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A Review of Analytics and Clinical Informatics in Health Care

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Abstract Federal investment in health information technology has incentivized the adoption of electronic health record systems by physicians and health care organizations; the result has been a massive rise in the collection of patient data in electronic form (i.e. "Big Data"). Health care systems have leveraged Big Data for quality and performance improvements using analytics—the systematic use of data combined with quantitative as well as qualitative analysis to make decisions. Analytics have been utilized in various aspects of health care including predictive risk assessment, clinical decision support, home health monitoring, finance, and resource allocation. Visual analytics is one example of an analytics technique with an array of health care and research applications that are well described in the literature. The proliferation of Big Data and analytics in health care has spawned a growing demand for clinical informatics professionals who can bridge the gap between the medical and information sciences.

Keywords Health care analytics · Medical informatics · Electronic health records · Clinical decision support systems · Integrated advanced information management systems · Health Information Technology for Economic and Clinical Health Act

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The United States government enacted the Health Information Technology for Economic and Clinical Health (HITECH) Act in 2009. This sizeable federal investment in health information technology (IT) incentivized health care organizations and providers to meet "meaningful use" regulations with health IT in order to improve the quality and efficiency of health care [1]. As a result, physicians and health care organizations have adopted electronic health record systems (EHRs) at a steady rate [2]. The HITECH Act was one component of the Accountable Care Act, which imposes financial penalties on health care providers who fail to meet specified standards for Medicaid and Medicare patients [3]. Thus, the HITECH Act laid the foundation for a transition to more outcomes-based reimbursement (i.e. a "pay-for-performance" model), as opposed to the traditional "fee-for-service" model [4]. Outcomes-based reimbursement, which focuses on actual benefit to the patient, is related to evidence-based reimbursement, which emphasizes payment for perceived patient benefit that is based on empirical clinical trial evidence [5].

The term "Big Data" is used to describe data sets whose massive size and complexity pose significant challenges to traditional data software applications. Repeated observations over time and/or space are what generate most Big Data [6]. Technological advances in computers, patient monitoring systems, networking, and EHRs have enabled hospitals to measure and record electronically an ever-increasing volume and variety of variables [7]. These advances, coupled with the incentivized proliferation of EHRs, has resulted in the massive accumulation of patient data that is more accessible, searchable, and retrievable than the former documentation method: written paper records [8]. A greater emphasis on evidence- and outcomes-based practice in health care has created an impetus for health care institutions and systems to enhance medical decision-making via the systematic integration of data from a variety of disparate sources in order to improve decisions and processes [9]. The term for this form of data analysis and application is analytics—the systematic use of data combined with quantitative as well as qualitative analysis to make decisions [10].

Applications of analytics in health care

Analytics methods include the use of mathematical and algorithmic based processing of data resources, as well as the use of techniques such as text mining, natural language processing, and visual analytics to generate descriptive, predictive and prescriptive models to analyze and derive insight from data [11]. Text mining and natural language processing involve the retrieval and extraction of nontrivial information from unstructured, semi-structured, and structured text, such as detecting surgical site infections via text mining of unstructured clinical notes in an integrated electronic medical record [12, 13]. (Visual analytics will be discussed in greater detail in a later section.) Advanced analytics methods have been applied and utilized across a wide spectrum of health care settings for many purposes. Examples of such usage include improving patient care, augmenting less-sophisticated rules-based systems, analyzing continuous feeds of physiological data, and optimizing financial processes and resource utilization.

Health analytics offers a myriad of methods for the potential improvement of patient care. For example, one predictive risk assessment platform involves utilizing risk assessment analytics to process EHR data to identify the patients at greatest risk for utilizing more resources than their peers with the goal of improving patient outcomes and managing costs [14]. The EHR data was input into a common data model that was then processed by various analytic techniques in order to stratify patients as high-risk. Another method described in the literature focused on the potential value of aggregating data enhanced with real-time analytics to provide point-of-care information to oncologists that was tailored to individual patients [15]. One group reported the application of predictive analytics for better targeting of disease management and innovative patient care approaches, while also warning of the unintended consequences that may arise—such as excluding disadvantaged populations [16]. Unlabeled and free-text databases such as mammography data can be transformed into searchable and accessible collections that are usable for large-scale health analytics [17]. Analytics can supplement real-time analysis of physiological data streams in the neonatal intensive care unit for earlier detection of worsening medical conditions [18].

Analytics may also be employed to enhance less sophisticated, rules-based systems that are already in use. One of the benefits of EHRs has been the integration of integrated clinical decision support (CDS) systems. CDS systems have been shown to reduce errors and improve clinical outcomes in certain settings, such as pediatric intensive care units [19, 20], and CDS can result in performance improvement on perioperative quality and process measures [21]. Some CDS systems that are designed to prevent medication errors are based largely on commercially available software packages that rely on relatively simple rules. Often, these products do not provide ideal rule sensitivity, and institutions must perform manual reclassification of drug-drug interactions to improve the efficacy of their CDS systems [22, 23]. Analytics may offer a solution to this challenge, as one can utilize analytics techniques to query and mine the EHR for meaningful connections, and then synergistically combine the knowledge-based rules with analytics applied to EHR data [24].

Analytics are utilized in health care applications outside of the traditional inpatient and outpatient patient care settings, such as wearable monitors that patients use at home. Wearable health monitoring systems consist of a variety of sensors, actuators, and multimedia devices, and enable low-cost, non-invasive options for continuous monitoring of health, activity, mobility, and mental status, both indoors and outdoors [25]. Thus, wearable monitoring systems provide continuous physiological data that may reflect the general health of the monitored individuals, and the use of wearable sensors in health monitoring systems is an emerging health care field that necessitates data mining and analytics of physiological measurements in a non-clinical setting [26]. Such health monitoring systems may reduce health-care costs by disease prevention and enhance the quality of life with disease management, and can be tailored to specific uses such as intelligent health monitoring of the elderly in nursing homes and for individuals with dementia or Parkinson's disease [27, 28].

Another application of analytics in health care is in finance—not only in cost savings based on improved patient care and outcomes, but also the identification of simple billing anomalies (i.e., revenue leakage). Most health care organizations find billing anomalies via a combination of rules-based approaches and manual audits; however, this approach is time-consuming and error-prone. Advanced analytics approaches (e.g., machine learning and predictive modeling) can be used to find patterns in billing records that are most likely associated with missing or erroneous charges. The computer-based advance analytic method, in conjunction with review by human billing experts, can form a "dual approach" that has been used successfully to reduce audit expenses by 75 % in one health system [29].

Health care organizations can use analytics not only to improve billing practices, but also to better manage resource allocation and demand throughout the organization. One example is to use analytics to determine factors impacting a patient's length of stay; each day of inpatient care increases the resources utilized by a patient while reimbursement may be a fixed amount that does not rise proportionately with length of stay. Hospitals consist of a broad network of departmental activities that impact a patient's stay, and these activities can be scrutinized using analytics methods (e.g. scheduling). One institution used analytics and determined that inefficiencies at the radiology department adversely extended a patient's length of stay beyond initial estimates. The authors subsequently advocated the use of proactive analytics assessments of networks of activities to enhance organizational efficiency [30].

Health care institutions have used analytics for a variety of other business-related purposes. Cost-cutting measures (e.g. reducing readmission rates) have been targeted and measured using analytics, as have revenue-generating interventions such as using marketing analytics and graphical information systems to target catchment areas [31–33].

Exploring a specific analytics method: Visual analytics

Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces, and has been utilized to enhance the evaluation of large, complex data sets within health care fields. EHRs generate a massive amount of data that can be navigated and represented visually in near-real time by the use of visual analytics software tools. First, the data is often stored in a dimensional database model, rather than a traditional relational database model. The user then uses the visual analytics tools to construct simple, easy-to-use dashboards that display histograms and graphs in order to identify and explore data trends. Visualization reduces the load on working memory, offloads cognition, and harnesses the power of human perception [34].

There are three main benefits to the visual analytics approach versus the traditional method of querying databases. First, the user can explore the data in a self-service fashion, as opposed to writing database queries by hand. Second, complex ideas can be communicated with clarity, precision and efficiency in visual graphs, rather than the tabular data output from a traditional database query. Third, visual analytics can display large volumes of filtered data in near-real time, which is a more onerous task when using traditional database queries [34].

Dimensional modeling is used in visual analytics instead of a highly normalized relational database model to facilitate data querying and analysis on a large scale. In general, relational models are refined to be highly normalized (i.e. data transactions are spread across a multitude of tables); thus, relational models are well suited for multiple users who are working concurrently with transactional data. However, the relational model is suboptimal for data analysis due to the highly complex, time-consuming query scripts that must be written to generate complex reports. Dimensional models, in contrast, are implemented using Online Analytical Processing systems that have been developed specifically to analyze very large data sets. Dimensional models accomplish this task by creating a unique fact table that contains all of the potential data transactions and then creating filters (dimensions) around the table that will be used to associate facts and measures throughout the dimensional database. This simplifies the querying scripts, resulting in script execution durations that are significantly shorter than those of the more complex relational model scripts [35].

Thus, visual analytics tools enable data exploration and hypothesis generation within a specific group of data, and empower users to access the data in a way that facilitates understanding—one of the most important goals of the application of analytics to massive amounts of data [36]. Data exploration during the visual analytics step can guide the selection and application of subsequent advanced analytics techniques. Visual analytics techniques in health care are utilized typically for one of three areas of analyses: business purposes, clinical operations (e.g. blood bank utilization), or scientific research in various health care-related fields, such as genomics, immunology, and epidemiology [37–40]. This discussion will focus primarily on the utilization of visual analytics techniques in clinical operations.

Wang and colleagues described one example of the successful application of visual analytics for exploration of patient data in health care [41]. The research group used a visual analytics application, Lifelines2, with providers in a variety of specialties (e.g. neurologist, osteopathic physician, emergency room director) to visualize EHR data with the goal of improving patient care. The authors described the providers' use of their tool for tasks that were difficult to answer with the providers' EHR software: studying hospital room transfer patterns, performing follow-up studies and replicating studies, among others. Of particular interest was the ability of their data visualization tool to visualize data from multiple EHRs, as many of the visual analytics tools described in the literature present a dashboard displaying a particular data set.

Visual analytics tools can also be used for data visualization to provide CDS at the point of care. Mane described a "VisualDecisionLinc" tool that displayed near real-time comparative population evidence generated from their institution's EHR data in order to provide CDS in psychiatric patients. The tool enabled the generation of EHR-data-based dynamic charts that helped clinicians weigh the risks of therapeutic options and outcomes [42, 43].

Visual analytics tools are used extensively at the authors' tertiary care pediatric hospital for a variety of purposes including exploration of patient data and CDS. One example of patient data exploration using a visual analytics tool is the Patient Encounter dashboard, which allows the user to view aggregated hospital-wide patient data, such as patients' demographics (Fig. 1). Visual analytics CDS tools include a

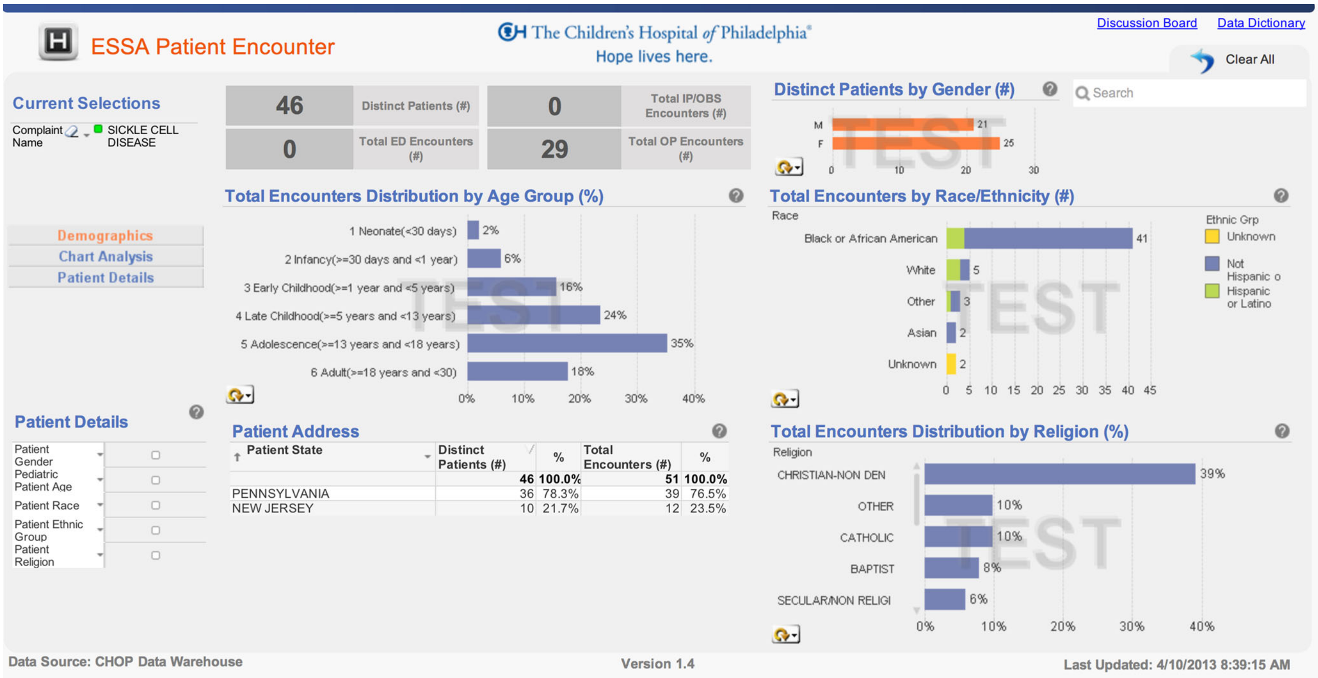


Fig. 1 A screen shot of The Children's Hospital of Philadelphia Patient Encounter visual analytics dashboard, which allows the user to view aggregate hospital-wide patient data

dashboard for exploring historic blood transfusion data based on patient demographics and procedure type prior to ordering blood products [44] (Fig. 2). Other uses for visual analytics dashboards at our hospital include monitoring EHR alerts filtered by provider type, date, etc., as well as dashboards for monitoring hand hygiene, nursing metrics, supply chain performance, and adherence to clinical guidelines (e.g. Febrile Infant Pathway dashboard) (Fig. 3).

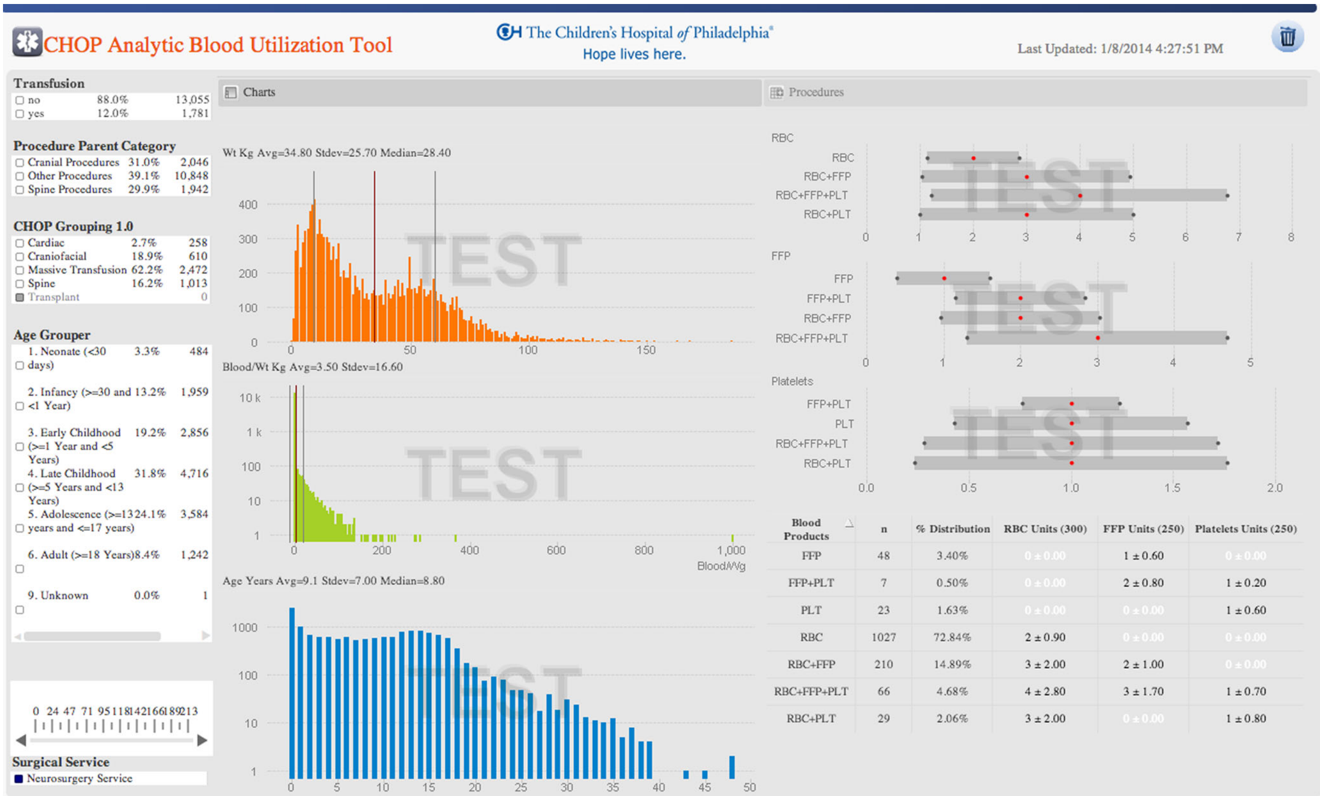
Visual analytics tools facilitate investigative research analysis by showing connections between entities, focusing on essential information, and reviewing hypotheses [45]. Many examples of visual analytics in health care are available in the literature, such as for tracking symptom evolution during disease progression, performing pharmacokinetic-pharmacodynamic analysis, building detection models for disease surveillance, and visualizing outcomes data [46–49].

Challenges and future of analytics in health care: Clinical informatics

The logical step following the proliferation of EHR systems is the application of analytics to gather valuable, meaningful information from clinical data repositories. However, one challenge presented by data is not only quantitative (i.e., managing massive data files), but also qualitative. For example, terabytes of data can be generated in rapid fashion by a hospital floor full of electronic patient monitors; however, each type of physiological monitor (e.g. pulse oximetry, capnography) is subject to artifact [50]. The subsequent application of analytics to data artifacts may produce faulty conclusions (i.e. "garbage in, garbage out"). One potential solution to this problem is the application of analytics such as machine learning and neural networks in data auditing to detect errors prior to analysis. Emerging trends for applications of analytics in health care include predictive models for identifying patients who are at risk for early readmissions, facilitating population health management and value-based accountable care, detecting fraud, and using targeted communication and education campaigns to facilitate patient engagement [51].

The proliferation of EHRs has resulted in massive amounts of data for hospitals and health care organizations to manage and analyze for various purposes, including practice management, quality improvement, and outcomes research projects. This has led to increased demand for professionals who are well versed in both informatics and medicine. To meet this demand, the American Medical Informatics Association spearheaded the establishment of professional-level education and certification for physicians in informatics, leading to development of clinical informatics as a formal, board-certified medical subspecialty [52, 53].

Clinical informatics professionals leverage information technology to improve the delivery and safety of healthcare via EHRs, telemedicine, and evidence-based medicine using tools such as CDSs and data analytics [54]. Indeed, patient-generated Big Data has been identified as a promising approach to personalized health care, as well as medical



Blood Products	n	% Distribution	RBC Units (300)	FFP Units (250)	Platelets Units (250)
FFP	48	3.40%	0 ± 0.00	1 ± 0.60	0 ± 0.00
FFP+PLT	7	0.50%	0 ± 0.00	2 ± 0.80	1 ± 0.20
PLT	23	1.63%	0 ± 0.00	0 ± 0.00	1 ± 0.60
RBC	1027	72.84%	2 ± 0.90	0 ± 0.00	0 ± 0.00
RBC+FFP	210	14.89%	3 ± 2.00	2 ± 1.00	0 ± 0.00
RBC+FFP+PLT	66	4.68%	4 ± 2.80	3 ± 1.70	1 ± 0.70
RBC+PLT	29	2.06%	3 ± 2.00	0 ± 0.00	1 ± 0.80

Fig. 2 A screen shot of The Children's Hospital of Philadelphia Perioperative Blood Transfusion visual analytics dashboard that enables to user to explore historic blood transfusion data (based on patient demographics and procedure type) prior to ordering blood products

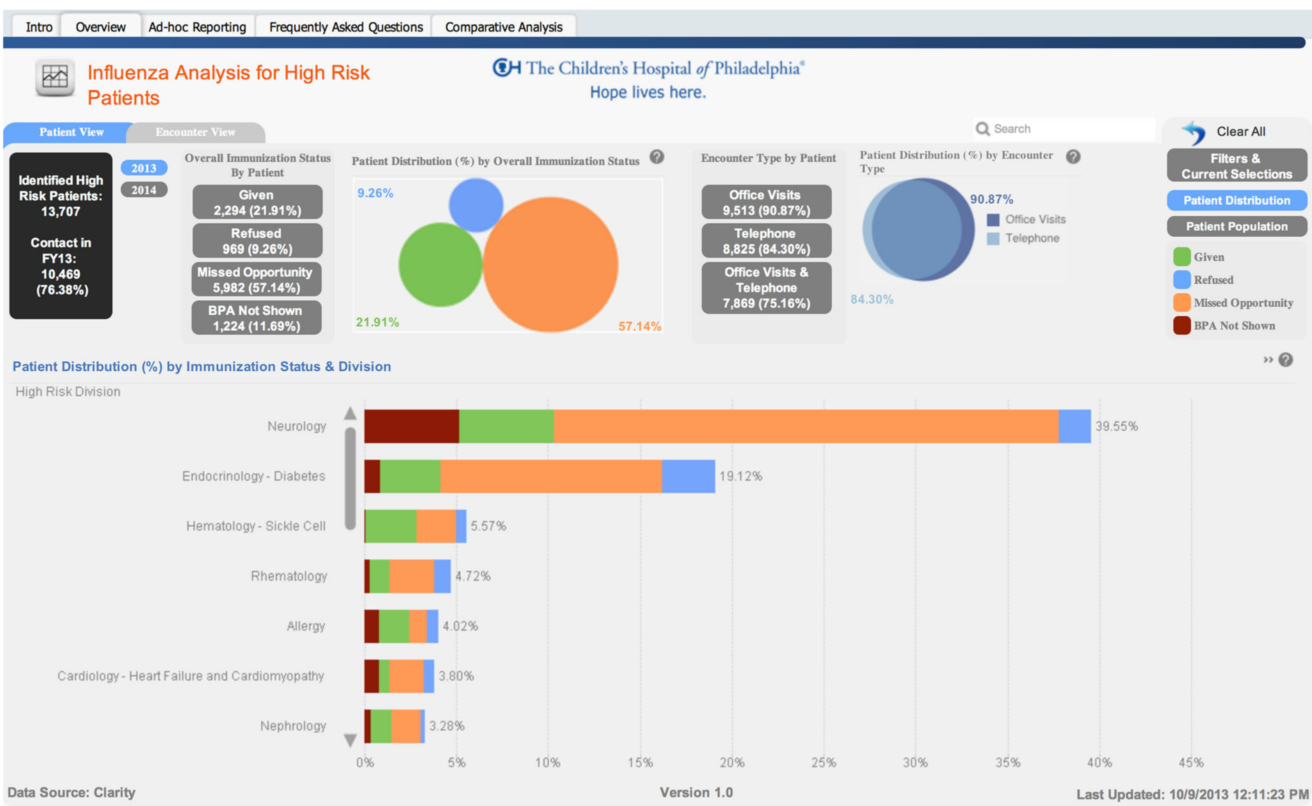


Fig. 3 A screen shot of The Children's Hospital of Philadelphia Influenza Analysis for High Risk Patients visual analytics dashboard that enables to user to explore the immunization status of various patient populations across the various hospital services and encounter types

diagnostics via data mining and the development of computer-aided diagnostic tools [55, 56]. The future of health care analytics will consist of an ever-increasing demand for and application of sophisticated analytics methods and tools (e.g. visual analytics dashboards) to explore and analyze data with the goals of improving patient care, increasing efficiency, optimizing resource utilization and allocation, and enhancing decision-making at both the clinical and enterprise levels. Health care professionals with knowledge and expertise in clinical informatics will be needed to design and implement the future analytic applications and innovations of EHR and communication systems to meet those needs.

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