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Psychology and the Mined: Overcoming Psychological Barriers to the Use of Statistics in Naval Mine Warfare

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Summary

Mine warfare (MIW) almost always entails uncertainty and imprecise assessments regarding risk. One approach to characterizing risks and understanding inherent uncertainties is to use data to develop probabilistic models that can support decision-making. Statistics can be combined with intelligence estimates to help a commander assess the number of residual mines after a clearance operation has been completed. Such assessments can provide a probability distribution for the number of residual mines (i.e., the probability that zero mines remain, that one mine remains, that two mines remain, etc.). Further mathematical or computational analysis, aided by intelligence-based assumptions regarding the mines' characteristics, can then be used to estimate the risk the mines pose to ships.

However, the use of statistical methods in MIW may be impeded by psychological phenomena that are common in risk assessment. This has been shown both in the context of psychological experiments and in historical MIW decision-making. Decision-makers, including those who are experienced with statistics, often make decisions that conflict with the statistical insights available to them. They may dismiss statistical analyses outright, or assume that the probability of an event is proportional to their ability to envision it. Decision-makers also frequently discern patterns in random phenomena, and often assume that small samples of any data set are representative of the whole. They are often led astray in their decisions by the way in which a question is framed, or by the order in which particular possibilities are discussed.

These psychological phenomena can have an operational impact in addressing mine warfare threats. Despite statistical guidance, a commander may overestimate or underestimate the risk of transiting a particular minefield, due to the common behaviors described above. This can lead to unnecessary impedance of an operation, if ships do

not transit low-risk areas, or unacceptable casualty rates, if ships transit high-risk areas.

This paper provides two means of reducing the risk that commanders' judgment will be overshadowed by these psychological influences, to the exclusion of statistical evidence. First, commanders who may make decisions in a mined environment can make themselves aware of these psychological tendencies, and thereby reduce their susceptibility to them. Second, they can actively attempt to debias their judgments, both by reviewing the statistics and by listing reasons why their instinctive responses may be wrong. These techniques can help to ensure that their decisions are as robust as possible, and that they have overcome many of the biases people are susceptible to when making decisions. This enhanced judgment is particularly important as mine warfare is mainstreamed, and commanders whose primary expertise lies in other warfare areas are increasingly called upon to make decisions relating to mine warfare.

Introduction

When deciding whether (or how) to transit mined waters, commanders face a high degree of uncertainty regarding the threat posed by the minefield. The commander of a ship or fleet has a mission to fulfill that would require transit or usage of the mined waterspace, but knows that this entails some risk of mines damaging or even sinking ships. The commander must weigh the importance of completing the mission relative to the uncertain threat posed by the naval mines.

Some of the commander's uncertainty can be ameliorated through the use of statistical analysis, in tandem with mathematical or Monte Carlo modeling to assess risk. Such analysis can provide a probability that a ship transiting a minefield will be damaged by a mine. When integrated with other sources of data (such as intelligence and insights gleaned from experience), it can help to inform decision-making and render it more effective.

Despite the potential value of statistical analyses in mine warfare (MIW), both experimental psychology and historical examples demonstrate impediments to their use. The purpose of this paper is to enumerate both means by which statistical analyses can inform and complement commanders' judgment, and to illuminate some of the psychological factors that can prevent such analyses from being used effectively. By increasing awareness of human biases in judgment, and offering tools for statistical assessment as well as active debiasing, the paper aims to help commanders make better decisions in a mined environment.

This paper is intended to be used by two distinct audiences. The first consists of officers whose focus is on MIW. They can use it to better understand how the concepts of risk, and the perception of risk, affect the actions and decisions of the larger fleet. In addition, non-MIW specialists who are responsible for decision-making regarding the potential use of mined waters can understand what MIW risk really means, and the impact of how information regarding risk is analyzed, interpreted, and presented. This can enable them to improve their decisions in the face of a potential MIW threat.

Overview of the paper

We begin by presenting a brief outline of how statistical analyses can be used in MIW. Next, we examine the psychology of risk, judgment, and decision-making. These analyses are integrated with mine-warfare examples, both historical and hypothetical, to demonstrate barriers to good decision-making. Finally, we draw some conclusions regarding the key points highlighted in the paper.

Statistical analysis of the MIW problem

Based on minefield clearance or reconnaissance data, statistics can be used to assess the number of mines that remain in a given field. These methodologies can also incorporate intelligence data and other insights to develop a quantitative portrayal of the field. Below, we begin by showing how the use of statistics can aid in assessing the number of residual mines in a field after clearance. Building on this, we then show how mathematical or Monte Carlo modeling can incorporate these results to gauge the overall risk that the minefield poses to ships.

Assessing the number of residual mines after clearance

The process of minefield clearance not only reduces the hazard that the minefield poses, but also provides information about the minefield itself. Specifically, the results of the clearance process can be used to determine the probability that a given number of mines remains after clearance has been conducted. For example, if a clearance process has a known independent probability of clearing any particular mine (under particular conditions), the number of mines cleared in a given area can be used to back-calculate the probability distribution for the number of mines remaining in that area. Table 1 illustrates a situation in which a clearance method (with 80% probability of clearing any given mine) has resulted in the clearance of 5 mines. Binomial calculations[1] are used to determine the probability that any given number of mines initially (5, 6, 7, etc.) resulted in the clearance of exactly 5 mines. This uses the binomial formula that for an independent probability **p** of clearance for each of **n** mines, the probability of exactly **y** (in this case, 5) successes is:

$$P_{y,n} = p^{y}\ (1\text{-}p)^{(n\text{-}y)}\ n! \ /\ [y!\ (n\text{-}y)!]$$

Assuming that we have no *a priori* information (e.g., intelligence from another source) regarding the number of mines initially, all probabilities are weighted equally in the Bayesian calculation that follows; i.e., to normalize the probabilities so that they sum to 100%, we divide each probability by their sum. This results in the distribution shown in table 1, indicating that the average of the distribution for the number of mines remaining is 1.50, which is an average of the ensemble over all cases in which 5 mines were cleared.[2] The most probable number of mines remaining is 1 and there is a greater than 95% probability that 4 or fewer mines remain.

Table 1. Probability distribution for the number of residual mines after clearance[a]

Initial number of mines	Number of mines remaining	Normalized probability that exactly 5 mines would be cleared	Cumulative probability	Contribution to average
5	0	26.3%	26.3%	0.000
6	1	31.5%	57.7%	0.315
7	2	22.1%	79.8%	0.442
8	3	11.8%	91.6%	0.354
9	4	5.3%	96.9%	0.212
10	5	2.1%	99.0%	0.105
11	6	0.8%	99.8%	0.048
12	7	0.3%	100.0%	0.021
Total		100.0%		1.496

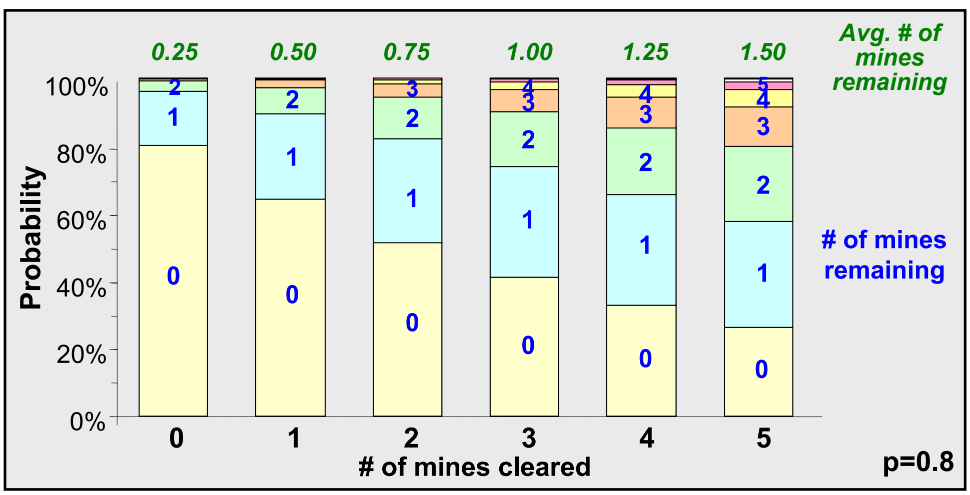
a. Binomial/Bayesian probability calculations were used. We assumed a clearance method that has an 80% independent probability of clearing any particular mine, and which cleared 5 mines. The average of the distribution is 1.50 (lower right cell), and there is a probability of greater than 95% that 4 or fewer mines remain.

1. In this paper, we briefly explain the application of binomial and Bayesian statistical methods, without delving into the mathematics behind their use. If the reader is interested in learning more about the basis for this type of analysis, almost any good probability or statistics textbook can provide such information. Several good ones are *Introduction to A First Course in Probability* [1] by Sheldon Ross, *Probability and Statistics for Scientists and Engineers* [2] by Walter Rosenkrantz, *Subjective and Objective Bayesian Statistics* [3] by S. James Press, and *Statistics Manual* [4] by Edwin Crow et al.

2. Obviously, there cannot be exactly 1.5 mines remaining, since "half-mines" do not exist. By way of analogy, the fact that a population has an average of 2.4 children per family does not imply that any given family has fractional children. However, knowing that the average value is 1.5 provides some insight into the actual whole number of mines that likely remain.

We have incorporated these calculations into a spreadsheet. The results from this spreadsheet are shown in figure 1, for an 80% probability of clearance, and different numbers of mines cleared. The black numbers at the bottom of the figure show the number of mines cleared, while the vertical axis shows the probability of any given number of residual mines. The blue numbers within each column show the number of residual mines. If three mines were cleared (corresponding to a 3 at the bottom of the graph), there would be a 41% chance that 0 mines remained (shown by the length of the bottom bar, marked with a 0, immediately above the 3). There would be a 33% chance that one mine remained (shown by the length of the light blue bar containing a '1' immediately above the bottom bar), and so on. The most probable number of mines remaining for any given number of mines cleared is indicated by the largest color block in each bar. The green number at the top, 1.35, is the average number of residual mines under these conditions.

Figure 1. Probability distributions for the number of residual mines[a]



a. This assumes an 80% probability of clearing any given mine, and no prior intelligence information about the number of mines present.

Assumptions

Our analysis incorporates a few assumptions which we state explicitly at this time. First, we have assumed that the probability of clearance is uniform and precisely known. The probability of clearance may be a function of the environment, the type of mine, operator experience, equipment reliability, and other factors. This probability may differ from that which was assessed based on earlier documentation and/or exercises. Moreover, clearing some areas may provide information that raises the probability of clearance in other areas (e.g., what to look for or where to look for it, based on an adversary's mining tactics). As a result of these factors, the probability of clearance may be uncertain and/or variable. Second, we have assumed that the number of mines cleared is known. While this is often the case, there could be circumstances under which suspected mines are destroyed by detonation. If no secondary detonation or follow-up identification occurs, it may not be entirely clear whether a particular object was or was not a mine. Third, we have assumed that the enemy is no longer engaged in hostile actions; these could include reseeding of the minefield and/or attacking mine countermeasures (MCM) assets.

Table 2 demonstrates the impact that such uncertainties can have on the assessed average number of mines remaining. If we know that 5 mines were cleared and the probability of clearance was 80%, then the average number of mines remaining would be 1.50. (There would be a probabilistic distribution of the number remaining, as was shown in table 1 and figure 1, but we have summarized that distribution by a single number here.) However, if the probability of clearance were somewhere between 75% and 85%, and the number of mines cleared were either 4 or 5, then the average number of mines remaining would be somewhere between 0.88 and 2.00. These data points are encapsulated in a box near the center of table 2.

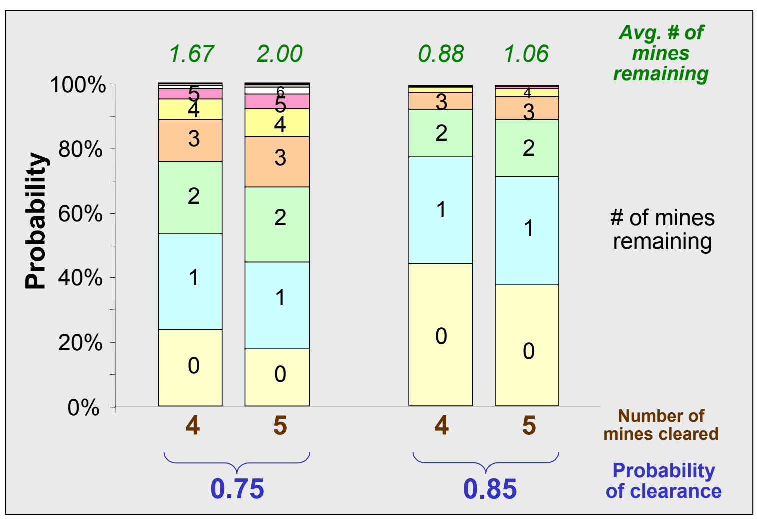
The range of possible numbers of mines remaining is greater than the range of the averages for the data points boxed above. The probability distributions for the number of mines remaining is shown in figure 2. For 5 mines cleared and a probability of clearance of 75%, there is a 22% chance that at least four mines remain; for four mines cleared and a probability of clearance of 85%, there is a 44% chance that no mines remain at all (and only a 7% chance that at least four remain).

Table 2. Average numbers of residual mines[a]

No. of mines cleared	p=70%	Probability p=75%	of p=80%	clearance p=85%	p=90%	p=95%
0	0.43	0.33	0.25	0.18	0.11	0.05
1	0.86	0.67	0.50	0.35	0.22	0.11
2	1.29	1.00	0.75	0.53	0.33	0.16
3	1.71	1.33	1.00	0.71	0.44	0.21
4	2.14	1.67	1.25	0.88	0.56	0.26
5	2.57	2.00	1.50	1.06	0.67	0.32
6	3.00	2.33	1.75	1.24	0.78	0.37
7	3.43	2.67	2.00	1.41	0.89	0.42

a. As a function of the number of mines cleared and the probability of clearance.

Figure 2. Probability distributions for the number of mines remaining.[a]



a. Given probabilities of clearance of 75%-85% and 4 to 5 mines cleared.

A second major caveat is that we have assumed that we have no prior information about the number of mines present. In mathematical terms, we would say that all possible numbers of mines have equal *a priori* probabilities. However, we could envision situations in which we have additional information about the number of mines, and we can use this information to complement data collected from clearance operations. For example, intelligence could indicate that 0-4 small boats, each with a capacity of 5 mines, were used to mine the harbor. We assume that there is a 20% probability that zero boats were used, a 20% probability that one boat was used, a 20% probability that two boats were used, etc., for up to four boats. We also assume that each boat, if deployed, deployed the maximum complement of 5 mines. Therefore, there is a 20% probability that 0 mines were laid, a 20% probability that 5 mines were laid, etc., up to 20 mines. Intelligence also indicates that each mine has a 10% probability of being defective.[3]

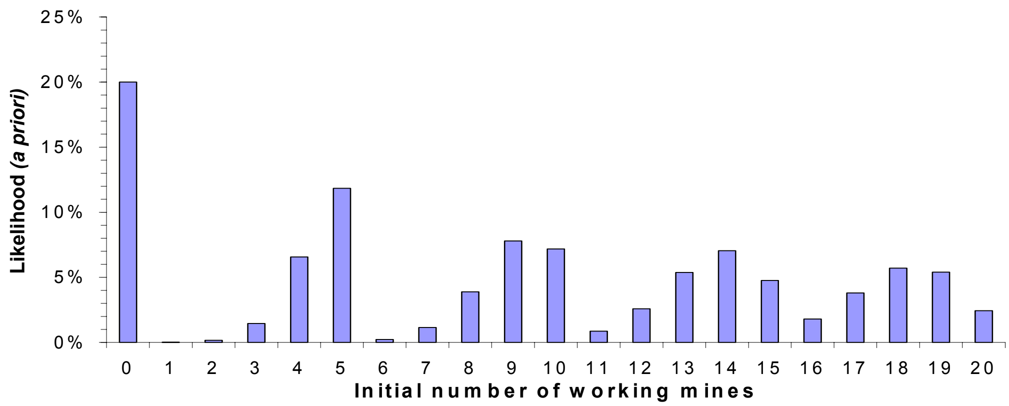
The probability for any given number of working mines is shown in figure 3. Applying Bayes' Theorem and assuming that we can clear any working mine with a probability of 80% via influence sweeping, we would obtain the probability distributions shown in figure 4 for the number of mines remaining.

3.In this case, the *a priori* probability that there are **z** working mines is

$$P_z = (0.2)\ (0.9)^z\ (0.1)^{(20-z)}\ \{20!/[z!\ (20-z)!]\}$$
$$+\ (0.2)\ (0.9)^z\ (0.1)^{(15-z)}\ \{15!/[z!(15-z)!]\}$$
$$+\ (0.2)\ (0.9)^z\ (0.1)^{(10-z)}\ \{10!/[z!\ (10-z)!]\}$$
$$+\ (0.2)\ (0.9)^z\ (0.1)^{(5-z)}\ \{5!/[z!\ (5-z)!]\}.$$

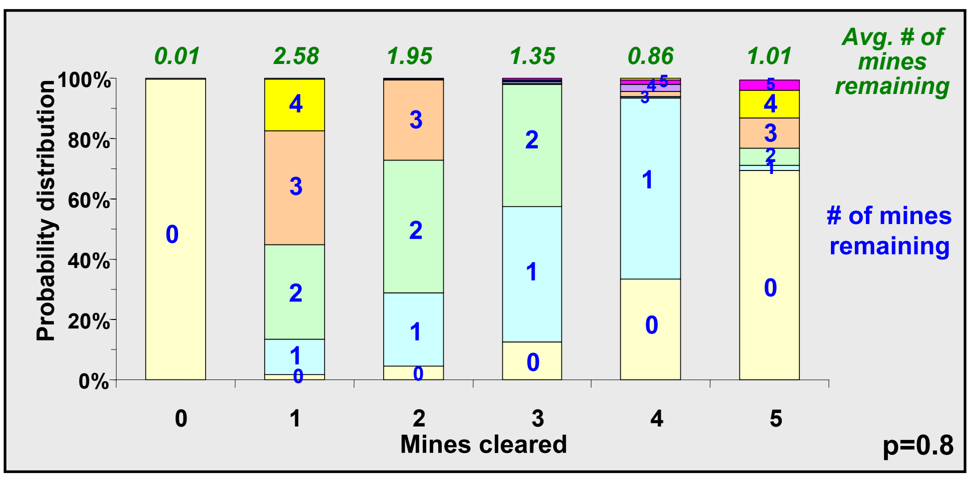
If z is greater than 5, the last term is removed from the equation; if it is greater than ten, the second-to-last term is also removed; if it is greater than 15, the third-to-last term is also removed. If z is 0, the *a priori* probability is 20%.

Figure 3. *A priori* probabilities for different numbers of residual working mines[a]



a. Assuming mines are laid in batches of 5, with a maximum of 20, and each mine has a 10% probability of being defective.

Figure 4. Probability distributions for the number of residual working mines[a]



a. Assuming an 80% independent probability of clearance for 0 to 5 mines cleared and *a priori* likelihoods as shown in figure 3.

The intelligence we have used in this situation results in some interesting changes relative to the previous case, in which we relied solely on clearance data. In the previous case, the average number of residual mines (shown in green at the top of figure 2) increased linearly as a function of the number of mines cleared. However, in the present situation, the average number of mines remaining (shown in green at the top of figure 4) does not rise monotonically with increasing number cleared; rather, it bounces around. This reflects the intelligence-based bias for initial numbers of working mines that are multiples of 5 (or slightly less). Since it is very unlikely that there were initially 1 to 2 working mines, clearing 1 to 2 mines implies that 2 to 3 more probably remain; clearing 4 mines, however, implies that 0 or 1 remain out of the group of 5.

Analysis of the threat posed by remaining mines

While we can use such calculations to assess the number of mines remaining in the field, these analyses alone do not characterize the risk that the mines pose to transitors. Risk is a primary measure of effectiveness (MOE) in MIW: the probability that a ship will be damaged by a mine is the most important metric for determining how (or if) mined waters will be transited, and whether more MCM operations will be conducted.

Unfortunately, risk is a more complex MOE than the number of residual mines. The risk to ships is a function not only of the number of mines, but also of various parameters governing mine-ship interactions (such as actuation and damage radii, the use of shipcounters, and mine reliability) and ships' navigational behaviors. Once assumptions have been made regarding these areas, either Monte Carlo or purely mathematical models (such as that currently incorporated into the MEDAL tactical decision aid) can be used to evaluate risk.

Monte Carlo analysis

Monte Carlo methodologies simulate the interactions of mines and ships, applying specified rules to assess the outcomes of these interactions. For example, a Monte Carlo simulation may consist of a computer program that creates minefields with particular characteristics. CNA has developed such a Monte Carlo, called CAPTMEIN, which will be described fully in forthcoming papers. Briefly, the program simulates MCM by clearing mines according to a particular rule set (e.g., each mine has an 80% chance of being eliminated). Subsequently, ships are assigned particular behaviors (e.g., straight paths through the minefield), and the program then determines whether ships' paths had crossed within the damage radii of mines. The program repeats this process thousands of times, and collects statistical data on how varying inputs affect the outcomes. The result is a probability statement that characterizes the likelihood that a ship would pass through this particular waterspace without being hit.

Mathematical analysis

Minefield risk can also be assessed using pure mathematics. This is the way in which the MEDAL program evaluates risk, based on user inputs and clearance data. However, relying on pure mathematics usually involves making many simplifying assumptions that enable complex situations to be made mathematically tractable.

We now present an example of such analysis. Ships need to transit a channel 1 kilometer wide, which contains mines with 75-meter actuation and damage radii. Ships transit perpendicular to the minefield, so each mine effectively represents a linear hazard zone 150 meters wide, perpendicular to the direction of transit. (In effect, the entire minefield can be treated as a linear rather than an areal entity.) The adversary, knowing the channel width and damage radius, has not placed any mines within 75 meters of the edge (to maximize the hazard posed). However, the adversary does not realize that the ships' drafts confine them to the middle 600 meters of the channel.[4] A layout of the minefield (assuming 3 mines are present) is shown in figure 5. The mines have no shipcounters or other mine counter-countermeasures, and all are 100% reliable. The probability of clearance (independent probability of clearing any individual mine) is 80%, and 10 mines have already been cleared. Any remaining mines are randomly distributed within the channel (i.e., they have a uniform probability of being anywhere within the channel).[5] All *a priori* probabilities for numbers of mines are equal.

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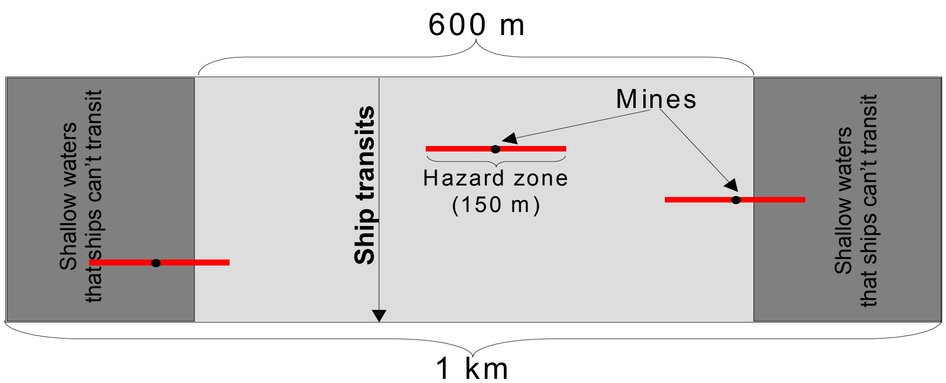
4. Confining transits to the central 600 meters of the channel eliminates edge effects (e.g., reduced hazard levels near the edges of the field). This makes the problem more tractable for the present example.

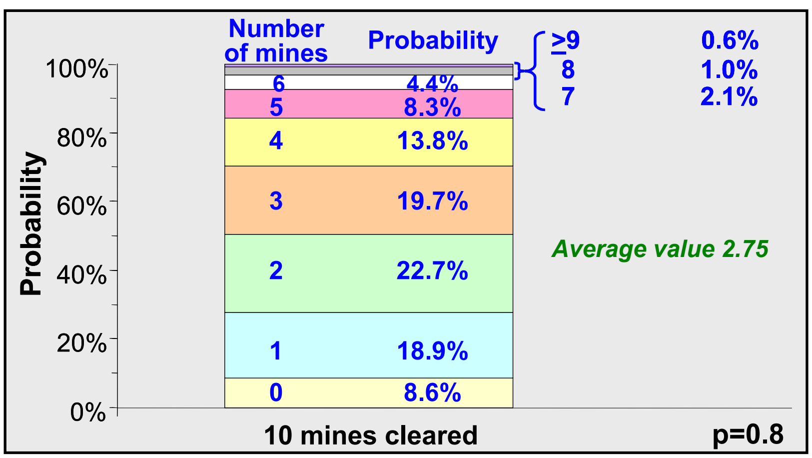
5. This allows for independent probabilities of clearing any given mine, even if their initial layout was ordered to some extent.

Figure 5. Diagram indicating the layout of the minefield.



Invoking the type of analysis described above, the probability distribution for the number of mines remaining is shown in figure 6 and the first column of table 3.

Figure 6. Probability distribution for the number of residual mines[a]



a. Assuming that 10 mines have been cleared, the probability of clearance is 80%, and *a priori* probabilities are uniform.

CAPTMEIN results for the threat to the first transitor (as a function of the number of mines) are shown in table 3. The risk that the first transitor is damaged by a mine is called the simple initial threat (SIT). The overall SIT is the sum of the products of the second and fourth columns (the probability that a given number of mines remains, multiplied by the SIT that such a number of mines would generate).

Table 3. SIT[a] as a function of the number of mines present

Number of mines remaining	Probability that this number of mines remains	Probability that this number of mines or fewer remains	SIT
0	8.6%	8.6%	0.0%
1	18.9%	27.5%	15.0%
2	22.7%	50.2%	27.8%
3	19.7%	69.8%	38.5%
4	13.8%	83.6%	47.8%
5	8.3%	91.8%	55.6%
6	4.4%	96.2%	62.3%
7	2.1%	98.4%	68.0%
8	1.0%	99.3%	72.9%
9	0.4%	99.7%	76.9%
Average (2.75 mines)			33.3%

a. SIT is the probability that the first transitor is damaged by a mine.

The probability that the first transitor is damaged by a mine is 33%. However, if a series of ships were to transit along a single uniform linear path, and a ship hit by a mine sunk immediately without obstructing the path, the average number of ships hit would be 0.41. This is simply the average number of mines, 2.75, multiplied by the fraction of the total channel that each covers, 0.15/1.00. In other words, while the probability that the pathway includes a nonzero number of mines is 33%, the average number of mines in the pathway is 0.41. CAPTMEIN Monte Carlo modeling generates the same result. Again, this example could be solved mathematically because of its relative simplicity. If we had introduced complicating factors (e.g., complex ship navigational behaviors or probabilistic mine effectiveness), a Monte Carlo model such as CAPTMEIN would likely have been the only means of analyzing the problem.

This result is not prescriptive in determining whether the ships should or should not transit the field; that question depends on the level of risk that the commander is willing to accept, and the operational advantages associated with transiting. However, this type of assessment can help the commander to quantify the risk and thereby make better decisions.

Naturally, it is always important to recognize the limitations and assumptions of statistical analyses, and not to use them in isolation or with undue reverence. Statistical and modeling analyses can help to inform the decision-making process, alongside insights that experience and intelligence bring to bear on the problem.

Summary of statistical analyses

MCM clearance operations not only reduce risk by eliminating mines, but also provide information that can be analyzed statistically to assess the number of residual mines in the field. As shown above, this information can be analyzed by itself, or it can incorporate additional intelligence insights.

After this has been done, a commander can use mathematical models (such as those contained within MEDAL) or Monte Carlo models (such as CAPTMEIN) to help assess the risk posed by these residual mines. These can serve as aids to decision-making in the face of a minefield, providing an indicator of the probability that ships entering the field will be damaged by the mines.

Psychology in MIW

The preceding section outlined methodologies for assessing the risk posed by minefields to ships. These can help commanders make well-grounded decisions about whether, or when, to transit minefields. By weighing the importance of their mission being completed in a timely fashion (or being completed at all) against the statistically calculated risk to their ships, they can arrive at a decision that incorporates the full breadth of knowledge available to them.

However, there are a variety of psychological factors that inhibit the effective use of statistical insights in assessing risk. These include:

- Dismissal of statistical evidence
- Confounding familiarity of scenarios with their probability
- Assuming that samples that are too small to be statistically significant are representative of a larger set
- Discerning patterns where they do not exist
- Having perceptions of a problem shaped by the way in which the problem is stated
- Over-attachment to the first quantitative values used in discussing a problem
- Overconfidence.

We begin by exploring how statistical information is often ignored, in MIW and other contexts.

Dismissing statistical evidence

Unfortunately, both history and psychology suggest that statistical analyses of minefields may be either ignored or unsought in the context of actual decision-making. In *Four Mining Campaigns: An*

Historical Analysis of the Decisions of the Commanders [5], James Meacham analyzed naval mining in the Dardanelles, the North Sea, Japan, and Korea. He concluded that in all of the campaigns, "There is no indication that a percentage risk was ever considered by the decision-makers faced with mines. On the contrary, there is much evidence that they did not." Rather, subjective perceptions and fears, often with little relation to reality, guided decision-making. For example, in the case of the Dardanelles [5]:

> The British were afraid of the minefields. Sir Roger Keyes in his memoirs declares, "There was never any question of taking battleships through unswept minefields." Nowhere does there appear any indication that anyone made even a rough attempt to calculate the chances of forcing the partially-swept field...In fact, the minefields were probably in bad shape. According to a German staff officer, a large number [of mines] had been carried away by the current or had sunk...It seems improbable that more than ten percent were really working.

Other historical accounts will be cited below, in tandem with corresponding insights from experimental psychologists, particularly Amos Tversky and Daniel Kahneman [6, 7].[6] They have documented that most people do not take statistical insights into account when faced with risk and uncertainty. In particular, they found that risk assessment is guided primarily by a series of heuristics[7] and inherent biases, regardless of the subject population's familiarity with statistical methods; doctoral candidates who used statistics frequently were as fallible as high-school students. Naval officers are unlikely to be less susceptible to these psychological biases than other individuals. Some of these heuristics and biases will be described below, together with their implications for MIW. Our aim is not to criticize naval officers for being subject, like other human beings, to biases in assessing probability and risk. Rather, it is to help them debias themselves and

6. A compendium of their work is included in the book *Judgment under Uncertainty: Heuristics and Biases* [6], as well as in a companion volume, *Choices, Values, and Frames* [7].

7. A heuristic is an approach to solving a problem.

enable them to use all of the relevant information available to them, partly by making them aware of common errors in risk perception.

Tversky and Kahneman made the case that people frequently dismiss statistics in circumstances when statistical analysis could help them make better decisions [8]. Tversky, Kahneman, and their colleagues conducted a number of experiments that corroborate this assessment [6]. In several experiments, doctors were given select information and asked to diagnose diseases. When no verbal information was given, the doctors used prior probabilities (the relative frequencies of diseases in the population) to assess the probability that patients had the disease. When verbal descriptions were provided, even ones that provided little useful information, prior probabilities were almost completely ignored [6]. A range of other experiments with different populations (e.g., college students trying to determine other students' majors based on statistics and verbal descriptions) yielded similar results.

In the context of MIW, a commander facing a minefield might be told that no US ship had suffered mine damage in the preceding 14 years. This statistic is almost completely irrelevant without additional information, such as the number of times US ships were exposed to minefields over this period, or the level of hazard that those minefields posed. Likewise, referencing Admiral Farragut's successful attack at Mobile Bay (when he famously said, "Damn the torpedoes—full speed ahead!") would provide no insight into the immediate hazard posed by mines. However, psychological research suggests that such information can often trump the types of statistical analysis that were demonstrated earlier in this paper, and have a greater impact on decision-making processes. Awareness of these biases, though, can ameliorate them; part of the purpose of this paper is to stimulate such awareness.

Availability

The availability heuristic entails believing that the more readily an example of an occurrence comes to mind, the more likely it is to exist. Often, this involves oversimplifying situations and confounding familiarity with likelihood; it usually complements the tendency to dismiss statistical analyses in favor of verbal accounts. According to Tversky and Kahneman [9]:

> Many of the events whose likelihood people wish to evaluate depend on several interrelated factors. Yet it is exceedingly difficult for the human mind to apprehend sequences of variations of several interacting factors. We suggest that in evaluating the probability of complex events only the simplest and most available scenarios are likely to be considered...The tendency to consider only relatively simple scenarios may have particularly salient effects in situations of conflict...The production of a compelling scenario is likely to constrain future thinking. There is much evidence showing that, once an uncertain situation has been perceived or interpreted in a particular fashion, it is quite difficult to view it in any other way. Thus, the generation of a specific scenario may inhibit the emergence of other scenarios, particularly those that lead to different outcomes...Continued preoccupation with an outcome may increase its availability, and hence its perceived likelihood.

The authors demonstrated the availability heuristic through a number of experiments [6]. One of these asked subjects whether it was more likely that a randomly selected word started with the letter K, or had K as its third letter. Although K is the third letter of a word roughly twice as often as it is the first letter, a clear majority of subjects thought that K was more commonly the first letter than the third. (Similar tests with L, N, R, and V, all of which are more commonly in the third position than the first, yielded comparable results.) This bias can be attributed largely to the fact that it is easier to recall words that begin with a particular letter than it is to recall words that have the same letter in the third position. Similarly, when given a list of ten people, subjects were asked to figure out whether there were more possible two-person or eight-person committees. The number of possible committees is exactly the same for both cases (45), but because it is easier to envision different two-person committees than eight-person ones, it was perceived that more two-person committees could be formed.

The availability heuristic is closely related to the dismissal of statistical evidence, which was cited above. For example, if a commander has trouble recalling an instance of a successful attack using mines, or does not have strong visual imagery associated with such an attack, he or she may discount the mine threat, regardless of other indicators regarding its importance. When a commander is preoccupied with another threat (e.g., submarine attack), the threat of mines may appear negligible, and decisions may be made in ways that do not consider the risk of mines as well as other threats. This is a particular challenge for MIW, since only a few percent of naval officers have extensive experience in this warfare area. Mines may not be perceived as a threat by those who have spent careers pursuing aerial combat, missile defense, or anti-submarine warfare.

Conversely, the mine threat can easily be overestimated if *any* ships are damaged by mines, regardless of the actual threat they pose. A historical example is cited by William L. Greer and James Bartholemew [10]:

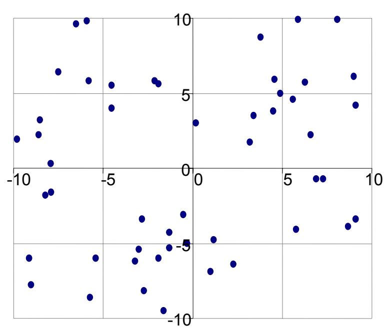
> In October 1943, a single U.S. B-24 bomber dropped three mines in Haiphong harbor. One of them sank a Japanese freighter. The next month, another B-24 planted three more mines, which sank another Japanese freighter. Then a Japanese convoy of ten ships refused to enter Haiphong harbor, for fear of mines. After loitering outside the harbor for a few hours, the convoy headed for Hainan Island. On the way, it was detected and six of its ships were sunk. Meanwhile, a small 30-ton ship was sunk by one of the remaining mines, and the port was closed to steel-hulled ships for the remainder of the war. When that decision was made, a maximum of three mines remained. The Japanese estimate of the remaining threat is not known, but there is little doubt that their fears were exaggerated.

Representativeness

In general, people have a predisposition to believe that even small samples are highly reflective of the character of the overall population from which they are sampled. This heuristic, called representativeness, relates closely to the availability heuristic. People assume that subsets of a sequence of events (e.g., coin tossings) should be representative of the whole, just as they assume that whatever they can most readily envision is also representative. Thus, when a coin is tossed and they see a sequence of multiple heads (or tails) in a row, they presume that the sequence is not random, despite the fact that occasional long streaks are likely to occur by chance [11]. (There is a 25% probability that a sequence of three coin tossings will result in all heads or all tails; if a coin is tossed a few dozen times, streaks of four or more will be common.)

To cite an example from MIW, figure 7 shows a randomly generated array of 50 mines in a 20 km x 20 km square. Each mine has a uniform probability of being anywhere in the square, but there are nonetheless some portions of the square that have much higher mine densities than others. Table 4 shows the mine density within each of the 16 squares of dimensions 5 km x 5 km. Fully 4 of the 16 smaller squares (25%) have mine densities that differ from the average density by at least 65%. Sampling any subset of the area could easily lead to a misapprehension of the overall mine density.

Figure 7. Sample diagram of 50 randomly distributed mines[a]



a. Each mine has a uniform probability of being located anywhere in the 20 x 20 square.

Patterning

Human minds have a tendency to seek out patterns, and to perceive them even when they are not there. For example, basketball players, coaches, and fans often perceive that players are more likely to successfully make a shot if the preceding shot succeeded (and less likely if the shot missed). Statistically, this has been shown to be almost universally incorrect; rather, the probability of making or missing a shot is almost independent of the previous shot [12]. Nonetheless, audiences (including the players themselves) often disbelieve the analysis.

Table 4. Numbers of mines in 5x5 sub-squares in figure 7

Number of mines in square	Number of squares with this many mines	Mine density of these squares (mines/km^2)
0	1	0.00
1	2	0.04
2	3	0.08
3	3	0.12
4	4	0.16
5	2	0.20
6	0	0.24
7	1	0.28
Average		0.12

This phenomenon is not limited to basketball, and can be partly explained by the response of subjects to randomly generated sequences of heads and tails (and similar experiments). As was mentioned earlier, when subjects view "streaks" of several heads (or tails) in sequence, they view the patterns as nonrandom. According to William Feller, a scholar of probability, "To the untrained eye, randomness appears as regularity or tendency to cluster." [13]

Revisiting figure 7, an observer who was unaware that the mines were randomly distributed might perceive patterns (e.g., clusters) within the figure. If this were part of a larger minefield, the belief that patterns were present could lead to misapprehension that similar "patterns" existed in other parts of the field, and MCM tactics could be (mis) adapted accordingly.

Framing effects

Decisions are often heavily influenced by the way in which a particular problem is framed. Tversky and Kahneman cite a particularly dramatic example of this, in which they presented separate audiences with two different scenarios [14]:

- **Scenario 1.** An unusual disease is expected to kill 600 people if no countermeasures are taken, but there are two possible programs to combat the disease. If program A is adopted, 200 people will be saved. If program B is adopted, there is a one-third probability that 600 people will be saved, and a two-thirds probability that no one will be saved.

- **Scenario 2.** An unusual disease is expected to kill 600 people if no countermeasures are taken, but there are two possible programs to combat the disease. If program C is adopted, 400 people will die. If program D is adopted, there is a one-third probability that no one will die, and a two-thirds probability that 600 people will die.

Audiences presented with scenario 1 preferred program A over program B by a wide margin (72% to 28%), while those presented with scenario 2 showed an even stronger preference for program D over program C (78% to 22%). However, the scenarios are exactly identical; programs A and C are the same, just as programs B and D are. When confronted with descriptions that specified the number of people saved, audiences preferred to save 200 people, rather than have a one-third chance of saving 600. However, when the same choices were presented in terms of the number of people who would die, most subjects preferred to take a risk in the hopes that no one would die, rather than accept 400 deaths.

Framing effects are also visible in other areas, such as choices about gambling losses and gains [6, 12, 15, 16]. In general, people are more willing to take risks to avoid losses than they are to take risks to increase gains. By carefully phrasing a question (and introducing an initial loss or gain that is not probabilistic), it is possible to obtain different answers. For example, informing a subject that they have just lost $10, and they are then able to gamble to get it back (at the risk of losing more money), will make them more willing to gamble than if they had not been told of the initial loss. This is despite the fact that the person's overall financial status is essentially unaffected by the $10, and the initial loss would seem unlikely to change the person's overall level of risk aversion.

In the field of MIW, it is easy to hypothesize situations in which framing effects alter decisions. Referring back to the situation portrayed in figures 5 and 6, CAPTMEIN results for the SIT (as a function of the number of mines) are reiterated in table 5. The overall SIT is the sum of the products of the second and fourth columns (the probability that a given number of mines remains, multiplied by the SIT that such a number of mines would generate).[8] Based on this information, a commander might be told one of the following:

- There is a 33% probability that the first ship will be hit by a mine.
- There is a 67% probability that the first ship will transit successfully.

The decision about how to proceed might depend on which of these equivalent statements was presented. This is not to intimate that commanders are not fully capable of understanding and appreciating that they are mutually equivalent; rather, it is because the mind does not do well at intuiting probability and statistics [14, 15].

Table 5. SIT[a] as a function of the number of mines present

Number of mines remaining	Probability that this number of mines remains	Probability that this number of mines or fewer remains	SIT
0	8.6%	8.6%	0.0%
1	18.9%	27.5%	15.0%
2	22.7%	50.2%	27.8%
3	19.7%	69.8%	38.5%
4	13.8%	83.6%	47.8%
5	8.3%	91.8%	55.6%
6	4.4%	96.2%	62.3%
7	2.1%	98.4%	68.0%
8	1.0%	99.3%	72.9%
9	0.4%	99.7%	76.9%
Average (2.75 mines)			33.3%

a. SIT is the likelihood that the first transitor is damaged by a mine.

8. Note that the SIT (33%) is lower than the average number of mines in a given straight pathway cited earlier (0.41). The SIT is the probability that a ship taking this pathway encounters any nonzero number of mines. The average number of mines in the pathway includes additional weighting for the possibility that 2, 3, or more mines are present.

Framing effects can be even more powerful when information is selectively presented, or particular items are highlighted. For example, based on table 5, the following statements are all true;[9] nonetheless, if presented individually, they can steer decision-makers into not properly taking all factors into consideration.

- There is a 50% chance that three or more mines remain. If this is the case, then the SIT is at least 39% (and it could plausibly be over 70%).
- There is a 50% chance that two or fewer mines remain. If this is the case, then the SIT is less than 28%, and it may be zero.
- There is a 16% chance that five or more mines remain. If this is the case, then the SIT is at least 56% (and it could plausibly be over 70%).
- There is a 70% chance that three or fewer mines remain. If this is the case, then the SIT is less than 39%, and it may be zero.

Anchoring

Anchoring entails the overuse of data that arises early in the decision-making process. In some cases, such data are not even relevant to the problem. One of the more dramatic experiments conducted by Tversky and Kahneman was to present audiences with one of two numbers (10 or 65); the audiences were told that the numbers had been selected randomly, and were then asked whether the percentage of African countries in the United Nations was lower (or higher) than the number they had given. Almost all respondents indicated that the percentage was higher than 10 or lower than 65 (depending on which question they were asked). When they were subsequently asked for the actual percentage of African nations in the UN, their answers were heavily biased by the initial, random data point which they had been given. On average, those whose initial number was 10 estimated that 25% of the countries in the UN were African, while those whose initial number was 65 estimated that 45% of them were [12]. Other experiments have shown that subjects tend to "anchor" around initial

9. Based on adding probabilities shown in the table.

numbers even when these are absurdly high or low; e.g., when they are given temperatures of -50 or 200 degrees, and then asked to estimate the median temperature in a particular country during a specific season [12].

In the context of MIW, anchoring can easily distract from the overall statistical profile of the situation. In the scenario characterized in table 5 (as well as figures 5 and 6 from the previous section), starting the discussion with either of the following statements could affect beliefs about minefields, and subsequent decisions:

- We did a good job clearing the minefield—I think the number of mines left is zero.
- There is a possibility that nine or more mines remain.

Overconfidence

In general, subjects are more confident of their predictive capabilities than statistical analyses or their own knowledge would warrant. For example, in a series of experiments by Edward Russo and Paul Schoemaker [12], subjects were asked about the diameter of the moon in miles, the air distance from London to Tokyo, Martin Luther King's age at death, and other quantitative data. They were supposed to give 90% confidence intervals for the answers to ten of these questions; that is, they provided low and high values for the numbers, and were supposed to be 90% sure that the numbers actually fell between those high and low values. On average, individuals' "90% confidence intervals" actually included the correct value only about half of the time. A number of other experiments corroborate the idea that people overestimate the accuracy of their predictions and assessments. While experts in various fields are usually more accurate than novices at their fields (as might be expected), they also exhibit overconfidence relative to their tested ability to correctly assess situations [6, 12]. For example, physicians initially diagnosing pneumonia or cancer, and psychologists diagnosing brain damage, have been found to overstate the accuracy of their diagnoses by 50% or more (based on subsequent diagnostic data) [6, 12]. Overconfidence by economists, physicians, nurses, and other experts has been repeatedly demonstrated in the academic literature [15, 17, 19].

Overconfidence, in MIW as in other fields, can be dangerous. Intense confidence (e.g., that "the enemy wouldn't mine" or "the mine threat is insurmountable"), when uninformed by relevant analyses, including statistical analyses, can lead to unfounded and inaccurate risk assessments.

Recap

The preceding discussion described a number of heuristics that inhibit effective assessment of risk using statistical evidence. These heuristics include:

- Dismissal of statistical evidence
- Availability (confounding familiarity of scenarios with their probability)
- Representativeness (assuming that samples that are too small to be statistically significant are representative of a larger set)
- Pattern perception (discerning patterns where they do not exist)
- Framing (having perceptions of a problem shaped by the way in which the problem is stated)
- Anchoring (over-attachment to the first quantitative values used in discussing a problem)
- Overconfidence.

All of these can contribute to misapprehension of risk in MIW (or other areas), and hence to sub-optimal decision-making. In the next section, we describe some of the ways in which these effects can be diminished.

What this means—implications

The previous section outlined a series of inhibitors to accurate assessment of MIW risk. These heuristics, singly or in combination, could lead to bad decision-making by personnel desiring to use or transit waters that may be mined to some degree. Specifically, they could result in ships being sent into mined waters despite unacceptable levels of risk (as defined by the fleet commander), unnecessary delay due to MCM being conducted beyond the level of acceptable risk, or the use of alternate (and less advantageous) waters.

In the psychological literature, there have been numerous examinations of how individuals assessing risk can try to diminish the effects of biases imposed by the heuristics described in the previous section [6, 18]. The two that have been found to be most effective are surprisingly straightforward:

- Making decision-makers aware of these potential biases
- Having decision-makers make an explicit list of reasons why their initial assessments might be wrong.

As with any area of psychology, awareness of a behavior can sometimes enable the subject to avoid it. By understanding anchoring and framing effects, the propensity to dismiss statistical evidence in favor of irrelevant verbal information, and other heuristics that lead to suboptimal assessment of risk, fleet officers responsible for decisions in a potentially mined environment can reduce their susceptibility to these errors in judgment.

In addition, once a preliminary decision has been made regarding whether to traverse potentially mined waters, composing a list of reasons why this judgment may be erroneous can help to improve the final decision. Of course, a commander must ultimately decide whether or how to use potentially mined waterspace, and creating such a list may seem to be an impediment to the process, rather than an aid to it. However, generating a basic awareness of some of the reasons why an assessment could be wrong is likely to result in more robust decision-making. The original judgment (or decision) may or may not change, but it is more likely to make the best use of all available information if this exercise is conducted.

Also, it is important that decision-makers only compile a list of reasons why the preliminary decision may be incorrect, not a dual list describing why the decision may be right or wrong. Psychologists have found that listing reasons why a decision may be either wrong or right does not debias the result; rather, it tends to reinforce the original judgment[6, 18]. When individuals are formally listing reasons why their preliminary decision was right or wrong, the reasons in favor of their original judgment are taken more seriously than those which conflict with it.

A naval commander facing a potentially mined environment is likely to be provided with data from the MCM commander (MCMC), who characterizes the risk to ships, as well as the delay and resource requirements associated with further MCM operations. In deciding how to interpret the data, and what actions to take based upon it, a knowledge of how risk can be misperceived can usefully improve the commander's chances success. Moreover, the naval commander who maintains the ability to question a preliminary decision regarding risk is more likely to make good decisions than one who does not.

Exercises and wargaming

As with any skill set, the ability to assess risk in MIW and to make decisions based on that assessment can benefit from practice. Exercises and tabletop wargames could be used as opportunities to teach non-MIW specialists about risk assessment in the context of MIW, and to help them practice making decisions regarding that risk. It would also give them the chance to exercise the debiasing procedures outlined above.

Conclusions and implications for the commander

Based on intelligence, reconnaissance, and clearance data, statistical methodologies can be used to assess the number of mines remaining within a particular minefield. Bayes' theorem, when combined with binomial statistics, can be used to develop a probability distribution for the number of residual mines. The average number of residual mines can be calculated, together with the probability that any given number of residual mines exists. As more information becomes available, such assessments can be revised to improve their accuracy.

Building on such analyses, either mathematical modeling (such as that contained in MEDAL) or Monte Carlo simulations (such as CAPTMEIN) can be used to assess the risk posed by residual mines. A commander can then use this information to make an informed judgment regarding whether, or how, to have their ships enter a particular area. Understanding the value of statistical analyses is particularly important in the context of mainstreaming of MIW. Officers with little exposure to MIW may be called upon to make decisions regarding this warfare area, and a modicum of education can help them to better appreciate how they can use statistics to make better decisions.

However, there are a number of psychological biases and heuristics that can inhibit the effective use of statistical insights in MIW decision-making. These biases and heuristics—which have been demonstrated in numerous psychological experiments—include:

- Dismissal of quantitative or probabilistic information in favor of verbal information
- The availability heuristic (assuming that the probability of an event is a function of how readily it can be recalled)

- The representativeness heuristic (assuming that even small samples of a population will be highly representative of the population as a whole)
- Discerning patterns in random phenomena
- Framing effects (in which a response to a question varies, depending on the way in which the question is asked)
- Anchoring (over-reliance on particular data points, however irrelevant)
- Overconfidence in the accuracy of judgments.

When evaluated experimentally, these biases have generally been shown to be largely independent of the subjects' prior knowledge of statistics, unless they were explicitly instructed to use statistics to solve the problems. The relevance of these psychological experiments to MIW is corroborated by the historical record. On a number of occasions, commanders have made decisions about whether to transit minefields without trying to assess the risks of doing so.

To prevent such episodes from recurring, commanders can make themselves cognizant of how statistical methods can inform risk assessment, and the common biases which lead to subjective misapprehension of risk. By doing so, they can more accurately assess risks in light of all available information. Conscious debiasing—explicitly considering the reasons why their assessments might be wrong—can also aid in improving their judgment. Such assessments reduce the likelihood that their decisions will unnecessarily inflict casualties or impede operations, and enable them to increase the overall effectiveness and safety of their forces.

Moreover, commanders can prepare themselves to make better decisions regarding minefield transit via exercises or wargaming. For example, board games or computer-based games could be developed to give commanders experience in assessing MIW risk. By repeating such games in a "safe" tabletop environment, they can be trained to think in nuanced and statistically sound ways about the threat posed by a minefield, minimizing their biases when faced with a challenging real-world choice.

References

[1] Ross, Sheldon. A First Course in Probability. New York: Macmillan College Publishing Company, 1994.

[2] Rosenkrantz, Walter. Introduction to Probability and Statistics for Scientists and Engineers. New York: McGraw-Hill, 1997.

[3] Press, James S. Subjective and Objective Bayesian Statistics: Principles, Models, and Applications. New York: Wiley-Interscience, 2002.

[4] Crow, Edwin L; Davis, Frances A.; Maxfield, Margaret W. Statistics Manual. New York: Dover Publications, Inc., 1960.

[5] Meacham, James. "Four Mining Campaigns: An Historical Analysis of the Decisions of the Commanders," *Naval War College Review,* June 1967, vol. 19, no. 10, pp. 75-128.

[6] Kahneman, D., Slovic, P., and Tversky, A., eds. *Judgment Under Uncertainty: Heuristics and Biases.* New York: Cambridge University Press, 1982.

[7] Kahneman, D., and Tversky, A., eds. *Choices, Values, and Frames.* New York: Cambridge University Press, 2000.

[8] Kahneman, D., and Tversky, A. "On the Psychology of Prediction," *Psychological Review,* 1973, 80, 237-251.

[9] Tversky, A., and Kahneman, D. "Availability: A Heuristic for Judging Frequency and Probability," *Cognitive Psychology,* 1973, 4, 207-232.

[10] Greer, William L., and Bartholemew, James. "The Psychology of Mine Warfare," *Proceedings of the US Naval Institute,* February 1986, pp. 58-62.

[11] Kahneman, D., and Tversky, A. "Subjective Probability: A Judgment of Representativeness," *Cognitive Psychology*, 1972, 3, 430-454.

[12] Plous, Scott. *The Psychology of Judgment and Decision Making*. New York: McGraw-Hill, 1993.

[13] Feller, W. *An Introduction to Probability Theory and its Applications*. New York: Wiley, 1968.

[14] Tversky, A., and Kahneman, D. "The Framing of Decisions and the Psychology of Choice," *Science*, vol. 211, 30 Jan 1981.

[15] Piattelli-Palmarini, Massimo. *Inevitable Illusions: How Mistakes of Reason Rule Our Minds*. New York: John Wiley and Sons, 1994.

[16] Kahneman, D., and Tversky, A. "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica*, vol. 47, no. 2, Mar 1979.

[17] Baumann, Andrea, Raisa B. Deber, and Gail G. Thompson. 1991. "Overconfidence among Physicians and Nurses: The 'Micro-Certainty, Macro-Uncertainty' Phenomenon." *Social Science & Medicine*, vol. 32, no. 2 (Jan 15):167-174.

[18] Kahneman, D., and Tversky, A. "Intuitive Prediction: Biases and Corrective Procedures," *TIMS Studies in Management Science*, 1979, 12, 313-327.

[19] Angner, Eric. "Economists as Experts: Overconfidence in Theory and Practice." *Journal of Economic Methodology*, 2005.

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