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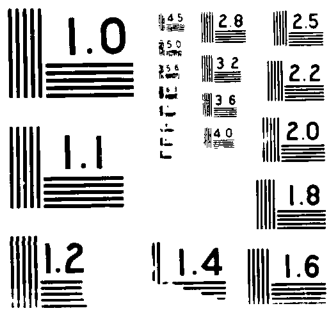
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NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

HEMOS: AN EXPERT SUPPORT SYSTEM PROTOTYPE FOR FORECASTING BLOOD REQUIREMENTS FOR MARINE CORPS MEDICAL SUPPORT

by

Michael A. Greenauer

March 1988

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UNCLASSIFIED
SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE

1a REPORT SECURITY CLASSIFICATION: Unclassified		1b RESTRICTIVE MARKINGS	
2a SECURITY CLASSIFICATION AUTHORITY		3 DISTRIBUTION/AVAILABILITY OF REPORT: Approved for public release; Distribution is Unlimited	
2b DECLASSIFICATION/DOWNGRADING SCHEDULE			
4 PERFORMING ORGANIZATION REPORT NUMBER(S)		5 MONITORING ORGANIZATION REPORT NUMBER(S)	
6a NAME OF PERFORMING ORGANIZATION: Naval Postgraduate School	6b OFFICE SYMBOL (If applicable): Code 54	7a NAME OF MONITORING ORGANIZATION: Naval Postgraduate School	
6c ADDRESS (City, State, and ZIP Code): Monterey, California 93943-5000		7b ADDRESS (City, State, and ZIP Code): Monterey, California 93943-5000	
8a NAME OF FUNDING/SPONSORING ORGANIZATION	8b OFFICE SYMBOL (If applicable)	9 PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER	
8c ADDRESS (City, State, and ZIP Code)		10 SOURCE OF FUNDING NUMBERS: PROGRAM ELEMENT NO / PROJECT NO / TASK NO / WORK UNIT ACCESSION NO	

11 TITLE (Include Security Classification)
HEMOS: AN EXPERT SUPPORT SYSTEM PROTOTYPE FOR FORECASTING BLOOD REQUIREMENTS FOR MARINE CORPS MEDICAL SUPPORT

12 PERSONAL AUTHOR(S)
Greenauer, Michael A.

13a TYPE OF REPORT	13b TIME COVERED	14 DATE OF REPORT (Year, Month, Day)	15 PAGE COUNT
Master's Thesis	FROM ____ TO ____	1988 March	106

16 SUPPLEMENTARY NOTATION
The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

17 COSATI CODES			18 SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB-GROUP	Decision Support Systems; Expert systems; Expert Support Systems; Artificial Intelligence; Prototype

19 ABSTRACT (Continue on reverse if necessary and identify by block number)

Research was conducted to demonstrate the applicability of artificial intelligence techniques to the problem of estimating blood resupply requirements in Navy medical units supporting Marine Corps commands engaged in combat operations. Prototyping methodology was used to develop a combination expert system and decision support system, termed an expert support system, which was named HEMOS (Hemologic Expert Support System for Marine Corps Operational Support). The prototype system was tested and compared with state of the art manual techniques, and was found to be notably more accurate in forecasting blood resupply requirements.

20 DISTRIBUTION/AVAILABILITY OF ABSTRACT: ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT ☐ DTIC USERS	21 ABSTRACT SECURITY CLASSIFICATION: Unclassified	
22a NAME OF RESPONSIBLE INDIVIDUAL: Prof. Taracad R. Sivasankaran	22b TELEPHONE (Include Area Code): (408) 646-2637	22c OFFICE SYMBOL: Code 54Sj

DD FORM 1473, 84 MAR — 83 APR edition may be used until exhausted. All other editions are obsolete.

SECURITY CLASSIFICATION OF THIS PAGE
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HEMOS:
An Expert Support System Prototype for Forecasting Blood Requirements for Marine Corps Medical Support

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Submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN INFORMATION SYSTEMS

for the

NAVAL POSTGRADUATE SCHOOL
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ABSTRACT

The purpose of this thesis was to improve combat blood requirements forecasting techniques used by Navy medical units in support of Marine Corps elements, and to apply artificial intelligence techniques in computerizing the process. Prototyping methodology was used to develop an expert support system named HEMOS (Hematologic Expert Support System for Marine Corps Operational Support). The prototype system was tested and compared with state of the art manual techniques. The HEMOS estimate varied from actual blood requirements by only 2 %, while current manual techniques varied by an average of 63 %.

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I. INTRODUCTION

A. OVERVIEW

Current naval and military organizations maintain medical support elements within their tables of organization to tend to the sick and wounded of their respective combat forces. These medical units perform many different tasks in fulfilling their mission which may be classified into two functional categories: medical care delivery and medical logistics. Medical care delivery includes tasks directly affecting the individual patient's condition (e.g., performing surgery). Medical logistics provides the means to perform medical care delivery (e.g., providing consumable supplies). Both facets of medical support require administrative oversite to perform the four classic functions of all management: Planning, Leading, Organizing, and Controlling [Ref. 1: p. 17]. This thesis will concentrate on the planning function as practiced in the conflict environment.

Historically, tactical medical planning for the Marine Corps has been performed at the unit level by the Medical Support Operations Center (MSOC) [Ref. 2]. The MSOC would use local historical data and guidance from higher commands in formulating estimates of requirements.

Recently, efforts have been made to elevate medical planning above the tactical force. Several systems are in development which would utilize a centralized control point to estimate medical requirements. The Deployable Medical System (DEPMEDS), for example, is applicable to equipment requirements. The Theater Army Medical Management Information System (TAMMIS), being considered for Marine Corps use, has subsystems for blood management and medical supplies. The World Wide Military Command and Control System (WWMCCS) has similar subsystems, while the Joint Operation Planning and Execution System contains a module to control medical supplies and equipment. All of these systems would function from a control point located outside of the theater of operations. [Ref. 3]

The intended advantages of such a centralized control point would be to consolidate resupply transportation planning, to take advantage of large mainframe computers for formulating estimates, and to achieve economies of scale [Refs 4 & 5]. However, removing planning from the tactical level could have adverse effects upon the individual unit [Ref. 6]. For example, the WWMCCS subsystems contain 309 diagnostic groups which are paired with the intensity of conflict to estimate medical supply requirements for an entire theater. Conflict intensities and diagnoses are bound to differ widely over an entire theater. It is highly unlikely that such composite estimates could fully satisfy requirements of diverse units involved with varied tactical situations in different sectors of a theater.

These inaccuracies could be reduced if locally prepared estimates could be made more accurate, and then consolidated at the centralized point of control into a theater wide estimate.

B. THESIS OBJECTIVE

The objectives of this thesis are to develop an improved medical logistics estimation technique which uses local information to identify agents causing casualties, and conditions affecting resupply requirements and to incorporate the technique into an artificial intelligence computer system prototype. This system is designed to operate on microcomputers organic to the MSOCs [Ref. 7]. The resultant prototype system will be compared with current manual estimation techniques to demonstrate the increased accuracy and usability of an artificial intelligence approach.

C. THESIS SCOPE

To reduce the complex realm of tactical medical logistics into a domain suitable for prototyping, only the area of blood resupply estimation will be addressed. This area is documented and contains many similarities with other areas of medical planning.

Prototyping methodology will be used to develop a working model of an expert support system for blood resupply. As with all prototypes, the system will contain elements which could be improved by further research. In particular, the prototype system is not intended for immediate use in forecasting blood requirements due to data constraints. Rather, its immediate purpose is to demonstrate the applicability of state of the art artificial intelligence methodologies to the problem of blood forecasting in a combat environment.

D. PREVIEW OF SUBSEQUENT CHAPTERS

Chapter II of this thesis will present an overview of the three most prevalent types of artificial intelligence systems. Decision support systems, expert systems, and expert support systems will be addressed. Emphasis will be placed upon demonstrating the evolution of expert support systems.

Chapter III will portray the current state of the art in blood requirements forecasting for Marine Corps combat units. Chapter IV will discuss the selection of data used to create the prototype forecasting system. The chapter also addresses activities which were used to construct the system, and how it was tested against current manual techniques. Chapter V presents the results of the comparison. Chapter VI presents a summary of the thesis, discusses conclusions derived from the thesis research, and provides recommendations for future research in the area.

II. ARTIFICIAL INTELLIGENCE SYSTEMS

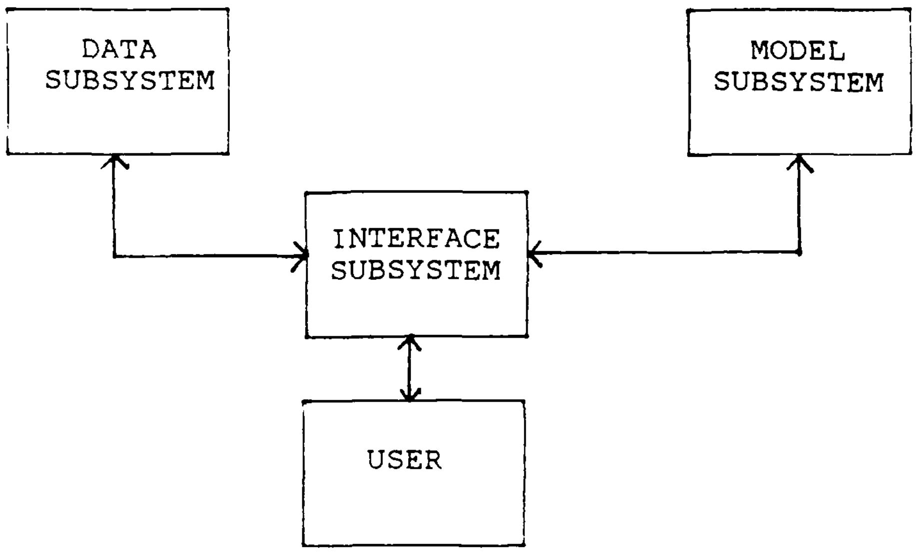
A. INTRODUCTION

Artificial intelligence may be considered as the process of embodying computers with the capabilities to either make decisions independently or to assist human decision makers [Ref. 8: p. 2]. Although relatively brief in its history, the Artificial Intelligence field to date as applied to decision making may be divided into two main types of systems: decision support systems and expert systems [Ref. 9: p. 21]. Of these two categories, the decision support system is decidedly the older concept.

B. DECISION SUPPORT SYSTEMS

In the 1970's the concept of decision support systems was conceived as a means of assisting human decision makers [Ref. 10: p. 36]. The method developed to allow such assistance was the decision support system generator, which operates by employing a mathematical model to perform computations, comparisons of alternatives, or projections. This model derives its required data from a database which may either be contained within the computer, or solicited from the system user [Ref. 11: p. 9].

If we consider the mathematical model and the database to be the first two elements of a decision support system, then we can identify the third required element as a conversational interactive interface for the user [Ref. 12: p. 21]. Since the ultimate intended user of a decision support system is not a computer expert but rather a line manager, the system must include an interface mechanism whereby the non-expert user can query and interact with the system, and derive answers to his queries. Graphically, the required elements of a decision support system are demonstrated in Figure 2.1. These elements may be considered as applicable to all decision support systems [Ref. 13: p. 271].



(Source: Ref. 9: p. 22)

Figure 2.1 Elements of Decision Support Systems

The intent of decision support systems was to improve management decision making in two ways: by assisting in problem solving, and by facilitating communication within the user's organization. Problem solving would be aided by deriving solutions from the decision support system, while communications would be enhanced by the need to gather data from throughout the organization for the database subsystem, as well as by readily having data available to respond to queries from within the organization in a timely manner [Ref. 14: p. 184]. These types of queries, which may be termed ad hoc or non-routine, were seen as a major benefit of decision support systems since such queries were ascertained to be the most time consuming for managers within organizations [Ref. 15: p. 121].

In addition to reducing the time required to respond to ad hoc queries, decision support systems were also intended to increase the precision of management decisions for which they were utilized by relying on statistical models rather than subjective reasoning, which sometimes failed to consider all factors affecting a situation [Ref. 8: p. 2]. However, for the system to be successful in accurately assisting management decision making, specifications for the system must be exact. Indeed, some researchers consider system requirements specification to be the most crucial step in developing a decision support system [Ref. 10: p. 37].

While classic systems analysis acts to define system requirements by specifying implementation and hardware specifications coupled with alternative logical approaches to achieving system goals, decision support systems require exceptional effort in the requirements specification [Ref. 16: p. 15]. In addition to the classic steps, efforts must also be made to delineate which of the organization's decision making activities can actually be helped by using a decision support system, to identify what data is available to the proposed system, to identify what training is required for prospective users, and to identify what organizational and interpersonal impediments exist to the proposed system (i.e., will managers willingly relinquish some decision making authority to a machine). Failure to clearly specify these requirements is noted as the principal cause of decision support system failure, even if all other functional aspects are satisfactory [Ref 15: p. 130].

If properly designed and implemented, decision support systems have been found to be highly useful in a diverse range of organizational enterprises. Although their employment covers a broad spectrum, the greatest benefit of such systems seems to be in either unstructured or loosely structured decision making environments [Refs. 17: p. 2 & 9: p. 21]. By combining the use of analytical modelling techniques with traditional data access and retrieval, a decision support system succeeds in imposing a logical structure upon the problem environment. This aspect makes such systems particularly attractive to applications where decisions are required under some level of uncertainty, or where the decision making parameters are not clearly defined [Ref. 18: p. 397].

Numerous decision support systems in such environments have been developed. For example, a system known as Geodata Analysis and Display System (GADS) was developed to assist civilain police departments in allocating crime fighting assets. GADS functions by comparing relative crime rates and indices in different geopgraphic conditions, and indicating where police assets could be most advatageously utilized. Another example would be the Portfolio Management System (PMS) which is used by financial investment managers to determine where clients' monies could be invested for a maximum return on investment with varying levels of risk. [Ref. 9: p. 25]

Other decision support systems have been developed for specific problem environments or applications. O'Keefe and Wade, for example, developed a decision support system using microcomputer assets which aided managerial decision making in areas such as production and inventory control, and personnel management in a remote sawmill operation [Ref. 19: p. 289]. Naylor in 1975 developed a system for use by executives engaged in corporate planning activities called SIMPLAN [Ref. 11: p. 15]. Ztrux, a major truck manufacturer, developed a decision support system called The Capacity Information System (CIS) for use in production planning [Ref. 11: p. 20]. All of these examples noted were found to be effective in aiding individual decision makers in problem solving activities in environments with little or no structure.

Current research in decision support systems has moved beyond the concept of a single decision maker, and concentrates on the efforts and interactive effects of several decision makers who are all involved in making a single decision. Termed Group Decision Support Systems, these systems seek to allow more than one problem solver at a time to work on a problem [Ref. 20: p. 9].

So far, the greatest limitation upon this new technology has been the requisite communications requirements. However, on going research promises to overcome such constraints by utilizing four types of modules in computer-based systems: a Group Norm Monitor, a Group Norm Filter, an Invocation Mechanism, and an individual decision support system to group decision support system Document Formatter. [Ref. 20:p. 9]

Thus, decision support systems are statistical model-based systems which work with decision makers through an interactive interface to aid problem solving activities, and are most applicable to environments where there is little or no structure; the lack of structure precluding a direct decision making approach [Ref. 21: p. 42]. By these criteria, there would appear to be numerous applications potential in the unstructured environment of military and naval combat operations.

B. EXPERT SYSTEMS

As the field of artificial intelligence matured, new techniques were sought which would provide greater flexibility to the computer decision making process. A departure from rigid statistical algorithmic approaches to problem solving was sought which would more closely mimic the cognitive processes of human beings. In pursuit of this goal, a shift in the research was noted in the early 1980s toward rule-based systems in the logic of artificial intelligence systems [Ref. 22: p. 98]. These efforts culminated in a new design technology which was termed expert systems, and was viewed as a progression beyond decision support systems within artificial intelligence [Refs. 23: p. 7 & 24: p. 315].

An expert system may be defined as a computer program which contains both declaritive knowledge (e.g., facts about objects, events, or situations) and procedural knowledge (e.g., facts about different courses of action), which is used in a rule-based methodology to emulate the reasoning processes of a human expert in a specified domain [Ref. 25: p. 104]. The rule-based concept implies that decisions or courses of action recommended by the system are derived from a pseudo-intuitive process which, usually, utilizes Boolean arguments (i.e., rules) acting upon an available database to produce the system's output.

Expert systems are notably different from decision support systems in several ways. Where decision support systems may be considered as causal in their approach to decision making, expert systems are construed as judgemental based upon some type of logical process [Ref. 24: p. 312]. Another area of distinction is the language used to code the programs. Decision support systems usually use a third generation language such as BASIC or FORTRAN. Expert systems, on the other hand, usually employ a fourth generation language such as LISP or PROLOG which embodies a logical chaining scheme more applicable to a rule-based methodology [Ref. 9: p. 24]. While mathematical models in a decision support system make decisions in a rigid sequence of steps using an algorithm, expert systems use knowledge derived from human experts in varying sequences (i.e., chaining schemes) to arrive at solutions in a manner similar to a human being who acts upon informed hunches [Ref. 26: p. 564]. This high reliance on captured human expertise (termed a knowledge base) serves to make the greatest problem in designing an expert system the acquisition of the knowledge from which the rules are formulated, whereas the specification of requirements is the greatest problem in decision support systems [Ref. 26: p. 564]. Further distinctions between the two types of systems are noted in Table I.

Expert systems possess several characteristics which make them unique within the realm of artificial intelligence. For example, they address only a specific and narrowly defined domain for their problem solving activities, and possess a specially stylized language for input and output functions so that users can track the system's reasoning activities as it

TABLE I
DISTINCTIONS BETWEEN DECISION SUPPORT
SYSTEMS AND EXPERT SYSTEMS

	ATTRIBUTE	DECISION SUPPORT SYSTEM	EXPERT SYSTEM
1.	Objective	Assist human decision maker	Replicate a human advisor
2.	Types of Problems	Ad Hoc; Unique	Repetitive
3.	Data Manipulation Method	Numerical	Symbolic
4.	Major Orientation	Decison Making	Rendering Advice

[Ref. 27: p. 123]

deals with a problem [Ref. 28: p. 273]. The systems also allow for incremental knowledge growth by the addition of individual if-then type rules, which is usually accomplished by a specialized knowledge engineer [Ref. 9: p. 200]. Indeed, a principal strength of expert systems is their ability to adapt to changing conditions or acquisition of new knowledge within their domains by way of the knowledge engineer's activities.

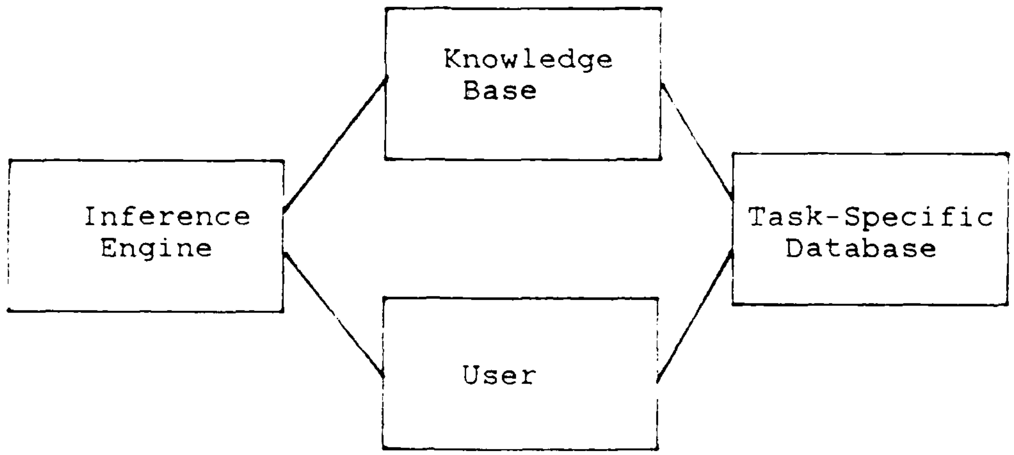
However, expert systems do possess some weaknesses. For example, systems which possess less than ten or more than ten thousand rules do not seem to be as successful as systems which possess a number within these boundaries [Ref. 23: p. 12]. This phenomenon may be attributed to a recommended design criteria that expert systems only be built for problems which would normally take a human expert between a few minutes to a few hours to solve [Ref. 29: p. 82]. Problems which fall beyond this range of complexity appear to entail too great an effort in requisite expert knowledge extraction for the development of a system to be worthwhile. Further, systems which must deal with domains which are too complex are, themselves, often too complex for use by non-expert users. Those which fall below it are so simple that developing a system would not be economically feasible.

Further inherent weaknesses of expert systems include their inability to reason on multiple levels, their inability to view problem domains from alternative perspectives, and their failure to know when to vary from their own rules to adapt to a changing domain [Ref. 9: p. 176]. In addition, expert systems are not truly applicable to well structured numerical problems, where the system's chaining logic is not adequately utilized and actually becomes a burden during the design phase [Ref. 23: p. 12]. However, despite these shortfalls expert systems have found notable success in applications in numerous fields. These will be discussed below.

A generic structure for an expert system may be seen in Figure 2.2. In the figure, note the inference engine where the logical chaining mechanism previously discussed resides.

Certain elements are required for the effective design of an expert system. These would include: facts about the domain, problem situations and potential solutions, and general problem solving strategies commonly employed by a human expert [Ref.

*26: p. 564]. Most of these elements are derived from one or more human experts, who pass on their knowledge to a system designer by means of interviews, on-the-job observations,



[Ref. 9: p.23]

Figure 2.2 Expert System Structure

questionnaires or a combination of all three. Information obtained from the human expert's experience with the domain is vital for problem-solving with the system [Ref. 30: p. 163]. However, acquired human knowledge is, by its very nature, subjective and may need to be modified as further experience with the domain is obtained, or domain parameters are altered over time and no longer provide a perfect fit to the expert's subjective experience. One technique effectively used in expert system design to overcome the subjectivity of expert knowledge is that of prototyping.

Prototyping entails developing a functional but temporary system which can adequately function in an actual domain, but which is implemented with the expectation and intent of modifying the system after observing its effectiveness and efficiency [Ref. 16: p. 212]. In expert systems this approach is particularly applicable since there are very few experts who not only know every piece of information about their problem domain, but can also relate that information completely so that it is captured in total within the knowledge base. Further, even if such a feat is possible, the domain may change or expand, making modification of the expert system necessary. This can be a costly and time consuming enterprise. Therefore, the preferred development scheme for expert systems is prototyping.

Prototyping for expert systems requires not only interaction with human experts who provide the knowledge base, but also explicit interaction with the potential users of the system [Ref. 26: p. 566]. Normally, these users are found to be mid-level or operational managers, where the majority of problem solving occurs within an organization [Ref. 26: p. 565]. High levels of interface with prototype users, even to the consideration of what types of hardware will be used to operate the prototype system, frequently result in higher acceptance and success of expert systems [Refs. 26: p. 565 & 29: p. 84].

Prototyping applications of expert systems has proven quite successful in a myriad of domains. Hurley and Wallace successfully used the technique in the public sector to develop functional systems in the fields of personnel administration and emergency management [Ref. 26: p. 563]. Significantly, their systems were developed totally on microcomputers of the same type which the users would employ. INTERNIST, a medical expert system which can assist physicians in analyzing approximately 3000 symptoms and diagnosing some 500 diseases,and PROSPECTOR, a geological expert system which aids field workers in searching for minerals, are other examples of successful expert systems which were developed using the prototyping methodology [Ref. 9: p. 25].

Current literature is filled with numerous other successful expert systems. Of particular interest to the current research are those involved in the field of medicine, where the subjective assessment and reasoning skills routinely utilized by physicians are admirably adaptable to an expert system's knowledge base. Some highly successful examples would include the Causal Associational Network (CASNET) system developed at Rutgers University to assist in medical diagnosis of glaucoma, IRIS (also from Rutgers University) which uses semantic nets and production rules to differentially diagnose opthalmic disease, and HEME (from Cornell University) which uses a combination of entered patient data and Bayesian theory to compute the probability that a patient has a disease contained in the system's database [Refs. 31: p. 177 & 25: p. 124].

Perhaps the premier expert system application in medicine has been that of MYCIN, which is a rule-based system employing a backward chaining scheme which was developed at Stanford University to assist clinicians in selecting appropriate antimicrobial therapy for hopitalized patients with diagnoses of bacteremia, cystitis, and meningitis [Ref. 25: p. 126]. Aside from its wide-spread acceptance by the medical community and its consideration as a benchmark for subsequent medical expert systems, MYCIN is noteworthy for its having been externally validated by being formally tested for its effectiveness relative to human experts. In 1979 a blind evaluation of MYCIN was conducted under the auspices of the American Medical Association. Acknowledged and independent experts evaluated the recommended courses of treatment of MYCIN and eight groups of clinicians representing skill levels ranging from medical student to medical school professors. In all categories, the MYCIN system was found to recommend a more effective course of therapy more often than any group . Thus, the MYCIN expert system was found to be superior to operational experts [Ref. 28: p. 281]

Expert systems continue to exert a significant impact upon research in artificial intelligence. One area of current research is that of causal models which formalize the factors within the domain of the system which affect the problem environment [Ref. 281: p. 275]. Methods are being examined to overcome problems of expert subjectivity noted previously.

The area of current research serves to incorporate both of these concerns, and is viewed as the next progression in artificial intelligence research. This new methodology combines elements of both decision support systems and expert systems into composite systems which have qualities of both, and which are called expert support systems [Ref. 32: p. 114].

C. EXPERT SUPPORT SYSTEMS

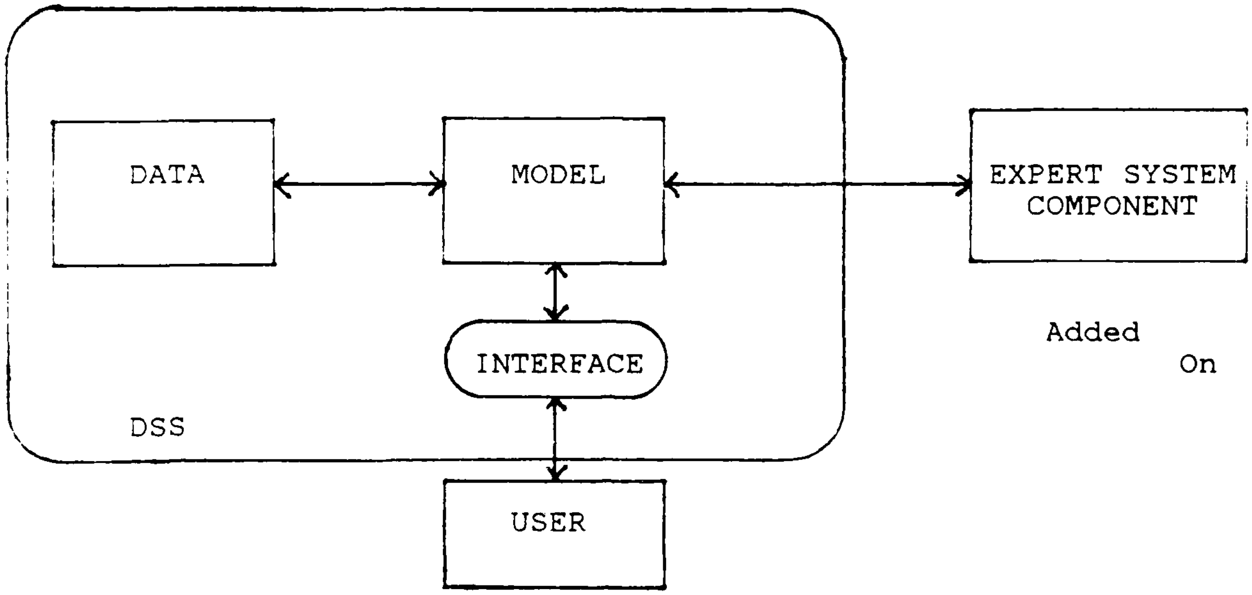
Expert support systems may be construed as a form of intelligent decision support systems, where the system symbolically understands relationships between activities and domain conditions [ibid]. Such understanding is derived from logical deduction processes, which in turn lead to goal directed behavior within the expert support system [Ref. 33: p. 44]. In this manner, such a system could more closely emulate human cognitive processes than either decision support systems or expert systems, since human beings utilize both mathematical /probabilistic and symbolic/relational reasoning in problem solving within their minds [Refs. 33: p. 86 & 34: p. 149].

Such human structuring or modeling of the world within the individual mind may be considered as a process whereby activities within the real world are reduced to basic cognitive goal-action relationships or rules. In expert support systems, such rules may be considered productions since the outcome of each rule is a product in the form of some type of action. A system composed of such productions could then be termed a rule-based production system since the output of the system would be an action product (i.e., a decision or problem resolution) of some sort [Ref. 9: p. 201]. The conceptual application of an expert support system as a production system is made possible if decisions requiring resolution by the system user are structured so that analytical tools, in conjuction with a knowledge base, are embedded in the system and are used to generate possible problem solutions [Ref. 32: p. 112].

Combining expert system concepts with those of decision support systems would allow inclusion of a human expert's inference capabilities as well as statistical models [Ref. 9: p.26]. There are two basic techniques in combining elements of expert systems and decision support systems. The first technique entails integrating an entire expert system into conventional decision support system components. This technique is considered to be quite complex, and entails exhaustive interface with human experts and full integration of the knowledge base with the statistical generator. Emphasis in this type of combinatorial system is upon the expert system components.

The second type of combined system employs an approach of using an expert system component as an additional feature of a traditional decision support system. With this technique, an "add-on" expert component is logically located outside of the decision support system, and requires only partial integration with the statistical generator. The schematic structure of this second combinatorial method is shown in Figure 2.2. In this combinatorial scheme it is the decision support system which is dominant.[Ref. 27: p. 121]

This add-on structure can overcome some deficiencies of pure decision support systems. Decision support systems do not include both primary and secondary processes. While the statistical generator may fulfill the primary process requirement, such systems lack a cognitive evaluation mechanism

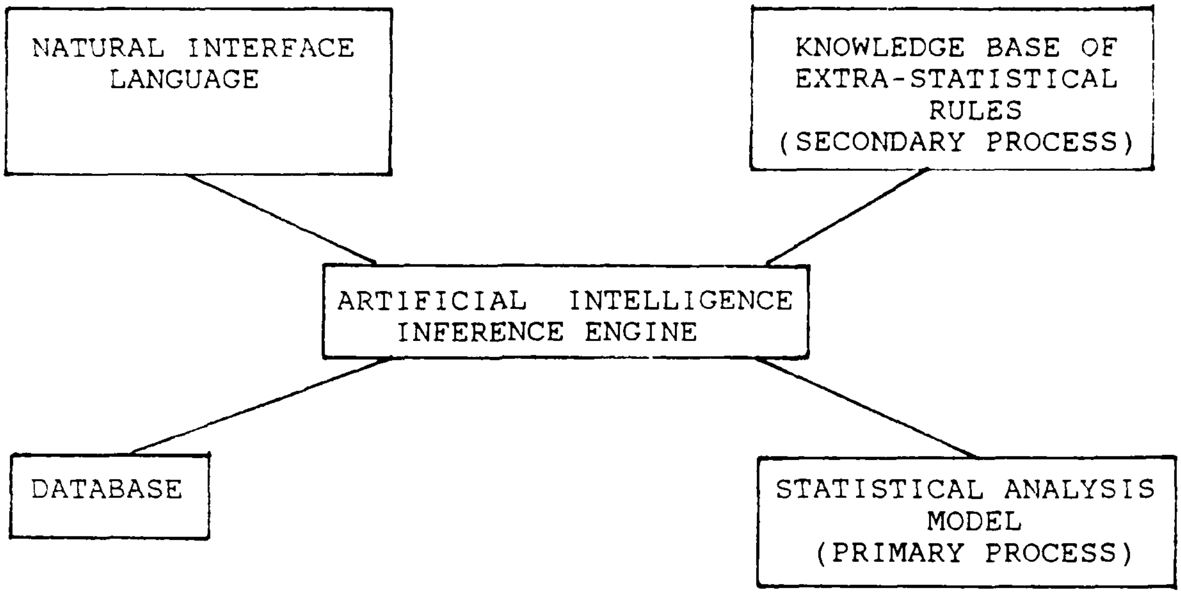


[Ref. 27: p. 129]

Figure 2.3 Expert System as a Component of a Decision Support System

(i.e., secondary process). Using the add on expert system component is one method to overcome this shortfall, and serves to remove cognitive limitations normally imposed on decision support systems [Ref. 35: p. 403]. This concept is illustrated by Figure 2.3. In addition to providing both primary and secondary processes the add-on expert system component can also increase the accuracy of forecasts or decisions over pure decision support systems [Ref. 27: p. 123].

Since the add-on methodology is notably less complex than the integrated technique, it is significantly more adaptable to a prototyping development methodology. Creating a functional prototype of a new expert support system results in several benefits, some of which include a noticeable improvement in



[Ref. 35: p. 412]

Figure 2.4 Combined Primary and Secondary Processing System

functional design quality over conventional techniques, easier testing of the design, and a much more thorough understanding of the application, as well as a more accurate estimate of required implementation effort [Ref. 36: p. 72]. The eight steps involved in developing a functional prototype of an expert support system are: 1) examination of the domain and logically structuring it into productions, 2) derivation of a statistical model, 3) interviews of expert(s) to derive knowledge base, 4) initial implementation, 5) case analysis, 6) refinement of the functional prototype, 7) user acceptance of the expert support system, and 8) documentation [Ref. 36: p. 71].

III. PROBLEM DEFINITION

Current manual estimation procedures for blood resupply requirements are not adequate to meet the needs of the force. Observations conducted during large military exercises (e.g., Ocean Venture-82, Solid Shield-83, Ocean Venture-84, Solid Shield-85) consistently demonstrate that methods in use to forecast blood requirements to support Marine Corps combat operations seldom result in an accurate estimate, but instead almost always result in one of two outcomes. Either too little blood will be forecast as a resupply requirement (which will jeopardize the health of wounded and ill casualties), or too much blood will be estimated as necessary (which will result in unnecessary strain upon logistics channels and waste of a perishable and valuable commodity). To alleviate unnecessary risk to engaged forces, military planners invariably choose to knowingly err with caution, and so willingly order more blood than is objectively justified [Refs. 4 & 37]. This inflation of blood resupply requirements may be construed as a positive force survival mechanism based upon its intent. However, if the practice is coupled with inherently inaccurate forecasting methodologies, then the result could be grossly inflated blood resupply requirements which will result in wasted blood.

The current manual blood forecasting techniques rely upon reference instructions to provide planning statistics for use in estimating blood requirements [Ref. 38]. These references utilize historical data for diverse combat theaters, tactical scheme of maneuver, and intensity of conflict to estimate casualty rates. These are then converted to blood requirements based upon observed usage rates in past conflicts. While the historical basis of estimating has considerable merit, the principal weakness of the current methodology is the reliance upon generalized estimates. And the principal cause of this weakness may be seen to be a structure favoring historical observation of usage rates rather than causal inference within the reference estimates.

By avoiding a causal perspective, the current estimating techniques cannot help but provide the medical planner with a generalized scenario which is, at best, a loose fit of his current tactical situation. Further, the planner has no opportunity to tailor the gross estimate obtained by the references to his current tactical situation by emphasizing factors causing blood requirements, while simultaneously deemphasizing or eliminating factors which are not causal in his current situation, but which are resident in the gross planning estimates provided by the references.

It is not the intensity of conflict alone, for example, which leads to blood requirements. An illustrative hypothetical situation could be a scenario where the enemy is vigorously resisting from entrenched positions, but only has incendiary weapons available for their use in combat. Based upon historical data where similar tactical situations existed (but not similar tactical threat), and where similar casualty estimates were encountered, a high blood requirement would be indicated. However, in reality no blood would be required to care for burn casualties [Ref. 39: p. 7]. Thus, in this hypothetical situation, the reliance upon generalized non-causal historical estimates would result in a seriously inaccurate forecast of actual blood requirements.

The on-site medical planner would no doubt take action to halt the shipment of unnecessary blood. In a like manner he would also take steps to increase his blood resupply if the forecast quantity were notably insufficient. However, the medical planner would be severely constrained in making an accurate adjustment based upon causal factors if he were not provided with causal planning statistics. Presently these are not available to him. At best, the present day medical planner can observe usage rates over his unit's recent history and hypothesize that the recent trend for usage rate will continue.

An alternative approach to locally adjusting generalized blood requirements estimates would be to identify causal agents, and observe their influence over time upon actual blood requirements. These causal agents could be construed to be cumulatively contributory to actual blood requirements. It is possible that, having identified such causal agents and having obtained such observations, forecasts of blood requirements could be based solely upon these factors. This process would effectively shift the blood forecasting process from the current consumption trend historical technique to an approach which is causal in nature.

However accurate the locally derived estimate is, though, it will not benefit the medical planner or the unit which he is supporting if his input is not eventually incorporated into the blood requirement estimation process. As discussed previously, recent trends in medical logisitics have been to remove the requirements estimation process from the tactical unit, and place it with a geographically distant and organizationally superior centralized planning agency who would consolidate all logistics requirements to achieve economies of scale and to take advantage of high powered data processing equipment not available on the battlefield. This process will not solicit estimation input from the local planners. Instead it will utilize blood usage rates from all units within a theater to estimate a composite blood requirement. Input from the local medical planner will be minimal and in a rigid format [Refs. 4 & 6]. The result could be seen to be a continuation of poor blood requirements forecasts for local Marine combat forces.

If the accuracy of local blood requirements forecasting could be improved, then the local estimate may come to be considered useful input to the centralized planning agency, and could result in overall increased accuracy of the composite theater estimate. However, before such an argument may be pressed, the efficacy of local causal forecasting must be demonstrated. One method of increasing the accuracy of the local estimates may be to automate the forecasting process using microcomputer assets. However, such an automated system must be accepted by the medical planner if it is to be successful.

Health care professionals possess unique character traits which have historically made their acceptance of fully automated decision making aids difficult to achieve [Ref. 40: p. 267]. Conversely, decision making systems which either function in conjunction with human experts or embody human expertise in an advisory or consultative mode have achieved notable success in medical environments (i.e., MYCIN, INTERNIST). Thus, it could be surmised that if an automated system is to be accepted in the medical planning environment it must incorporate human expertise, and that this human expertise should be evident to the system user. One method of achieving this goal would be to utilize an expert support system for blood requirements estimation.

Finally, for the system to be utilized, it must also be designed for use on the type of microcomputer hardware available to the Marine unit medical planner. Further, required training to use the system would need to be minimal. If training were too time consuming, then medical planners would be reluctant to remove their personnel from direct medical support tasks to let them acquire necessary expertise [Ref. 4].

In summary, increased accuracy in blood requirements forecasting may be possible using a causal approach rather than the observed trend methodology currently in use. Further, if such an approach were significantly more accurate, then the forecasting function could be justified as needing to be retained at the local tactical level. The system must include some semblance of human expertise to be accepted by medical professionals. And also, it must be able to be utilized with current microcomputer assets available to the local medical planner, and require minimal training time for user personnel to become proficient in using the system.

An expert support system was deemed to be applicable to these unique domain characteristics. While the process is predominantly inclined toward statistical processing, there are also notable subjective intuitive actions (secondary processing) which are usually accomplished as addendum processes to the statistical procedures. Thus, the domain appears to support the concept of an add-on type of expert support system.

The current research was undertaken to both demonstrate an improved blood forecasting methodology based on causal influences, and to automate this new methodology into an expert support system.

IV. FORECASTING MODEL AND SYSTEM DEVELOPMENT

A. DATA SELECTION

In order to develop an expert support system which would be applicable to the United States Marine Corps (USMC) environment, data was required which historically depicted actual human blood requirements for USMC units who have operated in active combat conditions. Further, this historical data would need to be organized in such a way that causal and influential factors affecting blood consumption could be directly observed or indirectly inferred. Ideally, this data would be available for multiple engagements in diverse environments and under varied tactical conditions.

Although historical data for the incidence of combat casualties was available, many of the databases could not be used for identifying USMC casualties [Ref. 41: p. 4]. Further, much of the data reviewed was derived from combat engagements many decades prior to the current research. While this data, some from the American Civil War, was of historical interest it was not felt to be contributory toward an expert support system which would reflect modern warfare scenarios. Even data from World War I and World War II was considered to be of little value since weaponry and tactics have changed so much over recent decades. The distribution and types of casualties from more recent conflicts are markedly different than casualties from all previous wars [Ref. 42: p. 3]. For example, blood requirements for combat against non-explosive artillery or low velocity projectiles (such as musket balls), are not likely to be encountered in modern warfare.

A decision was simultaneously made not to attempt to incorporate data for nuclear, biological, or chemical (NBC) casualties into the expert support system. There were several reasons for this decision. First, although estimates of NBC casualties resulting in modern tactical warfare have been compiled, no actual statistics are available [Refs. 43: p. 3 & 44: p. 63]. Developing an estimating tool which is itself based upon estimates would be difficult to evaluate. Secondly, it would be difficult to identify specifically which NBC weapons USMC elements would encounter. This is particularly true of biological weapons [Ref. 45]. Finally, blood requirements for any NBC environment have not been defined. Aside from blood needed to treat as yet unspecified casualties, the NBC environment would compound blood requirements contributory factors (e.g.,transportation of blood resupply, power requirements for refrigerated storage) to an unknown degree [Ref. 46]. In view of these considerations, no attempt was made to include NBC weaponry as causal agents in the expert support system.

Since the Vietnam conflict was the most recent large warfare environment in which the Marine Corps was involved where notable casualties were incurred, and since the weaponry employed throughout the conflict was construed to reflect modern armaments likely to be encountered by the Marine Corps in any combat operations in the near future, the search for data focused on that conflict. Casualty data from Vietnam was found to be readily available [Refs. 47: p. 9, 48: p. 128 ,49: p. 150, 50: p. 6, 41: p. 4, & 39: p. 3]. However, in much of this data separation of USMC casualties and identification of wound causal agents was difficult or impossible. Fortunately, one database was discovered which satisfied both of these constraints [Ref. 39: p. 11].

During the period January through June of 1968, a study was undertaken at the Naval Support Activity Hospital, Danang, Republic of South Vietnam to construct a surgical database. Medical data for 2021 male combat casualties, primarily United States Marines and Army soldiers, was collected. During this period there were 2008 casualties admitted to the facility, 13 of which were admitted twice during the six-month study period. For each casualty admitted to the facility, 63 data elements, displayed in Table II, were obtained and entered into a surgical database [Ref. 51]. This database was subsequently updated for each casualty as treatment continued.

Of particular interest to the current research was the data specifically compiled for CAUSE OF WOUND, BRANCH OF SERVICE, and NUMBER OF UNITS OF BLOOD GIVEN. This data was subsequently refined and published by the Naval Medical Research and

Development Command as a study depicting blood utilization at the Danang facility during the six-month period indicated [Ref. 39] The resulting statistics (Table III) were used in the development of an expert support system to be described later in this chapter.

It is significant to note that during the period 1964 to 1972, 15,113 (19.2 %) of the 78,726 Marine combat Wounded in Action (WIA) casualties in Vietnam were treated at the Naval Support Activity Hospital, Danang, even though they received their wounds in diverse regions of that country [Ref. 41: p. 10]. This suggests a large representative sample of all USMC WIA casualties incurred there. Further, the wound causal agents for the Danang facility WIA admissions were representative of and in reasonably close proportion to the wounding agents for all Marine casualties admitted to all medical treatment facilites during the Vietnam conflict (Table IV). Thus, the Danang statistics were construed to be a representative sample of all United States Marine Corps WIA casualties suffered during the Vietnam conflict.

B. METHODOLOGY

In order to develop an expert support system, one of the first tasks required is to examine the structure of the decision environment and ascertain that it is adaptable to both decision support systems and expert systems [Ref. 52: p. 207]. As previously noted, decision support systems are most

TABLE II
DANANG SURGICAL DATABASE DATA ELEMENTS

Admission/Hospital Data

1. SERIES NUMBER
2. CARD NUMBER
3. INTERVIEWER NUMBER
4. DATE
5. LAST NAME
6. INITIALS
7. SERVICE NUMBER
8. BRANCH OF SERVICE
9. MONTHS IN COUNTRY
10. DAYS ON OPERATION
11. PURPLE HEARTS
12. INJURY-TO-ADMISSION TIME
13. ADMISSION-TO-O.R. TIME
14. NUMBER OF PATIENTS IN TRIAGE
15. ADMISSION HEMATOCRIT
16. UNITS OF BLOOD THRU SURGERY
17. SURGERY IN O.R.
18. SURGERY IN ORTHO CLINIC
19. GENERAL ANESTHESIA
20. SPINAL ANESTHESIA
21. REGIONAL ANESTHESIA
22. LOCAL ANESTHESIA

Terrain of Injury

24. AIRCRAFT
25. AFOOT, WET
26. AFOOT, DRY
27. BUILDING
28. OTHER

Cause of Wound

29. GUNSHOT
30. ARTILLERY
31. THROWN GRENADE
32. MINE
33. BOOBY TRAP
34. BURN
35. OTHER
36. MULTIPLE CAUSES
37. NOT KNOWN
38. M26
39. M79

Disposition

40. TO DUTY
41. IN COUNTRY
42. HOSPITAL SHIP
43. WESTPAC
44. CONUS
45. OTHER

TABLE II (CONT.)
DANANG SURGICAL DATABASE DATA ELEMENTS

23. GROUND VEHICLE

47. RELEASED ALIVE

Injury

48. HEAD PENETRATING

49. HEAD NON-PENETRATING

50. EYE

51. ORAL

52. FACE (ENT)

53. FACE (NON-ENT)

54. NECK

55. CAROTID SURGERY

56. JUGULAR VEIN

57. TRACHEA

58. ESOPHAGUS

59. THORAX PENETRATING

60. THORAX NON-PENETRATING

61. DIAPHRAGM

62. BACK SPINE

63. BACK NON-SPINE

64. ABDOMEN PENETRATING

65. ABDOMEN NON-PENETRATING

66. LIVER

67. SPLEEN

68. PANCREAS

46. LENGTH OF STAY

72. SMALL INTESTINE

73. COLON

74. RECTUM

75. BLADDER/URETHRA

76. GENETALIA

77. VENA CAVA

Neck Examination

78. NECK EXPLORED

79. VAGUS

80. TRACHEA/LARYNX

81. ESOPHAGUS

82. C SPINE

83. OTHER

Neck Treatment

84. TRACHEOSTOMY

85. ESOPHAGOSTOMY

86. ESOPHAGUS REPAIR

87. LAMINECTOMY

88. DEBRIDEMENT

89. OTHER

90. TIME CAROTID OCCLUDED

Chest Tube

91. CHEST TUBE IN

TABLE II (CONT.)
DANANG SURGICAL DATABASE DATA ELEMENTS

69. KIDNEY

70. STOMACH

71. DUODENUM

92. DAYS IN PLACE

93. DAYS REMOVAL-TO-EVAC

TABLE III
BLOOD USE DISTRIBUTION BY WOUNDING AGENT
NAVAL SUPPORT ACTIVITY HOSPITAL, DANANG

Wounding Agent	Number of Casualties	Number of Casualties Given Blood	Percent of Casualties Given Blood	Number of Units Given	Mean Units
RIFLE/ PISTOL	481	114	23.7	539	4.7
ARTILLERY/ ROCKETS/ MORTARS	787	167	21.2	766	4.6
MINE	146	61	41.8	670	11.0
THROWN GRENADE	147	15	10.2	63	4.2
BOOBY-TRAP GRENADE (LF)	47	27	57.4	231	8.6
BOOBY-TRAP GRENADE (SF)	187	50	26.1	373	7.5
BURNING AGENT	6	0	0.0	0	0.0
GRENADE/MINE/ BOOBY-TRAP/ OTHER	32	5	15.6	15	3.0
MULTIPLE AGENTS	81	28	34.6	147	5.3
NOT KNOWN	86	45	52.3	324	7.2
OTHER	21	4	19.0	20	5.0
TOTALS:	2021	516	25.5	3148	6.1

[Ref.39: p. 10]

TABLE IV
COMBAT CASUALTIES BY WOUNDING AGENT
U.S. MARINES IN VIETNAM, 1964-1972

Wounding Agent	Number Diagnoses	% Total Diagnoses
ARTILLERY	733	0.9
ROCKETS/BOMBS	1827	2.3
SHELL FRAGMENTS	12477	15.8
MORTARS/BAZOOKAS	9606	12.2
MINES/BOOBY-TRAPS	21644	27.5
GRENADES	5467	6.9
BULLETS	21156	26.9
BAYONETTES	238	0.3
INCENDIARY	62	0.1
FIRES/EXPLOSIONS	3493	4.4
ALL OTHER AGENTS	2053	2.6
TOTALS:	78756	99.9 *

* Does not equal 100.0 due to rounding

[Ref. 41: p. 9]

applicable to environments where factors which affect the variable of interest can be identified, isolated, and quantified. Such factors are then incorporated into a decision support system using either probabilistic or Boolean techniques, or a combination of both [Ref. 53: 42]. Further, the level and type of decision-making must also be considered in determining whether or not a decison support system will be applicable.

There are three types of decisions in management contexts: Operational Control (decisions assuring effectiveness of operations), Management Control (decisions for acquisition and control of resources), and Strategic Planning (decisions related to setting policies) [Ref. 54: p. 976]. Each of these categories apply to a full spectrum of degrees of structure in specific decision-making environments. Decision support systems have been somewhat effective in semi-structured environments, and not effective at all in unstructured environments. Their greatest effectiveness is in their application to structured decision-making [Ref. 52: p. 217].

In this context, an analysis of the current procedures for blood requirements estimation and ordering used by Navy medical personnel in support of Marine Corps elements was undertaken, and an attempt made to identify decision elements applicable to a decision support system.

A review of available data indicated that the decision making process of estimating blood resupply requirements was quite structured, and seemed to fall within the decision categories of Operational Control (since it determined the effectiveness of the blood program operations) and Management Control (since it dealt with acquisition and control of blood resources). Thus, the blood resupply requirements decision seemed initially applicable to decision support system techniques.

It was clearly evident that all Marines received their wounds from a foreign object (e.g., a causal agent). In addition, throughout the Vietnam conflict wounds were consistently caused by the same agents [Ref. 41: p. 9]. Data for wounds caused by these agents was readily available in the aforementioned Danang database, including the percentage of total wounds caused by each agent, and the mean number of units of blood required for wounds from each agent.

As previously noted, current blood requirements estimation relies upon two primary variables: number of casualties anticipated, and blood storage capability available. While these decision criteria are widely employed, refinement is possible which could increase accuracy appreciably. Though it is convenient in manual estimation procedures to group all wounds together into a gross composite statistic, resultant estimation accuracy suffers. If data is available which clearly depicts how much blood is required for wounds caused by individual types of agents, and if the data further portrays what proportion of all wounds will be caused by each agent present, then a much more accurate requirements forecast should be derived using the agent-specific data.

To effectively utilize the available causal agent-specific data, the total casualties anticipated must be known. This variable, usually expressed as a percentage of the entire force and computed by the resident Marine G-1 Section (Administration and Personnel) is readily available to medical personnel upon request. However, this variable sums casualties in three categories: killed in action (KIA), wounded in action (WIA), and disease non-battle injury (DNBI). Of these categories, only those of WIA and DNBI will possibly require blood. The three categories must be separated to effectively utilize the agent-specific data.

At different periods of an amphibious operation, different percentages of total casualties will fall into the KIA, WIA, and DNBI categories. During an unopposed afloat transit to the combat zone, for example, all casualties would be DNBI. During an opposed landing/insertion phase, the highest levels of KIA and WIA would be expected. Further, during the land operations phase, the WIA and KIA proportions of total casualties will decrease from the landing/insertion phase, while DNBI casualties will probably increase.

Based on historical data, estimates of KIA, WIA, and DNBI casualties as percentages of total casualties at each of the three stages of Marine combat operations are available [Ref. 2]. Use of this data would enable the causal agent-specific data to be specifically applied to each discrete phase of Marine Corps combat operations, thus enhancing the accuracy of a decision support system employing such data even further over the current manual technique of blood requirements forecasting. Thus, to summarize briefly, knowing the size of the force employed in combat operations, the phase of the combat operations, the current casualty estimate, and the specific wound causal agents employed by opposing forces, it should be possible to develop a decision support system for use in estimating Marine casualty blood requirements.

C. DECISION SUPPORT SYSTEM COMPONENT

Since such a decision support system would be based upon statistical data rather than Boolean imperatives (i.e., is/is not situations), an effort was made to develop a model which would produce a blood requirement statistic.

In creating a forecasting model, a sequence of steps are generally required. After defining the parameters which affect changes in demand, the data sources are analyzed, alternative quantitative projection techniques are assessed, and model performance criteria are established [Ref. 55: p. i]. Since the parameters of interest have already been identified, we proceed to analyzing the data sources.

The Danang database only provided one data point to be used in forecasting. This placed severe limitations upon the types of forecasting models which could be constructed for the prototype. After a thorough review of available literature, a naive horizontal model was settled upon [Ref. 56: p. 51]

The naive model considers future demand estimates to be the same as the most current demand entry. For the current research, its principal strength was that it required only one historical observation period: the most current demand. A statistical depiction of the model would be

$$\hat{X}(T) = X \qquad\qquad T = 1,2,3,\ldots$$

where $\hat{X}$ = Forecasted Demand

and X = Most Recent Demand

and T = Future Demand Periods Being Forecasted .

Since the intent of the current research was to derive a forecasting model for the next period only, the value of T would be permanently fixed at T = 1. Thus, the model used in the current research would be

$$\hat{X}(1) = X \qquad \text{or} \qquad \hat{X} = X \quad .$$

Notable weaknesses were recognized in the use of such a model. The greatest weakness was that the forecast error would increase as the value of T increased. However this weakness could only be overcome by using a more refined forecasting approach which would require multiple data points (e.g., a moving average technique). As noted, only a single data point was available for the current research. Therefore, due to the constraints of the available data, and the intent to develop a prototype system which could be modified in future use when more demand observations are available, the naive model was adopted.

Within the Danang data, it appeared evident that the type of wounding agent exerted an influence on the individual casualty's demand for blood. Further, the previously noted parameters (e.g.: phase of operation, casualty estimate, and force size) were also considered to be contributory in a like manner. Each wound causal agent was held to act upon the WIA casualties, as derived from the same previously noted parameters, in a cumulative manner. Hence, the data seemed to support an additive causal effect approach to constructing a forecasting model.

Having defined the relevant parameters, analyzed the data sources, and assessed alternative quantitative projection techniques, the next step to be completed in developing a forecasting model was to establish required performance criteria. As previously noted, the current manual state of blood requirements forecasting in the Marine combat environment is notably less than perfect. The model resulting from the current research should at least produce a demand estimate which is closer to the actual demand than the current manual techniques. This performance criteria, in fact, served to generate the experimental hypothesis which was tested.

The author next attempted to identify all contributory variables of blood demand and incorporate them into an appropriate model. It is known that the percentage of the total casualties of the entire force which would be wounded, killed, or ill will vary as a result of the phase of the conflict [Ref. 2]. This phenomenon is presented in Table V. Since blood is required only for WIA and DNBI casualties, this breakdown is essential for accurate forecasting. For any given phase of a

TABLE V
PHASE/CASUALTY ESTIMATE

Phase	KIA Percent	WIA Percent	DNBI Percent
1	0.00	0 00	100.00
2	21 02	74.08	4.90
3	20.00	57.78	22.22

conflict, the numbers of WIA and DNBI casualties can be calculated by multiplying the force size by the casualty estimate. This product can then be multiplied by the WIA or DNBI percentage to derive the expected casualties in each category.

An assumption was made by the author that the possibility of being wounded by a given weapon was an event independent of being wounded by any other weapon. Being wounded by a bullet, for example, does not predispose a Marine to also being wounded by a mortar. He may indeed be subsequently wounded by a mortar, but the event would not be a direct result of his having been wounded by a bullet. The possibility of a second wound resulting from being immobilized by a first wound or by being in the act of medical evacuation when the second wound occurred was considered. However, this was determined to be extremely unlikely because of the small number of Danang casualties who received wounds from multiple agents (4.01%). The possibility of being wounded by each causal agent was therefore assumed to be independent of the possibility of being wounded by any other. The data for multiple agent caused wounds was retained, however, since the amount of blood needed would be different for casualties with wounds caused by several independent agents. Since the user could not be expected to provide contributory input data, values for these agents were computed and included in the final estimate without the user's awareness (Table VI).

Allowing W to represent the total number of WIA casualties, determined by multiplying the casualty estimate by the WIA Percent from Table V for the appropriate phase, and allowing A_i to represent the probability of the casualties caused by any given agent i requiring blood, and by letting C_i represent the expected number of units of blood required for each WIA casualty caused by any given agent i, we can write the equation for the expected number of units of blood needed for WIA casualties for agent i, R_i, as

$$R_i = W \times A_i \times C_i .$$

The expected total number of units E of blood required for all WIAs caused by all wounding agents 1 through n is then determined using the equation

$$E = R_1 + R_2 + \ldots + R_n .$$

TABLE VI
PROBABILITIES OF WIAs
CAUSED BY SPECIFIC AGENTS

Weapon Type	Number of WIAs	Percent WIAs	Probability
Rifle/ Pistol	481	23.80	.2380
Artillery/ Rockets/Mortars	787	38.94	.3894
Thrown Grenades	147	7.27	.0727
Mines	146	7.22	.0722
Booby-Trap (Small Frag.)	187	9.52	.0952
Booby-Trap (Large Frag.)	47	2.32	.0232
Burning Agent	6	0.30	.0030
Grenade/ Mine/Booby-Trap/Other	32	1.58	.0158
Multiple Agents	81	4.01	.0401
Unknown	86	4.25	.0425
Other	21	1.04	.0104
Total WIAs	2021		

It must be remembered that not all casualties requiring blood are WIA. Depending on the phase of the conflict a certain proportion of the total casualties will be DNBI. Based upon historical data it is known that each DNBI casualty will require an average of 0.5 units of blood [Ref. 2]. Thus, if T represents total casualties, and D represents the percent of total casualties which are DNBI, then we can write the equation for the number of units of blood required for all DNBI casualties, U, as

$$U = (T \times D) \times (0.5) \quad .$$

If the equation for WIA blood requirements for wounds caused by all agents 1 through n and the equation for DNBI requirements are summed, then the equation for the composite blood requirement, C, could be written as

$$C = E + U \quad .$$

This composite blood requirement could be utilized as the forecast of blood requirements for a given combat phase. It was included in this thesis as the decision support system component of the expert support system. It should be mentioned that the decision support system model has certain categories of wound causal agents either combined or not included.

Since no WIAs resulting from burning agents required blood, this agent was eliminated from the model. Also, to simplify computations and to minimize queries requiring user responses, the agents Booby-Trap (Large Fragment) and Booby-Trap (Small Fragment) were combined into an agent called Booby Trap. The agents Grenade/Mine/Booby-Trap/Other, Multiple Agents, and Unknown were combined into a single agent which was computed transparently to the user.

D. EXPERT SYSTEM COMPONENT

Having developed the decision support system component, efforts now were turned to developing the expert system component. As noted previously, for an expert system to be effective it must capture the experience and expertise of an expert, and present this captured knowledge in such a way that it is readily available to the user. The critical element in accomplishing these goals is the identification of an expert or experts with the requisite knowledge and experience. Although there are blood forecasting experts who derived their skills soley from some form of training, there presently appears to be a dearth of experts who possess both training and actual combat blood forecasting experience.

Although some recent combat evolutions have involved the Marine Corps (e.g., Grenada; Beirut, Lebanon), the encounters were extremely brief and were considered to have been atypical of historically normative combat operations [Refs. 57, 58, & 59]. Therefore, an expert was sought who had been directly involved in medical support of combat operations during the most recent lengthy and complete Marine combat evolution in Vietnam.

Headquarters, United States Marine Corps and operational medical commands were contacted to assist in identifying eligible Navy Medical Service Corps officers who might qualify as subject matter experts [Ref. 7 & 60]. A suitable expert was identified and contacted, and agreed to participate in the current research.

Previous research had shown that the most difficult aspect of knowledge acquisition for use in an expert system was getting the expert to define the initial knowledge domain [Ref. 28: p. 273]. This resulted from the expert's difficulty in restructuring his knowledge to the decision-making environment at hand. This difficulty could be overcome if the domain was structured for the expert prior to an attempt to acquire knowledge. In the current research, this domain definition was accomplished by utilizing locally available blood forecasting expertise from experts who possessed training but no actual combat experience. These experts were asked to identify factors likely to be present in a combat environment which might influence the demand for blood [Refs. 61 & 62]. Eight factors were identified which might influence them to alter a blood forecast statistic (Table VII). These influencing factors were then organized into a questionaire (Appendix A) and presented to the subject matter expert. In this manner, difficulties with the expert defining the data domain were minimized.

The expert was asked to assume that he had been provided with a blood resupply quantity from an external source (i.e., a

TABLE VII
BLOOD DEMAND INFLUENCING FACTORS

1. Meteorological Conditions
2. Type of Blood Resupply Transportation Available
3. Presence or Absence of Tactical Air Supremacy
4. Reliability of Blood Resupply Transportation
5. Evacuation Policy
6. Casualty Evacuation Waiting Time
7. Bed Capacity of Supported Force's Medical Units
8. Major Surgical Capability (Cases per Day) of Supported Force's Medical Units

medical logistician). He was to review each influencing factor shown in Appendix A and to respond based upon his training and experience as to what effect, if any, the factor would most likely have upon the provided estimate. He was asked to indicate by what percent he would increase or decrease the estimate, and to explain why he felt such a change was appropriate. Further, he was asked to identify any other factors which he felt could influence blood demand, and to assign percentage increase or decrease levels in a like manner.

The expert's responses are displayed in Appendix B. Based upon the knowledge acquired from the subject matter expert, six factors were included in the expert support system: 1) blood resupply transport available, 2) reliability of blood resupply transport, 3) evacuation policy, 4) dependability of blood storage facilities, 5) reliability of blood refrigeration equipment, and 6) air supremacy. It was interesting to note that based upon combat experience, the expert eliminated 50% of the factors supposed to have influence which had been identified by the experts without combat experience, and identified two factors which they had not considered dealing with the reliability of electrical power for blood refrigerators, and the type of structure which the blood would be stored in. A conjecture was made that the areas not indicated by the inexperienced experts were areas which had not been included in field training problems. Subsequent interviews revealed this to be the case. Blood storage facilities were never actually established during field training, so the experts without combat experience had no inclination that supply-threatening problems could arise in their operation [Ref. 63].

Using the subject matter expert's responses as inputs to the decision support system component, a modified model was developed which combined the decision support system and expert system components:

$$C + J(C) + K(C) + L(C) + M(C) + P(C) + Q(C) = \text{Blood Requirement.}$$

In this model, the composite blood requirement derived from the decision support system component is represented as C. The effect of transport type is represented by the function J(C), the effect of transportation reliability by the function K(C), the effect of evacuation policy by the function L(C), the effect of storage dependability by the function M(C), the effect of power supply by the function P(C), and the effect of air supremacy by the function Q(C). Each function is defined by multiplying the decision support system component by the respective expert system component factor, which was determined by the human expert.

Finally, it was recognized by all experts that any quantity of blood ordered as a resupply must be considered in light of two additional factors: the quantity of blood on-hand when the resupply order is received, and the total blood storage residual capacity. If the net storage capacity was equal to or greater than the blood requirement, then the requirement would be unchanged. If the available storage capacity was less than the requirement, the requirement was reduced to the storage capacity.

E. EXPERT SUPPORT SYSTEM

This protocol was joined to the decision support system and expert system components, and coded into a prototype computer system entitled HEMOS (Hematologic Expert Support System for Marine Corps Operational Support), which is displayed in Appendix C.

In coding the HEMOS prototype a suitable language needed to be selected. Numerous fourth generation computer languages had been used for decision support and expert systems by previous researchers. One, the M1 language created by TEKNOWLEDGE Inc., of Palo Alto, California, was attractive for its backward chaining algorithm. Further, the easily manipulated rule-based syntax indicated that M1 was notably appropriate for the loosely structured environment which the current research entailed. Also, M1's feature of automatic run tracing was quite attractive and indicated a minimal amount of time would be required for debugging and logic modification activities. In practice, the M1 fourth generation language appeared to satisfy all special needs of this problem.

F. PROTOTYPE TESTING

To test the experimental hypothesis (i.e., that the HEMOS system prototype would be more accurate than current manual techniques), the Danang database was randomly separated into three segments by a DEC minicomputer using the DATE data field with an SPSS-X utility randomization function [Ref. 51]. These segments are displayed in Appendix D. The HEMOS decision support system component was constructed using only segment C, which was randomly selected from the three segments. Segments A and B were reserved for use in hypothesis testing.

A null hypothesis was formulated that there would be no discernible difference in accuracy between the prototype expert support system and existing manual techniques in forecasting blood resupply requirements. To test this hypothesis, an experiment was conducted using a trained team of Navy Medical Service Corps officers who were experts by virtue of training, but who did not possess actual combat experience. The team was provided with a set of situational parameters derived from segment A of the Danang database. These are displayed in Figure 4.1. The parameters matched actual tactical and environmental conditions which were present when the Danang data were collected [Refs. 2, 58, & 59]. The parameters for Blood Remaining On-Hand and Blood Storage Capacity were artificially set to levels which would minimize the possibility that required blood exceeded available storage. This was done to facilitate experimental measurements, and was not considered disruptive of the forecasting process.

Team members were asked to estimate the blood resupply requirement using the same methods that they would employ in a tactical scenario. The computation time needed to formulate their forecast and the value of the forecast were recorded.

An identical test was conducted using HEMOS operating on a microcomputer system identical to the manufacturer and model possessed by all Marine Medical Support Operations Center units. These units would be anticipated to take these systems with them into a real world combat scenario. The results from the two tests are discussed in the next chapter.

FORCE SIZE BEING SUPPORTED	22433
CASUALTY ESTIMATE	3 %
COMBAT SCENARIO	SUSTAINED LAND COMBAT OPERATIONS
COMBAT INTENSITY	MODERATE
METEOROLOGICAL ENVIRONMENT	SEMI-TROPICAL
FRIENDLY FORCES ENGAGEMENT STRENGTH	<= COMPANY STRENGTH
BLOOD REMAINING ON-HAND IN 72 HOURS	0 UNITS
BLOOD STORAGE CAPACITY	2000 UNITS
ENEMY WEAPONS EMPLOYED	RIFLES/PISTOLS ARTILLERY/ROCKETS HAND GRENADES MORTARS BOOBY TRAPS INCENDIARIES LAND MINES KNIVES/BAYONETTES
NUCLEAR, BIOLOGICAL, CHEMICAL WEAPONS THREAT	NONE
BLOOD RESUPPLY TRANSPORTATION RELIABILITY	HIGH
EVACUATION POLICY	5 DAYS
AIR SUPREMACY FOR FRIENDLY FORCES	YES
BLOOD STORAGE FACILITIES HARDENED	YES
BLOOD REFRIGERATION ELECTRICAL POWER SOURCE RELIABLE	YES

Figure 4.1 Blood Forecasting Simulation Exercise Parameters

V. TEST RESULTS

The HEMOS test was conducted using Zenith 258 microcomputer hardware identical to that possessed by the Marine Corps Medical Support Operations Centers. To insure against operator bias, which could have slanted test results in favor of the prototype from familiarity with automated forecasting systems, a subject with no previous experience with HEMOS or any other expert system or decision support system was solicited. A suitable subject was randomly selected from an Army medical battalion assisting in the current research.

The selected subject was a female junior enlisted administration clerk with less than two weeks experience using any computer equipment. The subject had no previous experience or training in blood requirements forecasting. Training of the subject consisted of a seven-minute verbal overview of HEMOS, followed by one test run using randomly selected data with the subject operating the system. Total subject training time with the HEMOS expert support system was twelve minutes.

During the HEMOS test the subject operated the HEMOS system while the author acted as the MSOC officer and held the simulation data where the subject could not see it. The relative physical positions of subject and author were intended to approximate actual positions in an operational MSOC as closely as possible. The author gave no coaching to the subject regarding HEMOS operation during the test. When requested by the subject, the author verbally provided the test parameters, which the subject then entered into the HEMOS system. This procedure was repeated until 14 simulations were completed. The resultant mean blood requirements estimate for the 14 tests was 1050 units (range = 0, since the HEMOS system always gave the same value). The mean estimate preparation time was 2 minutes 21.6 seconds. The times ranged from 2 minutes 58 seconds down to 2 minutes 2 seconds. However, since only one subject was used for the HEMOS test, at least some of this decrease in time was probably due to a learning process in operating the system.

The manual method test was conducted using 14 trained but inexperienced male Navy Medical Service Corps officers who were experts in blood requirements forecasting, and who were available as subjects for the thesis research. The tests were conducted in an office environment. The subjects received the test parameters verbally, and transcribed them into personal notes. They then were asked to derive their estimation of blood requirements as quickly as possible using any references which they would expect to have available to them in an operational environment. The only constraint placed upon the subjects was the condition that no automated data processing equipment, with the exception of personal calculator devices, was to be used. The resultant mean blood requirements estimate derived was 1704 units. The estimates ranged from 1327 units to 2076 units, with a mean estimate preparation time of 17 minutes 30 seconds. The range of preparation times for the manual test was from 15 minutes to 20 minutes.

The results of both sets of simulations were then compared to the actual usage rate of 1067 units for segment A of the Danang database. The manual method test result deviated from the actual requirement by + 62.7 % , while the HEMOS test result deviated by - 1.6 % .

The HEMOS system is superior to the currently practiced manual estimation technique in two important areas. First, the average time required to obtain the manual estimate was more than 750% longer than the time required for an operator with minimal training to achieve an estimate using the HEMOS system. It is important to note that estimates made using both techniques were based upon identical data. Further, the manual estimations were computed in a quiet environment without the distractions inherent to an operational Tactical Logistics Operations Center (TLOC) where an MSOC officer would normally perform such tasks.

The second finding was that the HEMOS technique produced a much more accurate blood requirements estimate than the manual method. By deviating from the actual quantity by + 62.7 %, the manual methodology, on average, would have wasted 637 units of human blood. At the extreme end of the manual estimate range, this figure could increase to a waste of 1009 units. The HEMOS system underestimated the actual requirement by 17 units of blood, which might have had a deleterious effect upon the health of a small number of casualties (With an actual mean blood requirement per WIA casualty of 6.62 units, the inaccuracy in the HEMOS estimate would be expected to impact 2.57 casualties, or 0.38 % of all WIAs. This level was construed by the author to be negligible.

The accuracy of the HEMOS estimate suggests that the system is a successful functional prototype. Even in its preliminary state, the HEMOS expert support system succeeded in outperforming the current manual methodology both in the time required and the accuracy of estimate.

VI. CONCLUSIONS AND RECOMMENDATIONS

The current method used to forecast blood requirements for Marine Corps units operating in combat environments appears to be grossly inaccurate, and will quite likely result in unnecessary wasting of blood resources. The material presented in the preceding chapters indicates that an alternative method of blood forecasting which is more accurate can be developed.

The current manual procedure is driven primarily by available blood storage capacity and usage rate. Since usage rate is determined by highly variant forces in the combat environment, the technique is frequently inaccurate. To compensate for this, the current procedure inflates blood requirement estimates to minimize the risk of blood not being available for casualties who need it. The result is frequently an overstocking of blood, which is highly perishable and often expires before it can be used. Thus, significant quantities of blood, which must be shipped to the combat units at great logistical effort, are inevitably wasted.

An alternative approach would be to recognize which agents in the combat environment cause blood consumption. Historical data could then be used to project blood requirements caused by each agent. Individual agent projections could then be combined for a cumulative blood estimate. To facilitate acceptance by human users, hunch-like increases or decreases in the cumulative estimate could be made by the users based upon subjectively assessed conditions of the tactical situation. Thus, the alternative method would be causal in nature, while the current technique is inferential.

In the current research a prototype expert support system using this alternative method was developed and tested. The prototype was named HEMOS, and was found to be more accurate and notably faster than current manual techniques in a test situation.

Significant in the current research is that the HEMOS system was operated by a frankly non-expert user, and still succeeded in outperforming a team of experts. This observation certainly demonstrates the potential manpower and training savings possible with a refined HEMOS system.

The HEMOS expert support system prototype has a basic weakness in that it was developed using only one data point. It should have a better statistical forecasting model. Its decision support system component generator should be based upon multiple periods of causal observation. Unfortunately, no such data was available during the current research effort.

Initial response from operational medical personnel who are familiar with HEMOS and the prototype study results of the current research has been favorable. This would seem to indicate that if the deficiencies discussed above were satisfactorally rectified, HEMOS could gain operational acceptance from real world users. However, before such acceptance could be gained, other issues not directly related to an expert support system would also need to be resolved.

There are some reservations among operational medical personnel toward nuturing a dependence upon electronic decision making aids. It must be reiterated, however, that HEMOS is not intended to replace the human decision maker. It is intended, rather, to assist him in an inexact task environment. Further, it is doubtful that Marine commanders would place complete trust in a non-human system which would in effect control a life-and-death commodity, and which would directly affect the operational success of their mission. Human expertise complemented by manual methodologies will almost certainly remain in the tactical blood forecasting environment, at least as a reserve technique for use in the event of automated data processing failure.

However, the benefits in time and accuracy of automating tactical support planning processes cannot be discounted. In the area of blood requirements forecasting refinement of the HEMOS prototype could well serve as the basis for future research, and could result in a viable forecasting alternative for use by Navy Medical Department personnel. Even without it, the simple estimating model in the prototype should yield substantial improvements in both time and accuracy. It is recommended that research to refine and implement the HEMOS system be continued. Further, research is also recommended to identify how acceptance of automated decision-making systems could be enhanced by tactical commanders, and to determine additional areas in the tactical environment where automated decision-making aids would be applicable.

In conclusion, it is possible to state that HEMOS, even in its prototypical form, may be seen to be more accurate and less time consuming than human experts in certain tactical conditions, and that the system exhibits promise of becoming a valuable decision making asset, with needed refinements, in the field of tactical blood forecasting in support of Marine Corps combat units.

APPENDIX A
SUBJECT MATTER EXPERT
INTERVIEW QUESTIONS

QUESTION 1

Weather conditions may or may not affect blood requirements. For the following weather conditions, in your best judgement what percent (if any) would you increase or decrease the statisitcal blood forecast?

Weather Condition	% Change
HOT	:
COLD	:
WET	:
MODERATE	:

Comments ? :

QUESTION 2

The types of transportation available or not available for use in carrying resupply blood to supported medical units may or may not lead you to alter the statistical blood forecast. For the following types of transportation, what percent (if any) would you increase or decrease the statistical forecast?

TYPE OF TRANSPORTATION	% CHANGE IF THERE IS AIR SUPERIORITY	% CHANGE IF THERE IS NOT AIR SUPERIORITY
Air Only	:	:
Water Only	:	:
Ground Only	:	:
Air and Water	:	:
Air and Ground	:	:
Water and Ground	:	:
Air, Water, and Ground	:	:

Comments ? :

QUESTION 3

Even if blood resupply transportation is available, its dependability may vary (ie: whether the blood resupply shipments arrive at all and on time). How would the following levels of dependability cause you to increase, decrease, or leave unchanged the statistical forecast?

DEPENDABILITY LEVEL	% CHANGE
LOW ____________	:
MODERATE ____________	:
HIGH ____________	:

Comments ? :

QUESTION 4

Consider that patients awaiting evacuation out of the combat zone may require continued blood transfusions. With this in mind, how would the following Evacuation Policies cause you, if at all, to modify the statistical forecast?

EVACUATION POLICY	% CHANGE
Less than 1 day ______	:
1 Day ___________	:
2 Days ___________	:
3 Days ___________	:
4 Days ___________	:
5 or more days _____	:

Comments ? :

QUESTION 5

Assume that Evacuation Waiting Time refers to the period of time that casualties designated for evacuation out of the combat zone spend waiting at the evacuation site for their transportation to arrive, load them, and depart (eg: casualties waiting by an airstrip for MEDEVAC planes to arrive, or casualties waiting at a beach or port for seaward MEDEVAC). How, if at all, would the following levels of Evacuation Waiting Time cause you to alter the statistical blood forecast?

EVACUATION WAITING TIME	% CHANGE
Low	:
Moderate	:
High	:

Comments ? :

QUESTION 6

The cumulative Total Bed Capacity of all medical units being supported may lead you to alter the statistical estimate. For the following total bed capacities, what change (if any) would you make to the statistical forecast?

TOTAL BED CAPACITY	% CHANGE
60 or less	:
61 to 120	:
121 to 200	:
More than 200	:

Comments ? :

QUESTION 7

The number of Major Surgical Cases which can be performed by all supported medical units during a 24 hour period may cause you to alter the statistical forecast. Perhaps the greater the surgical capability, the more surgeries will be performed; thus a greater need for blood. Or, conversely, perhaps you believe that there is no relationship between the two factors. For the following Major Surgical Capabilities, what changes if any would you make to the statistical forecast?

MAJOR SURGICAL CAPABILITY	% CHANGE
0 to 50 cases per day	:
51 to 90 cases per day	:
91 to 120 cases per day	:
More than 120 cases per day	:

Comments ? :

QUESTION 8

Are there any other areas excluding those mentioned in the Project Overview which you believe could lead you to alter the statistical blood requirements forecast? If yes, then please list them and show what percentage change they would lead you to make to the statistical forecast.

APPENDIX B
SUBJECT MATTER EXPERT'S
RESPONSES TO INTERVIEW QUESTIONS

Question 1 : Weather Conditions

While cold weather could conceivably cause a requirement for "fresh" warm blood, this would not be a supply line problem. My experience prompts no correlation between weather and simple blood requirements.

Percent change for all weather conditions = 0.

Question 2: Transportation Types Available

The term "air superiority" as you used it must really be changed to "air supremacy", which is what you meant. That is when one side has full control of the air, while superiority infers only temporary control due to a tactical advantage of the moment. I would change the forecast statstic in the following manner:

TYPE OF TRANSPORTATION	% CHANGE IF THERE IS AIR SUPREMACY	% CHANGE IF THERE IS NOT AIR SUPREMACY
Air Only :	0	+ 20
Water Only :	0	+ 20
Ground Only :	0	+ 20
Air & Water :	0	+ 20
Air & Ground :	0	+ 20
Water & Ground :	0	+ 20
Air, Water & Ground:	0	+ 15

APPENDIX B (CONT.)

Question 3: Blood Resupply Transportation Dependability

In a combat environment I would consider "moderate" to be the norm. Also, I would prefer that you use the term "reliability" rather than "dependability". I would alter the statistic in the following way:

RELIABILITY LEVEL	% CHANGE
LOW	+ 20
MODERATE	0
HIGH	- 20

Question 4: Evacuation Policy

This is hard to quantify. Logically, there would probably be a progression, as indicated.

EVACUATION POLICY	% CHANGE
Less than 1 day	0
1 Day	0
2 Days	+ .20
3 Days	+ .35
4 Days	+ .65
5 or more days	+ .65

Question 5: Evacuation Waiting Time

I think that this factor would be irrelevant and wouldn't affect blood usage. Since evacuation out of the Combat Zone is an Air Force function, the MSOC would see little or no impact.

Percent change to the statistical estimate: 0 .

Question 6: Bed Capacity

Mostly irrelevant. Blood requirements are more likely to be a function of the complexity of surgery than the number of beds available to be filled by casualties.

Percent change to the statistical estimate: 0 .

Question 7: Number of Major Surgical Cases

As far as I can imagine, the increase based upon number of sugeries per day would be strictly a direct relationship with the numerical increase in casualties. Hence, I would not alter the statistic based upon this variable.

Percent change to the statistical estimate: 0 .

Question 8: Other Possible Influences

Two important considerations which you haven't mentioned would be storage method and the reliability of electrical power.

1. Storage method relates mainly to equipment being used and its suitability to the environment. The issue would be whether the blood was stored in a hardened facility (i.e.: a facility with genuine blood refrigerators which are alarmed with a temperature recorder, and which is hardened against attack).
   - if not hardened, increase the statistic by 15 %.

   - if is hardened, do not change statistic.

2. The power supply for blood refrigeration refrigerators must be assessed for:
   - reliability
   - circuit switching capability
   - an alarmed and monitored circuit
   - reserve capacity.

If any one of the above conditions are not met, then increase the forecast statistic by 10 %, otherwise leave it the same.

APPENDIX C
HEMOS SOURCE CODE

*****

H E M O S
****

(Hematologic Expert Support System for
Marine Corps Operational Support)

by

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Medical Service Corps
United States Navy

Computer Technologies Department
Naval Postgraduate School
Monterey, California

This system is intended for use by medical personnel assigned in support of Marine Corps combat operations, to be used in computing a recommended quantity of human blood to be included in a blood resupply request. The system is unique in that it:

1) Uses both a statistical algorithm AND an expert knowledge base to obtain a recommended blood requirements forecast,

2) Is a thoroughly comprehensive system relative to all aspects of combat operations,

3) Employs statistical estimates of casualties, obtained from historical statistics from the Viet Nam conflict, in a Bayesian algorithm,

4) The resulting recommended statistic could be employed in an Exponential Smoothing model after the third day of operations to produce a self-modifying

forecasting model in the decision
making process.

*

```
goal = fin_blood_req.

*          Rules 1 and 2 compare the blood request with the
           available blood storage capacity, and ensure that
           the final blood request will not exceed available
           storage capacity

*

rule-1: if fin_blood_req_a = ZZZZ and
        blood_room_avail = JJJ and
        JJJ >= ZZZZ
        then fin_blood_req = ZZZZ.

rule-2: if fin_blood_req_a = ZZZZ and
        blood_room_avail = JJJ and
        ZZZZ > JJJ
        then fin_blood_req = JJJ.

rule-3: if blood_on_hand = III and
        blood_req = ZZZZ and
        III >= ZZZZ
        then fin_blood_req = 0.

rule-4: if blood_on_hand = III and
        blood_req = ZZZZ and
        ZZZZ > III
        then fin_blood_req_a = ZZZZ.

*           Rules 5 and 6 compute a blood requirement using
            percentage weights for individual variables as
            determined by a subject matter expert.
*

rule-5: if comp_blood_req = V and
        transdep = CCC and
        evac_blood = DDD and
        air_blood = GGG and
        stor_blood = MMM and
        power effect = NNN and
        trans dep = 1 or
        trans_dep = 2 and
        V + CCC + GGG + MMM + NNN + DDD = ZZZZ
        then blood req = ZZZZ.
```

```
rule-6: if comp_blood_req = V and
        transdep = CCC and
        evac_blood = DDD and
        air_blood = GGG and
        stor_blood = MMM and
        power_effect = NNN and
        trans_dep = 3 and
        V + GGG + MMM + NNN + DDD - CCC = ZZZZ
        then blood_req = ZZZZ.

/*        Rule 5 incorporates the Disease Non-Battle Injury
          blood requirement into the tentative blood
requirement which was previously computed for the
Wounded in Action casualties.

*/

rule-7: if ten_blood_req = Q and
        d_blood_req = U and
        Q + U = V
        then comp_blood_req = V.

/*           Rule 6 computes a statistical blood requirement
             based upon conflict stage, population, casualty
             estimate, and weapons employed by the enemy.

*/

rule-8: if bull_need = J and
        gren_need = K and
        arty_need = L and
        boob_need = M and
        othr_need = N and
        mine_need = X and
        z_need = P and
        J + K + L + M + N + X + P = Q
        then ten_blood_req = Q.

/*         Rules 7 thru 59 compute a statistical blood forecast
           using a strictly algorithmic technique.

*/

rule-9: if d_cas = S and
        d_drip = T and
        S * T = U
        then d_blood_req = U.
```

```
rule-10: if d_pcen = R and
        num_cas = C and
        R * C = S
        then d_cas = S.

rule-11: if conflict
        then d_drip = .5.

rule-12: if bull_blood = WRB and
           bull_drip = CC and
           WRB * CC = J
           then bull_need = J.

rule-13: if bull_type = yes
           then bull_drip = 4.7.

rule-14: if bull_cas = WR and
           bull_brate = BB and
           WR * BB = WRB
           then bull_blood = WRB.

rule-15: if bull_type = yes
           then bull_brate = .2067.

rule-16: if bull_type = yes
           then bull_rate = .2222.

rule-17: if w_cas = E and
           bull_rate = AA and
           E * AA = WR
           then bull_cas = WR.

rule-18: if w_pcen = D and
           num_cas = C and
           D * C = E
           then w_cas = E.

rule-19: if phase = 1
           then w_pcen = 0.

rule-20: if phase = 1
           then d_pcen = 1.

rule-21: if phase = 2
           then w_pcen = .7273.

rule-22: if phase = 2
           then d_pcen = .049.
```

```
rule-23: if phase = 3
           then w_pcen = .5778.

rule-24: if phase = 3
           then d_pcen = .222.

rule-25: if pop_size = A and
            cas_rate = B and
            A * B = C
            then num_cas = C.

rule-26: if mine_blood = WMB and
            mine_drip = SS and
            WMB * SS = X
            then mine_need = X.

rule-27: if mine_type = yes
            then mine_drip = 13.2.

rule-28: if mine_cas = WM and
            mine_brate = TT and
            WM * TT = WMB
            then mine_blood = WMB.

rule-29: if mine_type = yes
            then mine_brate = .4167.
rule-30: if mine_type = yes
            then mine_rate = .0711.

rule-31: if w_cas = E and
            mine_rate = UU and
            E * UU = WM
            then mine_cas = WM.

rule-32: if gren_blood = WGB and
            gren_drip = DD and
            WGB * DD = K
            then gren_need = K.

rule-33: if gren_type = yes
            then gren_drip = 4.3.

rule-34: if gren_cas = WG and
            gren_brate = EE and
            WG * EE = WGB
            then gren_blood = WGB.

rule-35: if gren_type = yes
            then gren_brate = .129.
```

```
rule-36: if gren_type = yes
            then gren_rate = .0919.

rule-37: if w_cas = E and
            gren_rate = FF and
            E * FF = WG
            then gren_cas = WG.

rule-38: if arty_blood = WAB and
            arty_drip = GG and
            WAB * GG = L
            then arty_need = L.

rule-39: if arty_type = yes
            then arty_drip = 3.7.

rule-40: if arty_cas = WA and
            arty_brate = HH and
            WA * HH = WAB
            then arty_blood = WAB.

rule-41: if arty_type = yes
            then arty_brate = .196.

rule-42: if arty_type = yes
            then arty_rate = .40.

rule-43: if w_cas = E and
            arty_rate = II and
            E * II = WA
            then arty_cas = WA.

rule-44: if boob_blood = WBB and
            boob_drip = JJ and
            WBB * JJ = M
            then boob_need = M.

rule-45: if boob_type = yes
            then boob_drip = 10.46.
rule-46: if boob_cas = WB and
            boob_brate = KK and
            WB * KK = WBB
            then boob_blood = WBB.

rule-47: if boob_type = yes
            then boob_brate = .32.

rule-48: if boob_type = yes
            then boob_rate = .1111.
```

```
rule-49: if w_cas = E and
            boob_rate = LL and
            E * LL = WB
            then boob_cas = WB.

rule-50: if othr_blood = WOB and
            othr_drip = MM and
            WOB * MM = N
            then othr_need = N.

rule-51: if othr_type = yes
            then othr_drip = 3.0.

rule-52: if othr_cas = WO and
            othr_brate = NN and
            WO * NN = WOB
            then othr_blood = WOB.

rule-53: if othr_type = yes
            then othr_brate = .125.

rule-54: if othr_type = yes
            then othr_rate = .0118.

rule-55: if w_cas = E and
            othr_rate = OO and
            E * OO = WO
            then othr_cas = WO.

rule-56: if bull_type = no
            then bull_need = 0.

rule-57: if gren_type = no
            then gren_need = 0.

rule-58: if arty_type = no
            then arty_need = 0.

rule-59: if boob_type = no
            then boob_need = 0.

rule-60: if othr_type = no
          then othr_need = 0.

rule-61: if mine_type = no
          then mine_need = 0.
```

```
/*      Rules 62 to 68 compute an estimate of casualties
   caused by multiple wounding agents, as determined by
 historical data. This variable is automatically
included in all wounded blood requirements, and is
transparent to the user.
*/


rule-62: if z_blood = WZB and
            z_drip = PP and
            WZB * PP = P
            then z_need = P.

rule-63: if conflict
            then z_drip = 5.27.

rule-64: if bull_type or
            arty_type or
            gren_type or
            boob_type or
            mine_type or
            othr_type = yes
            then conflict.

rule-65: if z_cas = WZ and
            z_brate = QQ and
            WZ * QQ = WZB
            then z_blood = WZB.

rule-66: if conflict
            then z_brate = .3729.

rule-67: if conflict
            then z_rate = .0874.

rule-68: if w_cas = E and
            z_rate = RR and
            E * RR = WZ
            then z_cas = WZ.

/*       Rules 69 thru 91 modify the previously derived
         statisticial forecast for required blood by using
         per cent increase or decrease factors obtained from a
         Subject Matter Expert.
*/
rule-69: if trans_dep = 1
         then trans_dep_effecta = .20.
```

```
rule-70: if trans_dep = 1 and
         comp_blood_req = V and
         trans_dep_effecta = LOW and
         V * LOW = CCC
         then transdep = CCC.

rule-71: if trans_dep = 2
         then trans_dep_effectb = 0.

rule-72: if trans_dep = 2 and
         comp_blood_req = V and
         trans_dep_effectb = NEGA and
         V * NEGA = CCC
         then transdep = CCC.

rule-73: if trans_dep = 3
         then trans_dep_effectc = .20.

rule-74: if trans_dep = 3 and
         comp_blood_req = V and
         trans_dep_effectc = ALF and
         V * ALF = CCC
         then transdep = CCC.

rule-75: if evac_policy = 1
         then evac_effect = .0.

rule-76: if evac_policy = 2
         then evac_effect = .0.

rule-77: if evac_policy = 3
         then evac_effect = .20.

rule-78: if evac_policy = 4
         then evac_effect = .35.

rule-79: if evac_policy = 5 or
         evac_policy = 6
         then evac_effect = .65.

rule-80: if evac_effect = LONG and
         comp_blood_req = V and
         LONG * V = DDD
         then evac_blood = DDD.

rule-81: if air_sup = no and
         transport = 1
         then air_sup_effect = .20.
```

```
rule-82: if air_sup = no and
         transport = 4 or
         transport = 5
         then air_sup_effect = .20.

rule-83: if air_sup = yes
         then air_sup_effect = .15.

rule-84: if stor_dep = yes
         then stor_effect = 0.

rule-85: if stor_dep = no
         then stor_effect = .15.

rule-86: if stor_effect = HAIR and
         comp_blood_req = V and
         HAIR * V = MMM
         then stor_blood = MMM.

rule-87: if power_sup = yes
         then power_result = 0.

rule-88: if power_sup = no
         then power_result = .10.

rule-89: if power_result = JOLT and
         comp_blood_req = V and
         JOLT * V = NNN
         then power_effect = NNN.

rule-90: if air_sup = no and
         transport = 2 or
         transport = 3 or
         transport = 6 or
         transport = 7
         then air_sup_effect = 0.

rule-91: if air_sup_effect = NUTS and
         comp_blood_req = V and
         V * NUTS = GGG
         then air_blood = GGG.

rule-92: if blood_cap = HHH and
         blood_on_hand = III and
         HHH - III = JJJ
         then blood_room_avail = JJJ.
```

```
/*                    QUESTIONS
*/


/************************************************************/
/************************************************************/
/********  DETERMINE STATISTICAL BLOOD FORECAST  ************/
/************************************************************/
/*
             The first several questions will be used
             to obtain data necessary to formulate an
             algorithmic statistical forecast for
             blood requirements.

*/

/************* DETERMINE PHASE OF CONFLICT ******************/

/*            Phase of conflict determines proportion of
              total casualties which will be wounded, killed
              or diseased.
*/


question-1: enumeratedanswers(phase).
            question(phase) = '

             What phase of the conflict is it?
             1. Phase I [ Transit to AOA ]
             2. Phase II [ Amphibious Assault ]
             3. Phase III [ Land Conflict ]
            (Enter the number 1 thru 3 which applies)'.
          legalvals(phase) = [1,2,3].


 /********* DETERMINE WHICH TYPES OF WEAPONS ENEMY IS USING
****/
 /*                 Different types of weapons result in
                    various severity of wounds and, therefore,
                    blood requirements.
*/

question-2: automaticmenu(bull_type).
            question(bull_type) = '
            Is the enemy using bullet_type weapons such as
            rifles, pistols,machine guns, etc.?'.
          legalvals(bull_type) = [yes,no].
```

```
/**************** DETERMINE POPULATION SIZE *****************/
/*            Casualty estimates will be made by
              multiplying the population size by
              the per cent estimated casualties.
*/

question-3: question(pop_size) = '
              What is the size of the population being
 supported?'.
            legalvals(pop_size) = integer.

/**************** DETERMINE CASUALTY ESTIMATE ****************/

/*                The casualty estimate is computed and
                  provided by the G - 1 section of the
                  overall command. MEDICAL PLANNERS
                  SHOULD OBTAIN THIS STATISTIC FROM G - 1.
*/
question-4: question(cas_rate) = '
              What is the casualty estimate for friendly
              forces expressed in decimal format?
              (For example, 5% would be expressed as .05)'.
            legalvals(cas_rate) = real.

question-5: automaticmenu(gren_type).
              question(gren_type) = '
            Is the enemy using grenade type weapons?'.
            legalvals(gren_type) = [yes,no].

question-6: automaticmenu(mine_type).
              question(mine_type) = '
            Is the enemy using land mines?'.
            legalvals(mine_type) = [yes,no].

question-7: automaticmenu(arty_type).
              question(arty_type) = '
              Is the enemy using artillery or rockets?'.
            legalvals(arty_type) = [yes,no].

question-8: automaticmenu(boob_type).
              question(boob_type) = '
             Is the enemy using any type of booby trap?'.
            legalvals(boob_type) = [yes,no].

question-9: question(othr_type) = '
              Is the enemy using any other
              type of weapon such as knives, bayonets,
              blow guns, etc.? [ yes or no ]'.
            legalvals(othr_type) = [yes,no].
```

```
/*****************************************************************/

/**************   EXPERT KNOWLEDGE SECTION *******************/

/*****************************************************************/

/*               The following questions use knowledge
                 derived from a subject matter expert to
                 refine the statistical blood estimate
                 calculated in the first portion of this
                 system.

*/
question-10: enumeratedanswers(transport).
             question(transport) = '
             What types of transport are available for
             blood resupply?
                 1. Air only
                 2. Water only
                 3. Ground only
                 4. Air and Water
                 5. Air and Ground
                 6. Water and Ground
                 7. Air, Ground, and Water
             (Enter appropriate number)'.
           legalvals(transport) = [1,2,3,4,5,6,7].


question-11: question(trans_dep) = '
             How reliable is the blood resupply
             transportation?

                 1. Low
                 2. Moderate
                 3. High
              (Enter appropriate number)'.
           legalvals(trans_dep) = [1,2,3].

question-12: enumeratedanswers(evac_policy).
             question(evac_policy) = '
             What is the evacuation policy?
                 1. <1 day
                 2. 1 day
                 3. 2 days
                 4. 3 days
                 5. 4 days
                 6. 5 or more days
               (Enter the appropriate number)'.
           legalvals(evac_policy) = [1,2,3,4,5,6].
```

```
question-13: automaticmenu(stor_dep).
             question(stor_dep) = '
             Is the blood storage refrigeration equipment to
             be used in a hardened AND environmentally
             controlled facility?'.
           legalvals(stor_dep) = [yes,no].

question-14: automaticmenu(power_sup).
             question(power_sup) = '
             Is the electrical power supply to the blood
             storage refrigeration equipment:

                  - reliable?
                  - have circuit switching capability?
                  - on a monitored electrical circuit?
                  - have a reserve capacity?

             If it has ALL of the above answer yes.
             Otherwise, answer no.'.
           legalvals(power_sup) = [yes,no].

question-15: question(blood_cap) = '
             What is the total blood storage capability, in
             units, for the friendly forces medical facilities
             for whom the blood is intended?'.
           legalvals(blood_cap) = integer.

question-16: question(blood_on_hand) = '

                        H E M O S
                        ---------
          A Blood Requirements Planning System for use
             by U.S. Navy Medical Units supporting
                  Fleet Marine Force elements

                            by

                      LT M.A. GREENAUER
                    Medical Service Corps
                     United States Navy

                  Naval Postgraduate School
                    Monterey, California
                           1987

*************************************************************
```

```
What is the total number of units of blood in
the friendly forces medical facilities which they will have
available in 72 hours?´. legalvals(blood_on_hand) = integer.

question-17: question(air_sup) = ´
             Is there air supremacy for the friendly
             forces?
                yes
                no´.
           legalvals(air_sup) = [yes,no].
```

APPENDIX D
DANANG SURGICAL DATABASE
SEGMENTED SAMPLES
(Randomized)

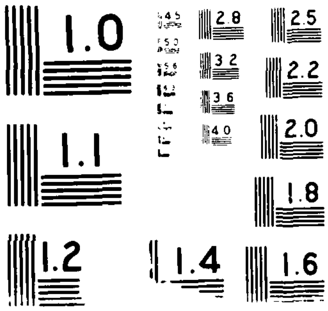
Sample A

WOUNDING AGENT	NUMBER OF CASUALTIES	NUMBER OF CASUALTIES GIVEN BLOOD	NUMBER OF UNITS GIVEN	MEAN UNITS
RIFLE/ PISTOL	172	43	164	3.8
ARTILLERY/ ROCKETS/ MORTARS	251	48	254	5.3
MINE	51	23	228	9.9
THROWN GRENADE	45	4	20	5.0
BOOBY-TRAP GRENADE (LG FRAGMENT)	14	4	20	5.0
BOOBY-TRAP GRENADE (SM FRAGMENT)	72	21	111	5.3
BURNING AGENT	1	0	0	0.0
GRENADE/ MINE/ BOOBY-TRAP/ OTHER	9	1	5	5.0
MULTIPLE AGENTS	30	11	52	4.7
NOT KNOWN	22	9	64	7.1
OTHER	6	2	11	5.5
TOTAL	673	166	929	5.66*

* Mean Number of Units of blood per casualty

AD-A194 726 HEMOS (HEMOLOGIC EXPERT MARINE OPERATIONAL SUPPORT): AN 2/2
EXPERT SUPPORT SY (U) NAVAL POSTGRADUATE SCHOOL
MONTEREY CA M A GREENAUER MAR 88

UNCLASSIFIED F/G 6/12 NL


1.0
2.8
2.5
3.2
2.2
3.6
4.0
2.0
1.1
1.8
1.2
1.4
1.6

APPENDIX D (CONT.)

Sample B

WOUNDING AGENT	NUMBER OF CASUALTIES	NUMBER OF CASUALTIES GIVEN BLOOD	NUMBER OF UNITS GIVEN	MEAN UNITS
RIFLE/ PISTOL	159	40	172	4.3
ARTILLERY/ ROCKETS/ MORTARS	266	66	315	4.8
MINE	47	18	179	9.9
THROWN GRENADE	40	3	9	3.0
BOOBY-TRAP GRENADE (LG FRAGMENT)	16	11	97	8.8
BOOBY-TRAP GRENADE (SM FRAGMENT)	57	17	125	7.4
BURNING AGENT	2	0	0	0.0
GRENADE/ MINE/ BOOBY-TRAP/ OTHER	11	2	7	3.5
MULTIPLE AGENTS	35	13	63	4.8
NOT KNOWN	33	20	179	9.0
OTHER	7	1	6	6.0
TOTAL	673	191	1152	6.15*

* Mean Number of Units of blood per casualty

APPENDIX D (CONT.)

Sample C

WOUNDING AGENT	NUMBER OF CASUALTIES	NUMBER OF CASUALTIES GIVEN BLOOD	NUMBER OF UNITS GIVEN	MEAN UNITS
RIFLE/ PISTOL	150	31	203	6.5
ARTILLERY/ ROCKETS/ MORTARS	270	53	197	3.7
MINE	48	20	263	13.2
THROWN GRENADE	62	8	34	4.3
BOOBY-TRAP GRENADE (LG FRAGMENT)	17	12	114	9.5
BOOBY-TRAP GRENADE (SM FRAGMENT)	58	12	137	11.4
BURNING AGENT	3	0	0	0.0
GRENADE/ MINE/ BOOBY-TRAP/ OTHER	12	2	3	1.5
MULTIPLE AGENTS	16	4	32	8.0
NOT KNOWN	31	16	81	5.1
OTHER	8	1	3	3.0
TOTAL	675	159	1067	6.62*

* Mean Number of Units of blood per casualty

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