

System-of-Systems Approach for Improving Quality of Kidney Transplant Decision-Making Support for Transplant Surgeons



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1 Introduction

Utilizing AI-powered machine learning in the healthcare industry is crucial, especially in the complex and interdisciplinary field of deceased donor kidney allocation. Evaluating hard-to-place kidneys for potential recipients can be immensely challenging, making an AI-powered platform like Organ Procurement Organization (OPO) AI indispensable [1]. This innovative tool is currently in the testing phase at the Mid-America Transplant. This paper aims to identify the best meta-architecture for capturing individualized practices and assessments of transplant surgeons through fuzzy associative memory. The model will be referred to as the transplant surgeon fuzzy associative model (TSFAM). The goal of the TSFAM is to complement OPO AI and provide valuable assistance to transplant surgeons in assessing deceased donor organs for their patients based on their practices, ultimately resulting in a more efficient kidney allocation process.

This research aims to create, evaluate, and select decision-making architectures for modelling the Transplant Surgeon FAM using genetic algorithms coupled with the fuzzy inference system. The primary objective of the SoS is to maximize the balance between the key performing parameters: performance, acceptability, usability, affordability, and robustness. The results of this research will provide a suggestion for the most successful human-AI system interaction model that can be used to improve the quality of kidney transplant decision-making support for transplant surgeons. The outcomes of this research will suggest the most desirable SoS meta-architecture that can be used to improve further the quality of kidney transplant

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© The Author(s), under exclusive license to Springer Nature Switzerland AG 2024
A. Salado et al. (eds.), *The Proceedings of the 2024 Conference on Systems
Engineering Research*, Conference on Systems Engineering Research Series,
https://doi.org/10.1007/978-3-031-62554-1_20

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decision-making support for transplant surgeons, with the goal of creating a successful human-AI system interaction model.

2 Background

Artificial intelligence (AI) is being scrutinized across all domains as there is a growing desire for humans to understand and have some control over AI. To manage the advancement of AI, scientific research interests and the government have established blueprints and guidelines. In March 2022, the National Institute of Standards and Technology released a unique publication that identified three categories of bias in AI: systemic bias, statistical bias, and human bias [2]. In October 2022, the United States White House published the blueprint for an AI Bill of Rights to make automated systems work for the American people [3]. This government blueprint emphasizes safe and effective systems, algorithmic discrimination protections, data privacy, notice and explanation, and the human alternatives-considerations fallback options. These areas apply to the healthcare domain, with a greater emphasis on the efficacy of systems, explainability, bias, and human interaction.

AI algorithms are commonly used in healthcare for biomarker discovery, drug discovery, limited disease diagnosis, patient risk stratification, and treatment recommendation systems [4]. These tools provide additional reference information to help clinicians identify anomalies in various diagnostic tools. However, the current AI tools do not provide a definitive decision recommendation for the clinician and only highlight what appears to be abnormal based on the tool's training. The data used to train the model defining what is normal vs. what is abnormal does not have a significant deviation. It is important to note that these decision-support tools are different from those used to assist in the acceptance of a deceased donor kidney for transplantation.

As previously acknowledged, kidney acceptance and transplantation are highly complex and require a collaborative effort from multiple disciplines. Each potential donor and transplant recipient has unique characteristics that do not conform to a standardized decision-making process. Moreover, the models trained on similar cases only provide an approximate solution. Research in the organ transplant field, particularly in deceased donor organ assessment (DDOA), has improved our understanding of AI capabilities in healthcare [1, 4–8, 10–12]. Various studies, such as the ones conducted by Ashiku et al. [5] and Threlkeld et al. [6], have collected data through workshops and interviews with stakeholders to better understand their requirements. This work has led to the development of the DDOA model and the current review of the digital twin model, which enhances decision-making support from a logistical perspective.

The DDOA interface, shown in Fig. 1, is publicly available to support transplant decision-making. The DDOA model is an advanced tool used by transplant surgeons to assess kidney allocation cases [7, 8]. The deep learning network model was

Deceased Donor Organ Assessment

Assess Hard-to-Place Before Procurement

Donor meets DCD criteria?

No

Age in years

55

Gender

☒ Male ☐ Female

ABOUT AI MODEL

Ethnic Category

Black or African American

Height in cm

185

Weight in kg

85

History of Diabetes

Yes, 6-10 years

History of Hypertension

No

Serum Creatinine (0 - 30.9)

12

Cause of Death

Cerebrovascular

HCV Status?

Inconclusive

Re-assess Hard-to-Place After Procurement

Clamp Time

Early Morning

Kidney on pump?

☐ No ☒ Yes ☐ Unknown

Kidney biopsy?

☐ No ☒ Yes ☐ Unknown

KI Glomerulosclerosis

Absent or 0-5

Interstitial Fibrosis

Minimal or 5-10

Vascular Changes

Unknown

KI Glomeruli count (0 for N/A)

30

CALCULATE KDPI

SAVE DONOR INFO

PREDICT HARD-TO-PLACE

Fig. 1 Deceased donor organ assessment (DDOA) app for AI model [8]. (<https://ddoa.mst.heka-demeia.org/#/>)

trained and tested using the organ procurement and transplantation network dataset, covering a period from January 1, 2016, to March 21, 2023.

The DDOA model is not designed to recommend acceptance of a kidney for transplant but rather to identify hard-to-place kidneys that could benefit from an accelerated placement path sooner in the allocation process. The DDOA outcome provides the kidney donor profile index and a prediction value for the difficulty of placing the kidney.

The use of AI in business to increase profits is truly fascinating. However, in healthcare, the approach is entirely different. Healthcare professionals are more concerned about ensuring that any new technology they adopt will have a positive impact on patient care. This is where things get tricky since it is difficult to process subjective knowledge that is represented by linguistic information. Large language models have proliferated in all domains but are heavily scrutinized for bias and producing implausible outputs (aka hallucinations) that can have catastrophic effects in healthcare [9]. Keeping the human expert in the loop is an important way to mitigate these challenges; however, words can mean different things to different people, and that's where fuzzy logic comes in. It's a clever way to model uncertainty and express expert knowledge in an easy-to-understand and analyzed way.

In this paper, we propose a novel approach to improve decision-making support for transplant surgeons by blending human input with AI decision-making algorithms. The proposed approach, TSFAM, is designed to integrate a network of systems and evaluate the surgeons' practices using fuzzy logic. The TSFAM model is based on the premise that human expertise and AI-powered decision-making algorithms can be combined to form a unified system that enhances decision-making support for transplant surgeons. The approach employs fuzzy logic, a state-of-the-art mathematical tool that can handle imprecise or uncertain data, to assess the surgeons' practices and integrate them into the system of systems. The TSFAM model is depicted in Fig. 2, which provides a visual representation of the integration of

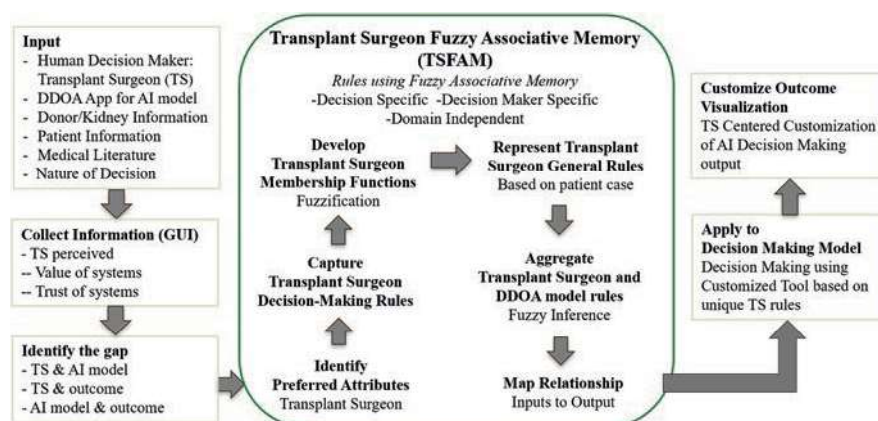


Fig. 2 Operational view of proposed transplant surgeon fuzzy associative memory model

human expertise and AI-powered decision-making algorithms in the proposed approach. The tool is expected to significantly boost decision-making support for transplant surgeons and potentially increase deceased donor kidney transplantation.

The aim is to engage transplant surgeons by bringing their individualized assessments based on their patients and general practices into an AI decision-making process, which will include:

- Identifying decision-making rules employed by the transplant surgeon as the human decision-maker.
- Tailoring the AI-based decision-making model to support decision cases in hand.
- Enhancing trust of the decision-maker in the AI tool.
- Fostering greater acceptance of AI machine learning decision-support outcomes.

The proposed model, TSFAM, includes evaluating the level of trust experienced by the transplant surgeon and applying fuzzy associative memory to identify their unique rules. It is anticipated that in the decision-making process, the transplant surgeon will have two models available for use when making placement decisions for a given kidney case, whereas the DDOA model provides an opportunity to assess the interaction of the transplant surgeon directly with an AI model built for the donor kidney domain. This interaction between human-AI systems is used to build the SoS model for evaluation with the SoS Explorer.

3 Approach

The integration of AI in domains beyond the healthcare industry is gradually gaining momentum. However, there is limited data or support available on how to integrate the human element into AI design. This is a critical issue as AI should not replace human decision-making but rather enhance it. Significant interests and activities exist in AI for social entertainment, as seen in the exploration of large language models. However, the healthcare industry requires clinical studies and data to validate any potential changes in the way a provider makes decisions for patients. This is because healthcare decisions can significantly impact patient outcomes. As such, the integration of AI in healthcare requires a human-centric approach that considers the needs of patients, providers, and caregivers. AI can be used to support decision-making, improve patient outcomes, and reduce costs. However, it should not be seen as a substitute for human expertise, empathy, and judgment.

The Department of Systems Engineering at Missouri S&T has developed a tool that is designed to provide an optimized architecture for various systems [10]. This tool works by performing complex computations based on several key factors and attributes, including key performance attributes, fuzzy inference rules, system characteristic values, and system capabilities. By analyzing these factors, the tool can generate an optimized architecture that is tailored to the specific needs of the system

in question. This can help improve system performance, efficiency, and reliability while minimizing the risk of errors or failures. Overall, the tool is a valuable resource for optimizing their systems and improving their overall performance.

When transplant surgeons are presented with a deceased donor kidney for transplantation, they consider various factors before deciding whether to accept it or not. The process begins with the input of natural language data, which is then transformed into a numerical value using fuzzy inference rules. These numerical values are used to generate a fuzzy set, which is then mapped based on the aforementioned rules. The outcome of this mapping determines the consequences of the rules, which are then used to balance the KPAs to represent an optimal architecture through an evolutionary algorithm. The evolutionary algorithm uses the input and the rules to determine a chromosome, which is then used to find the optimal architecture. The SoS Explorer generates the optimal architecture based on how one system can connect with another within the system-of-systems model; the system connections are shown as interfaces. The optimal architecture is then used to determine which factors are most critical when considering whether to accept a deceased donor kidney for transplantation.

This is a fifth-dimensional optimization problem that is solved based on finding the values for the variables $S(X,i)$ and $S(X,i,j)$ as used in the five objectives defined in Sect. 3.1. Objective 1 is performance, objective 2 is acceptability, objective 3 is usability, objective 4 is affordability, and objective 5 is robustness. The five objectives are subject to feasibility constraints. The characteristics provide parameters based on the domain selected for measuring objectives based on the selected architecture with the assigned values to $S(X,i)$ and $I(X,i,j)$. The fifth dimension is connected to one dimension using fuzzy inference, considering trades based on the customers' requirements as defined through their rules. This optimization problem is solved using non-gradient descent optimization using SoS Explorer, measuring the systems and interfaces of the model.

3.1 Key Performance Attributes

KPAs for this SoS were developed with consideration of the previous research work for AI model prediction in kidney donor disposition [11, 12] and meta-architecture optimization for kidney transplant systems of systems [13]. While the referenced work engaged the stakeholders in building their KPAs, the focus was primarily on what quantifiable data to include or not include for the development of the AI deep learning model. This contrasts with the focus of this work to incorporate the unique expertise and rules used by the transplant surgeon in the decision-making process for whether or not to accept a deceased donor kidney. The KPAs used for this model utilized similar quantifiable objectives like affordability and then added objectives reliant on the transplant surgeon's perspective, like acceptability and usability.

The SoS KPAs are calculated utilizing equations shown as objectives 1–5 in the SoS Explorer. Systems are defined as $S(X, i) = 1$ if the i th system participates in chromosome X of the meta-architecture, and 0 otherwise. The interfaces are defined as $I(X, i, j) = 1$ if the i th and j th systems have an interface connection in chromosome X , and 0 otherwise. The real-valued variables of $X(i)$ are evolved through recombination and mutation until they reach overall optimization, with the real-valued variables of $S(i)$ determining the chromosome of the real-valued $X(i)$. The delta (δ) variable represents the augmenting factor of the interfaces between active systems, which enables more or less value to be given to the equation based on the importance of that KPA to the system.

The key performance attributes are derived as follows, where N_s is the number of systems that contribute to the defined KPA:

Objective 1: The *performance* KPA utilizes kidney transplant success as measured in number of additional years of life given to the transplant recipient. Literature cites that 99% of kidney transplant recipients extend their life by at least 1 year, and 91% of recipients extend their life by 5 years [14].

$$\text{Performance} = \sum_i^{N_s} S(X, i) C_{\text{SuccessfulTransplant}, i} + \prod_{j \neq i}^{N_s} [1 + \delta S(X, j) I(X, i, j)]$$

Objective 2: The *acceptability* KPA measures how likely a transplant surgeon is to accept the decision-making support data as measured based on how trustworthy the surgeon perceives the information source.

$$\text{Acceptability} = \sum_i^{N_s} S(X, i) C_{\text{TrustworthyInformation}, i} + \prod_{j \neq i}^{N_s} [1 + \delta S(X, j) I(X, i, j)]$$

Objective 3: The *usability* KPA is a measurement of how intuitive the decision-making support system is for the transplant surgeon which is weighted more on the relevance of the information being provided, in addition to the impact on decision-making and trustworthiness of the information.

$$\begin{aligned} \text{Usability} = & \sum_i^{N_s} S(X, i) \left[\alpha C_{\text{RelevantTransplant}, i} + \beta C_{\text{ImpacttoDecisionMaking}, i} + \gamma C_{\text{TrustworthyInformation}, i} \right] \\ & + \prod_{j \neq i}^{N_s} [1 + \delta S(X, j) I(X, i, j)] \end{aligned}$$

Objective 4: The *affordability* KPA is derived by minimizing the overall cost of the system, using the interface costs and each individual system's cost. The value is based on real dollars, using the cost of a surgeon's time for any system that requires surgeon interaction.

$$\text{Affordability} = \sum_i^{Ns} S(X, i) C_{\text{OperationalCost}, i} + \sum_{j \neq i}^{Ns} I(X, i, j) C_{\text{InterfaceCost}, j}$$

Objective 5: The final KPA is *robustness* as evaluated by the impact of the decision-making support and the level of success found in the transplant results based on the decision.

$$\begin{aligned} \text{Robustness} = & \sum_i^{Ns} S(X, i) \left[\alpha C_{\text{ImpacttoDecisionMaking}, i} + \beta C_{\text{SuccessfulTransplant}, i} \right] \\ & + \prod_{j \neq i}^{Ns} \left[1 + \delta S(X, i) I(X, i, j) \right] \end{aligned}$$

3.2 Systems of Systems Explorer

The SoS meta-architecture is assessed using the SoS Explorer tool, which attempts to determine optimal prediction or decision-making architecture in other domains [15, 16]. As was used by Ashiku and Dagli [12], a single optimization of the model will be performed with a focus on augmenting the objectives to achieve a higher overall value. The objectives are used to determine the overall performance of the architecture. The equations listed above are used to calculate the crisp values for the objectives that are input into the fuzzy inference system. MATLAB is used to develop the objective equations and rules applied to the architecture. For the fuzzy logic designer interface in MATLAB, the Mamdani fuzzy assessor and centroid defuzzification methods are selected. The objectives are then evaluated by the simple self-organizing genetic algorithm (SOGA) evolutionary algorithm within the SoS Explorer. For this SoS, the genetic algorithm encodes the SoS with a chromosome that is a binary string length of 231, with the first 21 bits representing the systems selected, and the remaining 210 bits are the interfaces of the SoS. The systems used in this human-AI systems interaction have eight capabilities and seven characteristic or technical performance values used in the KPA equations to determine optimization.

When setting up the initial architecture, the impact of manipulating the fuzzy rules was explored, like the SoS approach taken by Curry et al. [16]. The five objectives were broken into a granularity of five from the beginning. The additional change made for this model was to supplement the initial 25 fuzzy rules with additional rules to produce a more desirable control surface.

The big “C,” capability of the SoS, is a decision-making support system for transplant surgeons. Within the SoS, each of the individual systems is evaluated for their ability to meet the small “c” capabilities. These capabilities include data visualization, organ assessment, medical evidence assessment, input patient information,

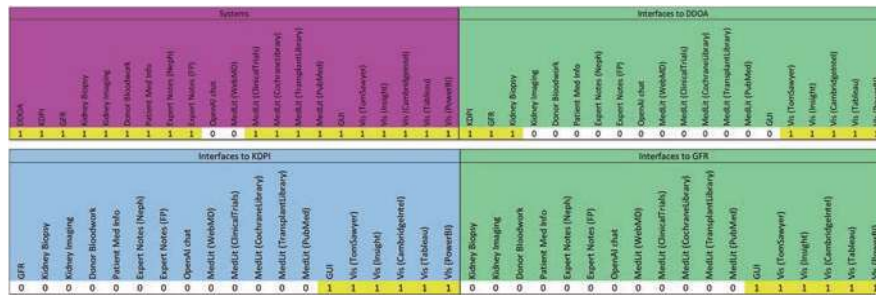


Fig. 3 Portions of the GA chromosome representing system selection and interfaces

display of donor information, data interactivity, storing data, and providing objective data analysis. If a system advances a capability, it is assigned the Boolean value of 1 for “true,” and if it does not, it is assigned the value 0 for “false.” These values are shown as the interfaces in green and blue in Fig. 3. All 21 systems are listed in the pink area, and the interfaces follow as alternating green and blue with three selected for the figure as representative of the full chromosome chart.

3.3 Membership Functions and Rules

The membership functions and rules used in MATLAB fuzzy assessor enable the system to handle uncertainty, make decisions based on imprecise information, and provide an assessment of various elements within the system. The membership functions define the degree to which the input belongs, and in this SoS, they have a granularity of five to help assess the complex system. When defining the membership function, it is essential to capture real-world characteristics close to the domain of the represented variables. They are defined for each input as *poor*, *feasible*, *average*, *good*, and *preferred*. The output granularity is also five and is defined as *very unacceptable*, *unacceptable*, *tolerable*, *desirable*, and *very desirable*. These terms resonate with human intuition, typically used to evaluate how well a function meets the required need.

The performance membership function, illustrated in Fig. 4, is a representation of how all the membership functions were measured. All membership functions are developed in the universe of discourse from 0 to 100. The overlap between the granularity recognizes that the inputs are not likely to be precise. This makes the decision process more realistic. The functions also demonstrate the incremental changes in the characteristics that impact the objective. The terms match simplistic linguistic scaling; however, these terms may need to be reviewed to ensure that the granularity levels align with the domain expert’s understanding and expectations of the input variables.

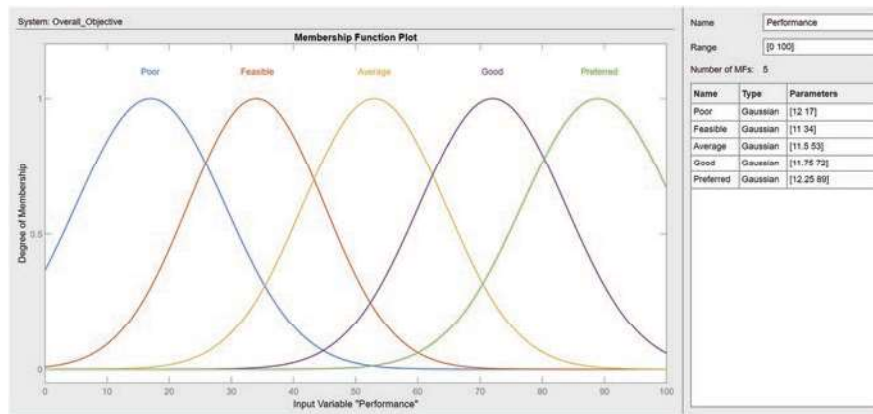


Fig. 4 Membership functions for KPA input

The control surfaces represent the overall membership function by comparing two objectives simultaneously. A total of ten control surfaces were produced and evaluated for smoothness. The goal is to have each control surface peak at the back top intersection and smoothly end at a point at the front bottom intersection. The amount and type of rules applied will affect these control surfaces. The rules are used to apply tradeoffs within the system. Twenty-eight rules are used to govern the assessment process and show expected smoothness in the control surfaces of the objectives, as viewed in Fig. 5, using the comparison standards of overall performance vs. each of the other objectives.

4 Results

The SoS Explorer has provided the output for the optimized architecture, which is depicted in Fig. 6. The potential systems are represented by circles, and their names are indicated beside them. If a particular system is included in the optimized architecture, it will be a filled circle. The filled circles, which represent the participating systems, are expected to be linked by a line to at least one other system to show an interface. This interface is necessary for the smooth functioning of the optimized architecture. If a filled circle does not have an interface, the architecture is considered infeasible. In such a scenario, the equations, characteristic values, and rules would need reassessment to determine where greater trade-off may be required. This is crucial because the optimized architecture is intended to ensure that all systems work together to achieve the desired outcome.

To achieve the optimized architecture, the manipulation of parameters in an interactive “what-if” approach was employed. This approach allowed for adjustments to be made while working toward the optimized architecture. The use of this

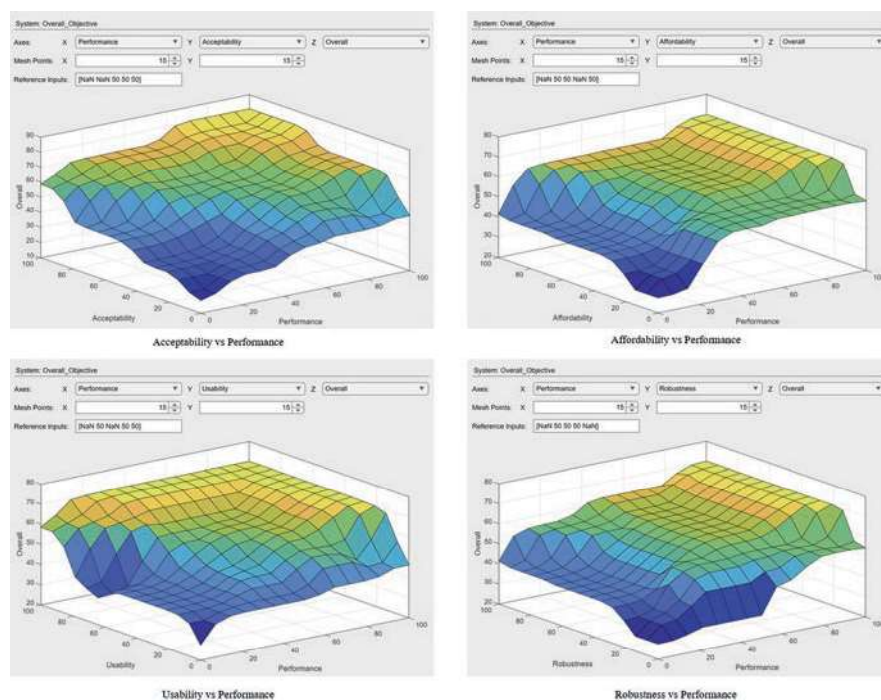


Fig. 5 Control surfaces representation. Acceptability vs. performance, affordability vs. performance, usability vs. performance, and robustness vs. performance

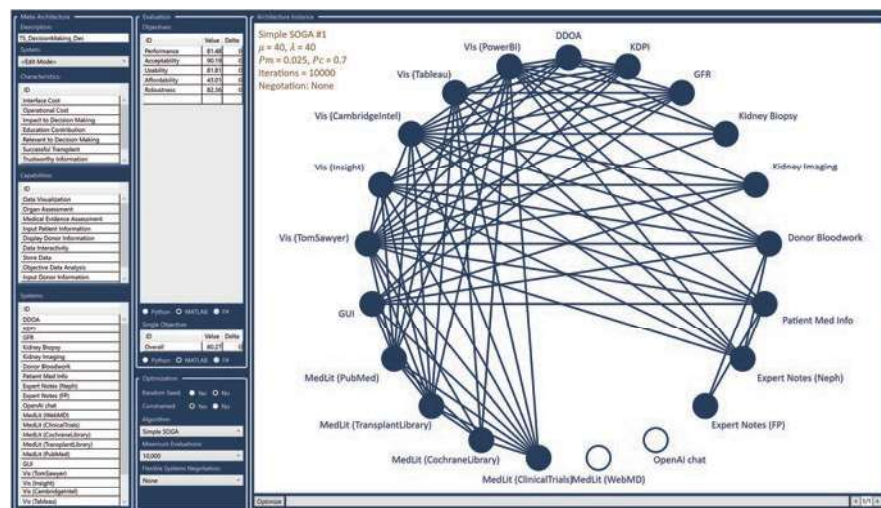


Fig. 6 Optimized architecture

approach helped to identify areas that needed improvement and enabled the team to make informed decisions.

This SoS meta-architecture has the best overall value of 80.27 among 10,000 iterations run, making this the most desirable architecture for the proposed human-AI system interaction model. All systems are utilized and are participating with select other systems. The population (μ) and offspring (λ) are both 40, probability of mutation (P_m) is 0.0025, probability of crossover (P_c) is 0.7, and the number of solutions generated is one. The objectives for this optimized architecture resulted in a performance of 81.48, acceptability of 90.19, usability of 81.81, affordability of 43.01, and robustness of 83.26. The objective values were all at least one point higher with the population and offspring set to 40 instead of an initial setup value of 60. There were no “single acting” systems where a system is identified as participating but does not have an interface. The results show a feasible architecture.

To further evaluate if this architecture is the best available, additional simulations run with variance of the simple SOGA parameters should produce the same or similar architecture. It is also important to look at how the systems are connected to the other systems as this identifies the interfaces between systems. Understanding how the systems interact with each other will assist in the development of the transplant surgeon fuzzy associative model.

5 Conclusions

A methodology was developed for designing the transplant surgeon fuzzy associative memory model using the SoS approach to identify the best meta-architecture. The utilization of fuzzy logic to account for the ambiguity of the human decision-maker provided the groundwork for this SoS evaluation. The results can be used to improve the quality of kidney transplant decision-making support for transplant surgeons by developing a parallel model to the DDOA through fuzzy associative memory that captures the transplant surgeon’s individual expertise. With good architecture in place, the development of the TSFAM will begin by setting up and utilizing an interface for transplant surgeon interaction with the DDOA model to enable testing and model design development. Future work will include coordination with transplant surgeons for gathering data and using surveys to build the characteristic values based on actual data compared to the simulated data used in this paper. Incorporating the unique rules of the transplant surgeons based on their own experiences and patient cases into an AI decision-support system will provide a customized model, leading to increased user trust and acceptance of the decision-support outcomes based on the decision in question. While current transplant-supporting algorithms are trained using regional or national datasets, the TSFAM will be built on very focused and specific input based on the local transplant team’s patient population to provide a more relevant decision-making support tool. The anticipated benefits of

this tool include improved accuracy and acceptance as well as a reduction in potential bias as it prioritizes local context in the decision-making process. The more the user, in this case the transplant surgeon, feels they are part of the AI development process, the greater the level of engagement, satisfaction, and continued improvement of the decision-making support tool. The optimized architecture developed using the SoS approach provides a roadmap for how to build the transplant surgeon fuzzy associative memory model, identifying the best tools to include and how to display. This will be used with the next step for efficient transplant surgeon rule collection.

Acknowledgments This work was partially supported by the Missouri University of Science and Technology's Kummer Institute for Student Success, Research, and Economic Development through the Kummer Innovation and Entrepreneurship Doctoral Fellowship.

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