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Letter from the Lead Editor

Dear INFORMS ORMS Community Members,

We are pleased to share with you the Fall/Winter 2021 edition of OR/MS Tomorrow! This issue is dedicated to diversity, equity, and inclusion (DEI) initiatives in the ORMS community. We have covered a myriad of topics including trustworthy artificial intelligence, equity in vaccine distribution, and the gender gap in engineering and science. Special thanks to Prof. Soroush Saghafian for sharing his view on the role of ORMS in healthcare analytics and a huge thank you to Prof. Michael Johnson for sharing with us how the ORMS community can contribute to research in racism and discrimination.

Attention job seekers! Ever wondered how to write the diversity statement for job applications? We are here to help. Many thanks to Prof. Amanda Jungels, Prof. Norean Sharpe, Prof. Cole Smith, and Prof. Willem-Jan Van Hoeve for sharing their valuable insights about preparing the diversity statement. Don't miss out on all the wonderful additional resources available!

We would like to thank Prof. Paul Rouse, Prof. Valery Pavlov, Prof. Cameron Walker, and Prof. Matthew Parsons for sharing the management science perspective on geriatrics, gerontology, and older patients. We would also like to thank Mr. Manav Kandhari, Prof. Kellie Schneider, and Prof. Corinne Mowrey for sharing their experience at The Foodbank where engineering helps relieve hunger.

Last but not least, congratulations to the winners of our 2021 mini-poster competition! We received numerous high-quality submissions globally on a wide variety of topics. The first place winning mini-posters from undergraduate and postgraduate levels are published in this issue. We would like to thank Prof. Dmytro Matsypura and Prof. Rohit Gupta for their valuable input in the judging process.

Submissions for the Spring/Summer 2022 issue are welcomed. Contact us via email at orms_tomorrow@mail.informs.org!

We hope you enjoy the content.

Jessica Leung

ORMS Tomorrow Editorial Team

This issue wouldn't have been possible without the effort of our team members:

Editorial Staff Writers
Srinivasan Balan, Egbe-Etu Etu, Abigail Lindner, Mihir Mehta, Piyal Sarkar, Elham Taghizadeh, Kimia Vahdat

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Webmaster
Harsh Anand

Social Media Coordinators
Kara Combs, Armagan Ozbilge

Faculty Advisor
Prof. David Czerwinski



Geriatrics, Gerontology and Older Patients: A Management Science Perspective



Abtin Ijadi Maghsoodi
Department of Information Systems and Operations Management
University of Auckland, New Zealand



Prof. Paul Rouse
Department of Accounting and Finance
University of Auckland, New Zealand



Dr. Valery Pavlov
Department of Information Systems and Operations Management
University of Auckland, New Zealand



Asso. Prof. Cameron Walker
Department of Engineering Science
University of Auckland, New Zealand



Prof. Matthew Parsons
School of Health, University of Waikato, New Zealand

Waikato District Health Board, Hamilton, New Zealand

1. Introduction

Mark Twain once said, "Age is an issue of mind over matter (…) If you don't mind, it doesn't matter…" However, the gradual impairment of biological functions due to deteriorative cell and structural component alterations over time is inevitable [1]. The United Nations reports that "by mid-century, one in six people globally will be aged 65 years or older" [2]; the global population aged 60 years was estimated around 962 million in 2017, more than twice as large as in 1980 when there were 382 million older people worldwide [2]. This number is expected to double again by 2050, projected to reach more than 1.5 billion. While life expectancy is rising and mortality rates are decreasing, it is unclear whether the additional years will be healthy. Meeting the health needs of older people is one of the most significant challenges of the 21st century. Therefore, a systematic approach to geriatric care planning is vital to explore the patients' journey from beginning to end to develop the most efficient strategy for performance measurement and continuous improvement for older patients.

2. Geromtology geriatric patients: Who will be there to care?

As we age, our body experiences many changes that ultimately impact our health. Older people are far more likely to suffer long-term conditions such as cardiovascular disease or diabetes, which tend to be more complex. Consequently, health systems across the Organisation for Economic Co-operation and De-

velopment (OECD) have prioritised the development of older person-specific services that integrate assessment and rehabilitation into treatment. Wards and indeed hospitals have been established that focus entirely on the health needs of older people (i.e., aged 65+). Multiple research projects have conducted various trials to evaluate the effectiveness of geriatric-specific interventions. Examples of the geriatric-specific models that were proposed to enhance the effectiveness of patients' journey include the Acute Care for Elders (ACE), Hospitalized Elder Life Program (HELP), and Geriatric Evaluation and Management Units (GEMU) [3]. Although some evidence showed better health outcomes when older people were given care based on a personalised model, it is not clear which 'pathways' are best suited for their clinical journey due to limited literature on geriatric patients' operations. Clinical pathways represent a form of guideline that could be perceived as a suitable tool for quality management, cost-cutting, and patient satisfaction. Processes and interventions within pathways have features that can be measured, analysed, improved, and controlled, providing opportunities for evaluation in terms of efficiency, effectiveness, and equity. For older patients, although the primary objective of investigating clinical pathways is to improve the effectiveness of the interventions (similar to conventional care), due to the complexity of their conditions, different strategies and policies should be utilised to reach better health outcomes and improve the geriatric-specific healthcare services.

3. Journey towards wellbeing and the role of OR/MS

The process of identifying and mapping clinical pathways is an efficient way to plan, standardise, and optimize the progression of administrative procedures and clinical treatments, which can reduce the complications and difficulties surrounding different phases that decision-makers need to address. In addition, the standardisation of pathways can reduce variability in service delivery. Utilizing various Operations Research and Management Science (OR/MS) methods to analyse and eliminate the bottlenecks and complications existing in the clinical pathways is beneficial for patients, practitioners, and health service managers. For patients, insights from their journey can enhance their experiences of the provided care, which is one of the important aspects of health literacy, and with bottlenecks eliminated, they can experience a better and improved health service. For practitioners, understanding the journey will help them gain knowledge of the patient's perspective and their journey, so they would be able to optimise and enhance their pathways and provide better services. Finally, for health service managers, understanding the patients' journey can help policymakers make informed decisions about where to focus funds, identify areas of inefficiency, and inform solutions to improve key metrics. OR/MS is a discipline that utilises advanced analytical methods to understand and optimize complex systems and aid in decision-making. OR/MS uses a wide range of problem-solving techniques and computational methods, including computer simulation, mathematical optimisation, statistics, and decision analyses, to help improve the operations of organisations. With its orientation towards improving efficiency, cost-effectiveness, and decision-making, OR/MS can be beneficial for analysing complex geriatric care issues. Evidence from the literature shows that despite the growing application of OR/MS in geriatric care [4, 5], the impact of OR/MS is still unknown in geriatric care operations as research studies rarely discuss the practicality and aftereffects of their findings or whether propositions were implemented.

Tools and techniques used in OR/MS usually replicate manufacturing systems to analyse the healthcare procedures. The process of identifying and mapping clinical pathways can be a clear instance of this approach. Various studies have drawn attention to the fact that OR/MS for geriatric care is beneficial in scenarios where conducting a real-world study might be considered impossible, impractical, too costly, or unethical [6-8]. More practical examples could be such as when choosing between implementing intervention "A" or "B", when controlled trials to compare a wide variety of available options would be unreasonable, or in case of geriatric patients when the risk of mortality is high and practical implications might have adverse effects. Other examples include the servicing of patient flow being modelled as a job shop scheduling optimization problem [4, 5], and the evaluation of potential interventions being conducted via modelling to compare a wider variety of options than would be feasible via randomised control trial or when the risk of mortality is high and practical implications might have adverse effects [6-8]. Additionally, OR/MS for geriatric care is also useful for complex financial evaluations such as assessing the most cost-effective intervention among various options or evaluating the optimal approach to allocate limited resources. Consequently, by investigating various stages of the patients' journeys and their associated operational and clinical flow, OR/MS tools can improve geriatric care operations.

3.1 Patient flow management: go with the flow

Healthcare organisations tend to manage critical tensions between cost-saving, services improvement, and equity of access while operating under capacity constraints and fluctuations in patient demand. Improving patient flow should be a priority to effectively match supply with demand given limited hospital resources. Patient flow can be defined as the movement of patients through healthcare facilities which involves medical care, resources (e.g., practitioners, nurses, beds, and more) and systems ensuring that patients are getting appropriate care at each point of their journey from admission to discharge while maintaining quality and patient satisfaction. Marshall et al. [9] suggest patient flow can be viewed from operational and clinical perspectives. From an operational perspective, it is the movement of patients through a set of locations in a healthcare facility. Clinical patient flow signifies the progression of a patient's health status. In recent years, operational and clinical patient flows have been analysed as the objective in OR/MS literature. Investigations showed many of these concepts were developed based on "Lean Thinking" [10], which has inspired broad discussions among studies on this direction in healthcare systems.

3.2 Admission emergency department: the first impression

The first stage of the patient journey is their presentation to the hospital at the Emergency Department (ED), accessed via ambulance or self-admission. Hospital admissions increase with age, which is why there are higher hospitalization rates in the older population than in the younger population. EDs are primary

treatment facilities responsible for providing medical/surgical care to patients needing immediate care, overseeing acute and emergency presentations of both young and older patients. Approximately 58% of the population aged 75 years old have had at least one visit to an ED, compared to 39% of those of all ages [11]. Due to the availability of coexisting complications, once older patients are in ED, they are more likely to have an adverse condition and be admitted to a critical care unit. According to Hwang and Morrison [11], the physical space of the current ED models is not aligned with the priorities and needs of geriatric patients. An essential aspect of the patient flow in ED is associated with complexities arising from day-to-day variability, resulting in overcrowding, limited resources, and bed blocking. The appearance of these problems shed light on an important connection between OR/MS techniques and ED operations to establish concepts such as capacity pooling, bed planning, staffing, and scheduling, which could be addressed with methodologies including simulation modelling, mathematical programming and optimization, queueing theory, Markov models and Markov decision processes. Although ED admissions have been analysed in recent years, the literature on this topic associated with geriatric patients considering patient flow is still narrow.

3.3 Readmission: you may have to fight a batter more than once!

Readmission can be defined as "unplanned or acute admissions following by discharge from an earlier admission" [12]. Reducing the number of hospital readmissions, based on periods varying between 1 day and 12 months after discharge, is a critical approach towards improving health care quality and lowering associated costs. According to Felix et al. [13], poor care coordination after discharge and inadequate follow-up are considered two main factors which affect hospital readmissions. Many studies have attempted at optimising readmission using OR/MS approaches. For example, Liu et al. [14] developed an effective check-up plan to monitor patients following discharge, using various check-up methods based on a delay-time analysis model to identify the optimal type of check-ups to implement post-discharge monitoring plans. Helm et al. [15] proposed a novel approach integrating prediction models with machine learning and Bayesian survival analysis and delay-time models of readmissions to empirically generate an individualized estimate of the time to the readmission density function to optimize a post-discharge monitoring schedule and staffing plan to support monitoring needs. Flood et al. [16] suggested the ACE model to examine variable direct costs from this interdisciplinary unit compared with the conventional care unit. Similarly, Hansen et al. [17] have drawn attention to the fact that various research studies have used geriatric-specific models, e.g., ACE and GEMU, to reduce hospital readmission in older patients. While the readmission rate has been considered a significant component of OR/MS studies, this measure has always been considered a secondary factor in geriatric studies. There is not a single study that has considered this factor individually.

3.4 Hospital discharge and discharge planning: the way to go home?

"…Hospital discharge describes the point at which inpatient hospital care ends, with ongoing care transferred to other primary, community, or domestic environments. Hospital discharge is not an endpoint, but rather one of the multiple transitions within the patient's care journey…" [18]. Due to the multilayer nature of discharges and the complexity of coordinating a significant number of factors, hospital discharges can be vulnerable, time-dependent, and high-risk episodes in the patient pathways. A notable example of such vulnerability is delayed discharges. Delayed discharges mostly have adverse effects on older patients. One of the leading solutions to comprehend delayed discharges is discharge planning. Goncalves-Bradley et al. [19] defined the process of discharge planning as the development of a personalised plan for patients who must leave the hospital with the goal of containing costs and improving patient health outcomes. Discharge planning aims to minimise the length of stay and unplanned readmission to enhance the coordination of services following discharge from the hospital. In the past few decades, discharge planning for geriatric patients has gained significant recognition as a process requiring improvements. Approximately 30% of older patients experience some type of delay in their discharge process, which makes them exposed to additional hospital-related risks, create emotional and physical dependency, incur additional costs, and restrict the availability of inpatient beds. Discharge without appropriate actions can also lead to patient recovery complications. Therefore, effective discharge planning for hospitalised older patients is necessary for hospital procedures. The early study of Cable and Mayers [20] can be regarded as one of the first attempts in discharge planning. Since then, identifying components of a proper hospital discharge for older patients has been a topic of various clinical and OR/OM research studies.

4. Journey towards a more inclusive and diverse geriatric care

Demographic changes and the growing demands on healthcare systems are among the greatest challenges of the next decades. This may be one of the primary reasons why healthcare-related problems especially for geriatric patients, are becoming the next trend. However, a reshaping of the current healthcare system should take place due to balancing the mismatch of supply and demand and the inequity in the delivery of public health interventions internationally [21]. Due to systemic and life-long discrimination, certain populations of older adults have been facing barriers in accessing the care they need and suffer poorer health as a result. However, along with the growing consensus on the importance of identifying and tackling such inequities in healthcare delivery, concerns have been raised regarding the conceptual clarity and rigour of research in this field. Therefore, a crucial need for greater attention to measurement, control, and optimization of geriatric care has been highlighted. Although in the past recent years, many studies have analysed different aspects of health delivery for older adults, the literature is very limited. Therefore, a more focused emphasis is required to plan, standardise, and optimize the progression of geriatric care procedures and treatments. Evidence from the literature shows OR/MS tools and techniques have a significant potential to plan and optimise geriatric care procedures.

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Engineering that Matters: A Summer Immersion at The Foodbank



Manav Kandhari
Department of Engineering Management, Systems and Technology
The University of Dayton



Dr. Kellie Schneider
Department of Engineering Management, Systems and Technology
The University of Dayton



Dr. Corinne H. Mowrey
Department of Engineering Management, Systems and Technology
The University of Dayton

Introduction

Households that do not have consistent access to a sufficient quantity of affordable, nutritious, and culturally appropriate food are said to be food insecure. In 2018, the USDA reported that approximately 1 in 9 Americans were facing food insecurity, or more than 37 million Americans, including more than 11 million children (age 18 and younger) [1]. Feeding America, the nation's largest domestic hunger-relief organization, tracks food insecurity nationwide. In a 2018 analysis, Ohio ranked 11th in the nation with a food insecurity rate of 13.9% [2]. With the devastating tornadoes ripping through the area on Memorial Day in 2019 and the ongoing COVID-19 pandemic, Feeding America estimates that Ohio's food insecurity rate for 2020 has increased to 18.1% [3].

In an attempt to combat food insecurity, the U.S. government has implemented many different programs over the past eight decades. However, many households still rely on the private food assistance network to meet at least some of their nutritional needs [4]. Within the private food network, food banks serve as central warehouses that collect, purchase, store and distribute food. The Foodbank. Inc. serves as the primary source of food for the Dayton, OH area network. Annually, The Foodbank distributes more than 17 million pounds of food through a network of more than 100 partner agencies, and were recently recognized as one of America's best food banks. The Foodbank's vision that "no one should go hungry" drives them to constantly strive for continuous improvement. Through an ongoing partnership with the University of Dayton, The Foodbank has focused on using community-based operations research (CBOR) to improve the efficiency of their truck routes.

Community-based operations research is defined as a set of analytical methodologies used to solve problems where the interests of underrepresented, underserved, or vulnerable groups in the local area are prioritized [5]. CBOR makes use of statistical models and analytical methods to address problems of core concern to the individuals, government, and non-governmental organizations seeking to address and work towards the issues of social inequity. Community-based problems place significant emphasis on the needs of specific populations in well-defined neighborhoods. The local nature of this work exerts a strong influence on the analytic models and resulting policy or operational decisions. This work is often considered "messy" as the formulation and solution of these problems are highly dependent on political and social considerations [5]. Examples of CBOR can be found in human services (humanitarian logistics, libraries and literacy, education and family support services), community development (housing, community/urban planning, transportation), public health and safety (health care, criminal justice, emergency services, hazardous/undesirable facility location, food insecurity) and non-profit management.

One of the most common problems encountered in transportation logistics is the vehicle routing problem (VRP). The VRP aims to minimize the total cost of transportation by finding optimal routes for multiple vehicles visiting a set of locations. The VRP generalizes the well-known traveling salesman problem (TSP) and was first introduced by George Dantzig and John Ramser more than 50 years ago [6]. Some examples of VRPs arising in urban transportation are the efficient routing of school buses [7], and the design of tourist tours to visit multiple points of interest in a city [8].

Although there are many software packages available to solve the vehicle routing problem, we specifically chose an open-source solver for our application. The VRP spreadsheet solver, introduced by Güneş Erdoğan, was specifically chosen because of its interface, ease of use, accessibility, and flexibility to run on any operating system with Microsoft Excel [9]. The VRP spreadsheet solver has been used by organizations in diverse sectors, but its application is most straightforward in the field of logistics. Our desire to use this solver grew stronger as a result of its tremendous potential to achieve savings by increasing efficiency, as well as its ease of handling computational complexity for small to medium-sized enterprises, like The Foodbank. The scope of our application of VRP in CBOR is limited to the U.S., as characteristics, including laws and regulations, may differ from country to country around highly sensitive issues such as poverty, food security, and homelessness.

Improving Retail Routes

The Foodbank's mission is to relieve hunger by acquiring and distributing food through a network of partner agencies. After a series of tornadoes devastated the area on Memorial Day weekend of 2019 [10], followed almost immediately by the global pandemic, The Foodbank faced operational hurdles as they worked to manage these crises. As a result, The Foodbank was forced to respond extemporarily to the increased need for food throughout 2020, focusing more on the effectiveness of their work rather than efficiency. The pandemic response made The Foodbank's work particularly challenging, as non-essential personnel was asked to stay home and volunteer services were suspended. The Foodbank's operations, however, achieved some stability as they received extra help from the National Guard who assumed many of the day-to-day operations [11]. With the widespread availability and distribution of COVID-19 vaccines, The Foodbank began to return to pre-pandemic operations. Personnel and volunteers were allowed to return to the warehouse and The Foodbank was able to return their focus on improving their operations. Because the University of Dayton (UD) has a long-standing history of working with members of the Dayton community, The Foodbank reached out to UD's School of Engineering and ETHOS Center for help. The Engineers in Technical Humanitarian Opportunities of Service-Learning (ETHOS) program is open to all engineering students at the University of Dayton. ETHOS seeks to provide service-learning experiences for students so that they may gain perspectives on how engineering and technology are influenced by varying conditions around the world. Participating students serve others by applying their engineering knowledge and skills for humanitarian purposes [12]. Working collaboratively, the ETHOS Center and the Department of Engineering Management Systems and Technology (EMST) sought to improve one part of The Foodbank's operations: its retail collection routes.

One of the primary ways The Foodbank acquires food is through donations from local retailers. Using a fleet of privately owned trucks, The Foodbank visits more than 40 retailers on a weekly basis to acquire donated food. The impacts of the Dayton tornadoes and the ongoing response to COVID-19 resulted in unbalanced collection routes that were formed ad hoc. The overall goal of this project was to increase the efficiency of collection routes by reducing the cost and time required to collect retail donations. The uniqueness of this project is highlighted by the fact that our work is community-focused and includes a component that specifically addresses an equitable distribution of work among all trucker drivers. The project's geographic scope was limited to the area served by The Foodbank, namely the region of Pebble, Greene, and Montgomery County. Our analysis of the data provided by The Foodbank allowed us to identify that multiple stakeholders need to be considered when evaluating the trade-offs between efficiency, effectiveness, and equity in our solutions. The primary stakeholders shortlisted are Donors (partner agencies, govt., non-governmental organizations, individual donors) and Service providers (employees, partner distributors, drivers, volunteers, etc.), whereas the list of secondary stakeholders includes Partner agencies and Customers (individuals/families receiving food from different programs).

The team utilized the following three steps to conduct the project:

1. **Understanding the project activities**
   This included reviewing existing retail routes to establish baseline parameters such as the number of routes required for the collection, the number of collections per week, and the total number of miles driven by each truck. The resources for our project were limited to a fixed number of trucks and drivers, as well as numerous time constraints that had to meet the retailer's expectations. Our project was responsible for reducing both the cost and time spent on truck routes. Upon further investigation, we discovered that the cost savings were a direct result of reducing the number of miles driven to cover the same number of stores by the truck, but the time to cover those stores was not, resulting in increased computational complexity. Travel time is considered highly variable since it is subject to a variety of unknown factors such as traffic, availability of drivers, weather conditions, etc.

2. **Establishing and evaluating baseline**
   The baseline evaluation of existing retail routes is based on the route sheets provided by The Foodbank at the start of the project in May 2021. Close collaboration with operations workers allowed for the integration of new retail donors into collection schedules, as well as recognition of each donor's preferences for collection days and hours. At baseline, there were 47 retail donors, and 4 trucks were used to make 126 collections per week, as summarized below in Tables 1 and 2. The research team worked closely with operations managers and truck drivers to understand the various restrictions and preferences of retail donors. For the 19 existing routes, a total of 926.08 miles were driven each week.

Table 1: Number of retailers visited per week by day of the week and by truck number.

Truck	Monday	Tuesday	Wednesday	Thursday	Friday
1	7	4	8	6	9
2	9	7	7	5	9
3	8	6	8	0	9
4	8	1	2	5	8
Total	32	18	25	16	35

Table 2: Distance traveled in miles per week by day and by truck number.

Truck	Monday	Tuesday	Wednesday	Thursday	Friday
1	35.7	64.5	41.63	57.71	59.92
2	46.76	41.89	46.90	28.52	46.76
3	42.59	48.44	57.44	n/a	44.69
4	53.15	24.88	36.54	65.35	82.7
Total	178.2	179.71	182.51	151.57	234.07

3. Optimization

The VRP spreadsheet solver was used to optimize retail routes on a daily basis [9]. Various settings in the VRP spreadsheet solver can be adjusted – such as the shortest distance vs fastest time, the truck capacity, the work start time, and the number of trucks – in order to create a series of proposals for the operations team to consider. A snapshot of the input to the VRP solver for the accepted (proposal) route on Tuesday is shown below in Figure 1.



Sequence	Parameter	Value	Remarks
0.Interface	Language	English	Please refer to the manual for modifying the interface.
	Optional - Bing Maps Key	AuglBQwuJ-Mli7EbC0qJKx6WBsZQYfv5DRpV8YZbGOsk_ekvfvj5k1PNI3pVbX8e	You can get a free trial key at https://www.bingmapsportal.com/
1.Locations	Number of depots	1	[1,20]
	Number of customers	17	[5,200]
2.Distances	Distance computation method	Bing Maps driving distances (miles)	Recommendation: Use 'postcode, country' format for addresses
	Duration computation method	Bing Maps driving durations	
	Bing Maps route type	Fastest	Recommendation: Use 'Fastest'
	Average vehicle speed	40	
3.Vehicles	Number of vehicle types	1	
4.Solution	Do the vehicles return to their depot(s)?	Yes - only once at the end	
	Time window type	Soft	
	Backhauls?	No	If activated, delivery locations must be visited before pickup locations
5.Optional - Visualization	Visualization background	Bing Maps	
	Location labels	Location IDs	
6.Solver	Warm start?	Yes	
	Show progress on the status bar?	No	
	CPU time limit (seconds)	120	Recommendation: At least 60 seconds

Figure 1: The input sheet for the VRP solver.

The next step in the process was to input the stores to be picked up and their corresponding street addresses. The VRP solver identified the coordinates (latitude and longitude) of each location using Bing maps. These coordinates were used to calculate the distance and travel time, as well as to facilitate the visualization of the solution. Once the coordinates were located, we input the different time constraints associated with each store in order to satisfy the preferences of the various retail donors. An approximate service time for each retailer was determined using driver feedback as well as data from previous projects. Figure 2 shows an example of a Tuesday location sheet with accurate pickup addresses, coordinates, and time constraints corresponding to each store. A map visualizing all Tuesday pickup points using the input coordinates is shown in Figure 3.



Location ID	Name	Address	Latitude (y)	Longitude (x)	Time window start	Time window end	Must be visited?	Service time	Pickup amount	Delivery amount	Profit
0	The Foodbank	56 Armor st, Dayton, Oh 45417	39.7484333	-84.2107105	07:00	23:59	Starting location	0:00	0	0	0
1	Sams Miller lane	6955 miller lane, dayton, oh 45414	39.8476906	-84.1946269	00:00	08:00	Must be visited	0:20	1	0	0
2	Sams Beavercreek	3446 new germany-trebin, beavercreek, oh 45431	39.7720945	-84.0584109	00:00	08:00	Must be visited	0:20	1	0	0
3	Kroger day/xenia	3165 dayton xenia rd, dayton, oh 45434	39.7251761	-84.0534402	00:00	09:00	Must be visited	0:45	1	0	0
4	Meijers englewood	9200 n main st, dayton, oh 45415	39.8583900	-84.2745991	00:00	13:00	Must be visited	0:30	1	0	0
5	Meijers springboro	5858 springboro pike, moraine, oh 45439	39.6709520	-84.2194859	00:00	13:00	Must be visited	0:30	1	0	0
6	Kroger Stroop	530 e stroop rd, kettering, oh 45429	39.6884971	-84.1621445	00:00	09:00	Must be visited	0:45	1	0	0
7	Meijer wilmington	4075 wilmington pike, kettering, oh 45429	39.6860231	-84.1322733	00:00	23:59	Must be visited	0:30	1	0	0
8	Kroger feedwire	5400 Cornerstone N Blvd, Centerville, OH 45440	39.6620100	-84.1036680	00:00	09:00	Must be visited	0:45	1	0	0
9	Kroger dorothy lane	2115 e dorothy lane, kettering, oh 45420	39.7042297	-84.1250218	00:00	09:00	Must be visited	0:45	1	0	0
10	Pepsi	526 milburn ave, dayton, 45404	39.7723666	-84.1796823	00:00	23:59	Must be visited	0:45	1	0	0
11	Dlm oakwood	2710 Far Hills Ave, Dayton, OH 45419	39.7065750	-84.1704925	00:00	23:59	Must be visited	0:45	1	0	0
12	Sams centreville	1111 miamisburg centerville road, dayton, oh 45458	39.6298606	-84.1898753	00:00	08:00	Must be visited	0:20	1	0	0
13	Aldi's Dayton mall	203 n springboro pike, dayton, oh 45449	39.6406320	-84.2275307	00:00	23:59	Must be visited	0:15	1	0	0
14	Kroger austin pike	10101 landing way, miamisburg, oh 45342	39.6023649	-84.2315485	00:00	09:00	Must be visited	0:45	1	0	0
15	Kroger heincke	155 north heincke rd, miamisburg, oh 45342	39.6419990	-84.2668440	00:00	09:00	Must be visited	0:45	1	0	0
16	Kroger Alexbell	2917 w alex bell rd, dayton, oh 45459	39.6742499	-84.2189998	00:00	09:00	Must be visited	0:45	1	0	0
17	Dlm centerville	6177 far hills ave, centerville, oh 45459	39.6568661	-84.1588737	00:00	23:59	Must be visited	0:45	1	0	0

Figure 2: The location sheet for the VRP solver.

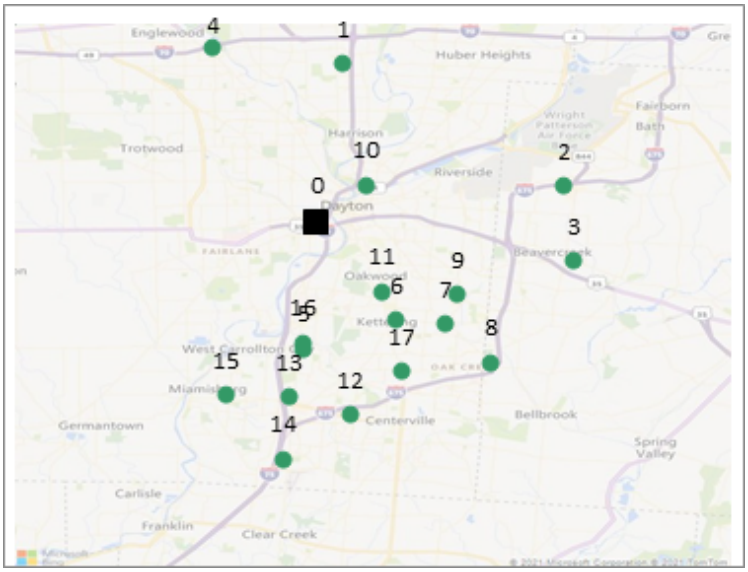


Figure 3: The map of the pick-up points for a Tuesday.

During the route optimization, we used different combinations of different input constraints, including vehicle capacity, number of vehicles, driving and working limits, etc. to obtain and identify several feasible solutions. The research team then discussed the results with The Foodbank operations team to select the best set of routes. The vehicle input sheet for the accepted proposal is shown below in Figure 4.

Starting depot	Vehicle type	Capacity	Fixed cost per trip	Cost per unit distance	Duration multiplier	Distance limit	Work start time	Driving time limit	Working time limit	Return depot	Number of vehicles
The Foodbank	T1	7	0.00	1.00	1.00	560.00	07:00	9:00	10:00	The Foodbank	3

Figure 4: The vehicle input sheet for the VRP solver for a Tuesday.

The key features of the VRP solver include its ability to calculate the distance between each pickup point using Bing maps and its ability to measure the travel time between each pickup point based on the specified average vehicle speed. Figure 5 shows a snapshot of Tuesday's distance sheet that includes the distance and duration between all listed stores.

From	To	Distance	Duration	Method: Bing Maps driving distances (miles) / Bing Maps driving durations
The Foodbank	The Foodbank	0.00	0:00	
The Foodbank	Sams Miller lane	7.94	0:14	
The Foodbank	Sams Beavercreek	12.34	0:17	
The Foodbank	Kroger day/xenia	9.98	0:15	
The Foodbank	Meijers englewood	14.73	0:18	
The Foodbank	Meijers springboro	6.40	0:14	
The Foodbank	Kroger Stroop	6.11	0:17	
The Foodbank	Meijer wilmington	8.75	0:21	
The Foodbank	Kroger feedwire	13.29	0:18	
The Foodbank	Kroger dorothy lane	8.12	0:16	
The Foodbank	Pepsi	3.70	0:08	
The Foodbank	Dlm oakwood	4.59	0:13	
The Foodbank	Sams centreville	12.43	0:16	
The Foodbank	Aldi's Dayton mall	9.25	0:14	
The Foodbank	Kroger austin pike	11.83	0:17	
The Foodbank	Kroger heincke	10.68	0:15	
The Foodbank	Kroger Alexbell	6.36	0:14	
The Foodbank	Dlm centerville	15.34	0:18	
Sams Miller lane	The Foodbank	8.23	0:12	
Sams Miller lane	Sams Miller lane	0.00	0:00	
Sams Miller lane	Sams Beavercreek	14.76	0:23	
Sams Miller lane	Kroger day/xenia	17.25	0:23	
Sams Miller lane	Meijers englewood	8.20	0:14	
Sams Miller lane	Meijers springboro	13.27	0:22	
Sams Miller lane	Kroger Stroop	14.51	0:25	
Sams Miller lane	Meijer wilmington	16.02	0:28	
Sams Miller lane	Kroger feedwire	20.56	0:26	
Sams Miller lane	Kroger dorothy lane	15.39	0:23	
Sams Miller lane	Pepsi	5.84	0:12	
Sams Miller lane	Dlm oakwood	13.12	0:22	
Sams Miller lane	Sams centreville	19.29	0:24	
Sams Miller lane	Aldi's Dayton mall	16.11	0:21	
Sams Miller lane	Kroger austin pike	18.69	0:24	
Sams Miller lane	Kroger heincke	17.54	0:22	
Sams Miller lane	Kroger Alexbell	13.22	0:21	
Sams Miller lane	Dlm centerville	22.20	0:26	
Sams Beavercreek	The Foodbank	12.02	0:18	

Figure 5: The distance sheet for the VRP solver for a Tuesday.

Results

After a lengthy selection process, our team was able to finalize the optimized proposals for the Tuesday, Wednesday, and Thursday routes, which not only met the given constraints but also matched the expectations of all drivers and supervisors. The key information on the optimized routes is provided below. A visualization of the baseline routes compared to the optimized routes for each day is shown in Figures 6-8.

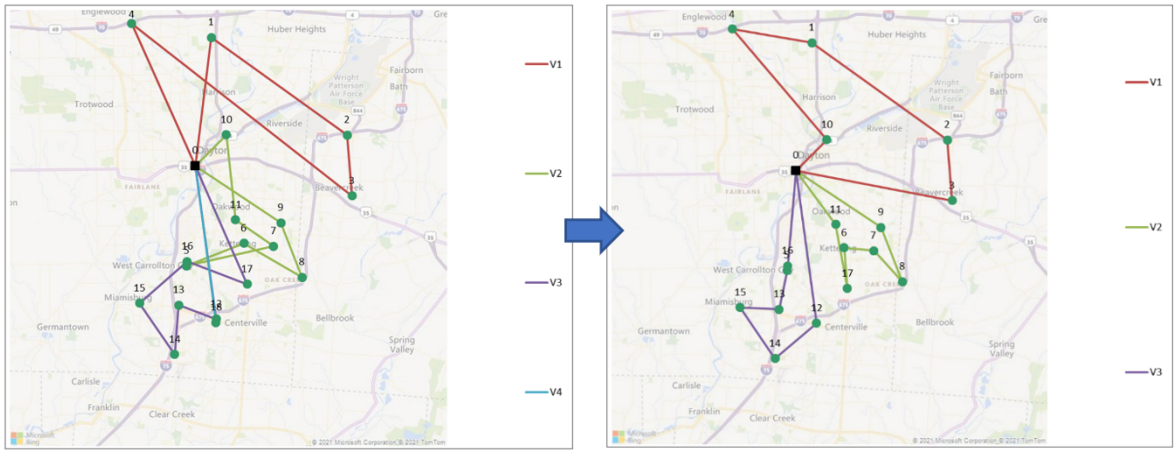


Figure 6: Tuesday's current route map (left) and its proposed optimization (right). Total miles reduced = 24.98, Total route time reduced = 60 minutes.

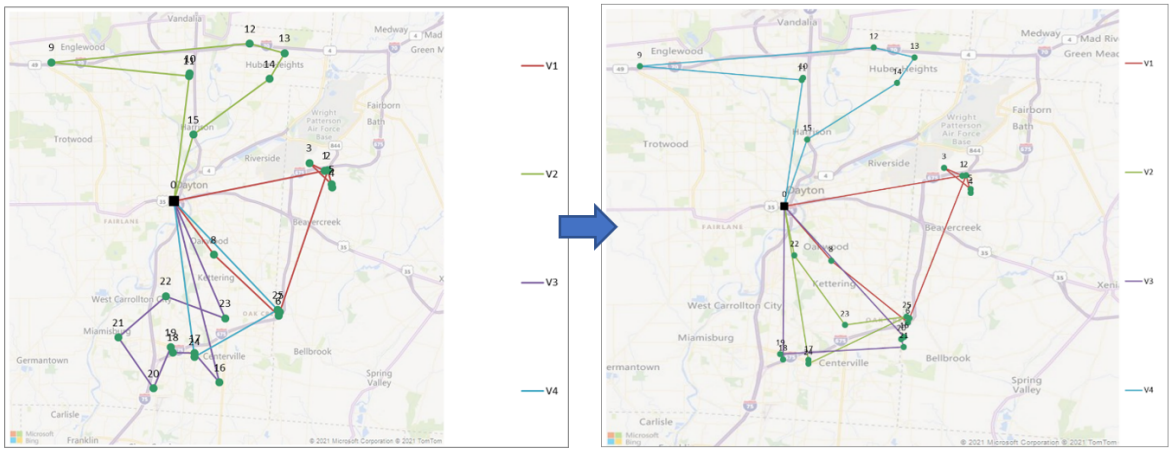


Figure 7: Wednesday's current route map (left) and its proposed optimization (right). Total miles reduced = 27.09, Total route time reduced = 20 minutes. The expectation of creating a training route (green lines) was also successfully fulfilled.



Figure 8: Thursday's current route map (left) and its proposed optimization (right). Total miles reduced = 26.91, Total route time reduced = 45 minutes.

Future Work

Due to the dynamic nature of fleet operations, it is necessary to occasionally update retail routes. The research team is pleased to continue collaborating with The Foodbank on improving operations. There may be opportunities in the future to further improve the efficiency of their fleet by optimizing delivery operations and other types of donation pickups (such as food barrels) that were not considered in this project. Another significant way to improve operations at The Foodbank is to train members of the operations team to use the VRP spreadsheet solver, giving them the ability to update routes on-demand, in real-time, in order to maintain their commitment to continuous improvement.



Figure 9: The Foodbank truck at one of the retail stores, ready for pickup.

Manav's Immersion Reflection

In both my academic and professional life, I have been consistently praised as focused by my professors and peers. Whether working on academic, extracurricular, or professional projects, I apply proven communication, management, and problem-solving skills, which I aimed to continue over the summer at The Foodbank. I think of myself as a combination of an imaginative and practical learner, which has served me well at The Foodbank. By conducting research, communicating to obtain feedback from my team, improving my optimization skills, and finally working with several solutions to find one that can meet both the standards and preferences of the operating personnel, I was able to combine real-world experience with theory while gaining hands-on experience. My approach to personal development during this immersion was based on the "3C's of the entrepreneurial mindset model" [13], namely Curiosity to learn and understand the work culture of a nonprofit organization, developing Connections to expand my professional network, and Creating value by applying my technical skills to support the overall growth of the organization. The photo of our Foodbank team (Figure 10) was taken at the ETHOS Poster Presentation Day, where I was able to offer an example of how engineers can have a significant impact on society.

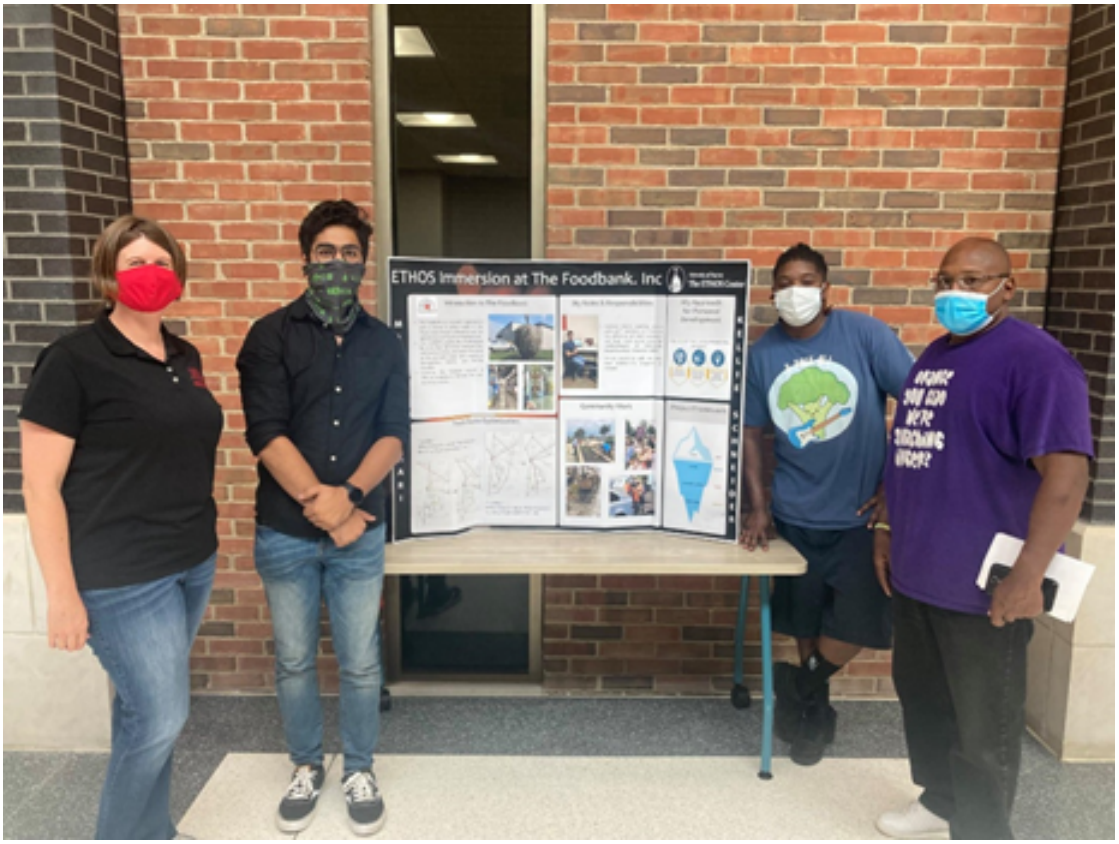


Figure 10: Our team at the ETHOS poster presentation at the University of Dayton.

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Preparing Your Diversity Statement: A Commitment to Inclusive Teaching and Research



Amro El-Adle
University of Massachusetts Amherst



Abigail Lindner
Regent University

Diversity statements, in which candidates for academic positions are asked to write about their experiences and abilities to positively impact diversity, equity, and inclusion (DEI) efforts on campus and specifically in their own classes, have become widespread in the academic community. These statements represent an opportunity to highlight how candidates' research, teaching, and service, or their own life experiences help them understand and support students from diverse backgrounds. In practice, these statements present a unique challenge, particularly for early-career candidates with nascent research topics or limited teaching opportunities. Moreover, the criteria for evaluating diversity statements are not universal.

For many private and public institutions of higher education across the country, particularly those operating in majority-minority communities, preparing students for a diversity of interactions with the people, environments, and world around them has become a central part of their teaching missions [1]. According to the 2020 racial and ethnic population estimates released by the U.S. Census Bureau, the nation is diversifying at a faster rate than demographers had predicted [2]. While the segment of the population identifying as White has gradually declined over the past few decades, the populations identifying as Black, Asian, and Hispanic have grown. Some projections suggest that by 2050, no single racial or ethnic group will constitute the majority of the U.S. population [2].

Many academic institutions thus seek to develop inclusive teaching practices amongst faculty, for whom a diversity statement serves as an increasingly important element of evaluation and potentially of distinction. To better understand the criteria by which institutions consider diversity and how job candidates may address them, we interviewed several academic guests with a variety of diversity-related training, research, and administrative experiences:

- Dr. Amanda Jungels, Associate Director of the Center for Teaching Excellence, Rice University;
- Dr. Norean Sharpe, Dean and Joseph H. and Maria C. Schwartz Distinguished Chair at the Tobin College of Business, St. John's University;
- Dr. Cole Smith, Dean of the College of Engineering and Computer Science, Syracuse University;
- Dr. Willem-Jan Van Hoeve, Carnegie Bosch Professor of Operations Research and Senior Associate Dean of Education at the Tepper School of Business, Carnegie Mellon University.

Defining Diversity and its Impact

Central to a successful diversity statement is developing a familiarity and depth of an institution's definition of diversity. For candidates on the job market, investing time to learn about a school's student body may yield a distinct advantage in both the diversity statement and the cover letter as part of the application. Dr. Smith recommends thinking about a diversity statement as a pyramidal structure: at its base, a candidate may take time to learn about the demographics of the student body, the university's standing in the local community, and with indigenous peoples whose ancestral lands may be part of the university's campus, as well as other DEI considerations particularly relevant to that institution. Continuing with the pyramidal analogy, Dr. Smith explained "Do [candidates] understand why [these issues are] important? Even better if [they] understand why [these questions are] important at Syracuse. And then as you go up... [how would candidates] see themselves as being a part of a solution to [these] problems?" In that vein, it is essential to acknowledge the specific values of the institution's commitment to inclusion. For example, while the term diversity has become a catch-all to represent DEI issues more broadly, some schools also consider accessibility a key part of their mission. Identifying these details in a diversity statement indicates to the reader a concern for understanding the depth of the topic.

Although academic institutions often rely on metrics on race, ethnicity, and gender, restricting the definition of diversity to a set of surveyable factors may understate the depth of certain challenges. For many institutions of higher education, there is a focus not only on the outward appearance of diversity – for instance, in tabulating the growth of particular groups of students on campus – but also on the diversity of experience and thought that a university gains by encouraging representation in enrollment and hiring. Dr. Smith, an industrial engineer, provides an example of the diversity of thought that positively benefits the learning and solution-finding process:

> You take non-engineers that jump into a problem and give a brilliant solution because they're not thinking about it using all the same techniques that we normally use.…[T]hey are so creative and they have a different way of approaching this.…That's actually what you're trying to promote is a collection of people that think about problems from a fundamentally different point of view. So then when I teach a class, why is it that I want everybody to think about the problem exactly the way that I'm thinking about the problem. I have diversity of thought in my classroom. Why am I trying to quash that?

With increasing, surface-level diversities may come a deeper level of diversity in upbringing that influences how students learn and approach problems. Diversity, according to Dr. Van Hoeve of Carnegie Mellon, is partly about understanding that "...people have different cultural backgrounds. They may react differently in classroom settings... it's not a matter of color or gender only.... [W]e try to create an atmosphere in the classroom that is inclusive."

Inclusion, the "I" in the DEI acronym, often receives less attention than the leading "D". Dr. Sharpe of St. John's defines an inclusive classroom as one in which,

> [We ask] how does a faculty member encourage class participation? ...[T]o be an inclusive, all students [should] feel that they're participating, that they're involved...[W]e look [for] faculty who have techniques... [to facilitate] a lot of interaction between the faculty member and the student. We want to hear about how do you involve students, how do you engage? And now of course, with COVID, we're looking for experience with online teaching. [Whether using] chat rooms, blogs... [or] creating breakout rooms for the students before bringing them back together to the larger class.

Inversely, making little or no effort to foster such diversity on campus might stifle academic growth and skew students' views of modern society. Dr. Van Hoeve notes, "We should have a diverse [environment] ... [that is] reflective of society. We cannot give our students an education where they don't have access to a diverse group of peers". In the 1970s, American essayist and cultural critic Wendell Berry explained that the university aims to produce "not just trained workers or knowledgeable citizens but responsible heirs and members of human culture" [3]. For the stewards of the university - the faculty - it may be important to inculcate the culture of scholarship in its many dimensions.

Diversity in the Classroom

To that end, faculty hiring committees seek evidence that an applicant's teaching methods and materials align with the school's DEI goals. It is helpful for students to see advisors and mentors with whom they identify; it is equally, if not more, important for students to enter an environment with which they can identify and contribute. According to Dr. Van Hoeve, "creating a more inclusive environment is, in fact, a skill" and, therefore, something in which a candidate must be "willing to invest some time." He went on to note,

> [T]here are many people who live in the US...who may not be fully aware of the challenges...even in their own country. …[T]his is a topic that requires...active study and cultivation. …If you give people teams with only white males or with only people from India, or only people from China, that's not going to be a good outcome for the students. [It] doesn't matter what your political opinions [are] if you look at it purely from an educational point of view. …[Y]ou want people to thrive in our current society. They need to have exposure to different settings. You have to force them into that because they need to learn those skills.

Composing a Diversity Statement

Although the expectations for diversity statements from candidates may vary by institution and department, Dr. Jungels of Rice University, who co-instructed an online course on inclusive

teaching (the link to which is available at the end of the article), explained that in general,

> [The] diversity statement is not intended to be really a recitation of all the ways that a particular candidate is diverse or their life story about adversity that they've dealt with or overcome. That certainly can be there. But it really is supposed to think about...is how is this person going to engage diversity, equity, inclusion issues if they become a faculty member here? What are they going to bring to the classroom? What are they going to bring to research? How are they going to advance the mission of the university or the department with relation to these topics?

Our panel unanimously suggested that candidates seek out relevant workshops, webinars, and conferences on training for inclusive teaching practices. Many of these resources are available freely or at reduced cost online, as listed at the end of this article. For example, Dr. Jungels cited a phenomenon known as the "leaky pipeline" at many science- and engineering-oriented departments, which contends that underrepresented student populations in these disciplines, such as women and students from racial and ethnic minority groups, drop out at a much higher rate than other students. There are academic teaching journals that publish articles investigating this and similar issues that can be addressed pedagogically. Beyond the academic literature, candidates may benefit from reading non-fiction about cultural and ethnic challenges in the United States more broadly. This can be an especially valuable resource for candidates who grew up outside the United States and are interested in the experiences of first-generation students.

Recognizing that many faculty candidates are graduating from doctoral programs, which are typically heavily research-focused and leave little room for DEI or training in inclusive teaching practices, our panel suggests focusing on acquired experiences, even if they seem limited. Dr. Van Hoeve suggests that a candidate might discuss "[f]or example, a specific cultural difference or maybe a discussion session that you found a little bit uncomfortable. Now, even recognizing that that is a challenge for you is I think the number one step towards improving it." Acknowledging the discomfort, and any subsequent steps taken to address that in oneself indicates an interest in "learning more, an understanding and growing in that direction."

Mentorship opportunities can also be valuable in this regard. Becoming a role model for college or high school students from diverse backgrounds may be an excellent experience through which a candidate can describe their motivation to learn more about inclusive teaching. According to Dr. Jungels, disaggregating diversity data can have a significant impact through this lens. In the absence of large-scale experience with inclusive teaching, having just a few rich experiences with students may be sufficient evidence to portend a commitment to DEI issues.

Just as institutions of higher learning evaluate research statements and publication records in search of candidates with potential for impactful work, diversity statements may be a signal of a candidate's willingness to invest time, effort, and accommodations into their time on campus to contribute to the school's research and teaching missions. Inclusive teaching, in particular, is a skill that can be inculcated, and the diversity statement should reflect how a candidate has developed in that dimension and may continue to do so over time. Finally, some schools publicize clear rubrics on how their hiring committees evaluate diversity statements. Several of these rubrics are provided in the resources at the end of the article.

Additional Resources

- Definition of Diversity, Equity, Accessibility, and Inclusion (American Alliance of Museums)
- Writing a Statement of Teaching Philosophy for the Academic Job Search (Center for Research on Teaching and Learning, University of Michigan)
- Developing and Writing a Diversity Statement (Vanderbilt)
- Diversity statements: What to avoid and what to include (Times Higher Education)
- Equity, Diversity, and Inclusion (EDI) Statement (University of Illinois)
- Examples of DEI Statements (UCSD)
- Writing a Diversity Statement (University of Nebraska-Lincoln)
- Inclusive Teaching: Supporting All Students in the College Classroom (edX)

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Gender Equality in Engineering and Science: Gender Gap and Inspiring Women



Elham Taghizadeh
Wayne State University

Although under-represented roles for women and girls in science, technology, engineering and mathematics (STEM) remains a global concern, according to the UNESCO Science Report, by 2030 53% and 48% of bachelor's/master's degrees and PhD's, respectively, will belong to women [4]. Nevertheless, in only 28% of STEM fields do women occupy a research position [4]. These predictions reinforce my personal experiences as a female engineer who had recently started her job search in industry. In the 20 interviews to which I was invited, a prevalent pattern emerged: a dearth of women involved in hiring groups. Of the 20 interviews, only two featured women as part of the leadership in the hiring team. And in each of those cases, there was a single woman on the hiring team. For computer science and engineering jobs, men are generally far more likely to be hired than women [6].

This article briefly summarizes possible reasons for the gender hiring gap in engineering and science fields. The article also presents potential solutions for these challenges, as well as highlighting a number of female role models who have found success as STEM scholars.

Current Gender-Equality Practices in Science and Engineering

Gender equality in STEM fields has progressed at different rates around the world. For instance, the share of women's graduation in engineering and science has increased in sub-Saharan Africa, the Arab States, and Asia. There were increases of 31% and 42% among female engineering graduates in the United Arab Emirates and Malaysia, respectively, since 2000. In Europe and North America, however, those rates were lower: Canada, Germany and the US reported a 19% increased, while Finland reported an increase of 22%. Moreover, considering just computer science, the UN reports a decrease (between 2-13%) of female graduates since 2000 [4, 5].

But in both Malaysia and India, there were steady increases in the rates of female STEM graduates [3, 5]. This may be the result of information technology (IT) sectors in those countries which prepare women and men equally well for the work environment. In addition to industry practices, cultures also play a role: families in those countries are generally supportive of their daughters' entry into prestigious industries. Indeed, computer science and engineering roles are viewed positively by society, with many female role models finding success. The United Arab Emirates has introduced a policy to train and to employ more Emiratei citizens, including a high percentage of females in the engineering field, to prioritize a knowledge-based economy. The government attracts more Emirate female engineering students by offering more careers in engineering and ensuring their involvement in creative projects. Combining culture, government policies, and appropriate infrastructure is a powerful tool to increase women's STEM roles [7, 5]. Encouraging female participation in STEM fields not only accelerates sustainable development in low-income countries, but also gives developed countries access to a new stream of change-makers and innovators [1].

Inspiring Women in Science and Engineering

This section summarizes the number of women leaderships and the process of presenting females in engineering in different nations.



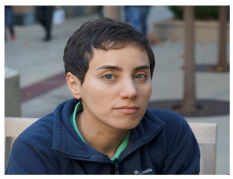
Marie Curie (1867-1934)



Sarah Al Amiri(1987-Present)



Tu Youyou (1930-present)



Maryam Mirzakhani(1977-2017)

There is an illustrious history of female achievement in STEM fields. Marie Curie was a French-Polish physicist who in 1906 became the first female professor at the University of Paris, and was the first person to win two Nobel Prizes. In 2015, Tu Youyou became the first Chinese woman to win the Nobel Prize in physiology or medicine, after discovering a malaria therapy. Maryam Mirzakhani was an Iranian professor of mathematics at Stanford University, and was awarded a Fields Medal, which is amongst the most prestigious honors bestowed upon mathematicians under the age of 40 [2]. Sarah al-Amiri is the first Minister of State for Advanced Sciences at the United Arab Emirates, where she has successfully led and coached different engineering and space projects. As U.N. Secretary-General António Guterres emphatically stated, "women and girls belong in science, and there is a dividend to be gained for countries that acknowledge this truth."

Moving Towards Gender Equality

UNESCO has published guidelines for improving gender equality in the STEM field [8]:

- Establishing new attitudes, social norms, and cultures towards engaging women in STEM society. This may happen by promoting and highlighting women with STEM careers, especially in leadership positions, business enterprises, and universities, and highlighting different gender perspectives in science communication and formal or informal STEM education.
- Encouraging girls and women to attend STEM primary and secondary education or technical and vocational training, as well as promoting gender balance among STEM teachers and in educational materials. By training this new generation, improvements in gender equality may be more permanent.
- Attracting and keeping women in STEM higher education at all levels (including graduate school) by preventing gender bias in the student admission and financial aid processes. Gender equality can happen by promoting it in the international mobility of students and making daycare/childcare facilities available for students, especially in STEM fields.
- It is essential to promote gender equality across industry as well as academia. Companies and universities can promote gender balance in leadership positions through STEM professional certification.

Although this report provides evidence of a gender-equality gap that still exists, it also specifies practical policies and strategies required to overcome that gap, specifically in STEM fields.

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Interview with Prof. Soroush Saghafian

The Role of ORMS in Healthcare Analytics



Abtin Ijadi Maghsoodi
Information Systems and Operations Management
Faculty of Business and Economics, Business School
University of Auckland, Auckland, New Zealand



Jessica Leung
Discipline of Business Analytics
The University of Sydney, Sydney, Australia
Department of Econometrics and Business Statistics
Monash University, Australia



We recently had the opportunity to speak with Professor Soroush Saghafian from the Harvard University about the role of Operations Research (OR), Management Science (MS), and Machine Learning (ML) in Healthcare Analytics and Healthcare Policy Planning, and their impact on Diversity, Equity, and Inclusion (DEI).

Professor Soroush Saghafian is currently an Associate Professor of Public Policy (Management, Leadership, and Decision Making) at the Harvard Kennedy School, Harvard University. He is the founder and director of the Public Impact Analytics Science Lab (PIAS-Lab) at Harvard University, which is devoted to advancing and applying the science of analytics for solving societal problems that can have public impact. He also serves as a faculty affiliate for the Harvard Ph.D. Program in Health Policy, the Harvard Centre for Health Decision Science, the Harvard Mossavar-Rahmani Centre for Business and Government (M-RCBG), the Harvard Data Science Initiative, and is an associate faculty member at the Harvard Ariadne Labs (Health Systems Innovation).

Could you tell us what makes healthcare analytics an exciting area of research?

The short answer is that you can save a lot of lives. As such, the public impact that you can have in healthcare is huge. Healthcare is one of those areas where you can reach a lot of people and create a large-scale impact. Most countries have significant challenges in healthcare. In the US, healthcare is a mess. We spend about 20% of the GDP on healthcare, and the outcomes are not good compared to other developed countries. Healthcare, essentially, is an area where challenges are both complex and lingering.

What do you think are some of the biggest research and practical challenges right now in healthcare analytics?

At different levels, there are different questions. At the policy level, many governments across the world are struggling with improving healthcare as a sector. But at a slightly different level, we have issues with healthcare decision-making where physicians are trying to come up with the best treatments for patients and they are usually not able to do that because of many reasons. Analytics can play a vital role (along with advancements in technology), can enable physicians to make better decisions and assist policymakers to find superior policies.

How has healthcare analytics changed in the last ten years, and where do you see it going in the future?

One of the main things we are seeing these days is in terms of using smart devices and smart technology to keep track of patients. Mobile health (mHealth) technologies are rapidly developing. If you think about traditional ways of delivering care, you needed the patient to be in a doctor's office or in the hospital. With mobile health devices, because now everybody has a smart device, you have the ability to reach them and monitor them to recommend treatments, even when they are busy with other activities. So, using smart devices, and sensors that can track patients wherever they are, we can allow physicians to come up with better decisions through what is called "continuous monitoring" (i.e. by supplying them with continuous information about their patients). Say, I'm sitting now too much for this interview; my phone may tell me that: "you should stand for your meeting" or "you should go for a 10-minute walk after the meeting". These are all enabled via technology, but the technology itself is not important unless there is useful analytics behind it. Using suitable algorithms along with detailed data can immensely reduce malpractices in the healthcare industry.

Do you see potential challenges in sharing that level of information with that level of transparency?

There are definitely challenges. We have just published a paper in the National Academy of Medicine, where we discuss the main scientific and regulatory challenges behind mobile health technologies. Because there are chances of data breaches and/or devices not working well with the hospital IT systems, there are several concerns that the governments are facing. For example, should they allow these mobile health apps to talk to each other? Even with the COVID contact tracing apps, there are tons of concerns regarding privacy and related issues that are still lingering. I think the regulatory challenges are still an important part of the picture. In addition, as we discuss in our paper published by the National Academy of Medicine, there

are various scientific challenges that need to be resolved before these technologies can reach their full potential.

Some of your work has concerned the public policy within healthcare analytics. Could you please explain what is and what will be the impact of healthcare analytics on DEI?

Unfortunately, there are severe disparities in healthcare, not only among patients but also among hospitals. A particular piece of research that we did (now published in Operations Research) aimed at studying ways to make healthcare more transparent. For instance, when you are shopping for a car you can go to various websites and you can compare the quality of different cars. What we have found is that public reporting can help in terms of equity, but it can also hurt various other social outcomes if it is done incorrectly. So, what we recommend is the information should not be only publicly available but should also be publicly understandable so that an average person can digest it and make better choices.

What would you consider as an equitable decision model or decision system in terms of allocation of scarce resources?

Let me give you a specific example regarding that. We have collaborated with the Massachusetts General Hospital trying to develop some algorithms for them to assist them in better allocating their new technology for treating cancer patients. This new technology is known as proton therapy, which is much more advantageous than X-ray therapy, in the sense that you can control the energy and release it once it reaches the tumor. Unlike X-ray, proton therapy does not ruin the surrounding parts of the tumor, because you have much more control over where and when to release the energy. Since the technology is very new, very few hospitals in the US have it. Massachusetts General Hospital is one of the hospitals that have the technology, and even them only have a few machines. That is, the resources are very scarce, but the demand for using this technology is incredibly high. We have been trying to help the hospital by developing algorithms that predict how much benefit a patient is going to gain by using this technology (versus the other options that are out there) and assign the capacity to patients who are going to benefit most from the technology. This is an example where you have very scarce resources with a lot of demand. Clearly, you have to make decisions. One of the possible ways is to think about who is going to benefit the most from it and give it to them. On the other hand, there are ethical issues with that. For example, consider a person who is 98 years old, and has applied to use this technology. The algorithm estimates that the benefit for this person is not much, because whether we give it or not, this person is going to die in two years. The question is: is it ethical for the algorithm to deny treatment because of that? The answer depends on your theory of ethics (e.g. utilitarian ethics, deontological ethics, or virtue ethics). But one useful and practical view is this: If there are two people, and one of them is going to gain more benefit than the other (all else equal), then, yes, give it to that person. However, don't deny the treatment to somebody, just because they don't have insurance or just because they don't have the money to pay for it, or just because they don't have the resources to get into the hospital. Some hospitals, unfortunately, have people who they cannot deny because they donate significant amounts of money to that hospital. I think it's very important for these algorithms to try to remove those biases and make sure that scarce resources are used in the best way.

When you are training the algorithm, are there any rules overseeing the training sample such that it is a diverse and unbiased training sample?

One of the problems is that people think the algorithms are biased. But the algorithms are often, not biased, as they are just trying to optimize an objective function. What is problematic is that we train them on biased data, and then we expect them not to be biased.

So while we have decision making algorithms to help us with allocating scarce resources, it is also important to treat what goes into the algorithm and what comes out of the algorithm with cautious?

Absolutely. I discussed this in my class with my students. With the algorithms and with the analytics, you aim to remove bias, address inequality, and make more fair decisions. We are human decision-makers, and by nature, we all have hidden spots that make us biased one way or the other. With the algorithms, you have the ability to remove such hidden spots and that's what's nice about analytics and algorithms. On the other hand, you have to be careful to avoid training them on data that is biased.

How can we use analytics to improve the effectiveness and efficiency in public policy implementation?

I think this is another area where analytics can play a substantial role. When you have expensive resources, you must use them carefully and efficiently, and this is very important in public policy implementations. So a lot of effort is devoted into trying to make the system more efficient and to reduce waste. At the end of the day, the hope is that analytics can beat politics, such that how resources are allocated or investment are made are not much affected by the political views of the person who is in charge. Instead, they should be based on what we learn from the data, what we learn from evidence, what we learn from analytics, and what unbiased algorithms tell us.

If a student were interested in studying these fields, what recommendations would you give to them? How can they start the conversation? And, where to begin?

In different programs, we try to teach our students different things in terms of how they can try to improve the healthcare sector. So, I think they should go to the right program, read the right books and articles. I'm not just talking about scientific articles, but sometimes reading daily newspaper also helps students to see where the problems are and what the sector is essentially struggling with. These are all good exercises for students to understand the main issues. And when they are in a good Ph.D. program, they will have good advisors, good people to work with, and good resources, all of which allows them to

do more impactful research.

One of the challenges coming from a background of industrial engineering and starting a healthcare analytics research program is not being familiar with the healthcare and medical dictionary. Do you have recommendations for students with manufacturing and industrial backgrounds?

Actually, that can be an advantage as you know the manufacturing settings. There are tons of things that have gone through the manufacturing processes to make them efficient. Unfortunately, the healthcare sector has been behind. So there is an opportunity to bring ideas from manufacturing to healthcare. A lot of people have been trying to do that as well to make the healthcare sector more like manufacturing settings where everything is standardized. I have been working with a lot of hospitals, and I have observed first hand that while you can get access to tons of datasets, there is not much data stemming from time studies. Time studies in manufacturing settings are ample. In contrast, in healthcare, we do not know how the most expensive resources, such as physicians, are spending their time. Every physician says "I'm super busy" and there are lots of patients waiting. People die in emergency rooms just because of long waiting times. Since there is no data telling us how exactly physicians are spending their time, it is not easy to offer solutions. In our research, for instance, we had to develop an iPhone application so that physicians can time themselves. Time studies like this in the manufacturing setting were done more than 150 years ago. I think the optimistic view is that it is actually an advantage to know how manufacturing processes work and try to bring useful ideas to the healthcare sector. At the same time, I think domain knowledge is incredibly important. One of the things I see students struggle with is that they do not have the domain knowledge. While you can bring the main ideas from manufacturing to healthcare, you have to understand physicians' perspectives, and what they have to deal with. Have domain knowledge, and then you can bring new ideas and shape them so that they become implementable and useful in the healthcare sector. I think it is also essential for students to spend time in hospitals. When I was a student, I shadowed a lot of physicians; I spent a lot of time just looking at what physicians do, and it helped me better understand their work.

Is there anything else you would like to share with our readers, and in particular, the students who are thinking about healthcare operations research and healthcare analytics?

I would like to encourage them. People with an analytical background understand how to optimize and improve things and I think they can do a lot for the healthcare sector. I also encourage them to spend more time trying to understand the medical side of things. In essence, you have to be bilingual and understand both the analytics and the medical side. Once you become bilingual, create an impact.

Once again, we would like to thank Professor Saghafian again for sharing with us. We are sure our readers are inspired by these thoughts and will tremendously benefit from it. Thank you!





OR/MS Tomorrow Mini Poster Competition 2021

Congratulations to all the winners!!

To nurture student researchers in developing the skills to summarize and articulate research ideas effectively and efficiently, OR/MS Tomorrow organised the mini poster competition again with the generous support from the **Seth Bonder Foundation** for another year! Over the past few months, we have received very high-quality submissions on a wide variety of topics from many universities. A myriad of interesting topics in different areas are presented, including incentive allocation for electric vehicles, cybersecurity, healthcare analytics, and many more. We would like to thank all participants for their support to our competition.

The competition was open to all students, including current INFORMS members and non-members. Candidates are required to design one letter sized or A4 page to communicate their research topic to the broader audience in the OR/MS community. Submissions are evaluated on the novelty of topic, maturity of content, quality of information engagement and aesthetics.

Winners from each group will receive a cash prize. Additionally, non-INFORMS member winners will receive a free one-year INFORMS student membership. To facilitate collaborations and future development, each participant will also receive comments and feedback from the judges.

Undergraduate Level Winning entries
First: Hui Zeng from Purdue University
Second: Tinghan Ye from Cornell University
Third: Colleen Wall from University of Wisconsin-Madison
Honourable mention: Matthew Beaudet from McGill University

Postgraduate Level Winning entries
First: Philippe Decoste from McGill University
Second: Sakshee Agarwal from Purdue University
Third: Kanak Agrawal from Purdue University
Honourable mention: Abhishek Chippa from Purdue University

We have included the winning entries from each group in the next page.

First place in undergraduate level: Hui Zeng from Purdue University

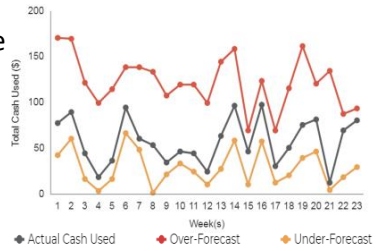
A Novel Approach to Align Forecasts to Competing Operational Business Outcomes

ABSTRACT

We develop an approach that quantities credit union's cash-on-hand forecasts and identifies the set of predictions among a set of competing models that balances competing KPIs among the Chief Membership Engagement Officer (CMEO) and Chief Financial Officer (CFO). This poster intends to demonstrate 1) how our forecast aligns to a couple custom business KPIs agreed upon among the CMEO and CFO, 2) how any model forecast could be evaluated from these business perspective metrics, and 3) a tool that the credit union can use in practice.

INTRODUCTION

The motivation for our study is that if a business tries to identify a model with the lowest prediction error, the "best" forecast could be different based on the error metric used. Furthermore, even using the same error metric, demand forecasts that have the same overall statistical performance will likely not yield the same business performance.



❖ The example forecasts above (Over-, Under-, and Balanced-) all have the same SMAPE of 75.

Research Questions:

❖ Can we develop a methodology that aligns statistical metrics and competing business KPIs?

❖ Can we develop a software tool that the credit union can use to identify the best forecast to deploy in practice?

METHODOLOGY

Model Development

- Explanatory Data Analysis
- Data Preprocessing
- Cross Validation
- Model Selection
- Model Formation

Analytical Hierarchy Process (AHP)

Six Potential Model:

- **S** Stacked Ensemble (H_2O)
- **P** Prophet
- **X** XGBoost
- **N** nnetar (Neural Network)
- **T** TBATS
- **A** ARIMA

Criteria for Model Comparisons:

- MAE
- RMSE
- MAPE
- SMAPE (1)
- SMAPE (2)
- Decision Maker Metrics ($)

STEP 1: Pairwise Comparison Matrix

Use a pairwise comparison, meaning two alternatives are compared according to a criterion and one is preferred.

STEP 2: Normalize to Synthesize

- Normalize the matrices.
- Prioritize the decision alternatives within each criterion.

STEP 3: Criteria Preference Matrix

Combine preference vectors:

	Criteria					
Model	MAE	RMSE	MAPE	SMAPE1	SMAPE2	Cost
S	0.139106	0.151247	0.178751	0.144988	0.090705	0.134144
P	0.157563	0.15985	0.199547	0.15429	0.177825	0.163961
X	0.208461	0.193085	0.105645	0.214831	0.234595	0.194808
N	0.141732	0.155605	0.152923	0.154205	0.207922	0.160665
T	0.175623	0.17018	0.177489	0.165697	0.08575	0.177354
A	0.177515	0.170034	0.185646	0.165989	0.203303	0.169067

STEP 4: Rank Criteria

Rank the criteria based on its relative importance to the decision markers.

STEP 5: Normalize Ranked Criteria

Normalize the criteria matrix from step 4.

STEP 6: Preference Vector for the Criteria

Calculate the preference vector for the criteria:

Criteria	MAE	RMSE	MAPE	SMAPE1	SMAPE2	Cost
Preference Vector	0.034274	0.034274	0.073628	0.140313	0.462549	0.254963

STEP 7: Overall Scores and Overall Ranking

Overall Scores

Model	Overall Score
S	0.1196
P	0.1713
X	0.2099
N	0.1802
T	0.1331
A	0.1859
Total:	1.0000

Overall Ranking

Ranking	Model:
1	Stacked Ensemble
2	TBATS
3	Prophet
4	nnetar
5	ARIMA
6	XGBoost

STUDY IMPLICATIONS

We developed a Shiny App in R for the deployment of TCU. By using our model evaluation App, the credit union can:

❖ Customize backorder cost and interest rate parameters.

❖ Identify the best forecasting model among a set of competing models, even when statistical metrics Might conflict.

❖ Lead to better business outcomes among competing decision makers.



CONCLUSION

❖ Our methodology can be widely used in other businesses in need of a model evaluation mechanism.

❖ We have successfully developed a practical tool to evaluate different potential models in order to identify the "best" forecast.

❖ "Your brilliant work will enable TCU to reach targets, provide our team members with valuable resources, which will enable us to provide consistent WOW service to our members. Great work!"

--- Nicole Alcorn, CMEO of TCU

First place in postgraduate level: Philippe Decoste from McGill University

Robot Navigation in Unknown Environments: Towards Topographical SLAM

Department of Mechanical Engineering, McGill University, Montreal, QC, Canada

McGill

Introduction

- *The ability of a robot to deterimne its own location relative to the world around it, also known as "navigation", is a crucial component of autonomous robotic exploration.*
- *There are many ways a robot can perform navigation, and each have their advantages and disadvantages in terms of performance and cost.*
- *This research focuses on navigation methodologies that exploit topographical change, changes in heights, to realize robot navigation in previously unexplored enviroments.*

Navigation and SLAM

- Navigation is the process of estimating robot states, such as position and orientation, that are not necessarily directly measured using sensors. Navigation is needed for both path planning and control of autonomous robotic systems.
- **S**imultaneous **L**ocalization **A**nd **M**apping (SLAM) is a specific kind of navigation where a map of the environment is estimated and the robot localizes itself within this estimated map.
- Navigation and, in particular, SLAM enable robot deployment in unknown, never before seen, environments.



Figure: Examples of the applications of SLAM.

Why are navigation and SLAM challenging?

Robots perceive their world through sensors. Though sensors may be accurate, their measurements always contain at least a small amount of noise, meaning their precision varies.

Ideal Sensor			Real Sensor				
$\underbrace{\mathbf{y}}$	=	$\underbrace{\mathbf{x}}$	$\underbrace{\mathbf{y}}$	=	$\mathbf{x}$	+	$\underbrace{\mathbf{w}}$
perfect sensor reading		perfect tracked state	imperfect sensor reading				noise

Sensor noise causes navigation error if not properly accounted for.

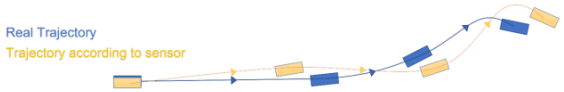


Figure: Representation of the error between real and estimated trajectories.

Therefore, properly accounting for sensor noise, and other uncertainties, is critical in any navigation or SLAM algorithm.

Objective

- A common solution to navigation in unknown environments is employing expensive and computationally heavy computer vision systems.
- The objective of the research is to investigate SLAM methodologies that used cheaper, readily accessible, sensors that leverage different feature of the environement, such as changes in topography.
- In theory, SLAM could be done using only simple sensors such as an *Inertial Measurement Unit* (IMU) and a height sensor to map uneven terrain, which is the starting point of this research.

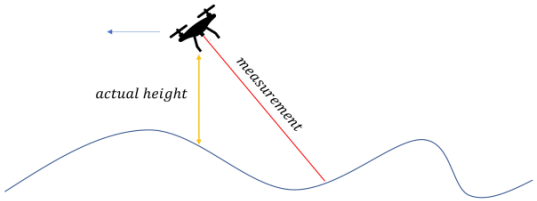


Figure: Representation of the topography-based SLAM problem.

Methods

- ***Kalman Filter*** (KF): The KF is the best, unbiased, linear estimator [1] of state at a certain time based on combined sensor inputs.
- ***Batch Least Squares Optimization*** (BLSO): Finding the most likely set of states that correspond to our sensor readings.

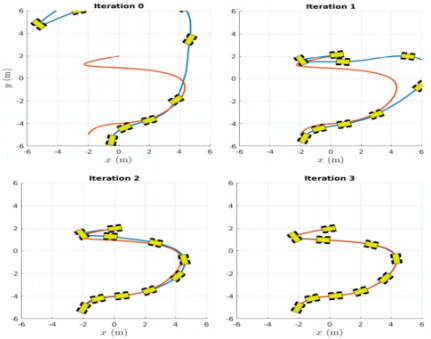


Figure: Batch least squares optimization [2].

- Derivation of state estimators done from **first principles**.
- Validation done on both **simulated and testing use, real datasets**.

Results

- Successful application of KF and BLSO methods has been completed on both linear and nonlinear systems.
- Efficiency of estimation methods has been compared.

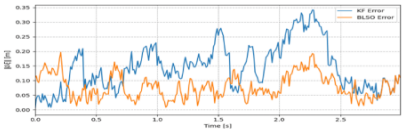


Figure: Comparison of **estimation error** of Kalman filter and BLSO methods for simulated 2D case.

- Simulations show that it is feasible to perform topography-based localization using only an IMU and a laser rangefinder by scanning a ceiling with a known profile.

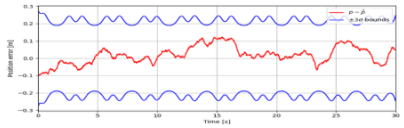


Figure: **Estimation error and $\pm 3\sigma$ bounds** of localization using topography sensing.

Future Work

- Extend topography-based navigation to topography-based SLAM.
- Simulate and validate a collaborative approach to topographical SLAM using UWB transceivers for inter-agent communication.

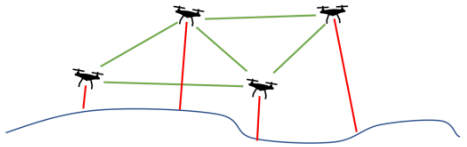


Figure: Collaborative Topographical SLAM.

Acknowledgements

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Interview with Dr. Michael Johnson

How can the OR/MS community contribute to research in racism and discrimination?



Kimia Vahdat
North Carolina State University

Dr. Michael Johnson is the professor and chair of the Department of Public Policy and Public Affairs at University of Massachusetts in Boston. His main research interests lie in decision support systems to improve nonprofit organizations and government agencies' operations and strategy design. We have invited Dr. Johnson for an interview to shed some light on ways in which the OR and Analytics community can contribute to research in the racism and discrimination space.



What is an equitable decision model or decision system in real life applications?

I want to introduce the word "effectiveness" as well as "equity". Many decision models have industrial motivations. So, for many of the most elementary examples of our applications, the primary goal of the model can be expressed in a straightforward way and quantified using measures that are easily available in the world around us. Also, there's usually not much confusion about why we wish to minimize miles traveled or maximize throughput. Surely, industrial engineers have thought very carefully about the precise way to do it. For many of these operations research examples, humans I would say are not at the center of the systems, which we wish to build or optimize; of course, trucks require drivers and machines require operators, but in the traditional conception of these problems, the truck drivers and machine operators are not considered to have real agency. For many social policy and urban affairs areas, humans are at the center of experiencing the problem, and in principle taking an important role in responding to it. In addition, understanding these problems requires a conception of social impacts

of outcomes that do not necessarily translate well to straightforward quantities that are associated with efficiency measures.

Housing is a great example; the question is: where and what kind (e.g., rental or owner occupied) might we wish to propose new housing to be built or rehabilitated? There are many dimensions of outcomes associated with housing for individuals and communities that don't align particularly well with traditional efficiency measures. When there is a public policy or social policy dimension to our work, we need to ask, what the impacts are and how we could associate decisions that could be prescribed through a decision model with the social outcomes that we want? So, measuring them is hard and that's where the effectiveness comes in. How do we know that locating housing of a certain type of this many units in this neighborhood as opposed to another neighborhood will have a better social outcome? There's also the matter of equity or fairness. When we talk about housing for low- and moderate-income people, that housing often must be subsidized in various ways to make it affordable to these individuals in the U.S., we have entrenched structures of inequality, bias, and racism, that result in many people believing that so-called affordable or subsidized housing, by its very nature, is bad for their neighborhoods. So, from the perspective of low- and moderate-income people, they would like housing that is in the most opportunity-rich neighborhoods that enable them to have the best opportunities for a productive and enjoyable life. So that's what fairness means to them. But for many middle-class Americans, who believe that the best neighborhoods are the ones populated by people like them, and who perceive new residents who have very different social backgrounds from them as a threat, the introduction of affordable housing would seem to them to be manifestly unfair and should be avoided. Therefore, for this kind of model, we have competing notions of equity, which makes it very hard to agree on a single objective to meet.

In a very simplified example, can you tell us about the work that has been done in this area to give us more insight?

This example is inspired by research I am doing where I'm having to read historically important papers that have had public policy impact, authored by Ed Kaplan, of Yale School of Management. One such paper came out in the late 90s, in the journal operations research, sought to understand how new policies on the lawful exchange of injection needles might reduce the incidence of highly communicable and deadly diseases, such as HIV AIDS by drug users. Kaplan's insight was that a particular sort of modeling framework focusing not on what people said they did with the needles, because self-reports can be unreliable, but relying instead on documented history of the needles themselves such as, when they were distributed, how long they were out, when they were returned, etc., can help us understand the trajectory of needle usage and to estimate whether needle exchange policies might actually reduce the risk of needle sharing and the exposure to the HIV AIDS virus. So, this is a kind of research that one could think of being focused narrowly on a technical question: how to properly model the life cycle of needles? It's finding support for a policy that even now is quite contested and controversial. And focusing, not so much on efficiency measures, but on public health outcomes, in other words, effectiveness, and taking the needs of the most vulnerable populations in our country, drug users at high risk of sexually and otherwise transmitted deadly diseases, seriously, and putting their needs and concerns at the center of the model. This is something that means a lot to me personally, and I hope that there can be more exciting research in the future.

What do you think is the responsibility of the OR community regarding DEI initiatives?

In the case of INFORMS, I like to distinguish between the discipline of OR/analytics and the profession of OR/analytics. I think of the discipline as the collective body of knowledge of OR/analytics and related fields that researchers contribute to, teachers draw from in their instruction, and practitioners use in their daily work. However, there is also the profession of OR/-analytics, which to me represents the jobs that are done, using various operations research and analytics tools and methods. So, the profession might encompass researchers, professors, analysts, and managers, and also encompass agencies such as, government organizations, and professional societies, like INFORMS. Oftentimes, we think of DEI within the context of the profession. First, we want our organizations to be more diverse and to be more supportive of the careers of historically underrepresented or marginalized populations, such as women and people of color. We want to enlarge the pipeline of future professionals who can come into our organizations and our schools. We also want to make our organizations more welcoming and supportive of them so that they persist and excel. Additionally, we want their professional successes to perpetuate so that organizations can increasingly better reflect the communities they serve and make a greater impact on social justice. That's what I believe DEI can do for the organizations we work for and for the society in which they're a part.

The DEI for the discipline is about answering questions such as, "what is there to know about research in the OR/analytics tradition that can help us generate more salient insights about policy interventions and organization designs in which issues of diversity and inclusion can play a central role?" There is a significant amount of work in this area. These studies can provide an evidentiary base for various kinds of policies and interventions. In other words, taking as given that on purely justice terms alone, interventions that can increase diversity and inclusion are worth doing, there's also the question of are they efficiency-enhancing? That's an unsettled question. Our society does not exist and does not serve its people without a firm commitment to justice and the rule of law. However, there's so much more to our society than justice and the rule of law, and we want our institutions to work to balance efficiency, effectiveness, and equity.

Another aspect of DEI in the discipline is answering what kinds of interventions we could design, if we put the needs of traditionally underrepresented or marginalized people at the center of what we do. So, take law enforcement as an example, in

which models generally try to give guidance to law enforcement personnel on where officers should patrol or how cars should be dispatched. The historical data can tell us where reports of crimes have been submitted, but that is not the same thing as where the crimes occurred. They can also tell us where arrests have been made, which is also not the same as the real crime that occurred. This is not the same as identifying those who may have committed the crimes. In addition, we know that historic inequities mean that certain populations, particularly African-American and Latino populations are more visible to law enforcement than other populations, and certain behaviors that are perfectly well accepted in white communities are not accepted in communities of color, surveilled and controlled by law enforcement. So, models focused on prescribing the best ways for police to respond to or intervene in so-called hotspots or to design the most efficient interventions like stopping and frisking may have, in fact, been unattended by severely disadvantaged and historically marginalized populations. Does this mean the models are bad? I don't believe that they are inherently bad, but I do think that where models are designed without the active participation of communities who are implicated by the effects of them, then there is increased risk that the models could be misspecified, poorly implemented, or their results may be misunderstood. Such models could have the impact of increasing marginalization, and disadvantage among already marginalized and disadvantaged communities. We could remedy this by enlarging our notion of modeling to include stakeholders, and representing communities that are implicated in these models and are affected by these models.

What is your advice for students who want to be more actively involved in the DEI research? How can they start the conversation and, where should they begin?

That is a really good question. I would recommend that students start not with the textbooks, the algorithms, and the math, but instead, look around their neighborhoods, communities, and cities and ask themselves, what about the community or the public policies could be done better. I'll give an example that I think is familiar to many of us. In many cities, we see people who are ill housed. They may be homeless, or may not have a secure place to live and you might ask what can be done? It occurs to me that our engineering training might be useful here; just as some of us are trained to look at a product and say, this needs to do something different and work better, and the engineers say, how can we build it? Well, maybe there's something analogous in the domain of social policy related to that, where we might see something in our community that we feel is not working the way it ought to, even if we don't know exactly why. We could challenge ourselves to say, well, is there a solution? Is there a response that is rooted in evidence that could provide clear guidance to practitioners and decision makers in the form of prescriptions? Do we have some notion of social objectives we wish to optimize, which can get you thinking on what kinds of model-based interventions might be possible? It has to start from us looking around and ask ourselves what could work better, and then do the reading. There may be a model based response that has the potential to improve social outcomes. In addition, there might be an opportunity for us to be part of that solution.

What do you think are the next steps for the OR/MS community to develop towards a more equitable organization?

I think we need to be honest and frank about some very basic issues regarding our practice. There was a radio show that interviewed a writer for The Atlantic recently, who wrote a book on inequality in higher education. He was explaining how he got his college education in Alabama at a historically black college, but he noticed not far away from their campus is a campus of the University system that was much better endowed with bigger libraries, better quality housing, greener lawns, etc. The writer reflected that, in many universities like these, even in states where there is a significant fraction of the population that is black and brown, the population characteristic is not reflected in the classrooms. Therefore, I would encourage those of us who are in the classrooms learning or teaching, to ask ourselves, who is in the classroom and who is not in the classroom? If your classroom has 1/3 women, but you know that the population of the state in which your university is located is half female, it's an opportunity to ask yourself, why is there this underrepresentation, what can we do about it, and what could that mean for the kind of knowledge that gets taught the kind of knowledge that it's generated through research? So, I really want students and younger people to look around and identify where there might be instances of underrepresentation, inequality, or injustice in various ways. Ask yourself, how can we fix it? What is the nature of this inequity? Where did it come from? And how could we think of remedying it? Then maybe, is there a role for doing so with tools that I'm being trained to use in OR.

Equity in COVID-19 Vaccine Distribution



Piyal Sarkar
Ryerson University, Canada

Effective vaccines to combat COVID-19 pandemic have been developed in record time. However, the virus is still moving with mutated versions at an even faster pace. The main challenge lies in vaccine equity (WHO, 2021). The vaccine equity refers to the fact that vaccines should be distributed equally to all countries, irrespective of economic status, race, or religion. The failure to vaccine equity is affecting the world's poorest and most vulnerable people. The World Health Organization (WHO) is of the opinion that to stop the pandemic at least 40 percent of people of every country should be vaccinated and closely 70 percent by the first half of 2022. To this end, the equity of distribution in vaccines all over the world is very essential. In order to achieve vaccine equity throughout the globe, we need to understand the challenges first. The distribution of vaccines is guided due to several factors such as political, economic, diplomatic, and social factors. Therefore, in order to develop equity in vaccines, there arises two primary questions:
a. How accessible are vaccines globally?
b. Are these vaccines affordable for all countries?

The problem here is that most of the vaccines are being administered in the high- and middle-income countries of the world. Data reveals that around 61.51 percent people of high-income countries are vaccinated with at least one dose; on the contrary only 3.31 percent of the people have been vaccinated for people with low-income countries as of September 22, 2021.

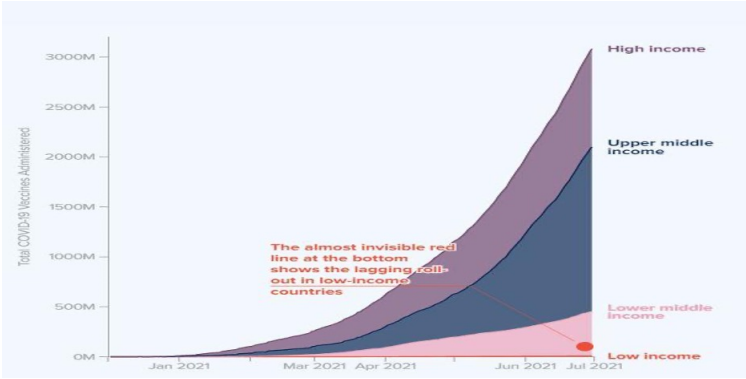


Figure 11: Source: https://data.undp.org

According to the data from UNICEF, the average cost for one COVID-19 vaccine dose ranges between US$2 -$40. The distribution cost is around US$3.70 per person vaccinated with double doses, considering a percentage of vaccine wastage. This is a significant financial burden for low-income countries, where the average annual per capita health expenditure may be around US$41. Though vaccination programs will increase healthcare costs across all countries, it is especially the case in low-income countries as they would need to increase their health expenditure by around 30-60 percent to reach seventy percent of their population under the current pricing of COVID-19 vaccines. This is quite a challenging task.

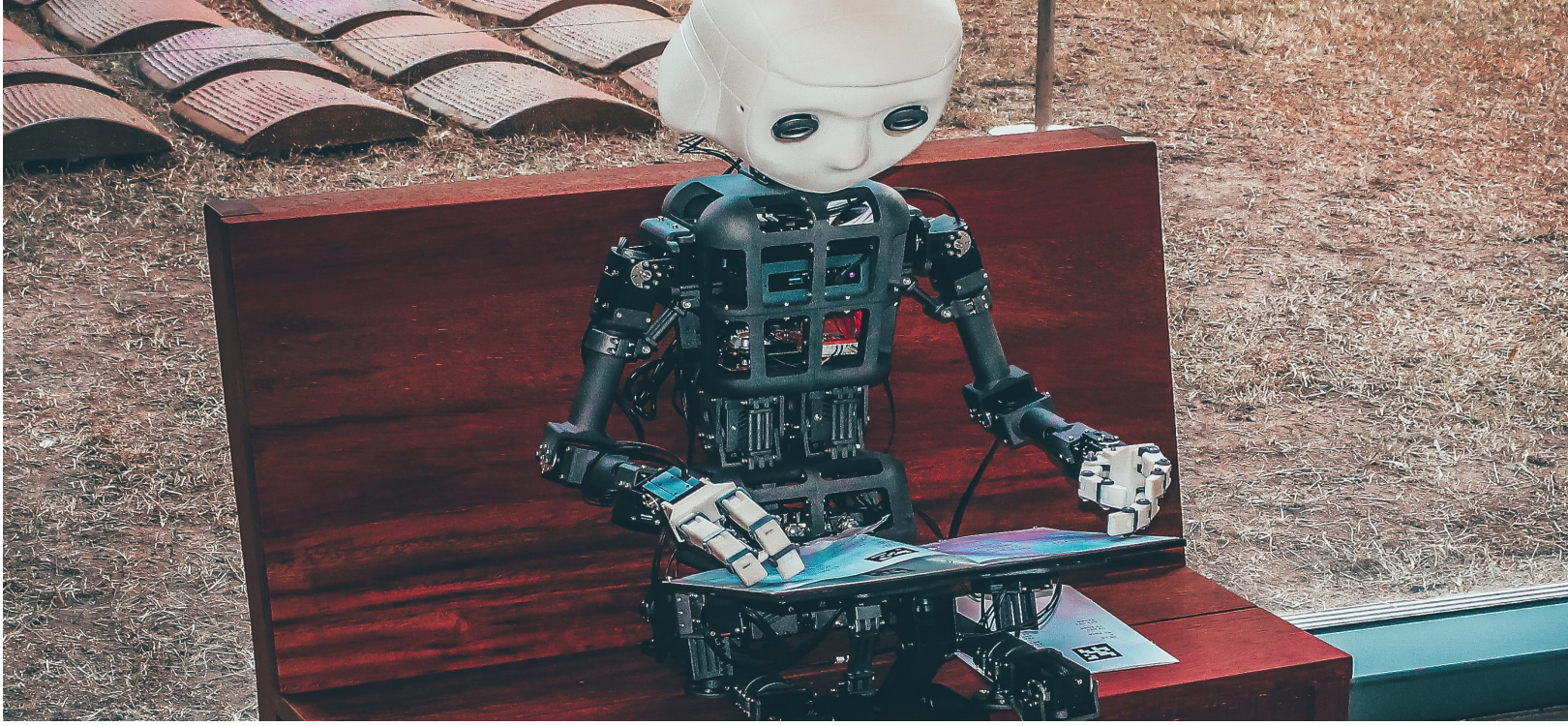
Strong action is urgently required to help low-income and middle-income countries to decrease their debt, which is sharply increasing due to the COVID-19 pandemic (NCBI Report, 2021). Vaccine distribution costs are significantly adding to this burden. New scenario analysis suggests that achieving the 70 percent vaccination target in these countries will require US$49.17 billion, assuming a price of US$15.80 per dose. This accounts to around 0.7 percent of their projected GDP in 2021. The picture is even more challenging when considering only low-income countries. More than US$8 billion, or about half of their projected GDP growth in 2021, will be required to vaccinate 70 percent of their populations. The most vulnerable countries are found in Sub-Saharan Africa, including Burundi, Malawi, Mozambique, and South Sudan where less than two out of 100 people have been vaccinated against COVID-19, as of July 2021 (WHO, 2021).

As a solution to these problems, the World Health Organization (WHO) has called for the vaccine equity programs. Following are the call to action for vaccine equity by a) Civil society can rally governments to exercise their power for change, b) Civil society can rally governments to exercise their power for change, c) Manufacturers can share intellectual property so that vaccine production can speed up and scale up, d) Governments can share vaccine doses, help secure funds, and remove any barriers to equitable distribution.

Through this article our aim is to make the ORMS community aware of the COVID-19 vaccine equity fact. For a clear review on the vaccine equity, we encourage readers to refer to the study of Su, Z., et al.(2021). We discussed the challenges, the real statistics, and some feasible solutions to these challenges as the World Health Organizations are undertaking. Accurate and up-to-date data and information are key components in guiding the international community's understanding of vaccine equity. Developed countries, in accordance with the guidelines of WHO should come up with feasible international strategies to help procuring vaccines to the low-income countries. The earth is a global playground and to fight COVID-19 effectively, vaccine equity is of utmost importance.

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Trustworthy Artificial Intelligence



Mihir Mehta
Pennsylvania State University

Mihir is a doctoral student and an instructor for an undergraduate engineering analytics course in the Industrial and Manufacturing Engineering Department at Pennsylvania State University. His research is focused on developing TAI-based healthcare applications. He holds a master's degree in statistics and has worked in the industry for over seven years in data science-driven roles. He also serves as an editorial staff writer for OR/MS Tomorrow.

Introduction

The COVID-19 pandemic has accelerated digital technologies adaptation across global organizations, creating an unprecedented amount of digital data at our disposal [mck]. This data has the huge potential to help us make better decisions and improve our lives. Thanks to enhanced computing and storing devices and efficient, easy-to-use software, we are deploying more and more artificial intelligence-based (AI) applications. These applications have shown immense potential to solve complex problems ranging from predicting the 3-D structure of proteins "AlphaFold-2" [8] within a few hours to determining algorithmic prudence to beating Go master by "AlphaGo" [4].

Our society exhibits disparities in different forms, including social [24, 29], economic [43], and health [22]. The COVID-19 pandemic has widened or made more prominent existing disparities gaps in data (both structured and unstructured data types) [50]. AI-based applications have been used to combat some of the challenges related to these disparities. For example, AI technologies have improved healthcare access in resource-poor settings [58]. However, the application of these technologies is not without unintended consequences. We have a responsibility to balance the overall performance of AI applications with their ethical and socially responsible usage. At times, AI-based applications have aggravated racial bias and discrimination (e.g., image data) [opi, bea], gender imbalance (e.g., medical imaging) [35], comprehension difficulties (e.g., electronic health records) [60], and poor generalizations (e.g., imaging transformations) [16]. These ill effects have generated multiple question marks on the trustworthiness of AI applications and created significant barriers to leverage them for societal welfare.

As digitalization continues to influence our societal growth and future, we need to make conscious efforts to develop socially responsible and ethical AI-based applications. This effort will minimize the post-implementation adverse effects and assist us in carving a path for an equitable, diverse, and inclusive society. Concurrently, trust in AI applications will be enhanced, facilitating their continued use in future societal welfare. Recent advances in the Trustworthy AI (TAI) domain are focused on meeting these objectives through appropriate trade-off strategies in relation to overall performance.

An AI-based decision-making system takes a data-driven learning path. However, this data is nothing but a mirror reflecting our present. As a result, it reflects existing disparities, biases, and injustices present in society. Hence, TAI strongly recommends making socio-technical justified adjustments to this data and these data-based algorithms while evaluating their performance. With a multi-faceted contextual and casual approach, TAI helps design safe, secure, unbiased, fair, robust, explainable, accountable, and dynamic AI applications that perform well.

This article provides an introductory overview of the TAI domain. In the beginning, it provides an overview of the guidelines and recommendations for TAI applications development. Then, it covers the motivations behind each of TAI's multiple attributes and lists key approaches taken to satisfy corresponding requirements. Afterward, this article lists the important research trends in verifiable claims that are vital for demonstrating and quantifying trust in the deployed AI applications. Finally, this article concludes with a summary. The ethical and responsible development of AI serves as the foundation for developing and deploying TAI-driven

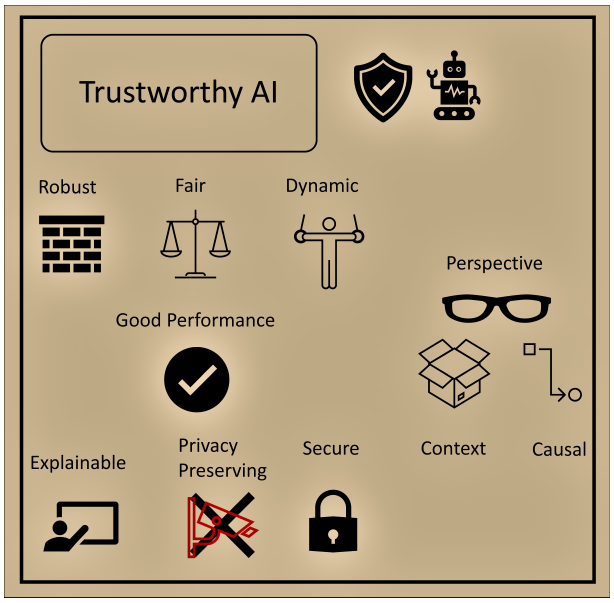


Figure 12: Trustworthy AI: An Overview

applications. TAI is based on the five principles of 'Beneficence' (sustainable and inclusive goodness), 'Non-Maleficence' (minimizing ill-effects), 'Autonomy' (considerations to human choices), 'Justice' (ensuring impartiality), and 'Explicability' (transparency and responsibility discussions) [26]. TAI discussions are engaged from multiple perspectives. A few examples of these perspectives are:

1. Academia-focused trustworthy machine learning technologies discussions [55]
2. Governance guidelines to shape Europe's digital future [eur],
3. Google's explainability and trust discussions provide an industrial perspective [goo]
4. Verifiable claims-based developmental recommendations through AI developer lenses [20]

All these perspectives emphasize a few key ideas:

1. Data investigation before feeding to the algorithm such as identifying Simpson's paradox in social data [14]
2. A consistent and impartial algorithmic methodology like a convex framework for fair regression [19]
3. Documentation-based transparency and verifiability enhancement like ABOUT ML (bench-marking of machine-learning lifecycles) [49]
4. Promoting community-level collaborative AI development tools and practices such as 'Model cards' [42] and 'Datasheets' [28]

Trustworthy AI Attributes

The TAI domain focuses on formulating specific methodologies to realize explainable, unbiased, fair, consistent, robust, secure, privacy-preserving AI algorithms. These algorithms are further augmented through causality and context-specific considerations. The overall deployment process manages trade-offs strategies between the overall algorithm performance and each of these considerations. With the development of verifiable claims, the overall TAI deployment process demonstrates and quantifies its trustworthiness.

Context

- **Why:** An AI-based application is a socio-technical toolkit used to obtain a specific societal welfare objective. As a result, its development process should account for an underlying social and professional context. The context helps to decide the required compliance rigor level. By accounting for the degree of criticality of the objective and the involved stakeholders, this attribute enhances the overall holistic TAI development.
- **How:** Two context-based examples are included.
  1. The “Sepsis Watch," a real-world AI-application deployment case study, is designed as a socio-technical toolkit for the clinical decision-making process [52].
  2. The ‘Artificial Intelligence and Machine Learning in Software as a Medical Device,’ the US Food and Drug Administration (FDA) regulatory framework, provides guidelines for context-based iterative digital health tool development [27].

Explanation

- **Why:** For the Sacramento region in California, AI-based algorithm results claimed that air pollution levels were safe for humans, contrary to the ground reality [sac]. In similar and increasingly critical contexts, AI-based algorithms need to explain their reasoning behind a decision. The explainable AI (XAI) attribute develops methodologies to explain the functioning of AI applications’ often involving complex architectures.
- **How:**
  1. These techniques take diverse approaches for explaining AI algorithms.
     (a) Quantifying the importance of input variables for the model like Shapley global explanations [38]
     (b) Intrinsically interpretable model development like decision sets [34]
     (c) Comparison involving a change in prediction values such as data perturbation for identifying the indirect influence of features [13]
     (d) Driven by the contestability by design [39] like effective contestability as explanations [48]
  2. All these explanations are evaluated by quantifying accuracy and uncertainty in their results [30, 15]

Robustness

- **Why:** With a minor addition of noise, the image classification AI application has classified a benign tumor image as a malignant tumor image [25]. Unstable and brittle AI algorithms like this one often result in unintended and ill consequences. Hence, robustness attribute-related research enhances the overall validity, consistency, and accountability of AI applications.
- **How:** These techniques assess AI application performance under multiple aspects:
  1. Consistency over time, for instance, performance under data distributional shift [46]
  2. Validity based on underlying assumptions and data like by using counterfactual explanations [54]
  3. The quantification of uncertainty by estimating distribution-free predictive intervals [47] and verification of limitations through formal methods [23].

Bias, Fairness, Privacy, and Security

- **Why:** A research study [53] found that the open image dataset entries are contributed from only six countries across North America and Europe. In another research [40], a strong correlation between race and zip code was observed. These kinds of disparities and biases limit AI-application capacity to make non-discriminatory and impartial decisions. The bias-reduction and fairness-compliant methodologies identify existing biases and discriminations, develop specific strategies to mitigate them, and finally, verify the success of mitigation strategies. Recently, AI applications have been vulnerable to privacy violations and security issues [hea, aih]. It is crucial to reduce their vulnerabilities.
- **How:** Numerous routes have been taken to develop unbiased, non-discriminatory, privacy-preserving, and secure AI algorithms.
  1. Defining different types of biases and discriminations [40] and mitigating them

(a) Distributional skewness similar to the earlier described images dataset often leads to a 'Representational Bias.' Hence, the investigative research work [53] advocates the vital need for geo-diversity and inclusion in open data sets, especially for the developing world.

(b) The inclusion of zip codes in AI-driven decision-making is vulnerable to 'Indirect Discrimination.' A casual framework-based approach has been developed to discover and remove these types of discriminations [63].

2. Mitigating bias in the data as in Data Statements for natural language processing [18], constraint-based or modified objective function-based methods such as fairness classification [56], and mitigation success verification strategies such as fairness inference on outcomes using causal graphs [45] are examples of input, algorithm and output focused strategies, respectively.
3. Model decisions should allow alteration by changing plausible input variables like actionable recourse [57]
4. Further work requires developing specific methods to discover unfairness, extending fairness definition beyond equality perspectives through, for example, such as context-driven [31] and temporal fairness [36] discussions
5. Privacy-preserving measures like decentralized [32] and differential privacy [41]-based techniques
6. Security approaches like holomorphic encryptions [12], secure multi-party computations [64], and secure hardware implementations [sec]

Causality

- **Why:** Data-driven AI applications leverage association learning and, at times, are susceptible to spurious correlation [21, 51]. Hence, a causal perspective inclusion in TAI development further bolsters AI applications' overall success and longevity. It also incorporates subject-matter knowledge.
- **How:** Casual-based approaches have been used to address multiple attributes of trustworthy AI development.
  1. Generative counterfactuals to explain AI applications [37], investigate fairness and improve robustness [54]
  2. Causal-based fairness quantification formula [62]
  3. Causality-manipulated data augmentations for robustness [61]

Verifiable Claims

- **Why:** TAI development needs to demonstrate and quantify its overall trustworthiness. Quantifiable and verifiable claims will further accelerate and promote TAI-based deployment.
- **How:** Three types of directions have been taken for developing verifiable claims:
  1. Theoretical methods like formal verification for deep learning robustness [23]
  2. Certification or grade-based approaches like compliance certificates [17] and care labels [44]
  3. Quantification techniques by combining one or more attributes of TAI, like causal regulator-based trust quantification [33] and fairness-based trust quantification [59]

Summary

The growing trends in technology advancement and digitalization make a strong case for AI-driven policy implementations. Verifiable trust quantification of ethical and responsible AI-driven policy implementations will bolster tomorrow's safer, inclusive, diverse, and equity-based society. AI-based applications should strive to find trade-offs between the overall performance and TAI attributes. These applications should demonstrate their trustworthiness by developing algorithms incorporating contextual and causally justified enhancements, transparent, fair, secure, and privacy-preserving, and robust capabilities. By ensuring these characteristics, these applications can become a vital medium to realize a safer, inclusive, diverse, and equity-based society. The progress of the TAI domain is significant and critical for a better tomorrow.

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