Treatment of the Multi-Attribute Decision-Making Rank Reversal Problem for Real-World Systems

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Abstract—**This paper describes an enhanced approach towards considering the Rank Reversal (RR) problem for certain Multi-Attribute Decision-Making (MADM) methods critical to Multi-Criteria Decision-Making (MCDM) systems. Prototypical testing environments for RR usually do not include key facets of Real-World Systems (RWS), such as the treatment of time, prospective Influence Dominating Sets (IDS) at play, sub-biases throughout the system, involved Decision Engineering Pathways (DEP) for consortial environments, and a more Transparent, Explainable, and Accountable (TEA)-oriented architectural construct, which are all desired in these contemporary times. These facets have been considered as Extrapolated Decision Quality (DQ) Thematics (EDQTs) of the Howard & Abbas six classically understood facets of DQ, and they are critical for MCDM RWS. Since various MADM methods vary in performance against the EDQTs, the approach utilized is to employ a robust Multi-Objective Decision-Making (MODM) module to discern the more optimal MADM methods to utilize in an ongoing fashion.**

Keywords-decision engineering pathway; decision-making; multi-criteria decision-making; multi-attribute decision-making; rank reversal; multi-objective decision-making; decision quality; artificial intelligence; machine learning; epistemic transparency.

I. INTRODUCTION

The issue of bias in Artificial Intelligence (AI) systems has been a prevalent topic. Major companies, such as in the 2019 to 2020 time frame, had withdrawn a number of AI/Machine Learning (ML) offerings from the marketplace due to the fact that mitigation against prospective biases (e.g., gender, racial/ethnic, etc.) had not been robustly considered in the design of those systems. Since that time, algorithmic bias has become an acknowledged issue, and the notion of equitable outcomes (as contrasted to "unfair" or "privileged" outcomes) has become an important aspect in the design of AI/ML-centric Tools, Platforms, Methodologies, Frameworks, and Systems (TPMFS). Confalonieri notes that while the Explainability in AI (XAI) movement has resurged in recent times, its origins trace back a number of decades via various research Lines of Effort (LOEs), such as "expert systems," "recommender systems," "neural-symbolic learning and reasoning," etc. [1]. Heder notes that Winograd had investigated the "issues of explanations and transparency" (critical to XAI) via LOEs, such as "phenomenology" and "cognitive science," and Hosain underscores Winograd's contributions [2][3]. Heder also investigated the notions of "epistemic opacity" (i.e., wherein functional details may not be clear, such as in a "black box" architectural construct) and the criticality of moving towards "epistemic transparency" [4]. The IEEE Standards Association has also opined the need for Autonomous and Intelligent Systems (AIS) to be comprehensible so as to be accountable, and standards, such as IEEE P7001 [Standard for Transparency of Autonomous Systems] (one of the P70XX series of standards), have emerged, received approval (e.g., 2021), and published (e.g., 2022) so as to put forth a delineation of Transparency/Explainability (T/E); for example, P7001 has a T/E scale of 0 (no T/E) to 5 (fullest attainable extent of T/E) [5]. While P7001 seems to have gained some traction in areas, such as robotics, advances in the area of XAI are still nascent/ongoing [6]. Winfield points out that P7001 is a process standard, wherein the involved T/E measures are not specified, and Winfield further asserts that the principal role of P7001 is to serve as a System Transparency Specification (STS) and as a System Transparency Assessment (STA) [7].

Beyond STA and the issue of transparency, the Association of Computing Machinery (ACM) accentuates *explanation* in its "Principles for Algorithmic Transparency and Accountability" [8]. Also, "the European Union's [General] Data Protection Regulation (GDPR) stipulates a right" "for consumers affected by an automatic decision" "to obtain 'meaningful information about the logic involved'" [1]; Confalonieri notes that this equates to a "right to *explanation*" [1]. Along this vein, Winfield notes that "P7001 recognises that AI technology cannot be separated from the larger Socio-Technical System [STS] of which it is a component" [7]. STS encompasses the interplay among *humans*, technology, and the environs, and while the overarching XAI and P7001-type movements further mature and burgeon, it is interesting to note that for some ecosystems, there has been a predilection for increasing the utilization of *humans*-in-the-loop for Decision Engineering (DE)/Decision-Making (DM) (to mitigate against "non-perfect" algorithmic and AI/ML-centric paradigms), particularly for "high-stakes tasks" [9]. The arena encompassing this Human-Computer Interaction (HCI)-centric DE/DM begets a new set of challenges, such as in the case of Multi-Criteria Decision-Making (MCDM) for AI Technology-Related Investment Decisions (TRID). This might beget the use of *human* evaluators, who in a number of cases, such as within the reviewer ecosystem, self-assess their own level of expertise in a Subjective Measure/Methodology (SM) fashion. Yet, the level of

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expertise should be context dependent; for example, various reviewers may rate their "AI hardware expertise" at the same level — such as when reviewing an AI whitepaper involving massive datasets, intricate Deep Learning (DL) (as contrasted to the less intricate methods of ML), accelerated computational performance, and energy efficiency — but in actuality, those with Tensor Processing Unit (TPU) and Graphics Processing Unit (GPU) proficiency may be better suited than those with simply Central Processing Unit (CPU) experience. After all, it is now generally understood that GPUs may offer better performance speeds for DL models with large datasets over CPUs (as the size of the involved dataset increases, CPU performance may decrease due to its constrained parallel processing capabilities) and for large-scale computation, TPUs may offer accelerated performance (as well as better energy efficiency "without jeopardizing the model's accuracy") over GPUs and CPUs [10][11]. Likewise, "technical expertise regarding AI" may also vary depending upon time frame and macro trends, such as those which can be gleaned from the U.S. Patent Trademark Office (USPTO) AI Patent Dataset (AIPD) and PatentsView Data, World Intellectual Property Organization (WIPO), etc. In many cases, this information is not being robustly considered for TRID-related reviewer assessments; indeed, the realm of assessments is heavily beset with SM, which are infrequently counterbalanced with Objective Measures/Methodology (OM) approaches.

A well-counterpoised Dynamic Assessment and Weighting System (DAWS) can be utilized to derive more appropriate weights, such as when considering the SM-centric self-assessment of the reviewers and OM-centric macro trend utilization. For example, during the time period 2000-2020, according to the USPTO AIPD and PatentsView data, the AI component technologies with the highest number of patents (with a government interest) were, in descending order, "Knowledge Processing (KP), [Computer] Vision (CV), Planning & Control (P&C), AI Hardware (AIH), ML, Natural Language Processing (NLP), and Evolutionary Computation (EC)" [12][13]; of course, the order changes depending upon the time frame chosen (e.g., 2012-2016 might differ from 2016-2020). In addition, there was a "2023 update to the AIPD" that incorporates various refinements (e.g. BERT for Patents) and overcomes prior limitations that might affect the sorting order [14]. The relative ranking of KP, CV, P&C, AIH, ML, NLP, and EC, among others, is likely to be significant for the review of a TRID, particularly if there is an accompanying supposition/reliance upon future governmental funding [12]. The DAWS, which is also referred to by various other terms of art, such as Adaptive Weighting Schema (AWS), Adaptive Weighting Methodology (AWM), Adaptive Assessment & Weighting Methodology (A2WM), Adaptive Criteria Weighting System (ACWS), etc., endeavors to overcome the SM biases with OM input. Moreover, the DAWS construct is also envisioned to have an enhanced T/E posture. To address the research goal and problem statement of achieving not only a more robust T/E, but also a DAWS that demonstrates more responsibility (more aspirational at this point), the paper delineates an innovative approach towards devising a construct with more epistemic Transparency, Explainability, and Accountability (TEA). The aspects discussed within this paper are presented in Table I (with utilized acronyms).

TABLE I. TABLE OF ACRONYMS

Acronym	*Full Form*
A&F	Aires & Ferreira
A2WM	Adaptive Assessment & Weighting Methodology
ACM	Association of Computing Machinery
ACWS	Adaptive Criteria Weighting System
AI	Artificial Intelligence
AIH	AI Hardware
AIPD	AI Patent Dataset
AIS	Autonomous and Intelligent System
AWM	Adaptive Weighting Methodology
AWS	Adaptive Weighting Schema
C&L	Cascales & Lamata
C&W	Choo & Wedley
CPU	Central Processing Unit
CV	Computer Vision
DAWS	Dynamic Assessment and Weighting System
DE	Decision Engineering
DEP	Decision Engineering Pathway
DL	Deep Learning
DM	Decision-Making
EC	Evolutionary Computation
EDQ	Extrapolated Decision Quality
EDQT	EDQ Thematic
F&H	Finan & Hurley
GDPR	General Data Protection Regulation
GPU	Graphics Processing Unit
HCI	Human-Computer Interaction
IDS	Influence Dominating Set
K&U	Kwiesielewicz & Uden
KP	Knowledge Processing
L&N	Liberatore & Nydick
LOE	Line of Effort
MADM	Multi-Attribute Decision-Making
MCDC	Multi-Criteria Decision-Making
ML	Machine Learning
MODM	Multi-Objective Decision-Making
MVP	Minimum Viable Product
NLP	Natural Language Processing
OM	Objective Measure/Methodology
P&C	Planning & Control
RR	Rank Reversal
RWS	Real-World System
S&V	Saaty & Vargas
SM	Subjective Measure/Methodology
SOTA	State-of-the-Art
STA	System Transparency Assessment
STS	System Transparency Specification
STS	Socio-Technical System
T/E	Transparency/Explainability
TEA	Transparency, Explainability, and Accountability
TPMFS	Tools, Platforms, Methodologies, Frameworks, and Systems
TPU	Tensor Processing Unit
TRID	Technology-Related Investment Decision
USPTO	U.S. Patent Trademark Office
W&W	Wijnmalen & Wedley
WIPO	World Intellectual Property Organization
XAI	Explainability in AI

Section I presented the narrative arc, which explains the title of the paper. Section II provides pertinent background information. Section III provides aspects of the theoretical foundations, which underpin the paper, as well as delineates some of the precursor research LOEs leading up to this point. Section IV presents an experimental construct. Section V summarizes with some reflections and puts forth future work.

II. BACKGROUND

Schmidt notes that current funding schemas (e.g., seed capital) may no longer suffice since the "next generation of technologies" (e.g., AI) will "increasingly require sustained and substantial amounts of resources to reach commercial scale" [15]; this alludes to the paradigm, wherein AI TRID might carry higher thresholds of risk/reward. To address this, Boucher and others have underscored the use of MCDM "in the evaluation of technology investment decisions" [16]. In addition, Triantaphyllou notes that "pertinent data are very expensive to collect," so a robust utilization/evaluation of this data, such as via MCDM, seems prudent [16].

A. MCDM

Fattoruso (as well as Rao, Sitorus, and of course, Hwan & Yoon) construe MCDM as being comprised of Multi-Attribute Decision-Making (MADM) and Multi-Objective Decision-Making (MODM) [17]. MADM involves "discrete decision spaces" (i.e., the number of alternatives is "finite and predetermined") [18]; in contrast, for MODM, "the decision space is continuous" (i.e., "the number of alternatives is infinite" and undetermined) [19]. Restated, MODM tends to contend with multiple objectives (often conflicting) and seeks to ascertain an optimal solution set among "undetermined continuous alternatives" while MADM tends to contend with a single objective and sorts/ranks so as to determine the optimal solution among "a finite set of discrete alternatives" [20]. MADM and MODM each have SMs and OMs that can be leveraged. Ideally, the OMs can somewhat mitigate against the SMs, and three distinct scenarios are presented, wherein this counterpoising would be invaluable.

1) Scenario #1

In a number of cases, reviewer evaluations (at the "same level of expertise") may be diametrically opposed. The choice of OM is non-trivial, as conventional generalized measures, such as h-index or i-index may be specious in deciding how to re-weight the reviewer's self-assessment [21]. In the case of an AI technology firm (e.g., whose intended market is, say, Japan and/or Germany) seeking funding for the advancement of the AI technique of, say, fuzzy logic, the reviewer with the stronger background in fuzzy logic might be of higher criticality and weighted more, as the need to determine the competitive barrier to entry in the involved countries is significant, particularly as the WIPO indicates that the referenced countries have notable strengths in the area of fuzzy logic [12][13][14][22]. Hence, the reviewer's expertise level varies by the involved locale, as what constitutes State-of-the-Art (SOTA) may vary geographically.

2) Scenario #2

As noted by various repositories on GitHub, startups and lean engineering teams seeking to develop the Robinson-Blank-Ries notion of Minimum Viable Products (MVP) might use various packages from Github for more Rapid Application Development (RAD) [23]. However, in some cases, technical issues for the package may abound (e.g., "signature consistency and dependency intricacies have been shown to result in errors and/or incorrect results") and may constitute "glass ceilings" (until resolved) [24]. In this case, the reviewer with the higher proficiency in numerical methods and experience with various libraries, toolkits, and frameworks (e.g., PyTorch, Tensorflow, etc.) might be of higher criticality (e.g., for having previously contended with incompatibility issues, conflicts with required libraries, as well as an assortment of "glass ceiling" matters) and, likely, should be re-weighted accordingly [25].

3) Scenario #3

In a number of cases, professional investors endeavor to mitigate against bias so as to enhance investment discipline and achieve a better Return on Investment (ROI). The use of Behavioral/Emotional Analytics (BEA) within this ecosystem has been increasing, and there have been some explorations with using BEA Multimedia (MM) feeds for re-weighting the self-assessment of reviewers involved with TRID. Differing from the predominantly volunteer reviewers within the academic community, reviewers for TRID tend to be paid professionals, and accordingly, they are more amenable to the stipulations of the investment firms, who engage their services. MM-based BEA has improved since the 1990s with enhanced resolution and more robust time series analytical tools to discern, among other measures, Duchenne indicators — "lip corner puller action unit (AU12)," "cheek raiser action unit (AU6)," lip corners pulled "towards the ears" (AU12), etc. — so as to, potentially, posit how fervently/sincerely the reviewer subscribes to his/her own self-evaluation of expertise on a topic [26]. The use of Duchenne indicators seems to supported by the increasing use of the "Automatic Facial Expression Analysis (AFEA), which automates the Facial Action Coding System (FACS)," and is noted by Clark and others as being "the most comprehensive, psychometrically rigorous, and widely used system to describe facial activity in terms of visually observable facial muscle actions (i.e., [Action Units or] AUs)" [27]. As TEA accountability can lead to more "trustworthy" TPMFS, it should be of no surprise that the use of Duchenne (e.g., "genuine") and non-Duchenne ("non-genuine)" indicators (e.g., smiles) have been of great interest as a prospective OM-centric MM feed [28].

B. *Effective MODM & MADM SMs/OMs*

Lyons-Padilla notes that “asset allocators manage more than $69.1 trillion dollars globally on behalf of governments, universities, charities, foundations, and companies” and retain “professional managers to generate returns” (i.e., ROIs) [29]. Despite the anticipated investment discipline, particularly given the magnitude of funds at stake, Lyons-Padilla and others have reported that professional investor human review teams remain subject to bias in their financial decisions [29]. Along this vein, a TRID human review team may be beset by a variety of predilections. For example, the teams may have been assembled using a variety of 360 evaluation, personality type, and conflict mode/management assessments that are predominantly SM-based (and, thereby, subject to inherent biases). In many cases, these assessment tools were matured/utilized, such as in the 1950s, 1950s/60s, 1970s, respectively, although the developmental origins tend to trace back to the 1930s and 1940s (particularly during the World War II time frame) [30][31][32]. As this was prior to the more prevalent use of AI/ML (since the 1990s), the counterpoising of SM with OM-based approaches remains a relatively unsaturated/nascent area. However, the arena of MCDM endeavors has leveraged both SM and OM so as to formulate a more practical/logical weighting, such as noted by Taherdoost (as well as Hwang & Yoon and others) [33]. Prior experimentation has shown that particular combinations of MADM/MODM SMs/OMs can achieve a modicum of efficacy; exemplars are shown in Table II.

TABLE II. EXEMPLAR MADM/MODM SMS/OMS

#	*TPMFS*	*MADM/ MODM*	*SM/ OM*
1	Analytic Hierarchy Process (AHP)	MADM [34]	SM [35]
2	Weighted Aggregated Sum Product Assessment (WASPAS)	MADM [36]	SM [37]
3	CRiteria Importance through Intercriteria Correlation (CRITIC)	MADM [38]	OM [39]
4	Data Envelopment Analysis (DEA)	MADM [38]	OM [38]
5	Technique of Order Preference by Similarity to an Ideal Solution (TOPSIS)	MADM [40]	OM [41]
6	Fuzzy VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)	MADM [42]	SM/OM [43]
7	Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) (e.g., I and II)	MADM [44]	SM/OM [45][46] [47][48] [49]
8	ELimination Et Choix Traduisant la Realité (ELECTRE)	MADM [50]	SM/OM [47]
9	Multi-Objective Optimization by a Ratio Analysis plus the Full Multiplicative Form (MULTIMOORA)	MODM [51]	SM [51]
10	Goal Programming (GP) Method	MODM [52]	OM [52]

Yet, even for the case of a well-counterpoised construct, the matter of TEA is a separate matter, and architectural constructs, from previous experimentation, are often not evaluated for TEA. This segues to the need for an experimental TEA construct, which is described in Section IV. Some of the theoretical foundations are delineated in Section III below.

III. THEORETICAL FOUNDATIONS FOR THE EXPERIMENT

Abbas and Howard had noted that there are, fundamentally, “six elements of Decision Quality” (DQ) (although Abbas later expands this to eleven elements) [53]. These include: (1) an understanding of the involved “uncertainty,” (2) a grasp of the problem boundaries (e.g., including the temporal constraints of (1)) and the “perspectives involved,” (3) identification of the reasoning involved (e.g., “values,” “trade-offs,” prioritization schemas, etc.), (4) the “commitment to action” by the Decision Maker (DM) “and the stakeholders…affected by the decision,” (5) the determination of “feasible” alternatives, and (6) the “choice criterion” to “choose the alternative with the highest expected utility” (e.g., use of the Neumann-Morgenstern utility function) [53][54]. Along this vein, various DQ dimensions have been explored, as is shown in Table II, by way of extrapolated LOEs/EDQTs. For example, (1) has been extended to the notion of ambiguity/uncertainty, (2) has been extended to more fully contextualize the “perspectives involved,” via Spatial-Temporal Knowledge Graph (STKG) Completion (STKGC)/STKG Reasoning (STKGR), (3) has been extended to contextualize the involved rationale, via DAWS (e.g., AWS/AWM/A2WM/ACWS), (4) has been extended to better comprehend the potential DE Pathways (DEP) and the accompanying operationalization schemas (e.g., Command and Control or C2) by the DM and/or the notion of Multi-Partner Enclaves (MPEs) or “coalitions of the willing,” (5) has been extended to better organize/sort/rank the prospective alternatives, via a Counterpoised MCDM (C-MCDM) (e.g., a balancing of MADM/MODM SM/OM), and (6) has been extended to consider the most apropos MADM (given RR considerations along with the considerations of (1) through (5)). The EDQTs are clarified in the following subsections A through F.

A. *LHM, an extrapolation of DQ#1*

The notion of “uncertainty” should not be treated in isolation, particularly when there is a temporal element. Time can be classified as Compressed Decision Cycles (CDC) (i.e., a “paradigm of ‘tight time constraints’”) and Uncompressed Decision Cycles (UDC) (i.e., a paradigm, wherein time is not necessarily of the essence) [56]. In a situation of CDC, the DM may tolerate “higher uncertainty (i.e., sparse data) given the condition of lower ambiguity” (i.e., a similar situation has happened before, so there is some prior experience on how to react) [56]. This paradigm of Lower Ambiguity and Higher Uncertainty is referred to as LAHU. In contrast, in a situation of UDC, the DM may not "simply accept the higher uncertainty" and might "proactively seek to use 'more data to lower uncertainty'," particularly given the condition of higher ambiguity (i.e., a comparable situation has not been encountered before, so there is no apriori experience of how to react) [56]. This paradigm of Higher Ambiguity and Lower Uncertainty is referred to as HALU. When conjoined, a LAHU HALU Module is referred to as an LHM [55][56].

B. Higher-Order Networks (HON), an extrapolation of DQ#2

Tian asserts that a Knowledge Graph (KG) "describes the objective world's concepts, entities, and their relationships in the form of graphs" [57]. The procedure of positing links and nodes is known as KG Completion (KGC). Building upon this, Chen and Ji assert that KG Reasoning (KGR) can "discover new knowledge from existing knowledge" [58][59]. However, in its base form, KGs are static, as they lack temporal information [60]. In turn, Temporal KGs (TKs) are critiqued for their lack of spatial information [61]. Also, Spatial-Temporal KGs (STKGs) are critiqued against the backdrop of Positive Influence Dominating Sets (PIDS) as well as Negative Influence Dominating Sets (NIDS), and the PIDS/NIDS effects are considered against the Abelian Sandpile Model (ASM) or Bak–Tang–Wiesenfeld (BTW) phenomenon of non-equilibrium systems so as to ascertain the prospective "Higher-Order Networks" (HONs) at play (i.e., other stakeholders), which is of critical import to discern. After all, without being cognizant of the potential HONS at play (as well as identifying the likely HONs at play), delineation of the boundaries and the framing of the problem will not be correct [62].

C. DAWS, an extrapolation of DQ#3

In a substantial number of cases, TPMFS are beset by selection bias (e.g., the choice/formulation of heuristics). In a number of these cases, even the DAWS involved are beset with confirmation bias (e.g., the choice/amalgamation of parameters). This effect is further aggravated when the utilized AI/ML is also beleaguered with inherent inclinations. A mitigation approach that has been utilized with some efficacy has been to utilize the Type-2 Fuzzy Sets (T2FS) and Spherical Fuzzy Set (SFS) versions of the TPMFS approaches of Table 1. Other enhancements include utilizing an Extended Matrix Shanks Transformation Accelerant (EMSTA).

D. C2, an extrapolation of DQ#4

DEPs may vary for the DM and the stakeholders of the MPE (and for the MPE itself, as it evolves or devolves); DEPs for urgent situations (i.e., "exigency circumstances") and non-urgent situations (i.e., "non-exigency circumstances) may differ greatly. This also relates to the notion that the Minimum Controllability Problem (MCP) is quite different from the Efficient Controllability Problem (ECP) (since ECP is more desirable for exerting control, when desired, over a more elongated period of time). In particular, control may need to be exercised during "exigency circumstances." DEPs may also vary depending upon the degree of resiliency incorporated into the involved system/paradigm. The ability to exercise action/operationalize, via the involved/available C2, is highly dependent upon the involved DEPs, MCP/ECP, and circumstances (e.g., exigency/non-exigency).

E. TEA, an extrapolation of DQ#5

Prior research had found that a cascading class of "ever smaller" convolutional filters is well-suited for DL (and the implementation of C-MCDM) since they well mimic a Convolutional Wavelet Transform (CWT) approach, which unlike other types of transforms, do not necessarily suffer as much from truncation, leakage, and other issues [63]. Hence, there is an advantage to leveraging "cascading 'CWT-like' convolutional filters" [63]. Also, bounds tightening can be employed (e.g., such as by a bespoke convex relaxations framework for the "tightest possible relaxation") so as to further delineate the successive steps being taken. This can be achieved via a Bespoke Implementation (BI), which was delineated in prior work and also lends towards operationalizing the MODM OM. Collectively, the approach lends to TEA.

F. Rank Reversal (RR) Challenge, an extrapolation of DQ#6

Despite the generalized promise of the MADM TPMFS of Table 1, the specific implementation is crucial. For example, in some instances, the MADMs of Table 1 can experience a "Rank Reversal" (RR) phenomenon and yield incorrect results. Belton and Gear (B&G) had first noted the RR dilemma, and recognition of the problem was affirmed by Triantaphyllou and others across the gamut of MADM approaches. Even newly introduced MADM methods are beset by the RR challenge. However, it has been reported that, among others, the Ranking of Alternatives through Functional mapping of criterion sub-intervals in a Single Interval (RAFSI) method can somewhat mitigate against the RR challenge, and it is also mathematically straightforward so as not to worsen the TEA goal [64].

Garcia-Cascales describes RR as a paradigm that manifests when a DM "is confronted with new alternatives that were not thought about" or available "when the selection process was initiated" [65]. Aires adds to this by noting that "RR refers to a change in the ordering among alternatives previously defined after the addition or removal of an alternative from the group previously ordered" and pointed out that the primary methods of MCP (e.g., "AHP, TOPSIS, ELECTRE, PROMETHEE and combinations thereof") "have been criticized due to the occurrence of" RR [66]. By way of background, RR discussions had commenced via Saaty, B&G, and Saaty and Vargas (S&V) in 1980, 1983, and 1984, respectively. The dialectic prompted others, such as Triantaphyllou, Finan & Hurley

(F&H), Liberatore & Nydick (L&N), Wijnmalen & Wedley (W&W), and others to engage in RR research. Simplistically, B&G argued that RR can manifest "when a new alternative is added or deleted," S&V argued that RR "can occur due to the presence of near or similar copies within the set of alternatives," Cascales & Lamata (C&L) asserted that "it is well known that when the projects are very close[,] the order between them can depend on the method used on their evaluation," Fedrizzi argued that RR "depends on the distribution of criteria weights" (i.e., entropy of the weight distribution") and that "the estimated probability of" RR "increases with the weights entropy," and Choo & Wedley (C&W), Lin, as well as others worked on "deriving the priority values from the pair-wise comparison matrix," but Kwiesielewicz & Uden (K&U) showed that the "pair-wise comparison matrix can be contradictory (inconsistent), yet it can pass the consistency check" [67][68]; this list goes on. Proposed RR mitigation methods, among others, have been put forth by Zizovic in the form of "the lattice MADM method," Kizielewicz's "Characteristic Objects method (COMET)," Dezert's Stable Preference Ordering Towards Ideal Solution Method (SPOTIS), and others [69][70][71][72]. Wieckowski points out that theoretical mitigation and practical mitigation for RWS are quite different and uses varying sensitivity analysis results to underscore the point [72]. Yet, "despite the great interest" in RR, Aires asserts that "given its importance for addressing the reliability of MCDM methods, there is still a paucity in the literature regarding this subject" [66]. This assertion was made despite the fact that Maleki & Zahir had "evaluated 61 papers…from 18 international journals," Aires & Ferreira (A&F) had evaluated "130 articles…from 37 journals," and others (e.g., Yu) [66][73][74].

A key factor for ascertaining the latent stability of MADM methods is to inject replacement alternatives into (or by removing alternatives from) the original set. Ideally, the MADM method would not exhibit any substantive change in the organizing/sorting/ranking of the alternatives. Zizovic's RAFSI constitutes a foray into better contextualizing resistance to RR; this paper endeavors to continue that foray. The research of this paper also considers the elements of: (1) time (e.g., CDC/UDC), such as in the case of LHM, (2) HON (e.g., PIDS/NIDS), such as in the case of STKGC/STKGR, (3) biases/sub-biases (e.g., chosen parameters, indices, heuristics, etc.), such as in the case of the DAWS utilized, (4) involved DEPs and the ability to exert C2, whether DM/MPE and/or MCP/ECP during varied circumstances (e.g., exigency/non-exigency), and (5) involved architectural construct (e.g., for the treatment of TEA), which needs to consider both the Method (M) and Architecture (A) involved. The prior research relating to the EDQTs atop the fundamentals of DQ#1 through 5, which segue to the novelty and contribution of this paper, is shown in Table III below.

TABLE III. EDQTS FOR THE VARIOUS DQ DIMENSIONS

DQ #	***DOI***	***EDQTs***
1	• 10.1109/GEM61861.2024.10585580 • 10.1109/IAICT62357.2024.10617473	LHM (UDC/CDC)
2	• 10.1109/AIIoT61789.2024.10579029 • 10.1109/IBDAP62940.2024.10689701	HON (PIDS/NIDS)
3	• 10.1109/CyMaEn57228.2023.10051057 • 10.1109/ICPEA56918.2023.10093212 • 10.1109/ICSGTEIS60500.2023.10424230 • 10.1109/AIIoT61789.2024.10579033	DAWS
4	• 10.1109/IEMCON.2019.8936241 • 10.1109/IAICT62357.2024.10617473	C2 (MCP/ECP)
5	• 10.1109/ICPEA56918.2023.10093212 • 10.1109/AIIoT61789.2024.10579033 • 10.1109/ICDCSW53096.2021.00014 • 10.1109/IEMCON53756.2021.9623140 • 10.1109/OETIC57156.2022.10176215	TEA (M/A)
6	This paper.	RR

For this paper, a particular Achilles heel of MCDM systems was explored and addressed. Hwang and Yoon had previously noted that the most utilized facet of MCDM was that of MADM, and Fattoruso had found that AHP was the most prevalent method utilized for MADM [17]. In addition, Fattoruso noted that methods, such as PROMETHEE and ELECTRE, were minimally used in various sectors; TOPSIS was used slightly more often, but its use still paled in comparison to AHP [17]. Despite the widespread use of AHP, ironically, Aazadfallah asserts that AHP is the most sensitive to RR, while TOPSIS, PROMETHEE II, and ELECTRE are more resistant/stable (yet still susceptible to RR as well) [75]. Other MADM methods are also sensitive to RR [76]. Even after B&G noted the AHP susceptibility to RR and the creator of AHP, Saaty, unveiled an updated version, B&G pointed out that Saaty's updated version was still susceptible under particular conditions; B&G released a version that was supposedly resistant to RR, but S&V asserted that the B&G version was susceptible as well [77]. Bottom line, AHP is still deemed to be susceptible to RR. Moving beyond the catch-all generalizations of RR, Resistance/Stability (R/S) is also subject to the RR Type (RRT), as shown in Table IV.

TABLE IV. TYPES OF RR (RRT)

RRT #	***Initial Ranking***	***Expected Ranking after change***	***Exemplar Manifested RR***
1	DEP_3,DEP_1,DEP_2	$(DEP_1 \sim DEP_4)$; DEP_3,DEP_4,DEP_2	DEP_2,DEP_4,DEP_3
2	DEP_3,DEP_1,DEP_2	$(DEP_1 > DEP_4)$; DEP_3,DEP_4,DEP_2	DEP_2,DEP_4,DEP_3
3	DEP_3,DEP_1,DEP_2	$(DEP_1 \sim DEP_4)$; $DEP_3 > DEP_4$ $DEP_4 > DEP_2$; DEP_3,DEP_4,DEP_2;	$DEP_3 > DEP_4$ $DEP_2 > DEP_4$; $(DEP_3 \sim DEP_2)$; $DEP_3 \sim DEP_2 > DEP_4$
4	DEP_3,DEP_1,DEP_2	$DEP_3 > DEP_4$ $DEP_4 > DEP_2$; $DEP_3 > DEP_4 > DEP_2$	$DEP_3 > DEP_2$ $DEP_2 > DEP_4$; $DEP_3 > DEP_2 > DEP_4$

In the case of RRT#1, let us take the classical case of a triplicate of choice: DEP_1, DEP_2, and DEP_3. Let us also presume that the involved MADM method ranked the DEPs as DEP$_3$, DEP$_1$, DEP$_2$. In the case, where DEP$_1$ is no longer available as an option (and it is supplanted by a comparable DEP$_4$), the expected outcome might be: DEP$_3$, DEP$_4$, and DEP$_2$. However, in the case of RRT#1, the actual outcome might be DEP$_2$, DEP$_4$, and DEP$_3$ (wherein the actual potentially optimal DEP$_3$ is displaced from first position). RRT#2 is similar to RRT#1; however, it differs in that DEP$_1$ and DEP$_4$ would not be comparable, such as for the case wherein DEP$_4$ is far less optimal than DEP$_1$ (expressed as DEP$_1$ > DEP$_4$). In the case of RRT#3, a comparison would be made between the overarching ranking against the sub-rankings; for example, taking the initial RRT#1 ranking of DEP$_3$, DEP$_1$, DEP$_2$ along with the replacement of DEP$_1$ with DEP$_4$, the sub-rankings might equate to DEP$_3$ > DEP$_4$ and DEP$_4$ > DEP$_2$. Yet, RRT#3 might manifest as having the sub-rankings of DEP$_3$ > DEP$_4$ and DEP$_2$ > DEP$_4$; DEP$_3$ and DEP$_2$ might be construed as being similar in that they are both > DEP$_4$ (expressed as DEP$_3$ ~ DEP$_2$), and an outcome could be DEP$_3$ ~ DEP$_2$ > DEP$_4$. RRT#4 is akin to RRT#3; however, it differs in that only sub-ranking inconsistencies are focused upon. For example, DEP$_3$ > DEP$_4$ and DEP$_4$ > DEP$_2$ could be construed as being consistent since DEP$_3$ > DEP$_4$ > DEP$_2$; if, however, the sub-ranking outcome was DEP$_3$ > DEP$_2$ and DEP$_2$ > DEP$_4$, which equates to DEP$_3$ > DEP$_2$ > DEP$_4$, then RRT#4 would have manifested itself. This progression continues for numerous other RRTs.

IV. EXPERIMENTATION FOR THE INVOLVED CASE STUDY

Zizovic et al. introduced the RAFSI method to mitigate against RR. Zizovic points out that a consistent/steady-state ranking across various scenarios (e.g., S0 through S5) constitutes mission success for the RR problem, such as exemplared in Zizovic's RAFSI Table 2 (exhibited as Table V) [64]. However, the anticipated results for the approach utilized in this paper would differ from Zizovic's RAFSI Table 2 (exhibited as Table V), as time is treated [64].

TABLE V. ZIZOVIC'S RAFSI "RANKING OF THE ALTERNATIVES IN SCENARIOS" [64]

Alternatives	*Scenarios*					
	S0	*S1*	*S2*	*S3*	*S4*	*S5*
A5	1	1	1	1	1	1
A1	2	2	2	2	2	
A4	3	3	3	3		
A2	4	4	4			
A3	5	5				
A6	6					

When considering just one of the EDQTs of Table III (e.g., EDQT#1, which centers upon the temporal aspect), the re-mapped (and simplified) table (using just the initial ranking of Table III) might resemble something like Table VI below.

TABLE VI. EDQT CONSIDERATIONS AND RE-MAPPING OF TABLE IV

Alternatives	*Scenarios*					
	UDC of LHM (EDQT#1)			*CDC of LHM (EDQT #1)*		
	S0	*S1*	*S2*	*S3*	*S4*	*S5*
DEP$_3$	1	1	1	3	3	3
DEP$_1$	2	2	2	1	1	1
DEP$_2$	3	3	3	2	2	2

Moreover, when considering EDQT#1 to 5, there are some significant reversals of findings when considering even simply UDC and CDC (of EDQT #1). For example, when comparing the medians of S1 (of the UDC scenarios) and S4 (of the CDC scenarios) of Table VI, whereas the initial ranking and expected ranking of DEP$_2$ were not in first position when treated generally, its ranking rose when considered against EDQT#1 to 5 (e.g., CDC), such as shown in Figures 1 and 2 below.

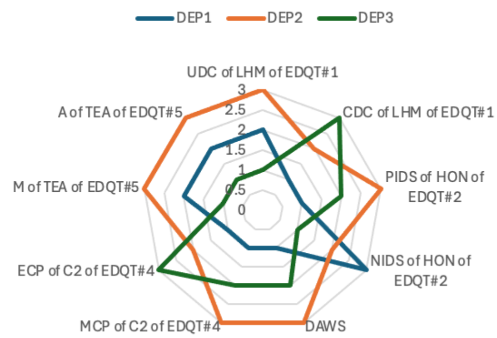

Figure 1. EDQT#1 to 5 for Scenario S1

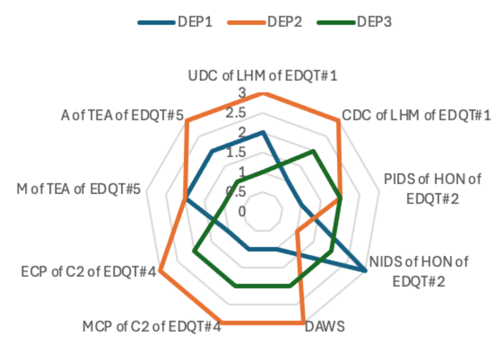

Figure 2. EDQT#1 to 5 for Scenario S4

Cognizant of the desired endstate so as to address RWS, a bespoke experimental architectural construct was further examined. Previously, the construct utilized was a plain vanilla MADM/MODM SM/OM counterpoising to comprise a C-MCDM. This is delineated in DQ#1 Bullet (B) 1 and B2, DQ#3 B2 and B3, DQ#4 B2, and DQ#5 B1 of Table III. For this paper, the construct was revised from that of Figure 3 (the TPMFS #s are from Table II) to Figure 4 so as to decrease the weighting of the MADM and to incorporate more apropos methods (that are more resistant/stable against RR); The BI is a Particle Swarm Optimization-centric Robust Convex Relaxation Framework (implementation details are delineated in DQ#1 B1, DQ#3 B1 and B3, and DQ#5 B1 through B5 of Table III), *is* equates to input set, and *ss* equates to solution set.

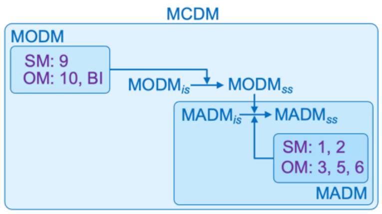

Figure 3. Prior Architectural Construct without RR Considerations

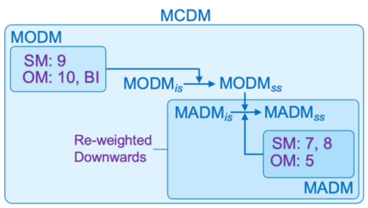

Figure 4. Current Architectural Construct with RR Consideration

Further experimentation was conducted to explore the TEA factor of the various methods employed. By way of example, PROMETHEE (TPMFS#7) was utilized as it is "easily… understood" [78][79]. Likewise, [fuzzy] VIKOR (TPMFS#6) was removed as it "less explainable than other more intuitive methods" [80]. These actions lend toward improving the System TEA (STEA). TPMFS#1 and 2 were removed for axiomatic RR reasons. TPMFS#5 remained in use and TPMFS#8 was added for their higher R/S with regards to RR.

This paper explored a particular facet of MCDM systems — the counterpoising of MADM/MODM SM/OM, wherein MADM would employ methods that exhibited higher R/S as pertains to RR and MADM, in general, would be re-weighted downwards. Given that the RR phenomenon greatly affects the most popular constituent component of MCDM — MADM — this constituted a non-trivial research goal. In addition, there was a constraint to select MADM methods that were more inclined towards the TEA aspiration (e.g., PROMETHEE is more intuitive and explainable). Among other advances, the research goal was approached from an EDQT vantage point, and the list of utilized methods was modified/winnowed from MADM SM 1,2 and OM 3, 5, 6 to MADM SM 7, 8 and OM 5. Two other non-trivial advancements should also be illuminated. First, the Abbas and Howard six fundamentals of DQ was extended for RWS via EDQT#1 through 5 and the foray explored within this paper — EDQT#6. The practicalities of EDQT#1 through 6 should not be underestimated. Second, the Zizovic RAFSI method to mitigate against RR was extended for RWS by considering the temporal element (from EDQT#1), such as that of UDC S0 to S2 and CDC S3 to S5. The aforementioned advancements were incorporated into the STEA advancement — the formulation of a bespoke architectural construct with RR considerations, such as reflected in Figure 4. The MODM OM BI was previously shown to have high efficacy in shaping an optimized selection of MADMs, so the new amalgam construct of Figure 4 constitutes an enhanced approach towards the treatment of RR. It should be noted that, depending upon the specific implementation, TPMFS#5 and 8 can exhibit drawbacks (when putting aside the TEA and R/S RR considerations) for factors, such as Flexibility (F) (for integration, hybridization, adaptation, etc.), Consistency (C), and Performance (P), as shown in Table VI below; TPMFS#6 is exhibited for comparison purposes only.

TABLE VII. EXEMPLAR BENCHMARKING FOR SELECT TPMFS

TPMFS #	*R/S RR*	*TEA*	*F*	*C*	*P*
5					
8					
6					

The range of MADM methods (e.g., ML, neural network, and other advanced computational methods) is constrained to those, for the purposes of this paper, deemed to exhibit higher practicality by way of being TEA-centric and suited for R/S RR.

V. CONCLUSION

This paper explores the challenges of RR in MCDM, specifically within MADM methods. Experimentation was provided through case studies that emphasize the temporal and control aspects. The paper integrates a variety of DQ dimensions (DQ#1 to DQ#6), which demonstrate: (1) how the model can be adapted to various DM contexts, and (2) how the overarching framework is well-suited for RWS applications. While various decision-making systems within the literature explore dynamic systems and/or describe time-sensitive DM, this paper differs via the unique amalgam treatment of EDQTs for the various DQs delineated in Table II. Planned future work includes a more granular comparison (the value of a quantitative comparison is still nebulous, as there are quantitative exactitude issues surrounding the involved benchmarking) as well as a prioritization list (e.g., a prioritization of TEA, R/S RR, C, F, and P), which will be informed by a survey to be conducted. Further MADM methods, pertaining to the listed factors, will also be explored.

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