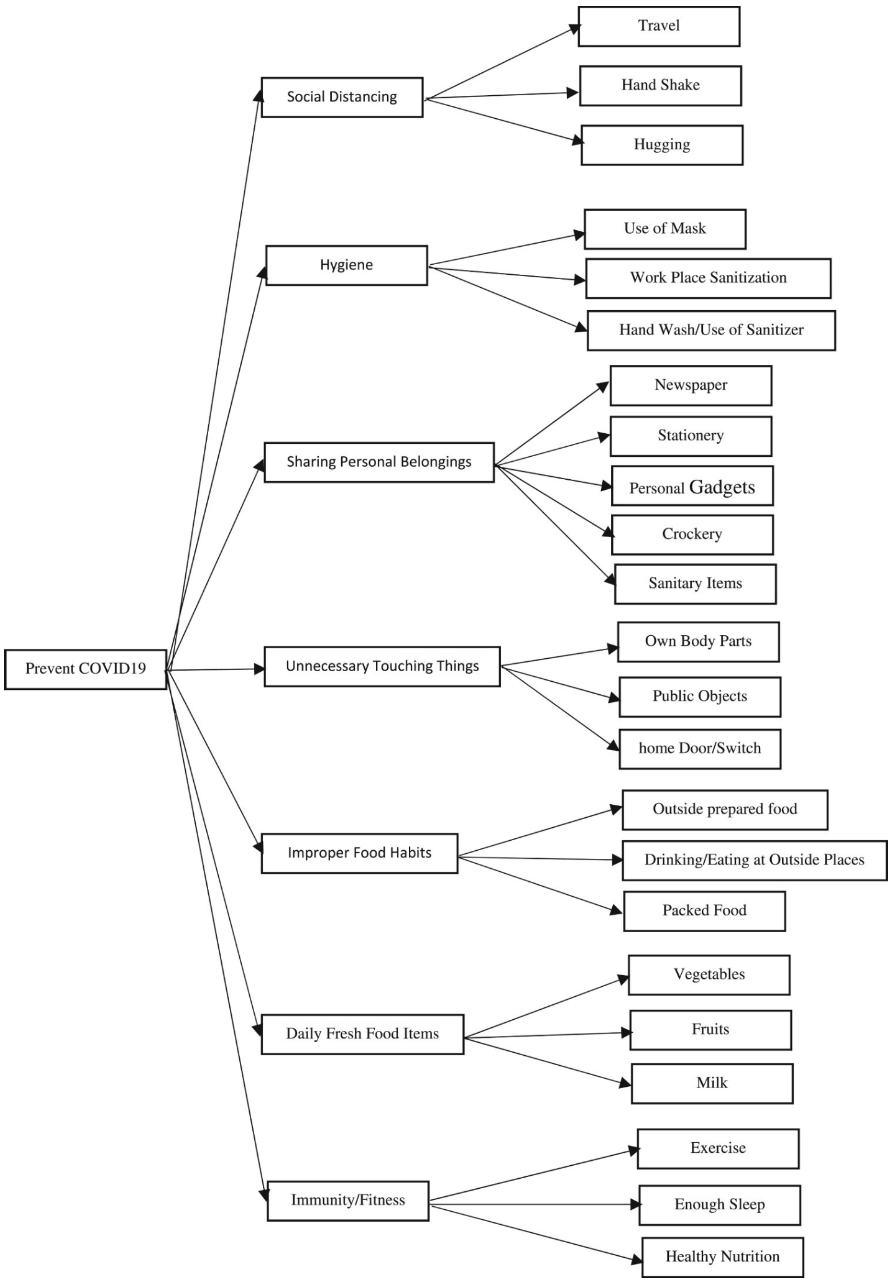


Figure 9: Hierarchy of criteria and their sub-criteria

In a similar context, an article published in the *Elsevier Public Health Emergency Collection,* titled (2020) *Helping doctors hasten COVID-19 treatment: Towards a rescue framework for the transfusion of best convalescent plasma to the most critical patients based on biological requirements via ml and novel MCDM methods,* looks at decision making regarding COVID treatment allocation [12]. Individuals that have recovered from catching the virus have COVID antibodies in their blood, and blood transfusion of these antibodies to deteriorating patients could theoretically help boost their immune system. Thus, the focus of this article is determining a framework to decide which COVID patients are prioritized to receive these blood transfusions [12]. These convalescent plasma (CP) transfusions occur daily and are one of the few treatment options to help the most severe COVID-19 patients. This article looks to use this framework for the prioritization of patients with COVID-19 as well as to identify the most appropriate CP for a corresponding prioritized patient with COVID-19.

The authors of this research paper opt to use a novel Multi-Criteria Decision Making approach called the best-worst method (BWM), which is similar to AHP in the sense that expert opinions are used to, "provide weights to attributes on the basis of decision-makers' perceptions and subjective significance to each attribute" (Singh 2020). BWM requires fewer pairwise comparisons than AHP and can derive the weights of criteria with high consistency - meaning that you can obtain similar results with a lower computational load. They go on to describe BWM as a method that "executes reference comparisons, indicating that it only needs to determine the preference of the best criterion over all other criteria and the preference of all criteria over the worst criterion" (Singh 2020). The BWM uses the same 1–9 scale to perform pairwise comparisons which are then used to calculate criteria weights. This study looked to develop a framework and thus did not implement this process with any real-life data. From this study, the authors were able to present seven recommendations for future work. Some of these recommendations were that this framework will hopefully be implemented and tested to serve and help healthcare and that the proposed framework can be run and performed in the indoor/outdoor hospitals over a telemedicine environment [12].

Aside from the treatment itself, COVID has placed other stressors on healthcare workers due to the limited number of beds in hospitals. An article published in the *Elsevier Public Health Emergency Collection* titled *Multi-Criteria Decision Analysis to prioritize hospital admission of patients affected by COVID-19 in low-resource settings with hospital-bed shortage,* takes a Multi-Criteria Decision Analysis approach to determine weights for 11 criteria. They used these criteria to prioritize COVID-19 non-critical patients for admission to hospital in healthcare settings with limited resources [13]. To determine these weights, the authors used an online Multi-Criteria Decision Analysis software called 1000minds, which implements a technique called: Potentially All Pairwise RanKings of all possible alternatives (PAPRIKA). A total of 96 experts correctly completed this online survey based on their experience working with COVID-19 patients. This included physicians based in emergency, infectious diseases, pneumology, and internal medicine departments and working in a variety of institutions. These experts were shown a series of pairs of combinations of levels on two criteria at a time. "Each pair of combinations involved a trade-off between the two criteria, such that when participants answered the question – by choosing one of the two combinations or indicating they are equal – they revealed their opinion about the relative importance of the two criteria" (De Nardo et. al., 2020). Based on these responses, the software was able to compute mean weights for the original 11 criteria as seen in figure 10. PaO2 (how well oxygen can move from the airspace of the lungs into the blood), peripheral O2 saturation, and chest X-ray findings were among the criteria with the largest weights.

An important aspect of this research that is worth mentioning is that the criteria selected by the researchers were deliberately chosen so that they could be applied in any healthcare setting, even by unskilled health personnel in low-resource settings. The authors intended for this model to be adapted to different settings and stages of the pandemic in response to emerging evidence. This is a drastic difference from previous Multi-Criteria Decision Making models and frameworks. For example, in the two AHP approaches to kidney allocation in Iran, the results of the studies would have been different based on which country the study took place in. Similarly, in the study that looked to determine factors impacting willingness to donate in the Malaysian context, results in a different country or region would likely be very different based on social and economic factors.

		PaO2 16.3%	Oxygen saturation (%) 15.9%	Findings at chest X-ray 14.1%	MEWS 11.4%	Respiratory rate 9.5%	Comorbidities 6.5%	Living with vulnerable people 6.4%	Body Mass Index 5.6%	Duration of symptoms 5.4%	C-reactive protein 5.1%	Age 3.8%
PaO2	16.3%		1.0	1.2	1.4	1.7	2.5	2.5	2.9	3.0	3.2	4.3
Oxygen saturation (%)	15.9%	1.0		1.1	1.4	1.7	2.4	2.5	2.8	2.9	3.1	4.2
Findings at chest X-ray	14.1%	0.9	0.9		1.2	1.5	2.2	2.2	2.5	2.6	2.8	3.7
MEWS	11.4%	0.7	0.7	0.8		1.2	1.8	1.8	2.0	2.1	2.2	3.0
Respiratory rate	9.5%	0.6	0.6	0.7	0.8		1.5	1.5	1.7	1.8	1.9	2.5
Comorbidities	6.5%	0.4	0.4	0.5	0.6	0.7		1.0	1.2	1.2	1.3	1.7
Living with vulnerable people	6.4%	0.4	0.4	0.5	0.6	0.7	1.0		1.1	1.2	1.3	1.7
Body Mass Index	5.6%	0.3	0.4	0.4	0.5	0.6	0.9	0.9		1.0	1.1	1.5
Duration of symptoms	5.4%	0.3	0.3	0.4	0.5	0.6	0.8	0.8	1.0		1.1	1.4
C-reactive protein	5.1%	0.3	0.3	0.4	0.4	0.5	0.8	0.8	0.9	0.9		1.3
Age	3.8%	0.2	0.2	0.3	0.3	0.4	0.6	0.6	0.7	0.7	0.7	

Figure 10: Relative importance of the criteria

Another research paper related to decision-making during the pandemic is titled (2021) *COVID-19 Vaccine: A neutrosophic MCDM approach for determining the priority groups.* Published this year in the *Results in Physics* journal, this paper aims to identify priority groups for allocating COVID-19 vaccine doses [14]. The authors use a neutrosophic Analytic Hierarchy Process (AHP) to identify the most important criteria and sub-criteria. The four main criteria and sub-criteria can be seen in figure 11. Figure 12 depicts the overlap between different criteria. An example of a person that would fit into multiple categories would be an elderly doctor that has health problems. The authors then use a neutrosophic TOPSIS method to rank the priority groups.

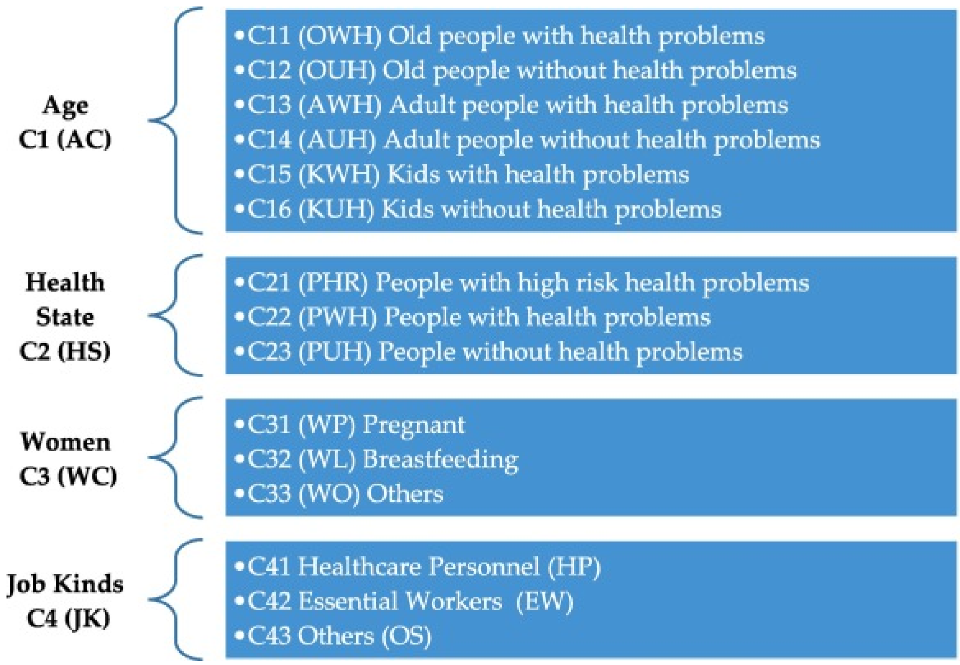


Figure 11: Main criteria, and sub-criteria used in the study

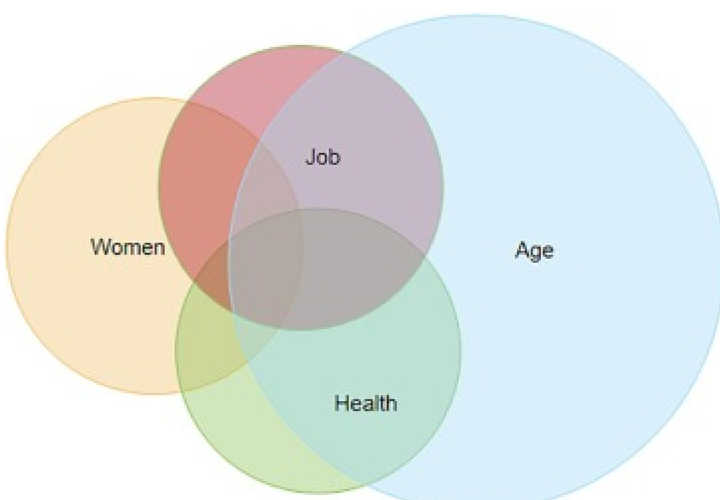


Figure 12: Main groups overlapping.

Using the AHP method, the hierarchy of criteria, sub-criteria, and alternatives was constructed and three experts were questioned to construct pairwise comparisons per usual. The weights are considered to be neutrosophic numbers, which are generalizations of fuzzy numbers. As discussed before, fuzzy numbers are not one single value but rather a connected set of possible values. To address this, the authors performed deneutrosophication of the neutrosophic numbers to real value using an equation, and then took the average. Following the typical steps of AHP, these values were then used in an evaluation matrix and the final weights were computed. From here the neutrosophic TOPSIS method is implemented, in which an evaluation matrix is constructed between the sub-criteria and alternatives by three experts. The same deneutrosophication of the neutrosophic numbers is carried out, and then equations to calculate the distance from the positive perfect and negative perfect solutions. From here the alternatives can be ranked by determining which alternative has the largest proportional closeness to the positive perfect solution, and calling that the superior alternative [14].

The results obtained from this study indicate that the healthcare personnel, people with high-risk health, elderly people, essential workers, pregnant and lactating mothers are the most prioritized people to take the vaccine dose first. This is consistent with the World Health Organization's reports on priority groups for vaccination and is a great framework to use in the future if vaccination shortages arise. Very recently, many places have begun accepting walk-in vaccination appointments, but just a few weeks ago these priority groups applied to vaccination sites all across the United States. With that, this study does lack some fundamental considerations related to cost, safety, availability, and delivery that were simply not known after this study [14].

Discussion

Decision-making in health care is crucial to help provide fair and equitable treatment, and also helps doctors and healthcare personnel make quicker decisions. As discussed throughout a review of the literature it is clear that methods such as the Analytic Hierarchy Process for decision making in the healthcare context are a very popular approach. Approaches such as this one involve surveying literature or getting subject matter experts to identify the essential factors to calculate weights for, and then using pairwise comparisons to determine tradeoffs between certain criteria. While this method is consistently used in modern-day health care decision-making, some people such as the authors of the paper (2019) *Are MCDM methods useful? A critical review of Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP),* argue that oftentimes AHP provides a ranking of options that would not be acceptable by a rational person. The aforementioned research discusses how when these pairwise comparisons are being made if the number of criteria goes beyond three, a consistency concern arises. This is because humans are not capable of keeping consistent pairwise judgments when the number of elements increases. A consistency test can be implemented by asking the decision-makers (experts) the same pairwise comparisons multiple times throughout a questionnaire. Whether a decision maker's responses fall above or below a consistency threshold (0.1) would determine whether the answers are used at all in the study [15].

The authors discuss how using a more traditional Multi-Criteria Decision Making approach may be more useful. This involves assigning weights to the criteria based on their relative importance. In a hypothetical example in which the weights of 1, 1.2, and 1.8 agreed upon were for the criteria "delivery", "price", and "quality", their normalized weights are computed by dividing the weights by the sum (1 + 1.2 + 1.8). This research article uses a simple example of the criteria "delivery", "price", and "quality", to show how AHP can incorrectly rank alternatives, while the MCDM approach is much more effective. This example (not based on real-life data) was one specifically created by the authors to highlight the problems with the AHP method, and thus there is some concern for the fact that the example was framed in such a way that it would purposely cause the AHP to incorrectly rank the alternatives. With that said, I think that it does a good job of highlighting a case in which the AHP method can incorrectly rank a set of alternatives. The authors conclude by explaining that the AHP method is highly effective in certain situations, but due to consistency concerns, it is often not nearly as effective as simple MCDM models [15].

There is validity to this claim, but as seen in the previously mentioned literature related to organ allocation and COVID treatment, I believe that these pairwise comparisons are an effective way to determine tradeoffs between criteria. With this said, there are ways to improve the consistency levels without completely using a new method. The main way to achieve this would be to have a small sample size of data to test on when an AHP method is developed. Having experts hand rank a list of 5-10 patients, and then comparing that to the results of the AHP is a good way to determine accuracy. This is an approach commonly used in machine learning, where there is a testing and training dataset. A well-performing model would rank the patients with a large amount of accuracy to the hand-picked expert list and could be modified if it performed poorly. I believe that including this end-of-study validation along with the use of a consistency threshold during the pairwise comparison portion of the paper would result in a fairly accurate and equitable ranking of patients.

As a whole, the use of Multi-Criteria Decision Making techniques comes with its own set of challenges that have the potential to be improved upon in the future. Throughout this literature review, it is clear that MCDM approaches to decision making are common in the healthcare industry, but not necessarily standardized. For example, none of the European health technology assessment bodies are currently using formal MCDM approaches, even when the European Medicines Agency has recently explored the application of MCDM for regulatory decision making [7]. Standardization of MCDM methods across different hospitals, companies, states, and countries may be necessary to make results comparable across different bodies and ensure equitable healthcare is provided everywhere. Considerations related to cost, which was not discussed in any of the literature that was reviewed, is another important topic that has not been thoroughly researched either [7]. The inclusion of factors such as cost-effectiveness is something that may be able to help identify relatively inexpensive interventions that can drastically improve health outcomes.

The implication that subjective questionnaires (such as pairwise comparisons) can lead to inconsistencies in criteria and weights is also something that needs to be further addressed as MCDM methods are used in the future. Included in this, the appropriate weighting technique must be determined, as well as the circumstances under which a specific technique should be used [7]. This is another reason why the standardization and consensus about which MCDM techniques to use in which situations are so important. Addressing uncertainty in healthcare decision-making is also crucial. This uncertainty can arise with decisions related to new technologies, where evidence may still be emerging about the benefits and risks and relative effectiveness or costs [6]. How can criteria be weighted in the context of technologies that have not yet been implemented? How much uncertainty is safe enough? What are the risks that the patients must accept for the benefits? These are all valuable questions that must be answered when introducing uncertainty into MCDM methods in healthcare.

All things considered, the utilization of structured MCDM methods are shown to be consistently more effective than relying on structuring heuristics and other biases (e.g., relying on “gut feeling”) [6]. In decision making at the individual patient level (such as what treatment a specific patient should receive), it is becoming common practice to include patients in the decision-making process rather than have them be passive recipients of care [18]. In the general healthcare setting as well, “Patient participation on advisory boards, panels and in the design and implementation of clinical trials is growing increasingly substantive—and in many circumstances, required,” (Balch 2017). Maybe on a larger scale, more diverse and inclusive groups of experts could help bring more perspectives and robustness when determining the important criteria, sub-criteria, alternatives, and weights. Ideally, a standardization of MCDM methods will also be developed by significant health technology assessment bodies, as this will help to address many current problems with MCDM methods. This review of literature and discussion was developed to assess the current state of Multi-Criteria Decision Making methods in health care and where they could be improved upon in the future. As previously discussed, similar techniques are used to address a variety of health care decisions, some of which include organ allocation, COVID treatment priority, and vaccination priority group designation. While these respective applications of MCDM methods were used in an academic sense, they may face challenges when trying to put these into practice. Nevertheless, the future of MCDM as a whole in healthcare decision-making is bright, and further research will most certainly lead to faster and more equitable decision-making.

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