

Using electronic health data to deliver an adaptive online learning solution to emergency trainees: A pilot study

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Abstract

Background: Electronic Medical Records (EMR) are a potentially rich source of information on an individual healthcare providers' clinical activities. These data provide an opportunity to tailor online learning for healthcare providers to align closely with their practice. There is increasing interest in the use of EMR data to understand performance and support continuous and targeted education for healthcare providers.

Objective: This objective of the study is to understand the feasibility and acceptability of harnessing EMR data to adaptively deliver an online learning program to early career doctors.

Methods: The intervention consisted of an online microlearning program where content was adaptively delivered using an algorithm input with EMR data. The microlearning program content consisted of a library of questions covering topics related to best practice management of common emergency department presentations. Study participants were early career doctors undergoing training in emergency care. The study design involved three design cycles which iteratively changed aspects of the adaptive algorithm based on an end of cycle evaluation, in order to optimise the intervention. At the end of each cycle, an online survey and analysis of learning platform metrics were used to evaluate the feasibility and acceptability of the program. Within each cycle participants were recruited and enrolled in the adaptive program for six weeks, with new cohorts of participants in each cycle.

Results: Across each cycle, all 75 participants triggered at least one question from their EMR data, with the majority triggering one question per week. The majority of participants in the study indicated the online program was engaging, and the content felt aligned with clinical practice.

Conclusions: The use of EMR data to deliver an adaptive online learning program for emergency trainees is both feasible and acceptable. However, further research is required on the optimal design of such adaptive solutions to ensure training is closely aligned with clinical practice. Clinical Trial: N/a

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Research Article

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Background: Electronic Medical Records (EMR) are a potentially rich source of information on an individual healthcare providers' clinical activities. These data provide an opportunity to tailor online learning for healthcare providers to align closely with their practice. There is increasing interest in the use of EMR data to understand performance and support continuous and targeted education for healthcare providers.

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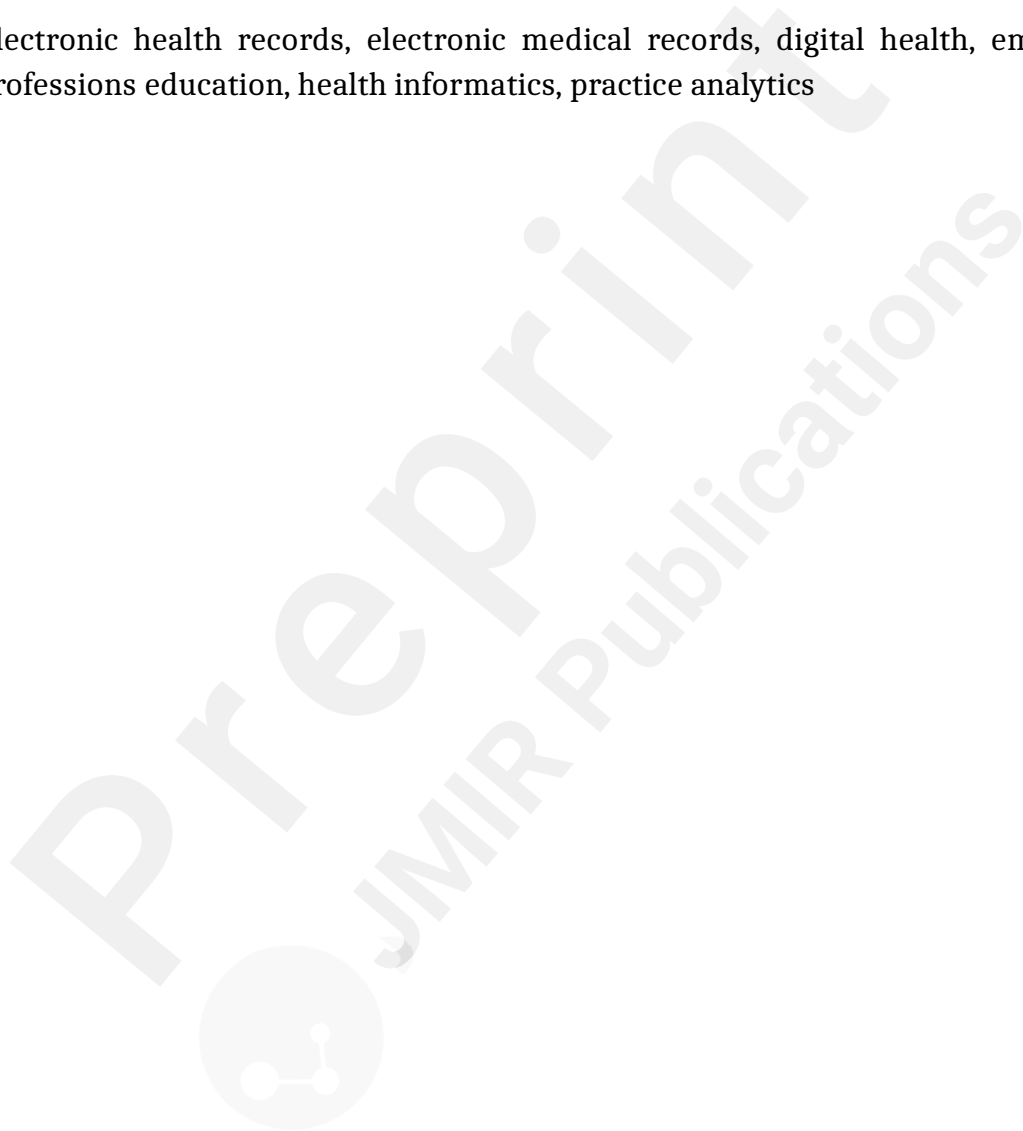
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data, with the majority triggering one question per week. The majority of participants in the study indicated the online program was engaging, and the content felt aligned with clinical practice.

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Keywords: electronic health records, electronic medical records, digital health, emergency care, health professions education, health informatics, practice analytics



Background

Medical practitioners engage in a variety of formal and informal training activities to stay up to date on best practice for delivering patient care. Activities undertaken by medical practitioners in the context of professional training can take many forms including mentorship and consultation with peers, attendance at local seminars and international conferences, journal clubs and other activities [1]. It has also been observed that medical practitioners dedicate considerable time to undertaking education and training activities. An observational study of doctors on hospital wards found that around 7% of observed tasks involved engaging in education or supervision [2]. Another study found medical practitioners early in their careers spend close to two hours every day engaging in training activities [3].

Digital technologies are increasingly being used to share knowledge and evidence between medical practitioners in the workplace [4]. Online learning as a mechanism for delivering training to the medical profession is also increasingly widespread [5]. Benefits of online learning include making training available when and where individuals would like to access it, potentially enabling more innovative approaches to teaching, and making information more easily accessible [6]. In the context of training medical practitioners, flexibility or adaptivity have been emphasised as a major advantage of online education [7]. However, online learning can also have disadvantages and there is disagreement in the literature as to whether delivering training to medical practitioner's online impacts learning outcomes [5]. Another potential issue is that online learning can require more self-discipline and greater time management skills to complete than face to face training [8]. This phenomenon may be why online learning has been noted to have high completion rates, with 60% being a high completion rate for many online courses [9].

One strategy for strengthening online learning for medical practitioners could be to align it more closely with clinical practice. It has been noted in the literature that current approaches to medical education disconnect learning activities from practice and care delivery [10]. To date there is limited research into how online learning could be personalised to align it more strongly with clinical practice. A recent scoping review of secondary use of data from all HITs identified education as one of four key domains for this purpose, but data was only used in this way in 1% of identified studies [11]. Another scoping review exploring the design of dashboards presenting data from HITs to support reflective practice found that these types of visualisation tools were often designed to present data to individual medical practitioners to allow them to reflect on their practice, but such platforms rarely incorporated scaffolds that would support learning or other improvement activities [12].

The field of learning analytics has also explored the significant potential of data collected about learners in online programs for enhancing learning. Learning Analytics broadly describes the collection, analysis and reporting of data about learners and their contexts for the purpose of understanding and optimizing learning and the environments in which it occurs [13]. A recent

review of the literature identified personalisation as a major focus of Learning Analytics, particularly in the context of online learning environments where large amounts of data about the learning process are routinely collected [14]. Research into Learning Analytics in medical education has identified a number of barriers in this space including implementation challenges, such as how to collect data to utilise in learning analytics; data management issues, such as governance and access to appropriate data; and outcomes challenges, such as how data can be used to assess learners, programs and systems [15]. Further, it has been noted in the wider literature on medical education that when training is delivered digitally analytics collected about learning progress is a potentially rich source of information, for informing evidence-based instruction [7].

In the context of online learning for medical practitioner education, routinely collected electronic health data such as that in Electronic Medical Records (EMRs) may have value for aligning learning with clinical practice. Whilst there are a wide range of Health Information Technologies (HIT) used in clinical practice, EMRs are a core technology that have been widely adopted in many healthcare organisations [16-17]. Data from EMRs have been identified as being useful for understanding the practice patterns of medical practitioners [18], and for supporting formative assessment of early career doctors in the workplace [19]. There is also literature suggesting that healthcare providers across a range of disciplines are interested in EMR data being harnessed to inform learning and training activities [20]. To date there has been limited research undertaken into the use of EMR data to support workplace learning for medical practitioners.

There is a small, but growing body of research exploring the intersection between EMR data and health professional learning. A recent study investigated the use of EMR data to support medical practitioners undertaking a learning needs assessment, which was subsequently used as the basis for delivering a customized continuing medical education program for the next year [18]. In this study medical practitioners were provided an EMR report showing their data compared to other participating practitioners, which they then used to identify personalised learning goals. Another study of this type used data from electronic prescribing systems has also been used to personalise the delivery of letters to prescribers advising them of their compliance with antimicrobial prescribing policy [21]. Researchers have also investigated the use EMR reports to populate dashboards in order to educate medical practitioners about their performance. In one such study a dashboard visualising EHR reports was made available to medical practitioners for six months with the goal of reducing over prescribing of antibiotics [22], though this study was not able to demonstrate a change in practice.

Although interest is increasing in the use of EMR to support training for medical practitioners aligned with clinical practice, the data has some limitations for this application. A considerable limitation is that there can be gaps in the data and that the data is not captured for the primary purpose of education [23] and there are limitations on how this data can be used to understand performance [19]. As has already been highlighted, a further limitation is the relatively few examples in the literature demonstrating how to use EMR data to design this type of

personalised education [18,22]. Further, current popular approaches for present EMR data to medical practitioners to support reflection lack scaffolds such as self-reflection tools, goal-setting options or learning plans that could be used to support professional learning [12].

Greater consideration of the role of electronic health data in medical practitioner learning may help individuals undertake activities that would enable more adaptive learning approaches. The need for adaptive expertise, the ability of the individual to adjust to practice challenges, has been recognised as valuable in the context of medical education [10]. The characteristics of this expertise are described in the Master Adaptive Learner (MAL) Framework [24]. The MAL is a conceptual model that emphasises the important role of adaption in activities that lead to effective skills acquisition and behaviour change by medical practitioners. The MAL describes four stages of this process; Planning - the process by which an individual identifies a gap between what is an what could be, selects an opportunity for learning and searches for resources to enable it, Learning - an individual's engagement in learning, Assessing - when the learner tries out what was learnt, and Adjusting - how learners incorporate what has been learnt into practice. Data captured within EMRs have the potential to support the types of adaptive learning described in the MAL, by helping characterise different aspects of professional practice and personalising learning to align with the practice of individual practitioners.

The aim of the study described in this manuscript was to understand the feasibility and acceptability of using EMR data to adaptively deliver an online learning program. A secondary aim was to understand how to design such a program so that learners felt content was well aligned with their clinical practice. The study investigated EMR data specifically due to the widespread adoption of this HIT in healthcare organisations [17] and the recognised utility of EMR data for understanding clinical practice patterns [18].

Methods

Study Design

The study used three design cycles to iterate on the design of the adaptive online learning program. At the end of each cycle a mixed methodology was used to evaluate the feasibility and acceptability of the program and refine it in response to learner feedback. Within each cycle, learners were enrolled in the adaptive program for six weeks, with new cohorts of learners in each cycle.

Participants and Study Setting

The study was undertaken within the emergency department at two public metropolitan hospitals in Sydney, Australia. The three design cycles were run over a twelve-month period between December 2018 and December 2019.

Potential participants were early career doctors who were undergoing postgraduate training. As part of this training process, doctors within two years of graduating from their medical degrees undergo 10-week terms in different medical specialties. All doctors who were undergoing their emergency term at the participating study sites were invited to participate in the study. In design cycle one, 22 doctors consented to participate, in design cycle two, 36 doctors consented to participate and in design cycle three, 18 doctors consented to participate in the study. No doctors formally withdrew from the study.

Study Procedures

Intervention Design

The online program was developed using a microlearning platform [25] that sent multiple choice questions to learners via email or smartphone app. In order to reinforce a single take home message, multiple choice questions provided learners detailed feedback on why the response they had entered was correct or incorrect. By default the platform delivered learners a small bundle of two to three questions at a time, so that it only took a few minutes to respond to the bundle. The platform would then repeat questions a set number of times depending on whether the learner answered incorrectly or correctly. In the intervention the default question allocation method used by the platform was overridden with an adaptive algorithm using data extracted from the EMR. Data was extracted from the EMR via a report that was run two times a week each week the adaptive program was running. The adaptive algorithm ingested EMR data related to the cohorts of patients an individual participant had encountered in the previous few days. The algorithm would subsequently tailor the delivery of microlearning questions for each learner based on the patients they had encountered in the reporting period. For example, if a participant had seen a patient with a heart condition they would be sent a question on best practice managing this patient group. If a peer of the participant had not seen a patient with a heart condition, but had seen a patient presenting with shortness of breath they would receive a question on best practice managing patients with this condition.

Questions were developed by a team of domain experts in emergency care and educational designers. The domain experts developed a curriculum that covered common clinical scenarios encountered in the emergency department that were considered opportunities to improve knowledge and behaviour related to best practice of potential participants. The educational designers undertook a structured review of EMR reports to understand the data that was available to trigger delivery of curriculum content in a manner that would adapt to an individual participants clinical encounters during the intervention. The curriculum and question set was designed to be relevant to improve clinical practice of participants as well as feasible to personalise through accessing EMR data, and was developed using an evidence based approach to developing microlearning questions [26]. The final curriculum consisted of cases on the management of care for patients presenting with the following symptoms: (1) Chest Pain, (2) Abdominal Pain (triggered by clustering two presenting problem codes), (3) Breathlessness, (4) Syncope (triggered by clustering two presenting problem codes), (5) Headache (6) Fever. A seventh category was added to the curriculum for the third cohort of

learners: (7) Mental Health (triggered by clustering ten presenting problem codes). A total of 45 questions were developed for the original six program categories. Five additional questions were developed for the Mental Health category made available for the third cohort of learners. Refer to Table 1 for an overview of the microlearning program curriculum and questions.

Table 1: Overview of the microlearning program including the topics, the question names and take home messages and the cohort that had access to the library

TOPIC	QUESTION ID	TAKE HOME MESSAGE	COHORT
Abdominal Pain	1	In females of childbearing age ectopic pregnancy should always be the first consideration and a diagnosis of exclusion regardless of the menstrual and conception history reported.	Cohort 1 Cohort 2 Cohort 3
	2	General supportive measures remain consistent in all resuscitation scenarios, especially in the bleeding patient. Warming patients may help prevent worsening coagulopathy and further bleeding.	
	3	Abdominal pain the elderly can be a challenging presentation. In contrast to younger patients a broad range of life-threatening differentials should be considered.	
	4	Abdominal pain the elderly can be a challenging presentation. In contrast to younger patients a broad range of life-threatening differentials should be considered.	
	5	In high stress settings cognitive readiness may be enhanced using simple techniques that minimise autonomic hyperarousal.	
	6	It is important to explore and investigate the causes of bloody or prolonged diarrhoea which in this case could be due colitis. Night time defecation is suggestive of an	

		underlying pathological cause.	
	7	Pancreatitis is inflammation of the pancreas and involves activation of proteolytic enzymes that may progress to haemorrhagic necrosis of the pancreatic parenchyma. Different geographic locations may report different incidences of aetiologies but universally ethanol and gallstones common causes.	
	8	Intrarenal calculi are not, on their own, an indication for referral to urology.	
	9	Examination of the testes is an essential part of the abdominal examination in young males, even if they do not report testicular pain. Torsion is the diagnosis of exclusion.	
Shortness of Breath	1	A structured approach to x-ray interpretation is required when reviewing in the ED because we do not normally have the benefit of a 'formal' report from a radiologist. Subtle pneumothorax is an easily missed diagnosis.	Cohort 1 Cohort 2 Cohort 3
	2	BiPAP (Bi-level Positive Airway Pressure) NIV therapy is indicated in patient with an acute exacerbation of COPD with a persistent respiratory acidosis despite appropriate initial treatment. A low level of consciousness is not an absolute contraindication the use of NIV.	
	3	The treatment of anaphylaxis requires a dose of intramuscular (IM) adrenaline. The EpiPen dose is 0.3mg. Typically, 0.3mg-0.5mg (1:1000 = 0.3-0.5mls) is the dose for an adult patient with anaphylaxis.	
	4	In a hypoxic patient with known COPD at risk of CO ₂ retention apply titrated oxygen first until target saturations are achieved.	

		Positioning the patient is also an important management step.	
	5	Patients with underlying cancer are at higher risk of life-threatening sepsis (associated with chemotherapy), pericardial effusions and pulmonary embolism.	
	6	A plain chest x-ray is practical, easily accessible and universally indicated for a patient with acute shortness of breath in the Emergency Department.	
	7	It is important to remember that there are non-cardiorespiratory differentials to shortness of breath. Patients with a metabolic acidosis will often present with tachypnoea (<i>Kussmaul</i> 'respiration).	
Chest Pain	1	Early diagnosis of Aortic Dissection (AD) requires a high index of suspicion. Blood pressure treatment should target control of both heart rate and the pressure itself.	Cohort 1 Cohort 2 Cohort 3
	2	Chest pain "PLUS" another symptom should trigger the thought, " <i>could this be a diagnosis of Aortic Dissection?</i> " Aortic Dissection (AD) may mimic Acute MI (including ECG findings).	
	3	No one factor can reliably rule out ACS in the ED setting. Pain radiating to the right shoulder/arm is considered more specific for ACS than pain radiating to the left arm.	
	4	An ECG should be performed in anyone presenting with chest pain. While well known, S1Q3T3 is uncommon in the setting of PE. Sinus tachycardia and anterior t-wave inversions are more common.	
	5	It is important to consider PE as a differential in cancer patients. There are	

		scoring tools available to assist you (Wells' and PERC being the most commonly used in the ED).	
	6	A CXR should be part of your workup for chest pain and shortness of breath. Special care should be paid to looking for pneumothorax and consolidation.	
	7	Myocardial Infarction (MI), Pulmonary Embolism and Aortic Dissection are three critical conditions to consider with any patient presenting with chest pain.	
	8	Aortic Dissection (AD) should be considered in any chest pain patient with risk factors (e.g. hypertension), or chest pain with a concurrent symptom such as neurological deficits.	
Fever	1	The presence of severe pain (pain out of proportion to the clinical findings) in an at risk patient should raise concerns about the diagnosis of Necrotising Fasciitis.	Cohort 1 Cohort 2 Cohort 3
	2	It is important to note the patient's allergy to penicillin. Tazocin (piperacillin/tazobactam) is a penicillin, therefore is relatively contraindicated for febrile neutropenia, though it remains first line in guidelines.	
	3	Early recognition of sepsis is paramount (new concept of q SOFA rather than use of non specific/sensitive "SIRS" criteria).	
	4	Patient is MRSA Colonised so we should consider Vancomycin as additional cover (with expert advice). Antibiotics choice should always be judicious - guided by guidelines and ID team support	

	5	You must cleanse your hands before and after any patient interaction. Alcohol is generally preferable over soap and water unless hands are soiled or if <i>Clostridium difficile</i> infection is an issue (i.e. spores are not necessarily killed by alcohol rub).	
Headache	1	In the event of a late (>6 hours) presentation with a typical SAH story further investigations are required to excluded the diagnosis. All headache cases should be discussed with a senior doctor prior to discharge.	Cohort 1 Cohort 2 Cohort 3
	2	If a patient presents with an acute severe headache plus fever, if the CT is normal consider a lumbar puncture to exclude meningitis. Consider giving early IV antibiotics and IV antivirals.	
	3	If a patient with no history of headaches presents with sudden onset headache, classic features of Subarachnoid Haemorrhage and a CT scan comes back 'normal' consider further testing. MRI/MRA and specialist review may be warranted under these circumstances.	
	4	When a patient presents with headache be sure to prescribe analgesia. Patients with papilloedema require ED evaluation with referral to both ophthalmology and neurology following neuroimaging.	
	5	Over analgesia (especially with paracetamol, codeine and aspirin) is associated with a paradoxical increase headache in some patients. While analgesia in the acute setting is a mainstay of our ED management, we should discuss refractory cases with a neurologist and arrange follow-up.	
	6	Typically, the CSF glucose concentration is two-thirds that of the serum glucose	

		concentration.	
	7	Temporal arteritis is a sight threatening condition that is also known as giant cell arteritis (GCA). Jaw claudication is a classic symptom.	
	8	Low CSF headache is a distinct and familiar syndrome that is seen most frequently following lumbar puncture. Typically, the headache is orthostatic and significantly improves on lying flat.	
Syncope	1	Patients presenting with syncope should be risk stratified based on overall history, examination and a period of observation. Risk scores (e.g. San Francisco or the Rose Criteria) may have some utility as an adjunct to your thorough clinical assessment.	Cohort 1 Cohort 2 Cohort 3
	2	An ECG is a very important test in a patient with Syncope. It is a mandatory test in the ED for a patient with syncope.	
	3	Dosing of NOACs can be confusing and factors such as age, weight, renal function and indication may affect dosage. Consultation with haematology and a pharmacist regarding dosing is pertinent.	
	4	Vertigo is a common ED presentation. The history given is concerning for a 'central' cause of vertigo. Age is an independent risk factor for stroke (Chen et al).	
	5	Early defibrillation and commencement of high-quality Basic Life Support (BLS) are critical to outcomes in cardiac arrest. While not contraindicated, checking for a pulse is no longer specifically recommended in	

		assessing for signs of life / confirming arrest.	
	6	Metoclopramide and prochlorperazine both worsen Parkinson's disease symptoms, and therefore are contraindicated in those with Parkinson's disease. Domperidone is more appropriate in these patients.	
	7	If in doubt with a case of 'wide complex tachycardia', call for help and assume the diagnosis is Ventricular Tachycardia (VT) until proven otherwise.	
	8	If in doubt with a case of 'wide complex tachycardia', call for help and assume the diagnosis is Ventricular Tachycardia (VT) until proven otherwise.	
Mental Health	1	This is a possible first presentation of schizophrenia with paranoid delusions. The importance of a mental state examination and collateral history is highlighted in this case.	Cohort 3
	2	Although there are some variations in practice, current guidelines for parental sedation have droperidol as the most appropriate first line agent. This should be done with care not to cause further harm to the patient, both through physical and medical means. Droperidol is a commonly used agent in the ED at Westmead Hospital.	
	3	Alcohol withdrawal can often present in unusual circumstances such as a change of environment limiting someone's access to alcohol. The presence of visual hallucinations, confusion and physical complaints make a purely psychiatric diagnosis less likely.	

4	A person may be treated without consent under two conditions: (1) Life threatening emergencies when a patient lacks 'capacity'; and (2) under the Mental Health act (but only for psychiatric treatments).	
5	There is no such thing as 'low risk' in assessing the suicidal patient. All mental health patients in the ED have a significantly higher long term risk of suicide than the general population.	

Intervention Delivery

During the six-week intervention period for the online program a report was extracted two times each week from the EMR. The EMR report was used to identify if participants had interacted with relevant patients in order to populate the adaptive algorithm in the microlearning program. If the EMR data indicated a participant had encountered patient presentations related to the microlearning program, they would 'trigger' a question related to managing that type of patient presentation. 'Triggering' a question meant that a participant would be allocated a relevant question in the microlearning platform, and it would subsequently be pushed to them via email or the smartphone app to complete. If a participant did not see any clinical presentations that could trigger a question in the reporting period, they did not receive any questions. If participants had seen clinical presentations that could trigger a question they were enrolled in the relevant question.

The number of questions participants could receive and the topics in the program was iterated on each cycle in response to analysis of data evaluating that cycle. Participants could be re-enrolled in a question at a later point in the intervention period if they had not previously attempted to respond to it, and the EMR data indicated they had triggered it again. Modifications were made to the delivery of algorithm for the cases each cycle.

During Design Cycle One each participant was assigned three questions chosen using the personalisation algorithm based on the cases they had attended during the EMR reporting period. If only one clinical presentation that could trigger a question was seen by a participant, they would receive three different questions on that topic from the question library. For example, in a single EMR report if a participant had seen only chest pain patients they would receive three chest pain questions; if that participant had seen one chest pain, one abdominal pain and one syncope patient they would receive one question on each topic; if a participant had seen non relevant patients they would receive zero questions.

During Design Cycle participants who saw relevant clinical presentations in each reporting period were assigned up to three questions chosen using the personalisation algorithm. They

only received one question per topic triggered by the EMR data, rather than multiple questions as was the case in Design Cycle One. This change was made to reduce the number of questions participants had to respond to in a single bundle, as analysis of temporal data collected in Design Cycle One indicated some participants were completing all cases in a single bundle at the end of each week. For example, in a single EMR report if a participant had seen only chest pain patient they would receive one question on chest pain; if that participant had seen one chest pain and one syncope patient they would receive one question on chest pain and one question on syncope; if that participant had seen one chest pain, one abdominal pain and one syncope patient they would receive one question on each topic; if a participant had seen no relevant patients they would receive zero questions.

During the final design cycle the delivery of questions was the same as in Design Cycle Two, however, questions related to the topic of Mental Health were added into the program. Mental Health cases were added to see if a less common patient presentation would increase the sense of alignment between the intervention and clinical practice.

Regardless of the design cycle, at the end of each week during an intervention period all participant in that cycle were unenrolled from any questions they had not responded to. This was done in order to ensure a large backlog of questions did not accumulate for participants to answer, also to ensure participants were not receiving questions that were not aligned with their recent clinical practice. Participants could also be enrolled in the same question multiple times during the design cycle if they had not attempted it on a previous enrolment and had subsequently been unenrolled. There were two situations in which participants would not be enrolled in a new question even if they had triggered it in the EMR report. The first reason a participant was not enrolled in new questions was if they already had questions they had been enrolled in and had not finished answering. The second reason was because a participant had answered all the questions on that topic correctly and had not triggered any other topics based on the EMR report.

Intervention Evaluation

To evaluate the program a number of data points were collected. EMR reports were used to trigger delivery of questions during the intervention, as well as to determine the time that had elapsed between seeing a clinical scenario and completing a question. Coupled with this metrics captured by the online learning platform were extracted to understand participant engagement with the intervention, participant progress during the program, the number of questions participants were enrolled in that they completed, the accuracy of their responses, and the time that elapsed between being allocated a question and answering it. Finally, an anonymous online survey was disseminated at the end of each design cycle to capture participant feedback on the program. The survey consisted of a combination of Likert responses and free text comments.

Data Analysis

Metrics captured by the online learning platform on participant progress during the program were descriptively analysed to understand how adaptations to the algorithm influenced participant behaviours. This data, combined with EMR reports was also analysed to understand how temporal factors related to alignment of questions with participant clinical practice influenced engagement with content. Reports extracted from the EMR were analysed to understand the link between participant test ordering, and allocation of questions in the online learning platform.

Structured data from the survey was descriptively analysed. Unstructured data from free text survey comments was content analysed to understand participant engagement with the content of the intervention, the online learning platform and the adaptive component. The content analysis was undertaken by one researcher (AJ) who read all the comments to get a sense of the data. Additional read throughs of the data were undertaken to code the data, and subsequently classify it into categories based on similarity of themes discussed.

Ethics Statement

The study received ethics approval from the Western Sydney Local Health District Human Research Ethics Committee. Protocol No: 2019/ETH02509. All participants provided written informed consent before agreeing to participate in the study.

Results

The following section presents a description of data from each Design Cycle of the intervention. Refer to Table 2 for an overview of key quantitative data for compared across each Design Cycle. There was a library of 37 questions across five topics during Design Cycle One and Two. There was a library of 43 questions covering six topics in Design Cycle Three. If a participant encountered a patient related to one of the topics in the bi-weekly EMR report (two times a week) during a design cycle it would trigger delivery of a question. Refer to Figure 1 to see the questions topics in the program, and the percentage of participants that correctly, incorrectly, or did not respond to each topic for design cycles one through three. Refer to Figure 2 for a visualisation of the top twenty presenting problems encountered by participants during the intervention period for design cycles one through three.

Table 2: Comparison of key quantitative data points across design cycle one, two and three of the intervention.

SUMMARY QUANTITATIVE DATA	DESIGN CYCLE ONE	DESIGN CYCLE TWO	DESIGN CYCLE THREE
No. Participants	21	36	18
No. unique questions participants enrolled in	9.72	9.69	6.27
Range of unique questions in cohort	3 – 20 (SD 4.62)	1 – 22 (SD 5.79)	1 – 17 (SD 4.93)

No. of participants attempting more than 50% of the questions	18	23	7
% of participants attempting more than 50% of the questions	86%	66%	37%
Total No. of patient presentations (including duplicates) for participant cohort that could have triggered a question	1931	4918	2961
Three most common presenting problems encountered by all participants in a cohort that could trigger a case.	<ul style="list-style-type: none"> Abdominal pain: 649 presentations Chest pain: 484 presentations Shortness of breath: 215 presentations 	<ul style="list-style-type: none"> Chest pain: 600 presentations, Abdominal pain: 573 presentations Shortness of breath: 335 presentations 	<ul style="list-style-type: none"> Abdominal pain: 357 presentations Mental Health: 159 presentations Shortness of breath: 156 presentations
No of Survey Responses	9	15	1

Figure 1: Questions in the program, and the percentage of participants that correctly, incorrectly or did not respond to for design cycles one through three.

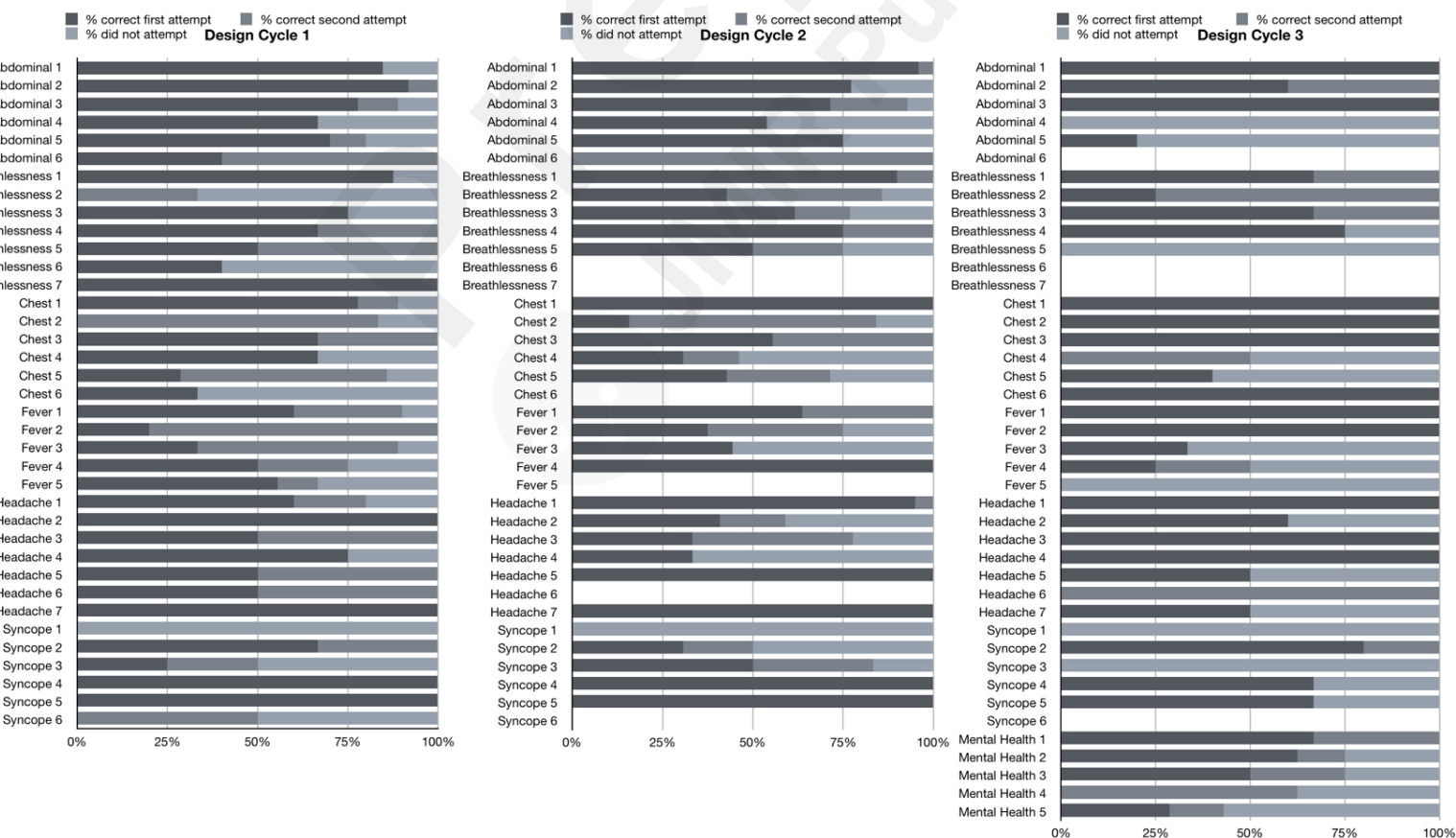
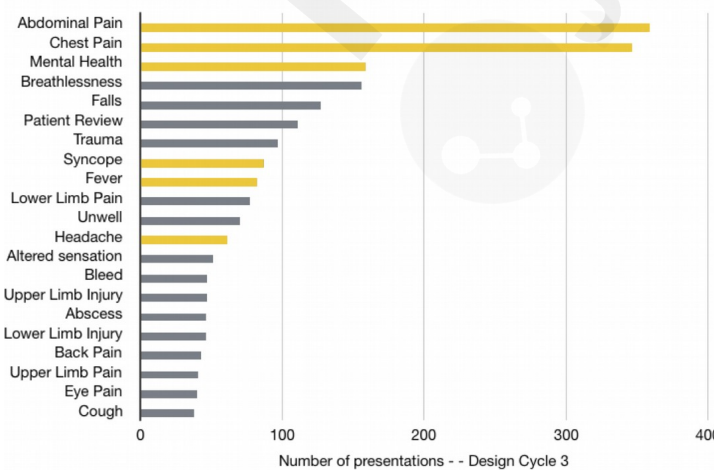
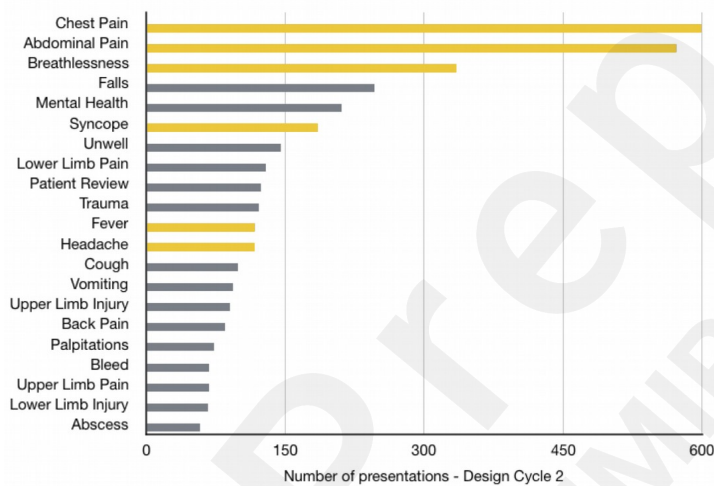
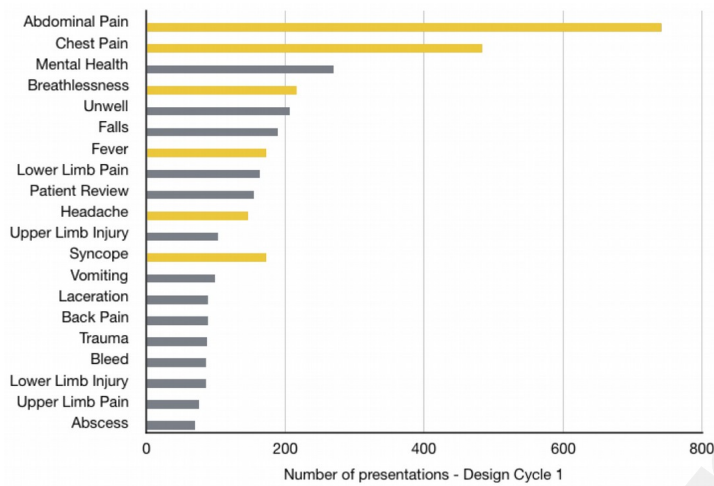


Figure 2: Visualisation of the top twenty presenting problems encountered by participants during the intervention period for design cycles one, two and three. The presenting problems that could trigger a question in the online program are highlighted in red.



Design Cycle One

There were 21 participants in cohort 1. Over the six-week intervention period the average number of unique questions participants were enrolled in was 9.72, with a range of 3 to 20 (SD 4.62) questions.

A total of 9 participants in Design Cycle 1 responded to the post-program survey. The majority of respondents, 67% (n=6), indicated they completed the cases during personal time, after work or on weekends, 22% (n=2) of respondents indicated they completed the cases when they had time during the workday, and the remaining 11% (n=1) of participants completed the program whilst commuting. The majority of respondents, 67% (n=6), agreed or strongly agreed with the statement that the duration of the course suited their needs, and 44% (n=4) of respondents agreed with the statement they would have like to have received more cases each week.

Regarding their experience with the online program 67% (n=6) agreed or strongly agreed with the statement they found the online program engaging, and 78% (n=7) agreed or strongly agreed they would recommend it to a colleague. A majority of participants, 89% (n=8), agreed or strongly agreed with the statement the program content was realistic, with 89% (n=8) agreeing or strongly agreeing with the statement that the content felt aligned with clinical practice.

When asked about personalising the online program using EMR data, 89% (n=8) of participants either agreed or strongly agreed with the statement that the questions in the program felt aligned or linked to their clinical practice. A total of 67% (n=6) of respondents agreed or strongly agreed with the statement that the program felt engaging because it used clinical data relevant to their practice. Finally, 56% (n=5) of respondents agreed or strongly agreed with the statement that they would like to see clinical data used to deliver personalised professional development in future.

Design Cycle Two

There were 36 participants in cohort 2. Over the six week intervention period the average number of unique questions participants were enrolled in was 9.69, with a range of 1 to 22 (SD 5.79) questions.

A total of 15 participants in cohort 2 responded to the post-program survey, but only 10 responded to the whole survey. Of the 14 respondents who provided feedback on when they completed the program, the majority of respondents, 64% (n=9), indicated they completed the cases during personal time, after work or on weekends. An additional 21% (n=3) of respondents indicated they responded to a question as soon as they received an alert, 7% (n=1) of respondents indicated they completed the cases when they had time during the workday, and the remaining 7% (n=11) of participants completed the program whilst commuting. When asked whether the duration of the course suited their needs, 80 % (n=12) of the 15 respondents agreed or strongly agreed, and 73% (n=11) of the 15 respondents agreed with the statement they would have like to have received more cases each week.

Regarding their experience with the online program 80% (n=12) of the 15 respondents agreed or strongly agreed with the statement they found the online program engaging, and 80% (n=12) of the 15 respondents agreed or strongly agreed they would recommend it to a colleague. In response to the statement the program content was realistic a majority 89% (n=8) of the 15 respondents agreed or strongly agreed, with 93% (n=14) of the 15 respondents agreeing or strongly agreeing with the statement that the content felt aligned with clinical practice.

When asked about personalising the online program using EMR data, all of the 14 participants who responded either agreed or strongly agreed with the statement that the questions in the program felt aligned or linked to their clinical practice. A total of 67% (n=10) of the 15 respondents agreed or strongly agreed with the statement that the program felt engaging because it used clinical data relevant to their practice. Finally, 100% (n=15) of the 15 participants who responded agreed or strongly agreed with the statement that they would like to see clinical data used to deliver personalised professional development in future.

Design Cycle Three

There were 18 participants in cohort 3. Over the intervention period the average number of unique questions participants were enrolled in was 6.27 with a range of 1 to 17 (SD 4.93) questions.

Over the intervention period EMR data indicated participants had a total of 2961 patient presentations that could have triggered a question. This number included duplicate instances of a participant seeing the patient presentation categories that could trigger a case. Of these the most common presenting problem encountered by participants was abdominal pain: 357 presentations, followed by mental health: 159 presentations, and shortness of breath: 156 presentations. Of the top twenty presenting problems participants' encountered during the intervention period, all seven presenting problem clusters that could have triggered a question in the online program were present (Figure 2).

One participant responded to the post-program survey for cohort three. The respondent indicated they the questions during personal time, after work or on weekends. When asked whether the duration of the course suited their needs the respondent indicated they agreed with the statement, but they were neutral regarding receiving more questions each week.

Regarding their experience with the online program the respondent agreed with the statement they found the online program engaging, but indicated a neutral responses regarding whether they would recommend it to a colleague. In response to the statement the program content was realistic the respondent was neutral, and disagreed with the statement that the content felt aligned with their clinical practice.

When asked about personalising the online program using EMR data the respondent agreed that the questions in the program felt aligned or linked to their clinical practice. However, the respondent disagreed with the statement that the program felt engaging because it used clinical data relevant to their practice. The respondent agreed with the statement they would like to see clinical data used to deliver personalised professional development in future.

Discussion

Findings from this study indicate that it is feasible to use EMR data to personalise an online program for early career doctors on management of common emergency presentations and link clinical practice directly with education in a timely manner. Regarding acceptability, findings suggested most participants found the program engaging and felt there was a level of alignment with their clinical practice. Additionally, study findings indicated that early career doctors in emergency departments would like to see online programs personalised using electronic data in future. This finding aligns with literature which has shown that healthcare providers across a range of professions are interested in seeing EMR data used in education and training [20]. Finally, the majority of learners in the personalised program attempted at least 50% of the program which demonstrates a retention rate on the higher end for an online program [9].

The potential value of using analytics related to interactions with training programs to personalise learning has been well researched in the context of Learning Analytics [14]. In the context of medical education harnessing practice data about learners in digital and online education has been noted as a means to improve evidence-based instruction [7], but there are still significant gaps in our understanding of how to do this. This study presents one of the first studies demonstrating how routinely collected EMR data can be used to personalise learning. This study demonstrated in the context of medical practitioner education there are unique opportunities to strengthen training using analytics of data from clinical sources such as EMRs, not just learner data generated by undertaking educational interventions [15]. Although it is feasible to adaptively deliver training using EMR data, findings from this study do not resolve how such an approach improves engagement with educational offerings. Whilst study participants reported generally positive experiences with the program, there was also a notable decline in participation between the first and third cohort.

Finally, findings from this study indicated that, whilst data can be used to personalise training, the quantity of data collected by EMR data sets is substantial and choosing which data to use to prompt learning can be complex. However, if training can be designed to harness EMR data in a way that considers or overcomes challenges such as this, there is potential for learning to be both better aligned with clinical practice, and delivered more efficiently. Improving efficiency is important in medical practitioner education because learners are time poor and have many competing obligations in their workloads beyond undertaking training, including completing core clinical responsibilities and administrative tasks [2-3].

Limitations and Future Research

A limitation of this study is that in the final design cycle only one participant completed a post-program survey, which limits understanding of how changing the content may have altered the learner experience with the program. Future researchers should consider further exploring how to design medical practitioner learning to be pedagogically sound and be well aligned with clinical practice. Further, it would be valuable to undertake studies that evaluate whether personalisation of training using EMR data effects learner retention rates, as well as can improve the processes and outcomes of care.

Conclusions

This study demonstrates that personalising an online learning program for emergency trainees using EMR data is feasible for this group of medical practitioners, and most also found it to be an acceptable approach to align learning with workplace interactions. This opens up considerable opportunity to tailor and personalise learning for health professionals that is aligned with their practice activities and performance. However, more research is needed to understand how to deliver these types of adaptive learning interventions in a scalable and sustainable way. To do this there is a need develop a better understanding of both how routinely collected data can be used to understand performance, as well as its suitability enabling health professionals to reflect on their performance and practice to support continuous learning. Relatedly, on the solution design side, there is a need to develop platforms that can automate the extraction, analysis and feedback of these data to support health professions education and practice reflection in a way that is streamlined use by health professionals. Considerable focus to date has been placed on the value of aggregating large data sets into single repositories, which represents a significant infrastructure achievement. However, moving forward it is as important to understand why data is being collected and how it will be collected to ensure the right information is available to provide benefits to the health system and support people's health and wellbeing.

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Conflicts of Interest

The authors declare no conflicts of interests.

Abbreviations

EMR – Electronic Medical Record
EHR – Electronic Health Record
EHD – Electronic Health Data

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