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Special Communication

Balancing volume and duration of information consumption by physicians: The case of health information exchange in critical care

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A R T I C L E I N F O

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A B S T R A C T

Background: The realization of the potential benefits of health information exchange systems (HIEs) for emergency departments (EDs) depends on the way these systems are actually used. The attributes of volume of information and duration of information processing are important for the study of HIE use patterns in the ED, as cognitive load and time constraints may result in a trade-off between these attributes. Experts and non-experts often use different problem-solving strategies, which may be consequential for their system use patterns. Little previous research focuses on the trade-off between volume and duration of system use or on the factors that affect it, including user expertise.

Objectives: This study aims at exploring the trade-off of volume and duration of use, examining whether this relationship differs between experts and non-experts, and identifying factors that are associated with use patterns characterized by volume and duration.

Methods: The research objectives are pursued in the context of critically-ill patients, treated at a busy ED in the period 2010–2012. The primary source of internal and external data is an HIE linked to 14 hospitals, over 1300 clinics, and other clinical facilities. We define four use profiles based on the attributes of duration and volume: quick and basic, quick and deep, slow and basic, and slow and deep. The volume and duration of use are computed using HIE log files as the number of screens and the time per screen, respectively. Each session is then classified into a specific profile based on distances from predefined profile centroids. Experts are physicians that are board-certified in emergency medicine. We test the distribution of use profiles and their associations with multiple variables that describe the patient, physician, situation, information available in the HIE system, and use dynamics within the encounter.

Results: The quick and basic profile is the most prevalent. While available admission summaries are associated with quick and basic use, lab and imaging results are associated with slower or deeper use. Physicians who are the first to use the system or are sole users during an encounter are less inclined to quick and deep use. These effects are intensified for experts.

Discussion: A trade-off between volume and duration is identified. While system use is overall similar for experts and non-experts, the circumstances in which a certain profile is more likely to be observed vary across these two groups. Information availability and multiple-physician dynamics within the encounter emerge as important for the prediction of use profiles. The findings of this study provide implications for the design, implementation, and research of HIE use.

1. Introduction

Physicians treat patients in emergency departments (EDs) under high levels of cognitive load, often caused by overloaded yet understaffed departments [1] and by life-threatening clinical conditions. The uncertainty that is inherent to the medical setting is intensified by the paucity of information, frequent interruptions, and the distributed team work that are widespread in emergency care [2]. Patients who visit the ED, particularly critically-ill ones, are often unable to provide information, thus vastly increasing the dependence on secondary sources such as information systems, paper charts, and family members. Despite the necessity of a longitudinal view on the patient's medical history for an efficient care plan [3], information is often partial or inaccessible. Stiell et al. [4] report that approximately one third of the emergency treatments are delivered with incomplete yet essential information,

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and that these information gaps are more prevalent in severely-ill patients.

Information gaps compromise patient safety and raise expenses, as they often result in duplicate tests and procedures, which are estimated at millions of dollars annually [5]. Some of these gaps are related to the fragmentation in delivery of healthcare services [6], which is particularly intensified for ED patients whose medical data are often dispersed across multiple facilities [7] and health information systems (HIS). Health information exchange systems (HIEs) are implemented with the intention to reduce information gaps [8] by integrating patient-level health data that originate in multiple information systems [9,10]. The implementation of HIEs is believed to have great potential benefits for EDs, as they assist the physician in acquiring a comprehensive and longitudinal view of the patient's history [3,11]. HIEs have the potential to enhance patient safety and quality of care (e.g., by reducing medication errors) and to vastly reduce the costs of emergency medicine (EM), particularly laboratory and imaging tests [12].

However, there is a lack of agreement on whether HIE implementations successfully realize their expected benefits [13,14]. First, many HIS implementation projects encounter difficulties, some technical and others emanate from a lack of compatibility with the users' workflow and needs [15,16]. Second, the measurement and evaluation of both the system implementation project and its effects are matters of controversy [17]. Nevertheless, studies agree that the realization of the potential benefits of HIE depends greatly on whether they are designed to meet the users' needs and on how they are used in practice, e.g., [18,19].

The patterns characterizing the use of HIEs and other HIS are the subject of several studies. These studies often define use in a binary manner, i.e., whether the system is used or not. Studies that expand this definition, e.g., [20–23] often pay little attention to two important attributes of use that may be valuable to understanding use patterns: volume (number of information units consumed) and duration (time devoted to each information unit consumed) [20,24,25]. The information processing approach to decision making highlights the importance of the amount of information processed and the time devoted to information processing, suggesting that humans become more cognitively loaded when the former increases or the latter decreases [26]. The relationship between these two attributes of use has not been explored in general or in ED settings in particular. This relationship may be affected by the cognitive load inherent to EDs, which may limit the use of the system and result in a trade-off between volume and duration (i.e., as more information is consumed, less time is devoted to processing each piece of information). In other words, human information processing limitations, especially in highly-constrained settings, may be reflected in limitations in either the volume of information that can be processed or the time devoted to processing each piece of information.

The volume and duration of use are important indicators of system use in clinical settings. These attributes have been shown to be associated with clinical decisions in the ED [20,27]. Moreover, the time efficiency of inquiring into the system is essential to ED physicians [15,28]. Hence, understanding these characteristics of use, their relationship with each other, and the factors that affect them may improve system implementation processes, system design to match user needs, and the utilization of these systems to their full potential. Such research efforts may enhance the existing knowledge on the clinical decision making process and thus potentially improve it.

EM experts may have information needs and use patterns that are different from those of physicians in other specialties. Furthermore, experts and non-experts generally employ different problem solving strategies, which are reflected by their information retrieval patterns [25,27,29]. Studies claim that experts generally make decisions in a more efficient, data-driven manner [30,31], yet may be more prone to biases [32]. Non-experts, in contrast, may lack domain knowledge and familiarity with the system. Few studies attempted to compare HIS use patterns of experts and non-experts, and those that did were often inconclusive, e.g., [27]. The relationship between volume and duration of use, which, as noted earlier, has yet to be explored, is thus particularly interesting in the context of varying levels of physician expertise. Such understanding has the potential to improve the customization of HIS to the information needs of physicians with varying levels of experience.

In previous analyses, we demonstrated the benefits of defining use by multiple attributes; this approach yielded meaningful patterns [21] that were valuable in predicting an admission decision [20]. The present analysis innovates by looking at system use patterns as the outcome variable and by focusing on volume and duration as the critical attributes given their probable susceptibility to environmental constraints. The literature on patterns of HIE use has paid little attention to the relationship between the attributes of volume and duration, as well as to the association between the relationship between these attributes and physician properties, the availability of information in the system, and dynamic of system use among the physicians that treat the same patient.

Attempting to address these gaps, the objectives of this study are threefold. First, this study aims at understanding the relationship between the volume and duration of HIE use by physicians. In particular, we are interested in whether a trade-off exists between these two attributes in the ED setting. The second goal is to examine whether this relationship is affected by the physician's expertise. Third, given the lack of research in this area, we also wish to identify the factors that are associated with time- and volume- based use patterns, namely factors that characterize the patient, physician (other than expertise), situation, information available in the system at the time of use, and dynamics of use among multiple physicians within a single encounter. We pursue these goals in the context of critically-ill patients who were treated at the resuscitation room (RR) in a busy medical ED.

This article is structured as follows: Section 2 contains a review of the literature, which explicates the motivation for this study and the three research questions that guide it. Section 3 describes the research methods, setting, and data that were used to test the research questions and Section 4 presents the results we obtained. In Section 5, the findings are interpreted and the implications, limitations, and future research avenues are discussed.

2. Background and research questions

2.1. HIE use patterns

Patterns of use of HISs, HIEs in particular, have been the focus of several studies, aimed at describing, characterizing, and identifying such patterns and their antecedents, e.g., [21,22,33,34]. The typical level of analysis is the individual encounter level; this level enables researchers to diagnose actual system use and its effects more accurately [10]. A better understanding of information needs and patterns of use may provide practical insights on system design, improvement, and measurement. Moreover, use patterns may serve as indicators of successful implementation [10,35] and, in turn, may increase the efficient use of these systems. Another motivating factor is that a thorough examination of HIE use patterns may also support the efforts to explore the link between system implementation and organizational performance [36].

Several studies have utilized large-scale datasets or performed observations in order to characterize individual use of HIE systems, e.g., [21,22,37]. A premise guiding such studies, including the present one, is that a dichotomous approach to HIE use (i.e., used/not used) is unable to grasp the complex nature of system use and of information needs [38]. Politi et al. [20,21] and Vest and Jasperson [22] have shown that a multidimensional approach to the characterization of use patterns yields novel insights on meaningful patterns of use and system design. The use of HIE systems is also associated with clinical decisions, emphasizing that use patterns are valuable factors to consider when investigating clinical decisions [20,23,39].

Several approaches have been applied to provide multidimensional descriptions of HIE use. One approach views system use as a set of separate and often independent *variables of use* and therefore it has been applied to describe the type, sequence, and frequency of accessed screens, e.g., [40,41]. A second approach examines combinations of attributes of use by modeling use as patterns of multiple variables, which may not be independent of one another [42], and therefore it describes *profiles of use*, e.g., [20–22]. The various approaches are not contradictory, but rather complement each other. The current study highlights the value of employing the second approach in addition to the first one.

2.2. Main attributes of use

A predominant measure of use is the *volume* of information that is displayed during the interaction with the system [20–22,25,43]. This attribute provides a measure of all items of information combined, assuming all information items are essentially identical in terms of their informative value. However, the most commonly accessed data in EDs (i.e., demographics, history of prior visits and hospitalizations, lab test results, and discharge summaries [3,22,40,44]) vary in terms of the level of detail and complexity of interpretation. In addition, the level of attention that is dedicated to a specific information item may vary among tasks [45,46] and users. Hence, solely observing the volume and types of information that are used may not be sufficient to determine the relevance of information items.

The dimension of time captures important dynamic aspects of the interaction with the system. The *duration* of time it takes to consume information can be employed as an indicator of both the interest the user has in that information and of the effort that is required to appropriately process it. Examining the duration of use becomes even more significant, as some physicians believe that information search in HIS may be time-consuming [15] and they sometimes even relinquish it for that reason [28].

The interaction with the HIE in EDs, particularly when treating critically-ill patients, is inherently limited in time. To devise an effective care plan, the physician may strive to attain a comprehensive view of the patient's history by deeply reviewing all the relevant information available in the information system. Such an approach, however, may be impractical as it is time-consuming and therefore potentially damages the effectiveness of the care plan by delaying its execution. We believe this conflict between the need to attain more information and the need to devote more time to each piece of information, caused by time constraints, frames the use of the information system in the ED and is reflected in a trade-off between the attributes of volume and duration.

Research Question I: *Is there a trade-off between the attributes of volume and duration in HIE use by critical care physicians?*

2.3. Expertise and HIS use

Numerous studies explore information needs and utilization, showing significant variance between domain experts and non-experts in the use of information technology (e.g., search engines and decision support systems). Domain experts tend to use different problem-solving approaches and information search strategies, as they usually require less time and fewer actions to comprehend and assess the problem they face [47–49].

In the medical domain, considerable work has been done on identifying skills and strategies applied by medical practitioners with different levels of expertise. Studies indicate that expert medical practitioners develop filtering mechanisms, which enable them to efficiently focus on relevant information and identify clinical patterns [31,32]. Moreover, experts tend to apply a data-driven approach to make decisions in clinical situations (i.e., data prompts a solution in a rather automated manner), based on a high level of knowledge of the patient's condition [30,31]. Non-experts, on the other hand, often lack sufficient knowledge or have difficulty identifying relevant knowledge, making them more susceptible to hypothesis-based reasoning (i.e., seeking data that can support or refute predefined hypotheses), which usually leads to more complex forms of information search and reasoning [30] and perhaps going through larger volumes of information [50].

Additional factors may account for the relationship between level of expertise and system use. Lack of expertise is associated with low levels of important capabilities, such as diagnostic skills, recall of patient data [51], and physician-patient communication [52], all of which influence information search and decision making. Furthermore, familiarity and experience with the information technology also plays an important role in forming the problem-solving strategy and in executing it efficiently, as a high level of domain expertise may fail to compensate for a lack of knowledge of the technological decision aid [49,53].

Disparities between experts and non-experts have also been examined in the context of HIS [27,29,54] and clinical search engines [25]. As opposed to search engines, HIS display information in a more structured fashion, often use a controlled medical vocabulary, have fewer possible navigational paths, and are more often used during the caregiving process [55]. Past studies showed that the use of HIS influences the interaction with patients [29], and that levels of domain and system expertise of users were reflected in type, sequence, and volume of the accessed information [25,27,29]. Some studies showed that use made by experts required less time and slightly fewer mouse clicks to complete tasks [27,56], while another study observed more prolonged and broad use of information by experts [25]. While the use of HIS guides less experienced physicians and helps in reducing cognitive load [29], non-experts and particularly novices still present inferior abilities in separating relevant from irrelevant information and in making accurate inferences [57]. These findings support the study of HIS as mediators of the decision-making process and the investigation of how system use patterns are influenced by physician expertise.

Several shortcomings have been identified in the relevant literature. First, differences in use patterns across levels of expertise have usually been studied in controlled environments, which often fail to reflect the fractionated and stressful nature of the caregiving setting [55]. Second, prior studies often did not control for both experience with the system and domain expertise and used a small sample of users and cases, making their findings harder to generalize. A third shortcoming is the scarcity of studies that investigate the effects of such differences in emergency care. Consequently, we aim at investigating how the relationship between the attributes of volume and duration of system use differs between EM experts and non-EM experts.

Research Question II: *Is physician expertise associated with use of the system in terms of information volume and duration? Does the* *trade-off between volume and duration vary between experts and non-experts?*

2.4. Factors associated with HIE use

While profiles of HIE use that relate to both duration and volume were examined as explanatory variables in previous studies [20], they have yet to be examined as explained variables. Various studies explored the factors associated with HIE system use in general, e.g., [22,33,34,40], most of which attempted to identify factors associated with the mere use of the system, i.e., whether the system was used or not. Few studies attempted to identify factors associated with more elaborate descriptions of use, often attained by using several use attributes or detecting profiles based on their combinations [22,33]. Furthermore, the current literature in this area generally disregards the dimension of time as a characteristic of use, while focusing on volume, diversity (e.g., classifying use as no use, basic use, or elaborate use [44]), and types of information (basic, repetitive, clinical, demographic) [22]. Previous studies found multiple factors to be associated with various levels of HIE use, among which are the following:

2.4.1. Patient and situational attributes

- Lower odds of using HIE systems are found in encounters in which there are *lower chances of finding external information* (i.e., that originates in another exchange site), or when the patient is not familiar to the caregiver [33,34,40].
- HIE is more likely to be accessed when the patient suffers from one or more *comorbidities* [34,40,44].
- In encounters with patients with *prior and recent hospitalizations* or *frequent primary care visits*, the use of the HIE system is more likely to be elaborate [33,34,37,40,44], characterized as access to more detailed screens, as opposed to summaries of the patient's clinical data [44].
- HIE use has been found to be both positively [58] and negatively [33,34,44] associated with *time constraints* caused by high workload in the ED.
- The patient's *level of insurance coverage* was associated with HIE use, as the odds of using the system were higher for patients for whom no payment could be expected [44].

2.4.2. Physician properties

- A study by Ortega Egea et al. [59] found no association between the *physician's gender* and any particular use pattern, whereas *age* was found to be slightly negatively associated with the general use of HIS.
- The distribution of use patterns, characterized by information diversity and types, varies across user roles (e.g., nurse, physician) and workplaces [22,60].

Several factors, possibly associated with use patterns, are not addressed in the existing literature. For example, while the clinical condition of the patient is often taken into account, the patient's gender and age are overlooked, although they are sometimes taken into account through the computation of the Charlson comorbidity index (CCI) [34,40]. Other potentially interesting effects on use patterns may arise from situational factors, which describe the setting and timing of system use (e.g., ED work load). These factors affect the caregiver's cognitive state and thereby may affect the decision-making process. A key factor that is largely absent in studies looking at factors associated with system use is the availability of information in the system. These are essential, for example, to discern cases in which little information was accessed due to its paucity, or in which the user made a conscious choice to ignore available information.

Studies on system use patterns in a medical context usually do not take into account the case where multiple physicians take part in attending a patient during a single encounter (e.g., consultation, hand-offs) and do not incorporate variables that reflect the dynamics of use within an encounter. This shortcoming contradicts the long-time demonstrated impact of information sharing among physicians on clinical decision making [61,62]. Finally, factors that are saliently absent from the study of the antecedents of HIE use patterns are physician properties, despite their documented effects on user decision making and judgement [63,64]. Specifically, the effects of expertise on HIE use patterns have not been examined. It is also undetermined whether the effects of the factors reviewed above on use patterns are contingent on the physician's level of expertise (i.e., whether there is an interaction between these factors and physician expertise in affecting use patterns). The discussion above regarding gaps in research on HIE use patterns naturally also applies to the ED setting.

Research Question III: *What are the patient, situation, information availability, use dynamics, and physician factors that are associated with volume- and duration-based use patterns? Are these relationships contingent on the user's level of expertise?*

3. Methods

We pursue the aforementioned research questions by conducting an observational, retrospective study of the use of OFEK HIE system (dbMotion, Israel) by physicians in a large Israeli tertiary hospital. We focus our analyses on 810 treatments given to 778 patients by 109 physicians in the RR of the medical ED during the period 2010–2012. Use patterns are observed on the basis of OFEK's log files, which document the information displayed to the physician while interacting with the system. In our setting, the ED and RR each have a central working area with multiple computers. Until recently, the ED and RR had no electronic medical records system and tests were ordered using an order-entry system. Also, OFEK HIE system served as the primary source for clinical information that could not be found in the paper charts. That is, in this setting, clinicians used the HIE system to access information that originated in systems both internal and external to the hospital (e.g., tests ordered during the ED treatment and diagnoses given in clinics, respectively).

Fig. 1 provides a graphical summary of the analytical workflow of this study, while highlighting elements of data collection and analysis that are described in the following sub-sections.

3.1. Setting

This study is conducted in the medical ED of Soroka University Medical Center (SUMC). SUMC is operated by Clalit Health Services, which insures over 50% of the Israeli population (approximately 4 million members) and is the largest healthcare provider in Israel. Clalit Health Services operates 14 hospitals, over 1400 primary care clinics, and hundreds of laboratories and institutes in Israel. The catchment area of SUMC encompasses over 1 million people, with 1063 inpatient beds.

SUMC's medical ED treats over 150,000 patients annually and contains 65 beds. On weekdays, the medical ED operates in two shifts: 8 AM–4 PM and 4 PM–8 AM the next day. On weekends, the ED operates in 24-h shifts that begin at 8 AM. Depending on the shift, the ED is staffed by 4–6 internal medicine physicians, both residents and senior physicians. Internal medicine physicians in the ED may either be board-certified EM experts or non-EM-

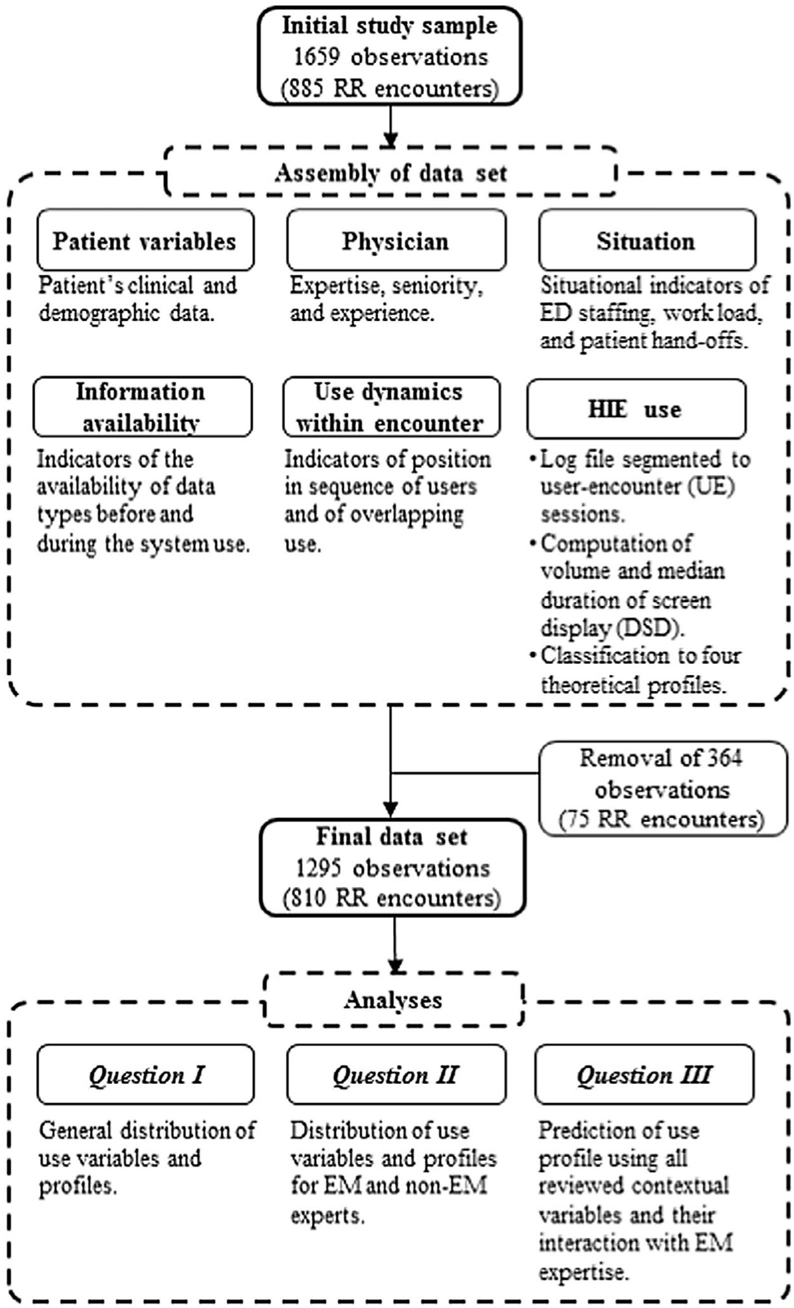

Fig. 1. Analytical workflow.

experts. The latter are either experts in other internal medicine specialties or in training to become experts. Senior physicians who are board-certified EM physicians are referred to as EM experts. We include all non-EM-experts in the same category as their non-ED experience renders them similar in terms of knowledge relevant for this study.

The RR, which is physically adjacent to the ED, operates only when treatment for critically-ill patients is required. To that end, the RR contains advanced medical equipment oriented toward intensive care and six additional beds, which serve approximately 500 medical ED patients annually. The resources provided in the RR, which include the working space, medical equipment, beds, and computers, are shared by surgical and medical EDs. However, the RR is seldom fully occupied. A patient may be defined as critical during nursing triage upon arrival or by the admitting physician in the ED, based on vital signs, state of alertness, and clinical appearance. Other patients are transferred to the RR following deterioration whilst being treated in the ED. Other critical patients arrive to the ED by emergency medical services directly to the RR. Patients in the RR are treated by a senior physician, who is a part of the ED shift staff and moves to the RR until the treatment is completed or until the shift ends, whichever comes first; patients are then admitted to either an ICU or a relevant ward for further treatment.

To gather relevant clinical information on the often non-communicative patient, the physician typically utilizes secondary information sources as the patient's medical paper chart, family members, and the HIE system. While the paper chart documents vital signs and treatment given by paramedics and in the RR, the only source of historical data available to the physician is the HIE.

3.2. HIE system: OFEK

OFEK HIE system (dbMotion, Israel) has been utilized in SUMC since 2005 and is connected to multiple HIS. Per user request, this system assembles patient-level data from various sources and displays it as an integrated patient file via a web interface. The HIE is connected to Clalit Health Services' information systems that make the following data available: demographic details, medication history, past diagnoses, outpatient and community clinic visits, visits in EDs, history of hospital admissions, discharge summaries from most Israeli hospitals, past procedures (e.g., surgeries, cardiac catheterizations), and laboratory and imaging tests results. These data are available for all treatments and tests that were conducted at any of Clalit Health Services' facilities. Patients are automatically included in the HIE and their consent is not required. As the system was implemented five years before the beginning of this study and its use has stabilized [65], we attribute any inexperience with the system to users and not to the status of the implementation project.

The first screen the user encounters when entering a patient's virtual file (i.e., the "gateway screen") is the "patient data summary" screen. This screen contains short summary tables of links to the 3–4 most recent diagnoses, procedures, prescribed medications, hospital admissions, and laboratory tests from the past week. From that point, the user is free to navigate to any information category (e.g., lab results) or specific item (e.g., specific biochemistry test result). Once the inquiry is finished, the virtual patient record is discarded. Subject to user role and access level, an integrated patient file is retrievable at all times. A 30 min idle logout is automatically enforced for reasons of confidentiality.

3.3. Dataset

The study sample includes all encounters in which adult (i.e., age ≥ 18) medical ED patients were treated at the RR between January 1, 2010 and December 31, 2012. The selection of patients that are in need of urgent medicine services at the same ED is expected to control for numerous confounding effects of situational and organizational variables. Moreover, the RR is an environment in which information systems are of substantial importance as a primary source of historical information due to the patients' condition. Given the objectives of this research, we include in the sample only encounters in which physicians accessed the HIE, i.e., at least one screen of the integrated patient file was viewed by a physician. After obtaining the approval of SUMC's institutional review board, we attained a roster of all RR treatments that followed the definitions above. Our initial dataset included 885 treatments given to 848 patients, which constituted 84.36% of all encounters during the examined three-year period. The unit of analysis (i.e., observation) in this study was the intersection of a specific physician and a specific patient, on a specific encounter. The initial dataset consisted of 1659 observations.

In this study, HIE log files are used to characterize system use. Log file analysis is considered part of "computational ethnography" techniques, which were introduced by Zheng et al. [66] as methods for conducting human-computer interaction studies in healthcare. The use of log files overcomes methodological problems related to self-reporting and reliability of measurement. Despite challenges that the clinical environment poses to this method [67], log file analysis is considered a common (e.g., [22,37]) and recommended method for the analysis of HIE use [10,35].

The log files utilized in this study document all screens displayed successfully to physicians, including a timestamp that indicates when screens were shown and identifiers for the physician (i.e., the user) and the patient. Data regarding the patients' clinical and demographic status, physician properties, situational variables, and information availability indicators were collected from databases operated by Clalit Health Services, the Ministry of Health, and the Ministry of the Interior. The clinical and information availability variables were retrieved from a one-year period preceding the encounter. All data were de-identified according to standards.

As the dataset included numerous variables from multiple sources, actions of integration, processing, and cleaning were required. Five observations (two encounters) were omitted due to unreliable patient age records. The RR and its computers are shared by both internal and surgical physicians, making it possible for internal medicine physicians to use computers already logged on by surgeons. This case is uncommon because of the automatic idle logout and as the RR is seldom used simultaneously for internal and surgical cases. Hence, it is likely that system use attributed in the log file to surgical physicians was in fact performed by internal medicine physicians. Such system use, consequently, cannot be attributed to specific physicians. Therefore, to preclude bias introduced by data about physicians that were not the caregivers, we excluded observations in which access was made from usernames of surgeons. Observations were also removed in cases where the physician's expertise and experience could not be obtained. A total of 359 observations were excluded due to these reasons. We compared the distributions of the explanatory and explained variables before and after the exclusion of observations using Chi-square tests and t-tests for categorical and continuous variables, respectively. The tests confirmed that the exclusion of 364 observations in total had no effect on the distribution of any of the variables, implying that the exclusion of observations introduced no bias to the analysis. The final dataset consisted of 1295 observations for 810 encounters (i.e., an average of 1.6 physician sessions per patient encounter) of 778 patients with 109 physicians.

3.4. Use patterns

This section describes the steps taken to define and analyze the patterns of use of the HIE system based on data residing in its log files. We first describe the operationalization of the concepts of volume and duration as attributes of system use. We apply multiple approaches to characterize use by first analyzing variables separately and then by observing combinations of these variables (i.e., use profiles).

3.4.1. Volume and duration as attributes of use

In accordance with the unit of analysis in this study, we observe a single physician's interaction with the system during an encounter with a patient. Each such session (observation) is defined as all screens that are viewed by a specific physician during an encounter with a specific patient. For each session, we compute the following quantitative variables that represent the volume and duration of use:

- The *volume* of information is measured as the number of screen displays (a screen display is counted even if the same is displayed more than once).
- The *duration* of use per item of information is measured as the median duration (in seconds) of screen displays (median DSD) within the session. To compute this measure, the screens in each session are sorted by access time, and the time per screen is computed as the difference in elapsed seconds between the time of access to that screen and the time of access to the consecutive one. In order to minimize the effects of unreliable durations, we apply a threshold on the display time of each screen; this approach is based on log file analysis methods, in which a threshold is defined as the maximal time for which is it plausible that the user has not left the system [68,69]. A

threshold of 60 s is applied, implying that durations longer than 60 s are truncated to 60 s. This threshold is selected following interviews with several physicians, who stated that based on their experience in the ED, a physician seldom views a screen for more than 30 s. We chose a more conservative threshold of 60 s to avoid the misinterpretation of longer screen views.
The median is used as a summary statistic [21,70] with the intention of using a representative measure that normalizes different information items (i.e., screens) in a way that is not affected by the total number of screens [49], i.e., volume. This choice diminishes the over-representation of volume in characterizing sessions and further lessens the effects of extreme and less reliable values.
Although the threshold is applied on the durations of 14.8% of screens (2000 out of the 13,433 screens), median DSD values, which are those included in the analysis, are affected in only 1.7% of sessions (22 out of the 1295 sessions). The findings of the comparison between EM and non-EM physicians are robust to the application of the threshold (the same findings are attained if the threshold is not applied).

3.4.2. Use patterns

A bi-dimensional space is generated by considering volume and duration as two orthogonal dimensions. The combination of volume and duration for each session determines its location in this space. Consistent with the literature on profiles in an organizational context [71,72], we define four archetypical profiles of use in this bi-dimensional space: *quick and basic* (low on both dimensions), *quick and deep* (low duration and high volume), *slow and basic* (high duration and low volume), and *slow and deep* (high on both dimensions). These profiles represent all possible combinations of low or high levels of duration and volume. They are defined quantitatively in the bi-dimensional space by assigning the value −2 to low attribute levels and the value +2 to high attribute levels. We represent the profiles with relatively extreme values in accordance with the literature on profiles in an organizational context [72]. Table 1 presents the four profiles and their operationalization. These values are selected because they represent a distance of two standard deviations from the Z distribution mean. We tested the sensitivity of our findings to other operationalizations (e.g., +1 and −1 for high and low values, respectively) and found them to be highly robust to such changes.

We next classify the observed sessions into profiles based on the shortest squared Euclidean distance [71,72], creating four relatively homogeneous groups. Each session was assigned to one and only one profile and no sessions were excluded from the analysis at the classification stage. This classification is preceded by standardizing session attributes to Z scores in order to prevent over-representing attributes with wider ranges. Based on the reviewed literature, we expect sessions characterized by short durations and access to few screens (i.e., *quick and basic* sessions) to be the most prevalent in general and among experts in particular.

Table 1
Use profiles and their operationalization.

Use profile	Attribute values[a]	
	Duration	Volume
Quick and basic	Low (−2)	Low (−2)
Quick and deep	Low (−2)	High (+2)
Slow and basic	High (+2)	Low (−2)
Slow and deep	High (+2)	High (+2)

[a] Scores are standardized.

3.5. Explanatory variables

Based on the review of variables that potentially affect use patterns (Section 2.4), the following variables are used as explanatory variables in attempting to answer *Research Question III*.

3.5.1. Physician properties

- Gender.
- Expertise: a binary indicator stating whether or not the physician is a board-certified EM physician.
- Variables that describe the level of physician experience: seniority, defined as the number of years from licensure, and recent ED experience, proxied by the number (in hundreds) of patients the physician discharged from the ED in the year preceding the encounter. Both variables proxy for experience in the EM domain and with the HIE.
- We include the specific physician as a random factor in the regression analyses to control for personal preferences and for the dependence among observations of the same physician across different encounters.

3.5.2. Patient clinical and demographic properties

- Clinical properties: multiple indicators are used to capture the patient's clinical condition. The Charlson comorbidity index (CCI) is computed based on the International Classification of Diseases, ninth revision – Clinical Modification (ICD-9-CM) [73]. We also include two binary indicators that serve as proxies of the severity of the patient's illness – 24-h and 7-day mortality (measured from the time of admission to the ED).
- We incorporate a binary variable to indicate whether or not the patient arrived to the hospital using an emergency transportation service (e.g., ambulance, helicopter). This variable was shown to be linked with clinical decision making, as arrival by ambulance was associated with higher odds of being admitted, in general, and to critical care, in particular [74]. Moreover, it may reflect time constraints, as patients that arrive by ambulance tend to wait less for treatment [75], possibly due to the ED personnel's stronger sense of urgency.
- We include the ED length of stay (LOS), measured in elapsed hours from admission to the ED until the discharge from the RR, as a longer time at the ED may be positively correlated with the volume of information that is accessed via the HIE.
- Demographic properties: age, gender, and an indicator for past immigrant status (whether or not the patient was born in Israel).
- A binary variable indicating whether or not the patient is insured by Clalit Health Services is also included, because it may influence information availability via the HIE.

3.5.3. Situational properties

The situational properties that are incorporated to reflect work intensity, staffing status, and patient hand-offs are as follows:

- Binary indicators for whether or not the patient arrived during a morning shift or during a weekday, as these shifts are usually busier and staffed with more physicians.
- Another measure of the ED workload is computed as the number of patients that arrived to the ED during the period between 30 min before and after the encounter.
- The number of hours between the beginning of the physician's shift and the beginning of system use (i.e., beginning of session), possibly accounting for the physician's fatigue.

- Because patient hand-offs are a source of information gaps [76] and may thus influence system use, we include a binary indicator for a physician shift change during the encounter.

3.5.4. Information availability

As the availability of information is a prerequisite to using the system, we include binary indicators that reflect the types of information that were added during the year preceding the encounter and therefore are available at the time of system use: visits to outpatients and community clinics, hospital admissions, ED admissions, surgeries and procedures, laboratory tests, and imaging scans. These variables also reflect the patient's recent medical history, which has been shown to be associated with system use [40,44]. Two additional binary variables indicate cases in which new imaging scans and lab test results were added to the system during the session.

3.5.5. Dynamics of system use within the encounter

Four binary indicators capture the dynamics of use made by several physicians within a single encounter, possibly occurring when receiving consultation or handing-off patients. The first variable indicates whether or not the physician was the only one to use the system during the encounter. The three additional variables refer to a situation in which two or more physicians used the system during the encounter and indicate whether the physician was the first to use the system, the last to use it, or used it concurrently with an expert (who was also inquiring the system about the same patient).

3.6. Statistical analysis

Research Question III is addressed with a mixed-effects multinomial regression analyses, employing a cumulative logit link function, in which the dependent variable, the use profile to which the observed session is classified, is regressed on all explanatory variables (Section 3.5). The *quick and basic* profile functions as the reference category in the analysis because of its anticipated prevalence in the RR setting. We include interaction terms between the EM expertise indicator and the other explanatory variables, to test whether the associations between explanatory variables and use profiles are contingent on physician expertise. By employing multinomial regression analyses, we can estimate the probability of observing a specific use profile relative to the probability of observing the reference use profile. In other words, we are able to estimate the odds of moving on the bi-dimensional space of volume and duration from the lower-left quadrant (*quick and basic*) to one of the other three quadrants.

For the multinomial regression analyses, multicollinearity is detected based on high variance inflation factors ($VIF \geq 5$) and high absolute bivariate correlation coefficients ($|\rho| \geq 0.7$) [77]. Given that a relatively high level of collinearity is detected, all explanatory variables are centered with respect to their means prior to the regression analyses, following a common approach to address collinearity that arises from incorporating both main and interaction effects of the same variables in a regression model [78]. As a result of applying this approach, the coefficients of the interaction terms represent how the effect of the physician being an EM expert changes as the interacting variable departs from its mean. Importantly, the values of regression slopes (i.e., variable coefficients) are not affected by this step. All analyses are conducted using SPSS 20.

4. Results

4.1. Descriptive analysis of system use

The frequencies of use profiles and the mean values of volume (number of screen displays) and duration (median DSD in seconds) for each profile (i.e., the profile centroids) are presented in Table 2. An average session, when the entire sample is considered, consists of 10.37 screen displays and a median DSD of 7.51 s per screen. When examining each use profile separately, the *quick and basic* profile is the most frequent (45.71% of all sessions) and the opposite *slow and deep* profile is the least frequent (10.74%). On average, whereas the *quick and basic* profile involves the display of 4.87 screens, each for 4.08 s, the *slow and deep* profile involves the display of 19.25 screens, each for 11.37 s. The other two use profiles involve combinations of low and high values on volume and duration. All pairwise differences between mean values for low and high dimension values across profiles (e.g., difference in mean volume between *quick and basic* and *quick and deep* profiles, difference in mean duration between *quick and basic* and *slow and basic* profiles) are found to be statistically significant.

A comparison of use profiles and use variables for EM experts and non-EM experts is displayed in Table 3. The distributions of profiles for usage made by EM physicians and non-EM physicians are not statistically different ($\chi^2_3 = 4.09$, $p = 0.252$). Whereas *t*-test comparisons between EM and non-EM physicians in the means of duration show that median DSD is similar for the two groups (Levene's test $p = 0.912$; $t_{1293} = 0.534$, $p = 0.593$), the mean of volume is found to be statistically lower for EM experts than for non-EM experts (Levene's test $p = 0.018$; Welch's $t_{858} = 2.016$, $p = 0.044$), implying that EM experts view less screens than non-EM experts, on average. The attributes of volume and duration are uncorrelated for sessions made by EM, by non-EM physicians, and when the entire sample is considered (Pearson's correlation coefficients are statistically nonsignificant, $p > 0.2$).

Fig. 2 plots the sessions in the bi-dimensional space of volume and duration, while highlighting the classification of sessions into use profiles. This figure demonstrates that sessions are less frequent as volume and duration increase. It also provides evidence that a certain degree of trade-off exists between volume and duration, showing that as one of these attributes increases, the other is likely to decrease.

4.2. Descriptive analysis of explanatory variables

Table 4 presents descriptive statistics for variables that relate to the physician, patient, situation, information availability, and use dynamics within the encounter. In our study sample, 30.66% of use was made by 11 EM experts. Twenty-eight percent of the sessions were the only sessions during that encounter (i.e., only one physician used the system when that patient was treated). In 30.73% of the cases, lab results arrived during the session. The majority of sessions took place when information on labs

Table 2
Classification of sessions into use profiles.

	Number of sessions (%)	Volume	Duration
Total	1295 (100%)	10.37 (10.18)	7.51 (7.38)
Quick and basic	592 (45.71%)	4.87 (2.46)	4.08 (1.67)
Quick and deep	320 (24.71%)	20.33 (12.36)	5.20 (1.29)
Slow and basic	244 (18.84%)	5.59 (2.27)	16.66 (11.56)
Slow and deep	139 (10.74%)	19.25 (10.16)	11.37 (5.74)

The volume (number of screen displays) and duration (median DSD in seconds) columns display the mean (standard deviation).

Table 3
Use profiles and variables by physician expertise.

		EM Expertise ($n = 397$)	Other (non-EM) Expertise ($n = 898$)
Use profile[a]	Quick and basic	197 (49.62%)	395 (43.97%)
	Quick and deep	92 (23.17%)	228 (25.39%)
	Slow and basic	72 (18.14%)	172 (19.15%)
	Slow and deep	36 (9.07%)	103 (11.49%)
Use variable[b]	Volume	9.56 (9.24)	10.73 (10.55)
	Duration	7.34 (7.08)	7.58 (7.51)

EM, Emergency medicine.
[a] The distribution of use profiles: counts (percent of total in expertise level).
[b] Mean (standard deviation) for use variables.

(91.81%) or imaging results (80.77%) was available in the system at their beginning.

4.3. Prediction of the use profile

Table 5 summarizes the results of the multinomial regression analyses, aimed at predicting the likelihood that a session is classified into one of the three profiles of *quick and deep*, *slow and basic*, and *slow and deep*, instead of into the reference profile of *quick and basic*. The table displays the change in the odds (odds ratio, OR) of observing a specific use profile when a unit is added to a specific variable, *ceteris paribus*. The interaction terms of EM expertise with patient gender and with the availability of information about prior ED admissions and visits to clinics are omitted from the analysis to alleviate the effects of multicollinearity.

Several variables emerge as statistically significant in predicting specific use profiles. The availability of information in the HIE system plays a significant role, as the presence of imaging scans and lab test results at the beginning or during the use of the system greatly increases the odds of observing the three predicted profiles (*quick and deep*, *slow and basic*, and *slow and deep*), in particular the two profiles involving deep (high volume) use. For instance, deep use of the system is significantly more likely (an increase of over 1200%) when lab tests arrive during the use of the system. Contrariwise, available information about history of hospitalizations and ED visits increases the likelihood of observing *quick and basic* use of the system (the odds of observing the other three profiles are decreased by over 50%). This effect is even stronger when the user is an EM expert, as evident by its significant interaction effect (OR values of 0.411 and 0.348) with available information about previous hospital admissions. Whereas the likelihood of observing the two profiles involving slow (high duration) use decreases when information about ED admissions is available in the system (OR values of 0.442 and 0.465), their likelihood increases when information is available about visits to clinics in the past year (OR values of 1.414 and 1.575).

The associations of physician-related variables with the various use profiles vary between EM experts and non-EM experts. In particular, EM experts are much less likely (by almost 70%) than non-EM experts to exhibit *slow and basic* use of the system. Conversely, the physician's seniority is generally associated with the two profiles involving slow use, although this effect is relatively small (OR values of 1.030 and 1.052). Male experts are associated with a *quick and basic* use of the system (OR values of 0.319, 0.384, and 0.077). Finally, the physician's experience in the ED slightly reduces the odds of slow and deep use (OR is 0.971).

Use profiles are also associated with dynamics within the encounter. When the system is used for the first time by a physician for a patient, regardless of whether this use is the only session or the first session (later followed by sessions by other physicians), *quick and deep* use is less likely than *quick and basic* use by more than 40%. *Quick and deep* and *slow and basic* profiles are also less likely to be observed when an EM expert is the last user of the system during an encounter (OR values of 0.209 and 0.364).

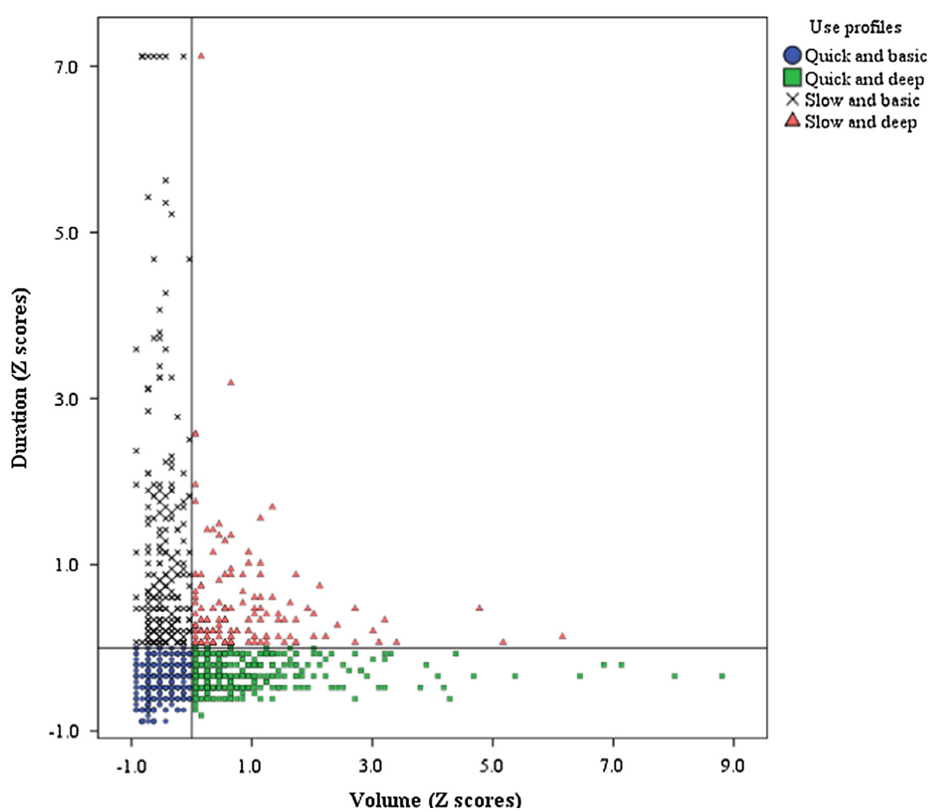

Fig. 2. Distribution of sessions in the bi-dimensional space of volume and duration.

Table 4
Descriptive statistics at the session level (physician-patient-encounter level).

Variable group	Variable[a] (at the session level)	Descriptive statistic[b] (with the number of sessions as the denominator)	95% CI[c]
Physician (system user)	Gender: male	76.53%	(74.14, 78.75)
	Seniority (years)	9.23 (6.64)	(8.81, 9.64)
	EM Expertise: expert	30.66%	(28.21, 33.22)
	Recent ED experience (×100 patients)	12.73 (10.81)	(12.06, 13.41)
Patient	Gender: male	57.22%	(54.51, 59.89)
	Past immigrant status	25.10%	(22.81, 27.53)
	Age	67.92 (16.70)	(66.88, 68.96)
	CCI	6.17 (3.15)	(5.98, 6.37)
	Arrival with emergency services	47.10%	(44.40, 49.83)
	24-h mortality	20.39%	(18.28, 22.67)
	7-day mortality	35.21%	(32.66, 37.85)
	ED LOS (Hours)	1.75 (1.86)	(1.64, 1.87)
	Insured by Clalit	68.88%	(66.31, 71.34)
Situation	Shift hand-off	74.52%	(72.07, 76.82)
	Morning shift	41.31%	(38.66, 44.02)
	Hours from shift start	6.99 (5.00)	(6.68, 7.30)
	Weekday	72.36%	(69.86, 74.72)
	ED work load (patients)	31.10 (12.87)	(30.30, 31.90)
Information available in the HIE system	Hospital admissions	53.82%	(51.10, 56.50)
	Visits to clinics	52.74%	(50.02, 55.45)
	ED admissions	63.01%	(60.35, 65.60)
	Surgeries and procedures	18.76%	(16.73, 20.98)
	Imaging scans, before	80.77%	(78.54, 82.83)
	Imaging scans, during	17.68%	(15.70, 19.86)
	Lab tests, before	91.81%	(90.19, 93.19)
	Lab tests, during	30.73%	(28.28, 33.30)
Use dynamics within encounter	Sequence of sessions	Only session = 28%, first (MTOE) = 28.49%, intermediate (MTOE) = 17.41%, last (MTOE) = 26.10%	Not applicable
	Overlap with other sessions	26.10%	(23.78, 28.56)

$n = 1295$.
EM: emergency medicine; ED: emergency department; CCI: Charlson comorbidity index; LOS: length of stay; MTOE: more than one session in encounter.
[a] An observation represents an encounter between a specific physician and a specific patient.
[b] The main descriptive statistic for categorical variables is percentage, otherwise it is the mean (standard deviation).
[c] 95% confidence interval (CI) for dichotomous variables is the Wilson score interval, otherwise it is the CI for the mean.

4.4. Robustness checks

The approach employed in this study looks at the volume of information in terms of quantity (number of screens) rather than in terms of quality (type of information included in screens). To examine the influence of this approach on the findings obtained, two alternative approaches for modeling profiles are also tested. The first approach incorporates the attribute of granularity to characterize each session, with granularity defined as 1 if the session contains access to at least one "specific" screen (a screen that displays information on detailed results, such as specific discharge summary or test result) and as 0 if the session contains only summary screens. Correspondingly, we create eight profiles that consist of all possible combinations of high/low volume, duration, and granularity. Very few sessions are found to be closest (and therefore classified) to profiles in which the level of volume differs from the level of granularity (i.e., one is high while the other is low). This finding is also supported by a Spearman's correlation coefficient of 0.682 ($p < 0.01$) between volume and granularity, suggesting that there is little value in including granularity in the analysis.

The second approach is to classify sessions to the same profiles presented in Table 1, but to define sessions as including only "specific" screens (summary screens are ignored). Then the values of volume and duration per session are computed solely on the basis of "specific" screens. This approach yields similar results to those presented above, suggesting that the findings are robust to alternative definitions of use profiles that incorporate qualitative attributes of the presented information.

The predicted variable in the analysis – a bi-dimensional profile based on the attributes of volume and duration – reflects the focus of this study on the trade-off of volume and duration. Nevertheless, to confirm the value of this bi-dimensional approach, we examine the effects of the explanatory variables on volume and duration of use separately using a linear regression analysis. The natural logarithm is taken for volume and duration in order to satisfy the assumptions of the regression analysis. We find that the separate analyses capture some, but not all of the effects described above, confirming the value of an approach that examines use profiles in addition to isolated use variables.

5. Discussion

5.1. Findings and implications

This study addresses several concepts that research on use patterns of HIS in general and HIE in particular has yet to address. To the best of our knowledge, this study is the first to examine the trade-off of volume and duration in the use of medical systems and the factors associated with it. Moreover, studies have yet to explore in naturalistic settings the differences in use patterns between experts and non-experts in the ED. To accomplish that, this study employs multiple approaches to describe HIE use patterns, and examines the associations between the emerging use profiles and an expansive set of variables. Several important variables are introduced in this study as contributing to the prediction of use patterns, such as user (physician) properties and variables that describe use dynamics in terms of sequenced and overlapping use. We next discuss the key findings and their implications in light of the three research questions.

5.1.1. Research Question I: The trade-off between volume and duration

While we find a statistically nonsignificant correlation between the attributes of volume and duration when describing HIE use with individual attributes of use, describing HIE use as profiles of use attributes suggests a trade-off exists between these attributes. The distribution of use profiles in the bi-dimensional space of volume and duration suggests that *quick and basic* use of the system is prevalent and that deep (high volume) or prolonged (high duration) consumption of information is considerably less frequent. The distribution of sessions within the other, none-*quick-and-basic* profiles stresses this point, as sessions higher on one attribute tend to be lower on the other. Moreover, an interesting insight derived from Fig. 2 and Table 2 is that the observed values of volume in the *quick and deep* profile and of duration in the *slow and basic* profile tend to be higher than those in the *slow and deep* profile. In other words, the high attributes in mixed (low-high and

Table 5
Prediction of use profiles.

			Use profiles Exponentiated coefficients (OR)[b]		
Variable group		Explanatory variable[a]	Quick and deep	Slow and basic	Slow and deep
		Intercept	0.295***	0.255***	0.06***
Physician (system user)		EM expertise	–	0.311***	–
		Seniority (years)	–	1.030*	1.052**
		Recent ED experience (×100 patients)	–	–	0.971*
Patient		ED LOS (h)	1.103*	1.079*	–
		CCI	–	0.939**	–
		Insured by Clalit	–	1.538**	1.794**
Situation		ED work load (patients)	–	1.015**	–
Information available in the HIE system		Hospital admissions	0.482***	–	–
		Visits to clinics	–	1.414*	1.575*
		ED admissions	–	0.442**	0.465**
		Imaging scans, before	2.235***	–	2.342**
		Imaging scans, during	3.347***	1.777*	4.554***
		Lab tests, during	12.388***	1.714**	13.845***
Use dynamics within encounter		Sequence of sessions: only session	0.573*	–	–
		Sequence of sessions: first (MTOE)	0.559**	–	–
		Overlap with other sessions	1.534*	–	–
Interaction with EM expertise	Physician	Gender: male	0.319*	0.384**	0.077***
		Recent ED experience (×100 patients)	–	1.044**	1.09***
	Patient	ED LOS (hours)	0.813*	–	–
	Situation	Morning shift	–	2.531**	–
		ED work load (patients)	–	–	0.96*
	Information available in the HIE system	Hospital admissions	0.411*	0.348**	–
		Lab tests, during	–	3.510**	–
	Use dynamics within encounter	Sequence of sessions: first (MTOE)	–	0.484*	–
		Sequence of sessions: last (MTOE)	0.209***	0.364**	–

This table includes only coefficients of explanatory variables that are statistically significant at the 0.1 level for at least one of the use profiles (the full model includes the variables that appear in Table 4 and their interactions with EM expertise). All main and interaction terms that are absent from this table, as well as terms that are marked with "–", are statistically nonsignificant at the 0.1 level. A random factor of the physician who used the system is statistically significant ($p = 0.035$) only for the *quick and deep* use profile.
EM: emergency medicine; ED: emergency department; LOS: length of stay; CCI: Charlson comorbidity index; MTOE: more than one session in encounter.
[a] Main effects are centralized; interaction terms are the multiplications of a centralized main effect with the centralized EM expertise variable. Reference categories (coded as 0 before centralization): EM expert: other or no expertise; Sick fund Clalit: other sick fund; gender: female; all indicators for types of available information: no available information; Sequence of sessions: intermediate session; Overlap with other sessions: no overlap with other sessions; Morning shift: other shift.
[b] Exponentiated coefficients for the variable, representing odds ratio (OR) values.
[*] $p < 0.1$.
[**] $p < 0.05$.
[***] $p < 0.01$.

high-low) profiles tend to be higher than those in the all-high profile. This finding supports the assumption about the existence of resource constraints in our research setting, which are reflected in system use patterns that are characterized by volume and duration.

The design of HIEs, especially in high-paced and constrained environments as the ED, should be mindful to the often basic use of the system and to the limited resources that the user can allocate to its perusal. As physicians frequently do not examine large volumes of information or dedicate considerable time to each item, it is advised that HIEs contain fewer transition screens (i.e., non-content screens that link sections of the system) and that summary screens (e.g., summary of previous admissions) give the user meaningful preliminary insights that would assist in determining the expedience of further inquiries.

5.1.2. Research Question II: Association of physician expertise with volume and duration

Whereas EM physicians are not different from non-EM physicians in terms of the duration of time devoted to each information unit, they inspect fewer pieces of information (i.e., volume is significantly lower for EM physicians). This finding emerges from looking both at the overall means of volume and duration and at the distribution of use profiles. We thus conclude that our proposition, consistent with similar propositions by others [27,56], that the relationship between volume and duration of system use is contingent on the physician's expertise, is not supported by our data and analysis. Although we do find that EM expertise has predictive value in observing specific use profiles, this finding is not related directly to the interrelationship between volume and duration.

These findings support the claim that HIS alter the decision making process and may assuage some of the difficulties of physicians who have less domain experience. A possible explanation for the lack of or slight difference in use between EM experts and non-experts may be that the relatively structured nature of the HIE may reduce information processing time or shorten navigational paths used when seeking for relevant clinical information.

5.1.3. Research Question III: Factors associated with volume- and duration-based use patterns

The findings show that use profiles are significantly associated with various contextual factors that describe the medical case, situation, user, information residing in the system at the time of use, and dynamics of use within the encounter. Whereas bivariate analyses indicate that no association exists between expertise and use profiles, a multivariate regression analysis, which identifies the added (i.e., marginal) value of factors when others are held constant, demonstrates that expertise is of value for the prediction of use profiles and that its effects may depend on the values of other factors (i.e., interaction effects). That is, while experts and non-experts do not differ in the distribution of use profiles, the likelihood of their use of the system in certain ways is affected by different factors. Several variables emerge from our analysis as valuable predictors of use profiles. The multivariate approach taken in this analysis highlights interesting dependencies and interactions among variables. Fig. 3 summarizes the findings of Table 5 by presenting the factors that affect the likelihood of observing use profiles, both for the entire sample (main effects) and for the group of EM physicians (interactions).

The availability of clinical information in the system is highly linked with use profiles, not necessarily implying that information availability leads to slower or deeper use. In fact, the presence of information about recent hospitalizations and ED admissions is associated with *quick and basic* use, conceivably because discharge documents summarize and organize information, thus facilitating its processing. The value of these summaries to ED physicians may be expressed not only by high access rates, as reported in previous studies [21,37,44], but also by their association with *quick and basic* access, which may be perceived as a more "resource efficient" form of system use. Whereas this finding may seemingly contradict findings that prior hospitalizations are associated with "novel" use of the system [33,44], novel use is defined in these studies as the display of more than two screens, which in the current study may still be classified as basic use. The format and content of admission summaries should be carefully considered, especially because access to these screens is less likely to be followed by a search for additional information.

Inversely, available information on visits to clinics and on lab and imaging results, particularly those that arrive during a session, greatly increases the likelihood of the use being non-basic. In such cases, the trade-off between duration and volume reflects an increase in the latter attribute (higher volume and lower duration). Such behavior may stem from seeking specific information, as the physician rapidly reviews the sought information. Our findings suggest that this behavior is particularly prevalent among experts, which can be explained by non-experts not being clear on their goal or about how to achieve it. Given the potential for judgement biases among experts [32,55], considerable attention should be given to these information types during HIS design. The disparity between the effects on use profiles of different types of information (e.g., admission summaries versus laboratory tests) may be the consequence of fundamental differences in their characteristics, such as their granularity (summary as opposed to detailed), the purpose they serve (initial review of medical history as opposed to specific and recent clinical measures), and possibly their display format.

By themselves, the clinical variables examined in this study do not emerge as extremely valuable in the prediction of use profiles. One possible explanation for this is that the specific, homogeneous clinical setting of the RR may mitigate the influence of clinical variables on use profiles. Another possible reason for that is the dominant effects of information availability variables, which also reflect the patient's recent medical history and comorbidities [34,40]. Following this logic, studies that employ electronic medical data to predict clinical phenomena, e.g., [79] may wish to consider including indicators of available information in HIS as proxies for the patient's long-term clinical status. Similarly, few situational variables are associated with use profiles, possibly due to characteristics unique to the RR environment, which may focus the physician on the specific treatment, relatively unaffected by considerations external to the RR.

Complex relationships are revealed when considering the combined effects of the various variables and expertise. While system use is overall statistically identical for EM and non-EM users, a more careful analysis of the data reveals that similar settings may induce different use of the system. This raises the possibility that the associations between expertise and system use may be moderated by other variables. For example, while the physician's gender seems unassociated with the observed use profile among non-EM physicians, male EM physicians tend to *quick and basic* use more than female EM physicians. Interestingly, individual user variability (reflected by the random factor in each category) provides explanatory value only for the prediction of *quick and basic* use. The lack of explanatory value for the prediction of the other use profiles may suggest that individual preferences are less consequential for the occurrence of such forms of use. Such insights may assist in forming distinguished HIS implementation plans for different segments of the ED physician population.

The construct of use dynamics within the encounter, as first defined and examined in the current study, plays an important role in the prediction of use profiles, particularly when considered with the user's expertise. These variables provide insight on teamwork and consultation mechanisms, reflecting the often interrupted and multitasking nature of ED treatment [2]. For example, when the system is used simultaneously by two physicians, it is more likely for use to be *quick and deep*. A possible interpretation of this finding is that during consultation, the involved physicians quickly navigate and scan specific information, such as test results, which may take less time to be evaluated by an expert. Furthermore, these variables accentuate that a user is not completely independent of others who previously used the system for the same patient, particularly when the user is an EM physician. For instance, when an EM physician is the last user of the system in an encounter, that physician is less likely to use the system in a *quick and deep* or *slow and basic* fashion. These conclusions imply that the design of HIS, their implementation, and the exploration of their use should be performed while considering elements of teamwork and information exchange among the intra-departmental staff.

5.2. Limitations and future research

This research has several limitations. First, the findings of this study are based on a particular cohort of patients and users, clinical setting, and HIE system. The HIE system in this study functions as the only source of historical clinical data, internal and external, in SUMC's medical ED. This characteristic is likely to increase use rates substantially and may have some effect on use patterns compared to EDs in which HIE systems only provide access to information external to the hospital. While this lack of variance strengthens the internal validity of our findings, decreasing the likelihood of confounding due to extraneous variance, generalizability to other settings and systems is limited. In particular, caution should be exercised when generalizing the findings of this study to settings in which HIEs do not act as the primary source of both external and internal clinical data. The methods presented in this study can be implemented in different settings, although they may yield different findings (e.g., in other wards, quick and basic sessions may be characterized by more screens viewed for longer durations), as clinical situations, decisions, and use patterns may vary among localities, e.g., [37]. Second, by basing use patterns on log files, use is described by information that is available in the HIE system, selected by the user, and successfully displayed. The log files cannot disclose whether or how the attained information is actually used. Third, as stated in the description of the dataset, a possible source of bias in attributing use to specific users is the possibility that logged-on computers are shared. Such potential biases are minimized by focusing on RR treatments and by excluding observations as described in the methods section.

Because this study is observational, it cannot establish causality and determine that the various factors that describe the patient, physician, situation, information availability, and use dynamics

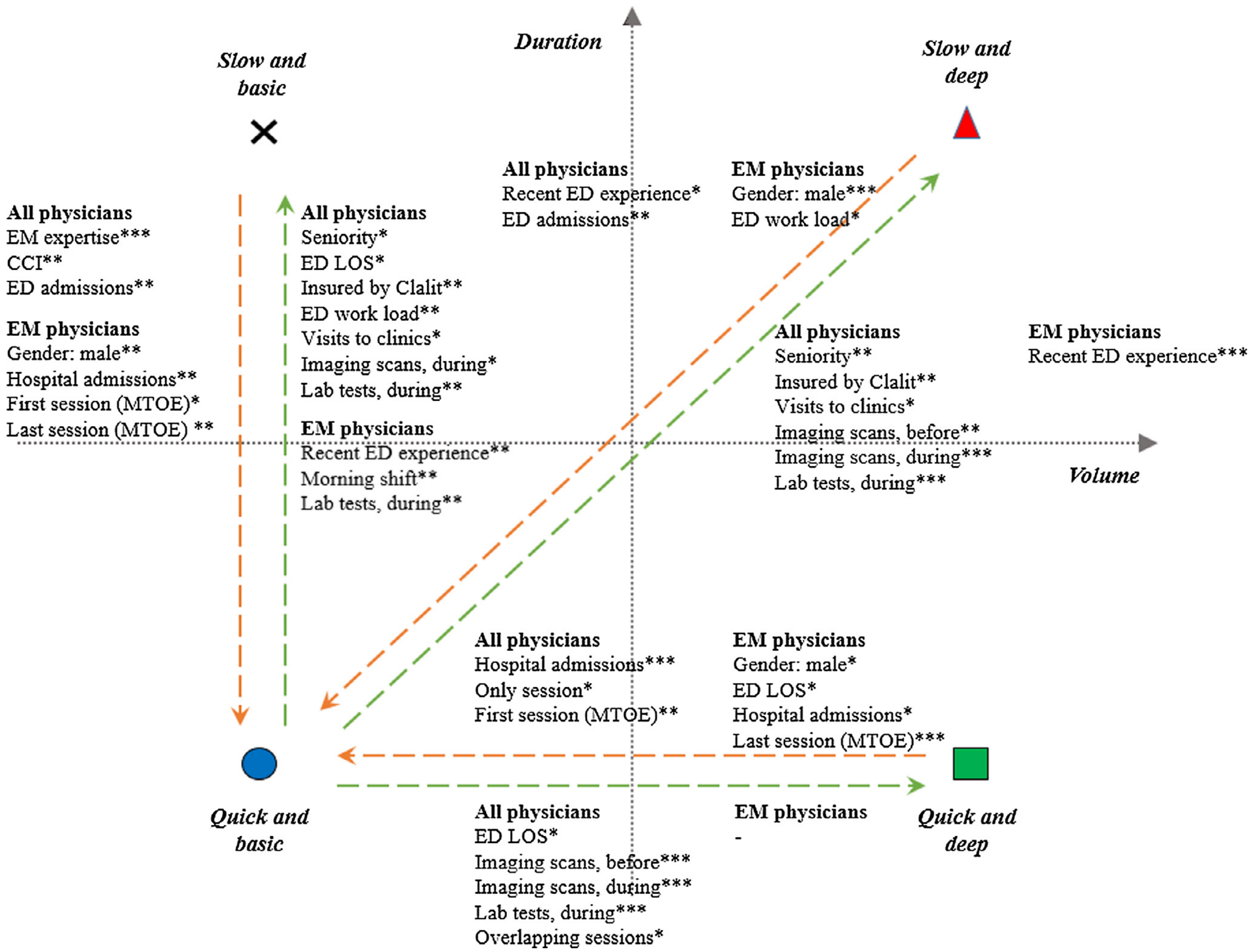

Fig. 3. Factors associated with the odds of transitioning between use profiles. This figure is based on Table 5 and illustrates the statistically significant factors that are associated with transitioning, on the bi-dimensional space of volume and duration, from (to) the quick and basic profile to (from) one of the other three profiles. An arrow that points from some profile A to another profile B, and the variables that are adjacent to it, describe the factors that increase the odds of observing profile B over profile A. For each arrow, factors are presented in two lists: one for all physicians (including experts), reflecting the results for main effects, and another for the group of EM experts, reflecting the results for interaction effects with EM expertise. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. EM: emergency medicine; ED: emergency department; LOS: length of stay; CCI: Charlson comorbidity index; MTOE: more than one session in encounter.

cause certain use profiles. Furthermore, while the naturalistic orientation of this study better reflects the complex and dynamic medical setting being explored [55,80], it implies that variables are not independent of one another. For instance, recent experience and expertise are highly correlated in our dataset (Pearson's correlation coefficient is 0.601, $p < 0.01$). Such correlations may hinder the ability to isolate the effects of each variable on use profiles.

Several variables that emerge as significant in predicting use profiles should be further explored. For instance, gender differences seem to play a role in determining how EM experts use the system, yet as our sample included 11 experts, further corroboration is required. The findings also highlight the importance of observing the collective use of the system by the medical staff involved in the treatment of a patient. Such factors have been identified as having a significant influence on the quality of care [61,62] and on staff satisfaction [81]. Future observational and experimental studies on HIS use are thus advised to observe and control for information exchange among physicians. A possible approach to the integration of use profiles by multiple physicians could be to identify configurations or sequences of profiles (e.g., a sequence of *quick and basic* profiles as opposed to a sequence involving both *quick and basic* and *slow and basic* profiles).

Future research may also apply additional approaches to further explore the factors associated with use patterns. The configurational approach, for example, emphasizes the examination of combinations of variables and strives to identify patterns of mutually supportive variables, i.e., configurations [42]. This approach, traditionally employed in organizational research [71], can be used to detect profiles of *explanatory* variables that are associated with certain profiles of use. For example, it should be interesting to look at profiles of patient and physician attributes and at their relationships with use profiles. While the current study uses this approach to a certain extent by creating profiles based on the attributes of volume and duration, extending this approach to additional variables in likely to lead to new insights, particularly in settings with high clinical variability.

Although this study examines system use patterns, it does not intend to debate their suitability for a specific context or task. The purpose of the present work is to better understand use patterns and to look at them as the outcome of predictive models that include relatively large numbers of contextual variables. In our view, future research that attempts to measure the appropriateness of an observed use pattern, in terms of *effectiveness* and *efficiency*, is highly important for the design of HIS and for the definition of meaningful use [82]. Whereas the common perception of *efficient* system use is the use of little information for a short time period, we suggest that this form of use may not always be *effective* and thus propose to include clinical outcomes when examining use in a certain context. The correctness of the choice of whether and how to utilize the system may depend on the situation. While *quick and basic* use may be insufficient in certain clinical conditions, such profile of use, or even relinquishing the use of the system altogether, may be suitable in other cases, such as surgical emergencies.

6. Conclusion

This work addresses the proposition that resource constraints characterizing the ED setting in general and critical care in particular are likely to culminate in a trade-off between volume and duration of HIE use by physicians. The analysis of data residing in HIE log files, combined with data collected from other sources, provides evidence in support of the predicted trade-off, suggesting that physicians have limited cognitive resources that can be expended either by consuming more information or by devoting more time to each piece of information. When the observed use sessions are categorized into four profiles based on the attributes of volume and duration, almost half of the sessions are classified as being low on both attributes (the *quick and basic* profile). The other three profiles, however, demonstrate that either volume or duration are high, but seldom both. While this trade-off is not found to be affected by whether or not the physician is an EM expert, we find that EM expertise has significant interactions with multiple explanatory variables in predicting use profiles. The implication of this finding is that the effects of these explanatory variables on the likelihood of observing use profiles is contingent on EM expertise. The contribution of this study lies in addressing the trade-off of volume and duration in medical system use, while looking at how this trade-off in particular and use patterns in general are affected by numerous variables describing the patient, physician, situation, information available in the HIE system, and use dynamics within the encounter. This broad view offers new insights into how physicians use information systems and why their use patterns vary.

Conflict of interest

The authors declare that they have no competing interests.

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