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The Military Demographic Equity Support Tool

A Tool for Helping Decisionmakers Address Disparities in Career Success

Personnel chiefs of all the military services continue to reckon with the reality that women, racial minorities, and ethnic minorities are less likely to achieve the traditional markers of career success. The U.S. Navy chartered an effort in July 2020, "Task Force One Navy," that sought to "identify and make recommendations to dismantle barriers" to career success (Task Force One Navy, undated). The task force features five lines of effort, each focusing on a different area of human resource management (HRM), which produced 56 recommendations and areas for further study. In the same time frame, the U.S. Army commissioned a review of racial disparities, specifically in the military justice system (Lacdan, 2020). The Department of the Air Force Inspector General has published two independent reviews of racial, ethnic, and gender disparities in career success. The first report focused on disparities for black servicemembers (Department of the Air Force Inspector General, 2020), and the second described disparities for women and other minority groups (Department of the Air Force Inspector General, 2021). These reviews identified many disparities across different HRM areas and career milestones and called on stakeholders to identify the root causes of these disparities and implement "systemic and lasting corrective measures" (Department of the Air Force Inspector General, 2021, p. 2).

These recent efforts to highlight disparities and recommend ways to promote full participation for all racial, ethnic, and gender groups in the armed forces are part of a long line of policy initiatives dating back to President Harry Truman's implementation of desegregation in the 1950s (Military Leadership Diversity Commission, 2011). Although there has been general progress over time (for instance, in the proportion of *accessions*, or newly appointed officers, who are female or nonwhite), many of the patterns identified in recent reports have been previously noted and remain remarkably stable despite attempts to change them.

To briefly summarize these patterns, workforce data show: (1) lower rates of advancement in grade for racial and ethnic minority servicemembers (particularly for black men and women) and

Impetus for the Military Demographic Equity Support Tool

Few areas of HRM have received as much study as the problem of redesigning personnel management systems to promote equitable career outcomes. Many of these outcomes, despite being well understood for decades, have not improved over time. For example, senior leaders in all services tend to arise primarily from combat or operational occupations, and minority and female servicemembers are underrepresented in these occupations. It is not possible to eliminate these entrenched patterns all at once. Instead, the services must make incremental progress in how the system classifies officers into career fields and promotes them, being careful not to implement policies that produce unintended and undesired downstream outcomes. This is but one example of an early career point that contributes to long-lasting racial, ethnic, and gender disparities across pay grades.

At a minimum, addressing such a long-standing and complex problem requires up-to-date, unambiguous information on the state of the workforce. However, HRM leaders and analysts face significant challenges in sorting through all the career factors at play, prioritizing their programs for impact, and understanding and anticipating causal chains where foreseeable results could undo hard-won progress. To help HRM leaders, we developed a concept and prototype for an analytic tool, the Military Demographic Equity Support Tool (MDEST). The tool provides a holistic, interactive picture of the HRM environment. MDEST represents the product of an effort, using existing Department of Defense (DoD) data and open-source software, to design an interactive system that addresses this information gap. This tool concept and prototype document are intended to provide a high-level description of the method behind the tool and illustrate its initial functionality. The document closes with recommendations for further refinements for those interested in developing the concept and putting it into production.

(2) lower rates of retention for midcareer women (Asch, Miller, and Malchiodi, 2012). Regarding advancement, research examining bias in promotion boards has found that servicemembers are treated generally fairly: Equivalent records are not treated differently on the basis of a servicemember's race, ethnicity, or gender (Lim et al., 2014; Lim et al., 2021). Therefore, mitigating advancement disparities requires the implementation of policies to address differences in career development that occur before selection boards. This is a significant challenge because career development involves a complex sequence of voluntary decisions by servicemembers and involuntary circumstances that are governed by policy. Chief among these differential career development patterns is that women, racial minorities, and ethnic minorities are less likely to enter and succeed in operational occupations, which results in a disproportionately low number of individuals at the most senior ranks in all services (Military Leadership Diversity Commission, 2011).

In addition to advancement, differences in career factors, such as occupation, could contribute to gender differences in retention. However, this observation does not fully explain or identify effective policy mitigation options (Asch, Miller, and Weinberger, 2016; Lim et al., 2021). Although racial, ethnic, and gender differences in occupations contribute to career disparities, the processes that the services use to classify servicemembers into occupations are a nesting doll of additional eligibility factors and servicemember decisions that mitigation efforts must unpack and address if they are to succeed (Schulker, 2021).

Beyond the complexity and interrelatedness of military career outcomes, a further challenge for measuring progress arises because military careers unfold slowly. The military workforce is a closed system, and there is limited ability to hire individuals directly into higher positions. Thus, a policy change affecting a new cohort will take at least two decades to affect the senior leadership ranks. Because of this time lag, workforce demographics do not necessarily reflect the existing state of the personnel system, and the disconnect between existing personnel policies and member demographics grows with increasing rank because higher-ranking officers might have been affected by personnel policies that have long

since changed. A concrete example of this phenomenon is the direct combat exclusion rule that rendered certain occupations partially closed to women. The policy was lifted in the mid-2010s, changing the environment for cohorts that accessed in the years that followed. However, the policy was in effect when most midcareer and senior officers in the workforce received their occupations.

Wicked problems are a class of problems that are hard to tackle because they lack clear definitions and boundaries, involve complex interdependencies, and do not have objectively "correct" solutions (Rittle and Webber, 1973). Many features contribute to the problem of addressing demographic disparities in career success in the military services, including the following:

- Underrepresentation of women and minority servicemembers is the result of many diffuse factors that accumulate to produce a large impact at the senior level. Thus, multiple systematically effective policies applied at the right points in the career life cycle are needed to address underrepresentation.
- Some of these factors reflect decisions of servicemembers. Thus, some policies must incentivize servicemember decisions to produce the desired outcomes.
- There is a significant time lag between the implementation of a policy and its effect on workforce demographics at the senior level, making it difficult to link disparities to root causes and understand progress over time (Robbert and Crown, 2021).

Policymakers Need a Campaign Assessment Tool for Equity

Decisionmakers can turn to joint doctrine for operational planning when they must plan and execute a strategy in a complex and constantly changing environment. The joint doctrine summarizes a program of operation assessment to determine whether a given operation is on track to accomplish strategic objectives. Joint Publication 5-0 describes the need for operation assessment in the following way:

Throughout campaign planning and execution, the CCDR [Combatant Commander] and staff continually observe the OE [Operational Environment] and assess the efficacy of the campaign plan. . . . Because campaigns are conducted in a complex and dynamic environment, commands must be able to detect, analyze, and adapt to changes in the OE during execution. (Joint Publication 5-0, 2020, pp. vi–2)

This description clarifies that decisionmakers require the ability to continually observe the operational environment and detect changes while implementing their strategies. Existing assessment practices, reflected in the reports by Task Force One Navy (undated) and the Department of the Air Force Inspector General (2020, 2021), certainly track demographic patterns and trends very closely. Although tracking is important and informative, **these changes are slow to affect trends, and they do not immediately reveal how progress in a particular area affects the overall campaign to address racial, ethnic, and gender disparities in career outcomes.** Hypothetically, one of the services could implement an initiative that boosts female representation in operational career fields by a significant percentage. Because occupational classification typically occurs at the beginning of a servicemember's career, it would take many years before demographics in the senior pay grades reflected this change. Furthermore, it would be difficult for decisionmakers to anticipate how much other disparities (such as gender differences in retention) might undermine these gains. Because of this information gap, decisionmakers find themselves in the position of continually trying out a long list of new initiatives with a very limited under-

Abbreviations

BN	Bayesian network
COA	course of action
CPT	conditional probability table
DoD	Department of Defense
HR	human resources
HRM	human resource management
MDEST	Military Demographic Equity Support Tool

A decision support tool could help human resources decisionmakers understand the impacts of policy efforts on demographic diversity as they unfold.

standing of how the initiatives affect the operational environment (i.e., the career life cycle).

To help inject better information into the services' campaigns to address racial, ethnic, and gender disparities, this document presents a concept and prototype for a decision support tool that, if developed further (as we describe in the concluding section), could help human resources (HR) decisionmakers understand the impacts of policy efforts on demographic diversity as they unfold. To address the challenges that we described, such a tool must meet the following requirements:

- Inputs and metrics should be easy to understand and explain and should reflect the cumulative impact across career stages.
- The tool should incorporate contributing factors in addition to race, ethnicity, and gender in a way that points to the root causes of disparities.
- The tool should present results that reflect the current state of personnel policy in each area of the career life cycle.
- The tool should incorporate new information as it becomes available and answer what-if queries so that planners can input the goals of their initiatives and assess the impact of these initiatives on the personnel system.

Bayesian Networks as a Basis for an Assessment Tool

In a campaign to address demographic disparities in career success, two related attributes of the personnel system are most important:

1. whether servicemembers from different demographic groups have similar advancement rates across pay grades
2. whether demographic representation for nonwhite or female servicemembers declines with increasing pay grades.

The Task Force One Navy report (undated) contains examples of both attributes. The report shows promotion rates for each racial, ethnic, and gender group (an example of attribute 1). The report also describes the existing state of the Navy with a table showing that the percentage of women, racial minorities, and ethnic minorities falls with increasing pay grade (an example of attribute 2). From a mathematical standpoint, these attributes represent two sides of the same coin. In the first case, the interest lies in the likelihood that a servicemember will reach a certain grade level given their characteristics. The second deals with the likelihood of having certain characteristics, given that the servicemember has attained a particular grade level.

The solution to the problem of designing a tool to assess these two attributes of the personnel system lies in creating a statistical model that represents the relationships between servicemember characteristics and career milestones, and then operationalizing that model so that decisionmakers can monitor either attribute 1 or attribute 2 as reflected in the existing policy environment. We propose a method for creating such a model: a Bayesian network (BN) (Korb and Nicholson, 2011; Nagarajan, Scutari, and Lèbre, 2013). A BN is a statistical model that links together tables—each containing the probabilities of an outcome given different servicemember attributes—to represent the entire career life cycle. The resulting model can answer any probability question that decisionmakers might ask, such as

- Does the probability of reaching the grade of O-6 differ between white servicemembers and racial and ethnic minority servicemembers,

and how would this change if both groups entered the same occupations?

- How does female representation at the O-6 level compare with representation at the O-1 level, and how would this change if policy changes were successful in reducing gender retention gaps?

How Do Bayesian Networks Meet Our Assessment Tool Requirements?

Table 1 reprises the assessment tool requirements from the previous section and describes how BNs address each need. First, BNs are transparent and can be discussed with nontechnical stakeholders. BNs most often are represented as diagrams with shapes representing the variables and arrows connecting those that are related to one another. Furthermore, the basic input to a BN is a conditional probability table (CPT), which is intuitive and can be directly examined (in contrast to parameters from other "black-box" machine-learning models). By connecting many CPTs together with patterns at various career milestones, a BN of a whole military career can produce the directly interpretable metrics that are most important to policymakers.

Second, BNs address the issue of having many factors, in addition to race, ethnicity, and gender, that could potentially drive outcomes with machine-learning algorithms. When using the BN technique, HRM experts can specify relationships that they know to be important based on prior research while leaving other links as an option for the algorithm to consider if warranted by the data. To address the challenge of the time lag between early career policies and subsequent outcomes, the researchers can calculate the CPTs using only recent data. If every stage of the network uses patterns in the recent data, the model outputs will reflect the system in real time, unlike the demographics of current personnel, which (at least partially) reflect policies of the past. Finally, incorporating new information (such as updated promotion rates from a recent board) or answering what-if queries is natural to the BN technique. The BN technique is sometimes called a Bayesian *belief* network because it can combine expert beliefs with empirical patterns to predict the model outcomes.
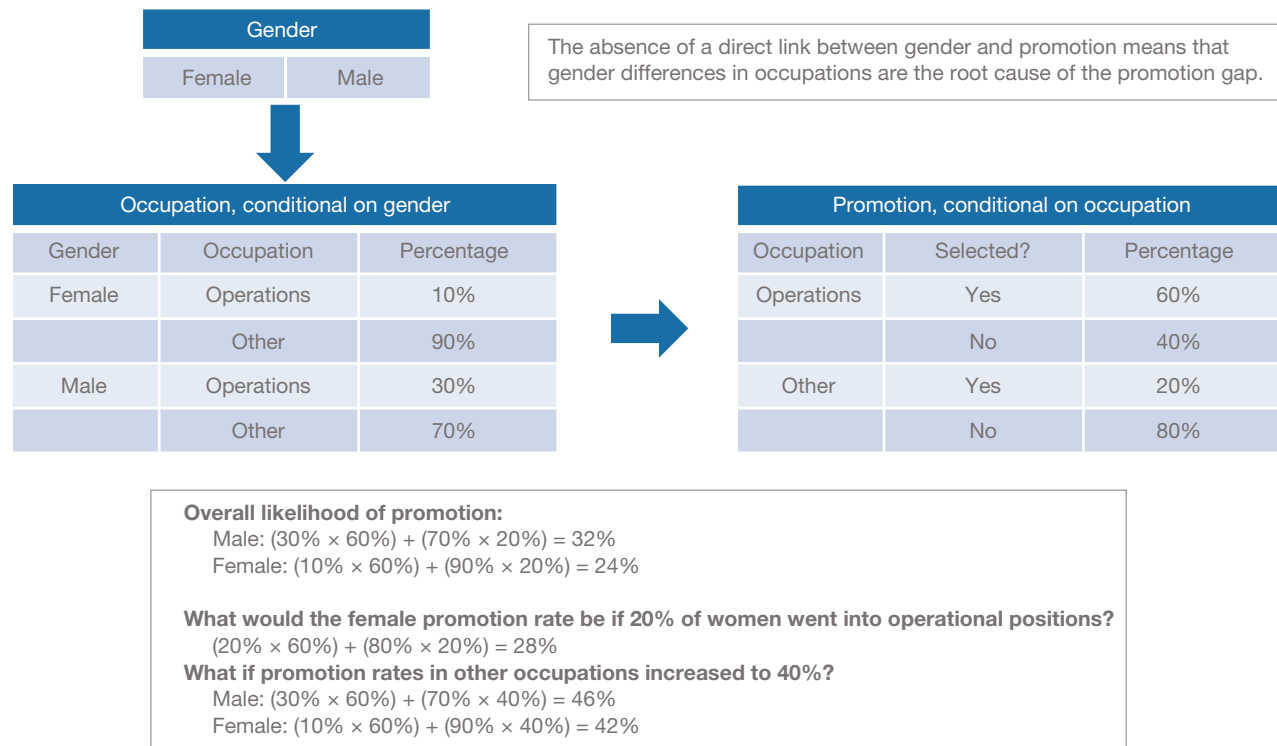
A Simplified Example of a Bayesian Network Applied to Career Success

Figure 1 shows a hypothetical example of a BN that includes one demographic characteristic (gender), one career factor (whether the servicemember serves in an operational occupation), and an outcome (whether the servicemember is promoted). A BN consists of two parts: (1) the structure, represented by arrows, showing which variables affect the probabilities of the other variables, and (2) the estimated CPTs, representing the probability of each combination of characteristics. Either part can be learned

TABLE 1

Demographic Disparity Assessment Tool Requirements and Bayesian Network Capabilities

Requirement	Bayesian Network Capability
Inputs and metrics are cumulative and easy to understand and explain.	Model inputs are probability tables, and metrics match the two attributes that are most important to policymakers: success likelihood and representation.
Incorporate contributing factors and point to root causes.	Machine-learning algorithms can determine the structure of the network for areas in which it is unclear whether certain characteristics strongly relate to career outcomes.
Results reflect the real-time state of personnel policies.	While today's workforce can reflect past policies, a model that uses probability tables that are derived exclusively from recent data will produce statistics that reflect the real-time environment.
Incorporate new information and answer what-if queries.	Users can modify the network structure or probability tables and observe the impact of these modifications on equity metrics.

FIGURE 1
A Notional Bayesian Network for Gender Disparity in Promotion

Gender	
Female	Male

The absence of a direct link between gender and promotion means that gender differences in occupations are the root cause of the promotion gap.

Occupation, conditional on gender

Gender	Occupation	Percentage
Female	Operations	10%
	Other	90%
Male	Operations	30%
	Other	70%

Promotion, conditional on occupation

Occupation	Selected?	Percentage
Operations	Yes	60%
	No	40%
Other	Yes	20%
	No	80%

Overall likelihood of promotion:
Male: (30% × 60%) + (70% × 20%) = 32%
Female: (10% × 60%) + (90% × 20%) = 24%

What would the female promotion rate be if 20% of women went into operational positions?
(20% × 60%) + (80% × 20%) = 28%
What if promotion rates in other occupations increased to 40%?
Male: (30% × 60%) + (70% × 40%) = 46%
Female: (10% × 60%) + (90% × 40%) = 42%

from the data; provided by the researcher; or learned from the data, given information that the researcher provided.

The structure in this example shows that servicemember occupation depends on gender, while promotion likelihood depends on servicemember occupations. The lack of an arrow linking gender to promotion means that promotion rates between men and women are similar within each occupation category. Thus, the structure reveals that the root cause of the promotion disparity is a gender difference in occupations. The CPTs reflect this structure. Men and women have different probabilities of being in operational versus other occupations, and each occupation group has different promotion rates, **but the promotion rates are not calculated separately for each gender within an occupation**.

The box at the bottom of Figure 1 describes some notional uses of the example BN. First, it shows that the gender difference in occupations, coupled with the fact that operational occupations are favored in the promotion process, will tend to

produce a gender disparity in promotion likelihood. The BN reports this difference in the most intuitive way—the overall cumulative difference in promotion likelihood between the genders. This hypothetical finding suggests that there are two ways to reduce gender disparities in promotion: increasing the proportion of women entering operational occupations and increasing promotion rates in nonoperational career fields. In weighing their courses of action (COAs), planners can use what-if queries to project the possible effects of policy changes in each area on the gender disparity in promotion if they are successful.[1] Figure 1 illustrates a sample query for each COA, both of which would cut the overall gender disparity in promotions from 8 percentage points down to 4.

For simplicity, Figure 1 does not depict the time dimension in the context of the assessment problem facing decisionmakers, but it is critical to understand how a system that uses recent data improves the decisionmaker's picture of the operational environment. One more example illustrates this facet of the

proposed technique. Consider a scenario in which 10 percent of the women at a recent promotion board are in operational occupations, producing the same overall promotion disparity in Figure 1 (24 percent likelihood for women versus 32 percent for men). If policy efforts increased the proportion of women going into operations up to 20 percent for more recent cohorts who have not yet reached the promotion milestone, the real-time overall likelihood of female promotion is actually 28 percent according to the BN, rather than 24 percent as measured by the recent board. Therefore, the board results are *backward-looking* and do not reflect recent progress in occupational classification, whereas the BN provides a more accurate picture of male versus female careers as they stand in real time.

Applying the technique at the scale of reality adds significant complexity to the challenge of determining the network structure and calculating the CPTs and output metrics. Still, the results of our analysis on real-world DoD data in the following section show that, with some algorithmic assistance, the process of understanding disparities and their root causes can still be straightforward from the perspective of the user.

Results Using Department of Defense Data

Research on racial, ethnic, and gender disparities in military career success in DoD going back to the mid-1990s has established a viable method for defining career progression milestones and linking them to officer characteristics (Asch, Miller, and Malchiodi, 2012; Hosek et al., 2001). We combine these data sources and definitions of career progression with the BN technique to form our proposed operational assessment tool for equity: MDEST. The "Summary of Military Demographic Equity Support Tool Data and Modeling" text box provides a brief methodological summary of the data sources, variables, outcome definitions, and notes on some particulars of how we applied the BN to DoD data stores.

As a part of this effort, we developed a minimally viable prototype application using open-source software.[2] This section gives an overview of the MDEST prototype application and illustrates its capabilities (Table 2) before closing with recommended steps for further development.

TABLE 2

Overview of Military Demographic Equity Support Tool Capabilities

Capability	Available?
Explore relationships between variables through a network visualization.	Yes
Remove disparities at key points and observe effects on career success.	Yes
Add links to the network to represent planned policy changes.	Yes
Incrementally adjust disparities and observe effects on career success.	No
View and modify conditional probability tables to explore effects on career success.	No
Save, reuse, and download scenario descriptions and results.	No
Refit BN model using different assumptions or algorithms.	No[a]

[a] This capability would require the application to have access to person-level microdata, creating potential security concerns for data protection.

Summary of Military Demographic Equity Support Tool Data and Modeling

Data Sources

We assembled monthly records for every servicemember in the active-duty officer workforce from the Defense Manpower Data Center, from January 2014 through December 2019. We used basic career characteristics from the Active Duty Master extracts, demographic information from the Defense Enrollment Eligibility Reporting System extracts, and recent deployment information from the Activation and Deployment files.

Variables

We include the following career characteristics, in addition to race, ethnicity, and gender, in our career model:

- service branch
- source of commission
- prior enlisted status
- educational attainment
- occupation category
- professional military education
- days deployed in the previous year
- current or prior service in a command position
- marital status and presence of children.

Career Outcomes

We follow the procedure described in Asch, Miller, and Malchiodi (2012) to create a picture of career success using promotion and retention rates at each pay grade through O-6. The procedure uses observed grade changes to identify service-specific windows at each grade in which servicemembers are considered for promotion, while defining retention at each grade according to whether servicemembers remain in the workforce long enough to reach the promotion consideration window.

Model Application Notes

The following is a summary of key decisions we made in the process of operationalizing the BN in the context of our problem. An advantage of this technique is that it allows an expert to input prior knowledge—such as known causal relationships between factors—into the network and it then learns the strengths of those and of other relationships.

- The only allowed links are between the status of career factors at the beginning of each window and the outcomes that immediately follow (e.g., marital status at the beginning of the O-3 promotion window can affect promotion to O-3, but marital status as an O-1 cannot).
- Career factors at each milestone can be affected only by factors at the previous milestone.
- Asch, Miller, and Malchiodi (2012) and Asch, Miller, and Weinberger (2016) found that marital status, number of children, and demographics affected retention as an O-3; gender affected retention at O-5; marital status and number of children affected promotion to O-4 and to O-6; and race and ethnicity affected promotion to O-5 and O-6. We added this expert knowledge by forcing the network to include links between demographic factors and these specific career outcomes. The network was allowed to automatically learn all other links.
- Service branch, race, ethnicity, gender, source of commission, and prior enlisted status are fixed for each individual at the most recent observed value.

Overview of MDEST Prototype Application

When the MDEST application runs, the user first sees an introductory screen that describes the purpose of the tool—to allow policymakers to formulate plans to mitigate racial, ethnic, and gender disparities (Figure 2). The user can select from the options displayed along the left-hand side of the screen to access the tool's different capabilities.

MDEST presents an interactive visualization of the relationships among demographics, other characteristics, and the career outcomes of promotion and retention (Figure 3). The visualization organizes the variables into rows that represent the characteristics, columns that represent the career milestone, and arrows that represent links between the variables. If two variables are linked with an arrow, this means that the state of the second variable depends on the values of the first. On the other hand, if the network does not have a link between two variables, this means that the states of the two variables do not depend on one another, once the network has taken all of the linked variables into account.[3]

MDEST calculates the probabilities that officers will reach different career milestones and displays these probabilities by race, ethnicity, and gender (Figure 4). The user can view three outcomes: (1) the overall probability that an officer will advance to the grades of O-2 to O-6; (2) the probability that an officer will be retained for long enough to be considered for promotion to O-2 through O-6, given that they reached the previous grade; and (3) the probability that an officer will be promoted given that they were retained long enough to be considered. These probabilities are broken out by race, ethnicity, and gender, and they are shown as a baseline scenario along with an alternate scenario containing user-specified changes. Cell colors reflect differences in outcome probabilities between demographic subgroups and reference categories.[4]

MDEST also calculates race, ethnicity, and gender representation by grade (Figure 5). This view is complementary to the conditional probabilities displayed in the Career Outcomes Tab. The cumulative application of the conditional probabilities underlies variations in demographic representation by grade.
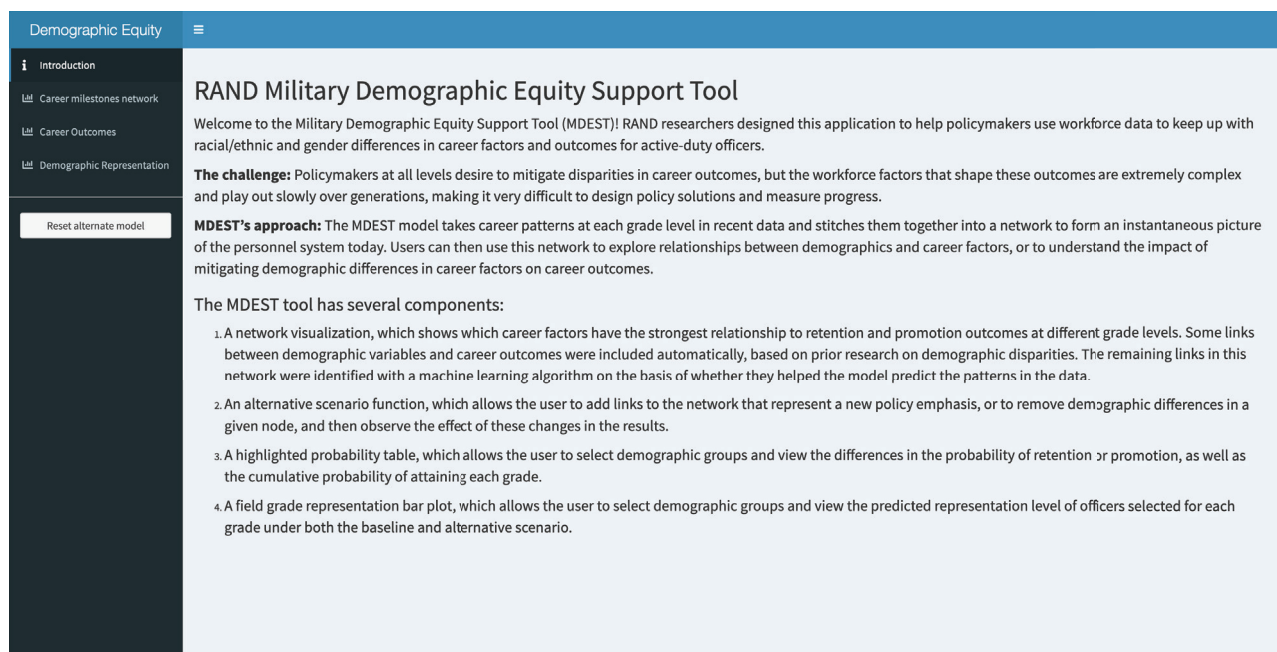
FIGURE 2
Introduction Tab

Demographic Equity

- i Introduction
- Career milestones network
- Career Outcomes
- Demographic Representation

Reset alternate model

RAND Military Demographic Equity Support Tool

Welcome to the Military Demographic Equity Support Tool (MDEST)! RAND researchers designed this application to help policymakers use workforce data to keep up with racial/ethnic and gender differences in career factors and outcomes for active-duty officers.

The challenge: Policymakers at all levels desire to mitigate disparities in career outcomes, but the workforce factors that shape these outcomes are extremely complex and play out slowly over generations, making it very difficult to design policy solutions and measure progress.

MDEST's approach: The MDEST model takes career patterns at each grade level in recent data and stitches them together into a network to form an instantaneous picture of the personnel system today. Users can then use this network to explore relationships between demographics and career factors, or to understand the impact of mitigating demographic differences in career factors on career outcomes.

The MDEST tool has several components:

1. A network visualization, which shows which career factors have the strongest relationship to retention and promotion outcomes at different grade levels. Some links between demographic variables and career outcomes were included automatically, based on prior research on demographic disparities. The remaining links in this network were identified with a machine learning algorithm on the basis of whether they helped the model predict the patterns in the data.

2. An alternative scenario function, which allows the user to add links to the network that represent a new policy emphasis, or to remove demographic differences in a given node, and then observe the effect of these changes in the results.

3. A highlighted probability table, which allows the user to select demographic groups and view the differences in the probability of retention or promotion, as well as the cumulative probability of attaining each grade.

4. A field grade representation bar plot, which allows the user to select demographic groups and view the predicted representation level of officers selected for each grade under both the baseline and alternative scenario.

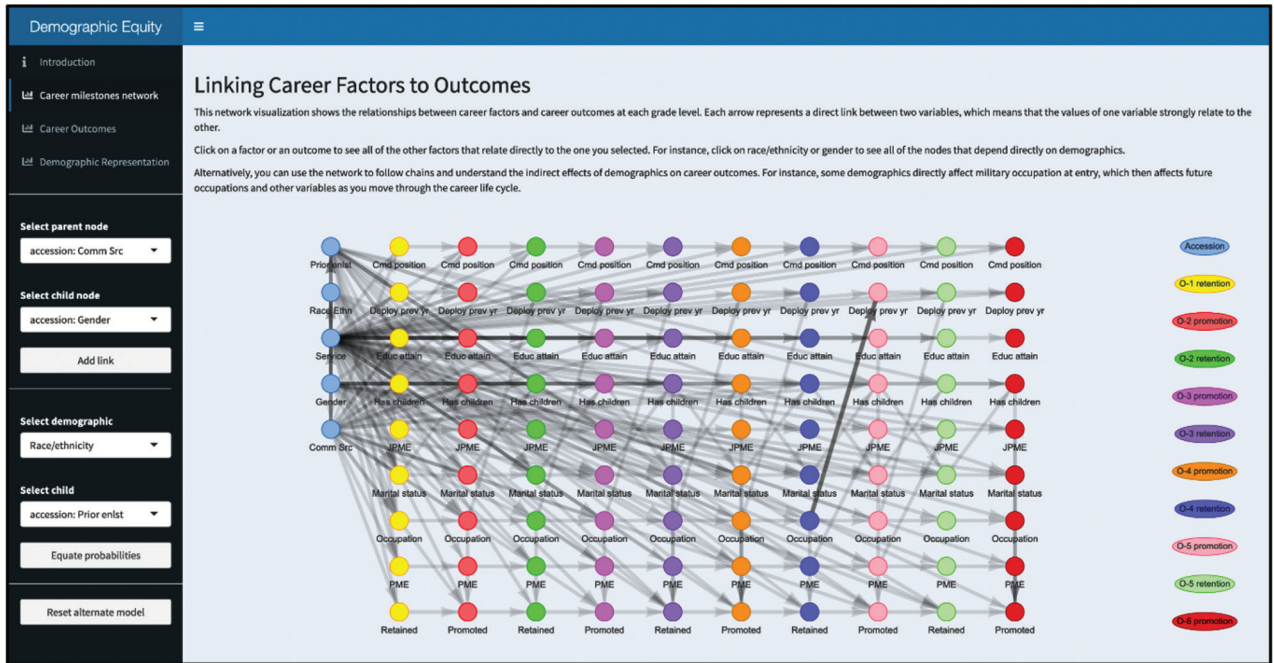FIGURE 3
Career Milestones Network Tab
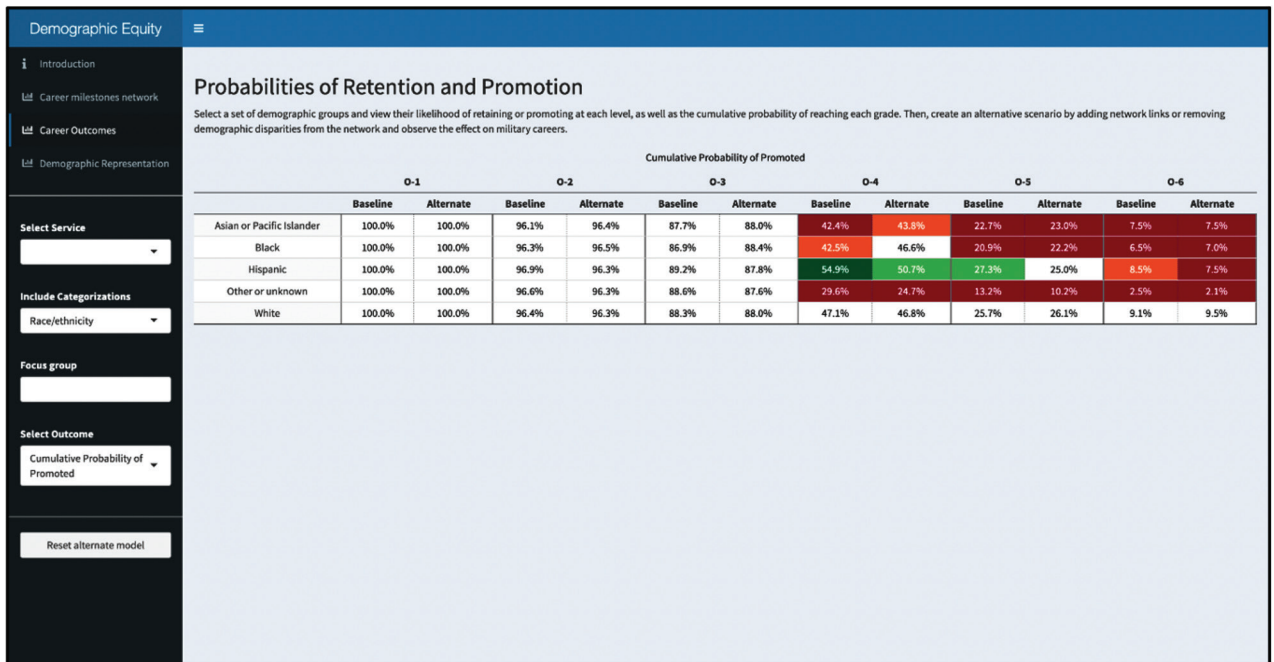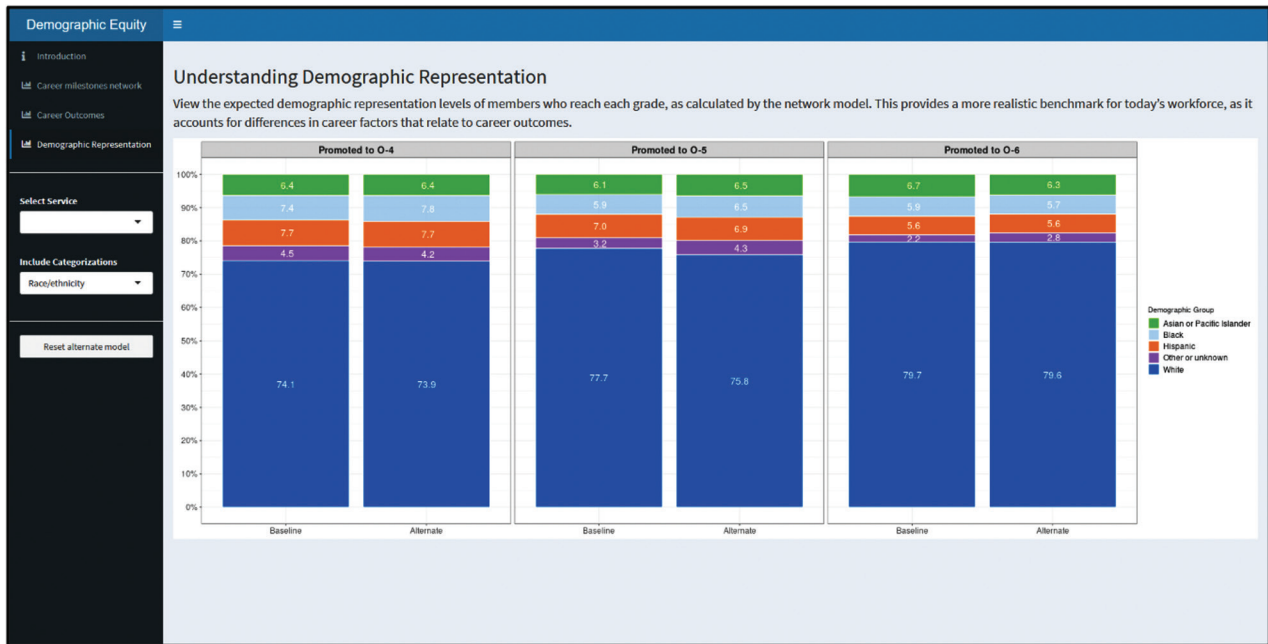

FIGURE 4
Career Outcomes Tab

FIGURE 5
Demographic Representation Tab

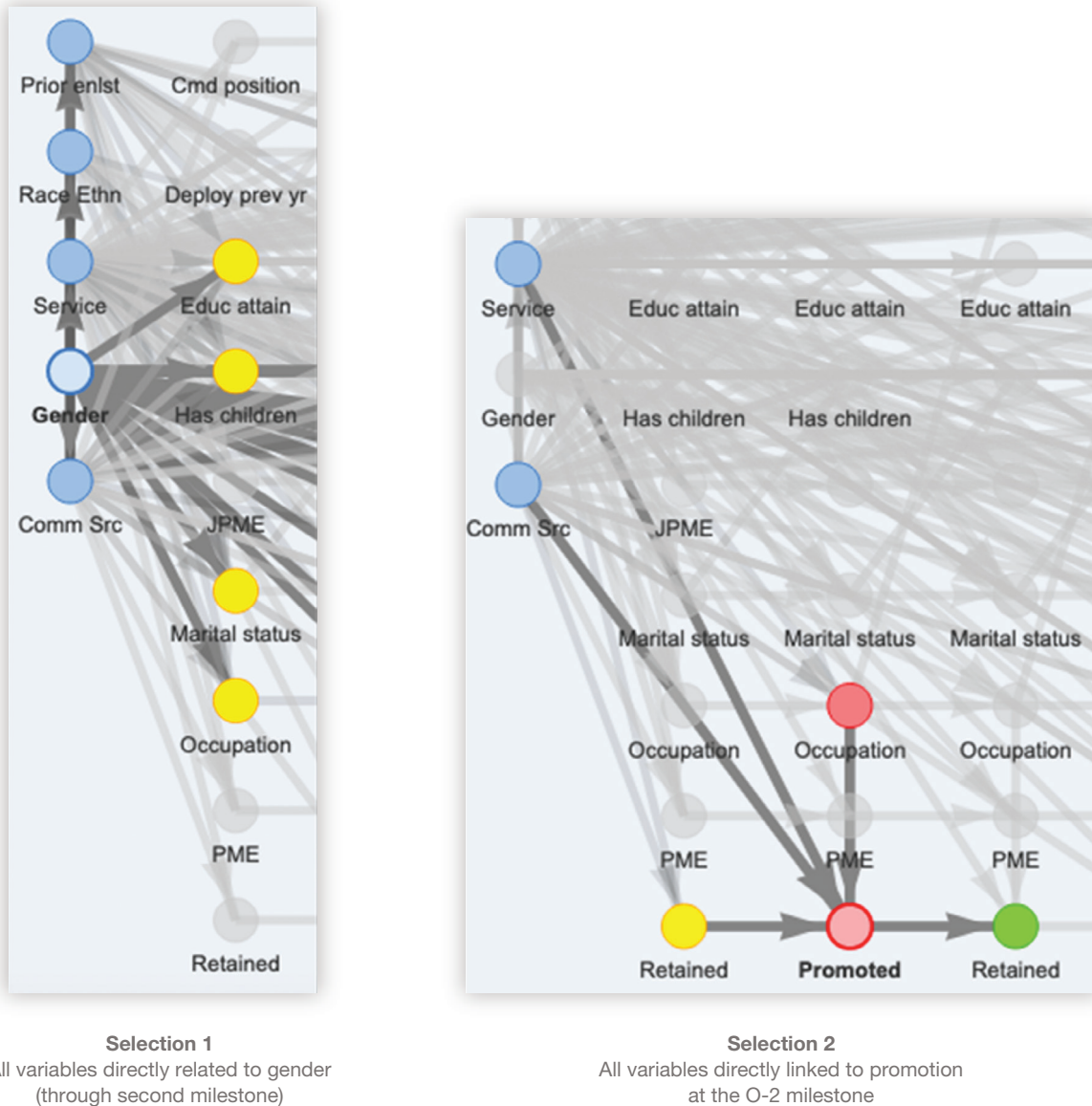
Illustration of MDEST Capabilities

MDEST allows the user to explore the relationship between variables through the network visualization. In this way, the user can identify disparities at key points and observe the effects of addressing those disparities on long-term career success.

Explore Relationships Between Variables Through a Network Visualization

The key contribution of the MDEST network visualization to understanding disparities lies in its interactivity. By clicking on an individual variable, the visualization highlights all variables directly linked to that variable. Figure 6 shows two informative examples of how a user might explore the network. In the left panel, the user has selected a demographic variable—gender—and the network has highlighted all other variables directly associated with gender. The selections show that all accession variables differ by gender, and gender directly relates to levels of education, marital status, the presence of children, and occupation values at the first milestone. The fact that the first outcome, retention, is not directly linked to gender means that there are no gender differences in the probabilities for this outcome after taking the other characteristics into account. The right panel shows an alternative in which the user begins by selecting an outcome to learn which variables affect it. The highlighted variables show that the probability of promotion to O-2 depends most strongly on servicemember occupation, service, and source of commission (it also relates to the previous and subsequent retention outcome, by construction). Knowing this, the user could trace the links further back to determine whether demographics affect occupations, which would mean that occupations could be a contributing factor to demographic differences in the promotion outcome.

FIGURE 6

Example Interactive Response to Selecting Individual Variables

Selection 1
All variables directly related to gender
(through second milestone)

Selection 2
All variables directly linked to promotion
at the O-2 milestone

Explore Scenarios by Removing Differences in Contributing Factors

Links between characteristics in the network show how variables relate to one another. These links inform potential strategies for mitigating career disparities. The BN technique also offers the capability to generate hundreds of thousands of simulated careers under the baseline assumptions and then compare these outcomes with simulations under alternative assumptions designed to represent potential policy impacts. In our MDEST prototype, users

can select variables linked to demographics (variables known to differ by demographic group) and then eliminate the demographic differences to observe the impact on career outcomes.

For example, prior analysis on historical officer career data reveals that black officers have relatively high representation in the Army relative to the other services. Furthermore, because of differences in the grade structure between services, promotion opportunities also differ for servicemembers at each milestone, depending on the service that they are in

(Asch, Miller, and Malchiodi, 2012, Appendix A). The fact that black servicemembers are more likely than white servicemembers to serve in the Army could lead to a racial disparity in promotion at career milestones where Army officers have lower promotion opportunities than the other services. At the same time, milestones for which the Army's grade structure leads to greater promotion opportunity would work in favor of greater equity on average across DoD.

Figure 7 shows MDEST's simulated results for this scenario. First, a comparison of the solid blue line with the solid red line reveals that black officers in DoD are slightly more likely than white officers to reach the O-3 retention milestone, or to reach the point where they would be considered for promotion to O-4. However, racial differences in promotion to O-4, and in turn, promotion to O-5, produce a gap of 4 percentage points in the likelihood of reaching the latter grade level. The dotted red line shows simulated outcomes for black officers under a scenario in which their tendency to serve in the different DoD services mirrors that of white officers.[5] The shift in the branch of service for black officers produces higher rates of retention as O-3s and brings the likelihoods of promotion and retention at the O-4 grade to parity. However, the likelihood of reaching O-5 shows that this parity is undone by a newly created promotion disparity, which arises because Army officers in the BN have a greater likelihood of promotion at this level. The hypothetical policy, therefore, could increase equity in midcareer outcomes but not necessarily at the senior grades. In this way, MDEST's ability to provide feedback on the cumulative career impacts offers important feedback to planners when deciding priorities for their programs.

FIGURE 7

Simulated Career Outcomes for White Officers Versus Black Officers in the Department of Defense
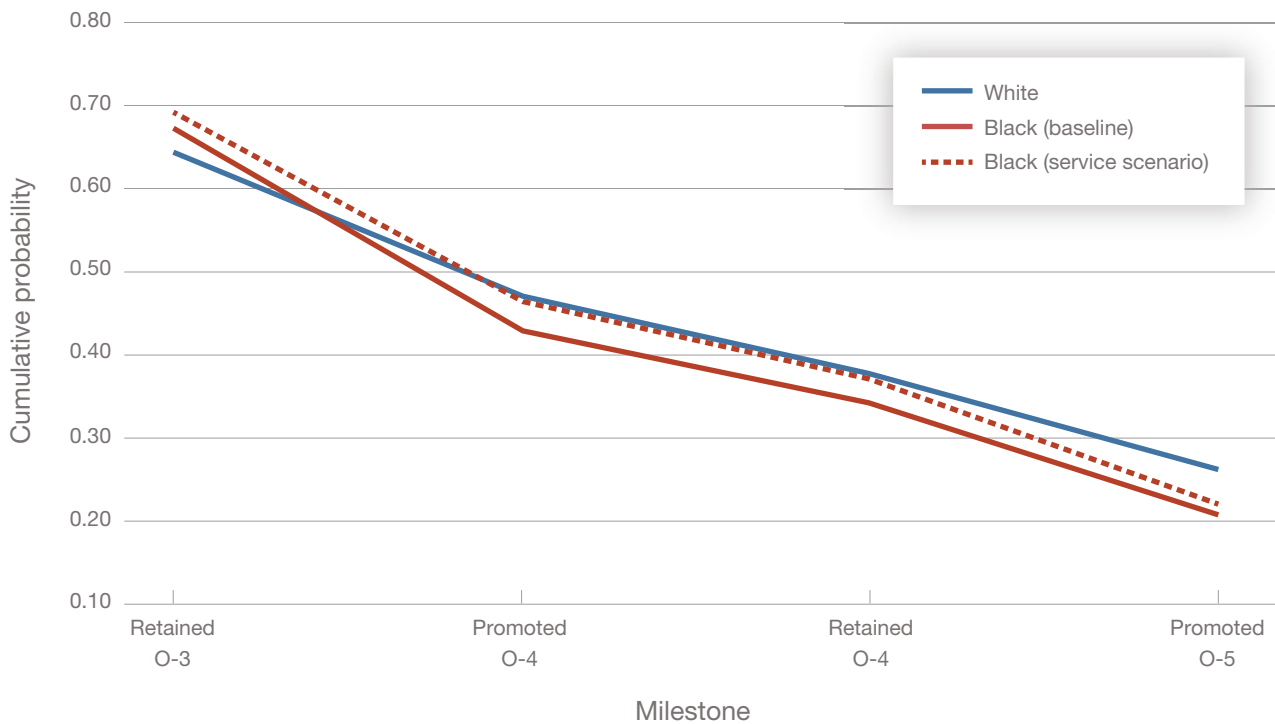
NOTE: The service scenario adjusts the branch of service at entry for black servicemembers while keeping all other relationships in the network constant. The change in career outcomes shows the isolated impact of service on the career outcomes shown on the horizontal axis. Career outcomes are cumulative, representing the overall probability that an officer of each race reaches each career milestone.

View Representation Metrics for Senior Grades

In addition to the likelihood of achieving career milestones, a key metric for progress on diversity initiatives is the level of representation for minority and female officers at senior grades. However, as previously discussed, the existing levels of representation at senior levels reflect policies and patterns from the past, making it difficult to interpret their implications for policy adjustments going forward. MDEST addresses this problem by producing a more instantaneous representation metric for each grade level, using solely the recent patterns in the data. Figure 8 shows a sample subset of these outputs by comparing the percentage of officers at entry—and then at grades O-4, O-5, and O-6—who belong to each

racial and ethnic category. The first bar shows that recent DoD accessions (pooled across all services) were 72.5 percent white officers, 7.8 percent black officers, and 19.7 percent officers of other minorities (which include Hispanic, Asian, Pacific Islander, and multiple or unknown race or ethnicity). The second bar shows that white officers are overrepresented among recent promotions to O-4 relative to accessions (76.6 percent versus 72.5 percent). However, the representation level from MDEST suggests that the early career patterns have improved somewhat and that the expected representation level for white officers at O-4 is closer to the level of accession than the recent promotions suggest. Moving to the right, the bars in Figure 8 show similar results for the O-5 and O-6 pay grades.

FIGURE 8

Representation Levels in 2014–2019 Data Compared with Representation Levels from Military Demographic Equity Support Tool (MDEST)
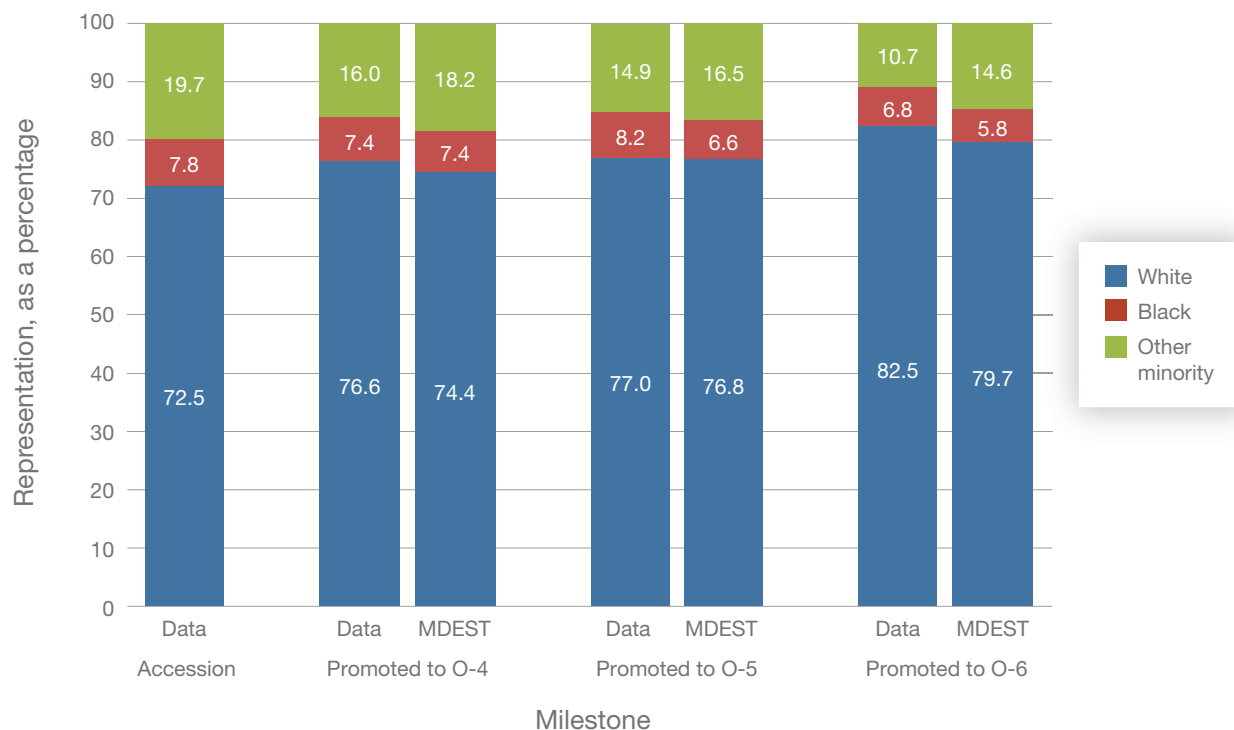
NOTE: The representation levels from the data are calculated as a percentage of all officers reaching the milestone from 2014 through 2019. The representation level is calculated from the BN probability tables as the probability distribution of the race and ethnicity variable, conditional on reaching each milestone.

Next Steps for Tool Development

Our focus in this initial effort was to implement the MDEST concept in a way that was cost-effective and achieved a minimum viable product with only basic features. Because of this scope, we largely relied on existing models and software for implementing this first version of the tool. Improving MDEST and putting a future version into production requires refinements in three main areas.

Improving the Data Flowing into the Tool

The most readily available data for this project lack precision on officer characteristics and career outcomes compared with the information that HRM practitioners use. We used regular workforce snapshots from the services' personnel management systems, which meant we could define promotion and retention outcomes based on changes in pay grade only. There is a significant time lag (sometimes a year or more) between when servicemembers are selected for promotion and when they "pin on" a new grade, making our outcomes less precise than the exact information possessed by the services about when servicemembers are considered for promotion and whether they are selected. This lag limits the ability to detect relationships between the outcomes and important characteristics. Detailed information from data specific to each service could also improve the quality of the characteristics included in the MDEST model.

Improving the Model Behind the Tool

Beyond the data inputs, our experience fitting a fully discrete BN suggests that the technique tends to underestimate racial, ethnic, and gender disparities compared with other techniques that have been used in past research.[6] The reason for this is that CPTs grow exponentially more complex with each additional link between a predictor and an outcome. From the perspective of the algorithm, the model becomes less accurate at a certain level of complexity after the most-important predictors have been included. Thus, the algorithm tended to leave out

The information value of MDEST would significantly improve if users could click on arrows or nodes in the network and view precisely how one variable influences other variables.

demographic effects that were not substantial enough to justify the additional complexity. The discrete BN made sense for this effort, because it was the most readily available technique, but future development could test more-flexible models and methods that do not have this downside.[7]

Improving the Interactive Functionality of the Tool

Finally, the first version of the tool demonstrated how the network structure and simulation capabilities can be informative to understanding demographic disparities and root causes. However, MDEST does not automatically identify root cause variables. Future versions should develop a method to flag characteristics that have explanatory potential for career disparities. In addition, MDEST does not allow the user to browse the CPTs and understand the meaning of a link for root cause analysis. The information value of MDEST would significantly improve if users could click on arrows or nodes in the network and view precisely how one variable influences other variables and, eventually, modify the relationships and simulate the resulting effects.

The MDEST results show promise as a tool for senior HRM leaders to use in assessing and planning programs and policies that aim to promote greater equity in military personnel.

Conclusion

The MDEST concept demonstration and initial results show some promise for its viability as a tool for senior HRM leaders to use in assessing and planning programs and policies that aim to promote greater equity in the military personnel system.

A version of this tool, validated for accuracy and designed with end-user testing, could greatly improve planners' understanding of the personnel environment and make it easier to communicate at different levels concerning the real-time state of the system and ongoing efforts to improve it.

Notes

[1]   Figure 1 shows results in terms of the likelihood of promotion, but, as our real-world examples in subsequent sections show, the BN has everything it needs to calculate gender representation in the promoted population if the user desires this metric as well.

[2]   The team used the bnlearn R package to fit and perform queries on network models (Scutari, 2010). The team created an interactive web tool using R's shiny framework to allow analysts to interact with network models (Chang et al., 2021). The tool includes a network visualization that is generated with the visNetwork R package (Almende, Thieurmel, and Robert, 2019).

[3]   The interpretation of the links between variables depends on how one determines the network structure. Most of the links in the example network were learned using a hill-climbing greedy search algorithm (Nagarajan, Scutari, and Lèbre, 2013). This algorithm begins with any links that we forced it to include using prior information, and then it explores possibilities for adding and deleting links according to how well they explain the patterns in the data, until the point at which the network can no longer find improvements. Thus, the links represent the subset of variables that are most important in explaining each outcome.

[4]   Male officers were treated as the reference category for gender comparisons, and white officers were treated as the reference category for race and ethnicity comparisons.

[5]   U.S. Space Force officers would be included with the U.S. Air Force in the time of the historical data.

[6]   To assess the fit of demographic disparities, we compared actual disparities in the data with predicted disparities from networks that used different combinations of algorithms, thresholds for including variable links, and methods for fitting probabilities. Even at very low thresholds for including variables, the algorithms tended to leave out links with demographic variables once career factors had been taken into account. The reason for this behavior is that the discrete BN has no targeted way to add in a demographic effect, so a new link must add a demographic adjustment to every row of the existing CPTs, adding significantly more complexity to the model. The resulting network models tended to predict smaller disparities than those observed in the data. In our results, we mandated the inclusion of demographic links where prior research identified significant unexplained disparities, which helped produce a better fit of the disparities in the data.

[7]   Specifically, we recommend testing BNs using binary regressions, perhaps with shrinkage applied to avoid overfitting in the case of many categorical parameters. The regression technique would allow for marginal effects for particular demographic groups, whereas the CPTs must make an "all or nothing" decision on whether to include effects for every demographic group conditional on every other variable in the table.

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About This Tool

Addressing racial, ethnic, and gender disparities in career success is a significant challenge facing military human resources (HR) decisionmakers. Policymakers frequently emphasize the goal of building a military workforce that represents the U.S. population, but women, racial minorities, and ethnic minorities tend to be underrepresented in the workforce as a whole and particularly among higher-ranking officers. Although these patterns are well documented, understanding the root causes behind them and tracking the progress of mitigation efforts is not easy or transparent because many complex factors in addition to demographics shape career outcomes over a protracted time horizon. As a result, even if new policy efforts were extremely successful, their results might not be apparent in broader workforce demographics for many years.

This challenge highlights the need for a business intelligence capability to help decisionmakers understand the impact of policy efforts to improve the representation of underrepresented groups as it unfolds, rather than waiting to observe long-term changes in workforce demographics. A continuously updating picture of racial, ethnic, and gender disparities in key career milestones and the contributing factors to those disparities could make it possible to refine policies and prioritize efforts around the goal of maximizing the cumulative impact on career success for women, racial minorities, and ethnic minorities.

This document presents a concept and prototype for a decision support tool that, if developed further, could help HR decisionmakers do just that. The tool uses U.S. Department of Defense workforce data to inform a model of how demographics and other factors contribute to career success at each stage. The key innovation of this model is that it combines recent patterns at each career milestone into a single instantaneous picture of a career life cycle. Compared with the commonly reported statistics of racial, ethnic, and gender representation in the workforce, these results provide a more accurate view of the largest barriers. The tool would allow decisionmakers to simulate the impact of early-career interventions on downstream promotion or retention outcomes.

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