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Adaptive e-learning environments for health professionals and students: a systematic review and meta-analysis

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TRANSPARENCY DECLARATION

The lead author (the manuscript's guarantor) affirms that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

ABSTRACT (300 WORDS)

Objective: To systematically identify, appraise, and synthesize the evidence regarding the effectiveness of adaptive e-learning environments (AEEs) in improving knowledge, competence, and clinical behavior in health professionals and students.

Design: Systematic review and meta-analysis.

Methods: A search for studies published between January 2005 and April 2017 was performed in CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science. Studies were eligible if they were controlled, and evaluated the effect of an AEE on knowledge, competence or clinical behavior in health professionals or students. AEEs were reviewed with regard to their clinical topic, theoretical framework, and adaptation process. Studies were included in the meta-analysis if they were randomized, and had a non-AEE control group. Effect sizes (ES) were pooled using a random effects model. Two authors screened studies, extracted data, assessed risk of bias, and coded quality of evidence independently.

Results: From a pool of 5,580 articles, we included 17 eligible studies enrolling 333 health professionals and 628 students. Risk of bias was generally high due to issues related to allocation concealment, similarity of baseline characteristics, blinding, and outcome data. Clinical topics were mostly related to diagnostic testing, theoretical frameworks were heterogeneous, and the adaptation process was characterized by 4 subdomains: goals, targeted variables, techniques, and timing. The pooled ES was 1.04 for knowledge (95% CI, -0.86-2.94; *P* .28), and 1.55 for competence (95% CI, 0.50-2.60; *P* .004). Statistical heterogeneity was high in all analyses.

Conclusions: AEEs may improve only competence, not knowledge, in health professionals and students. The adaptation process within AEEs may be more beneficial more learning

competencies since they are complex in nature, rather than learning knowledge, which generates less cognitive load. Future research should report more clearly on the design and adaptation process of AEEs, and target higher-level outcomes, such as clinical behavior.

PROSPERO registration number: CRD42017065585

Keywords: Computer-assisted instruction; medical education; nursing education; e-learning, meta-analysis

66 ## ARTICLE SUMMARY

67 ### Strengths and Limitations of the Study

68 - To our knowledge, this is the first systematic review and meta-analysis examining the effectiveness of adaptive e-learning environments in improving knowledge, competence, and clinical behavior in health professionals and students.
71 - Strengths of this review include the broad search strategy, and in-depth assessments of the risk of bias and the quality of evidence.
73 - High statistical heterogeneity resulting from clinical and methodological diversity limits the interpretation of findings.
75 - Quantitative results should be treated with caution, given the small number and risk of bias of studies included in the meta-analysis.

INTRODUCTION

The use of information and communication technologies (ICTs) in the education of health professionals and students has become ubiquitous. Indeed, e-learning, defined as the use of ITCs to access educational curriculum and support learning[1], is increasingly present in clinical settings for the continuing education of health professionals[2 3], and in academic settings for the education of health professions students[4]. The interaction of health professionals and students with e-learning environments during the learning process generates a significant amount of data[5]. However, designers of e-learning environments and educators rarely make use of this data to optimize learning effectiveness and efficiency. Thus, in recent years, educational researchers have strived to develop e-learning environments that take a data-driven and personalized approach to education[6-9]. E-learning environments that take into account each user's interactions and performance level could anticipate what types of content and resources meet the user's needs, potentially increasing learning effectiveness and efficiency[9].

E-learning environments integrate information, in the form of text and multimedia (e.g., illustrations, animations, videos). They can include both asynchronous (i.e., designed for self-study) and synchronous (i.e., a class taught by an educator in real time) components[1]. E-learning environments can be either *nonadaptive*, *adaptive*, or *intelligent*[10] (see **Figure 1**). In the fields of computer science and educational technology, the term *adaptation* refers to the process executed by a system based on ICTs of adapting educational curriculum content, structure or delivery to the profile of a user [10].

Nonadaptive e-learning environments (**Type A**) provide a standardized training for all users. While they can include instructional design variations (e.g., interactivity, feedback, practice exercises), they *do not* consider users' characteristics to provide a personalized training. They are generally considered to be as effective as non–e-learning educational interventions, such as large-group classroom instruction and printed text, in improving learning outcomes[11 12]. Adaptive e-learning environments (AEEs; **Type B1**) collect data to build each user's profile (e.g., navigation behavior, preferences, knowledge), and use simple techniques (e.g., adaptive information filtering, adaptive hypermedia) to adapt the content, navigation, presentation, multimedia, or strategies to provide personalized training[7 8]. Intelligent e-learning environments (IEEs; **Type B2**) are a subtype of AEEs that use advanced adaptation techniques and user-modelling techniques derived from artificial intelligence (e.g., machine learning, rule-based systems, natural language processing) to provide a more personalized training for each user[6 13-16]. In the context of this review, our use of the term "AEEs" includes IEEs.

In recent years, AEEs have been developed and evaluated primarily in academic settings for students in mathematics, physics and related disciplines, for the acquisition of knowledge and development of cognitive skills (e.g., arithmetic calculation). Four meta-analyses reported on the effectiveness of AEEs among high school and university students in in these fields of study [13-15 17]. The results are promising: AEEs are in almost all cases more effective than large-group classroom instruction. In addition, Nesbit, et al. [18] point out that AEEs are more effective than nonadaptive e-learning environments.

The variability in the degree and the complexity of adaptation within AEEs mirrors the adaptation that can be observed in non–e-learning educational interventions (**Type C**). Some interventions, like one-on-one human instruction and small-group classroom instruction, generally have a high degree of adaptation since the instructor can adapt his teaching to the individual profiles of learners and consider their feedback [19]. Other interventions, like large-group classroom instruction, generally have a low degree of adaptation to individual leaners. In some interventions, like paper-based instruction (e.g., handouts, textbooks), there is no adaptation at all.

Despite evidence of the effectiveness of AEEs for knowledge acquisition and skill development in areas such as mathematics in high school and university students, their effectiveness in improving learning outcomes in health professionals and students has not yet been established. To address this need, we conducted a systematic review and meta-analysis to identify and quantitatively synthesize all comparative studies of AEEs involving health professionals and students.

Systematic Review and Meta-Analysis Objective

To systematically identify, appraise, and synthesize the best available evidence regarding the use and the effectiveness of AEEs in improving knowledge, competence, and clinical behavior in health professionals and students.

Systematic Review and Meta-Analysis Questions

We sought to answer the following questions with the systematic review:

1. What are the characteristics of studies assessing an AEE designed for health professionals' and students' education?
2. What are the characteristics of AEEs designed for health professionals' or students' education?

We sought to answer the following question with the meta-analysis:

3. What is the effectiveness of AEEs in improving knowledge, competence, and clinical behavior in health professionals and students in comparison with nonadaptive e-learning environments, and non–e-learning educational interventions?

METHODS

We planned and conducted this systematic review following the Effective Practice and Organization of Care (EPOC) Cochrane Group guidelines[20], and reported it according to the Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) standards[21] (see **Supplementary File 1**). We prospectively registered (International Prospective Register of Systematic Reviews #CRD42017065585) and published the protocol of this systematic review[22] [23]. Thus, in this paper, we present an abridged version of the methods with an emphasis on changes made to the methods since the publication of the protocol.

Study Eligibility

We included primary research articles that assessed an AEE with licensed health professionals, students, trainees, and residents in any discipline. We defined an AEE as a computer-based learning environment which collects data to build each user's profile (e.g., navigation behavior, individual objectives, knowledge), interprets these data through algorithms, and adapts in real-time the content (e.g., showing/hiding information), navigation (e.g., specific links and paths), presentation (e.g., page layout), multimedia presentation (e.g., images, videos), or tools (e.g., different set of strategies for different types of users) to provide a dynamic and evolutionary learning path for each user[6 10]. We used the definitions of each type of adaptation proposed by Knutov and colleagues[8]. We included AEEs with variable levels of technological complexity, ranging from simple adaptive functionality (**Type B1**) to the use of artificial intelligence (IEEs,

Type B2). We considered for inclusion primary research articles in which the comparator was: 1) a nonadaptive e-learning environment; 2) a non–e-learning educational intervention; 3) another AEE with design variations. While included in the qualitative synthesis of the evidence for descriptive purposes, the third comparator was excluded from the meta-analysis. Outcomes of interest were knowledge, competence (including skills), and clinical behavior[24 25]. Finally, in terms of study design, we considered for inclusion all controlled, quantitative studies in accordance with the EPOC Cochrane Review Group guidelines[26].

Study Identification

We previously published our search strategy[22]. Briefly, we designed a strategy in consultation with a librarian to search CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science for primary research articles published between January 2005 and April 2017. We limited our search to articles published after 2005 since earlier studies seem to have a bias toward more positive results[15], which could be explained by the effect of the novelty of e-learning on student motivation and learning outcomes. The search strategy revolved around 3 key concepts: "adaptive e-learning environments", "health professionals/students", and "effects on knowledge/competence/behavior" (see **Supplementary file 2**). To identify additional articles, we hand-searched 6 key journals (e.g., *British Journal of Educational Technology*, *Computers and Education*) and the reference lists of included primary research articles. We sought relevant articles published in English or French.

Study Selection

We worked independently and in duplicate (G.F. and M.-A.M.-C./T.M.) to screen all titles and abstracts for inclusion using the EndNote software V8.0 (Clarivate Analytics). We resolved disagreements by consensus. We then performed the full-text assessment of potentially eligible articles using the same methodology.

Data Extraction

One review author (G.F.) extracted data from included primary research articles using a modified version of the data collection form developed by the EPOC Cochrane Review Group [27]. The main changes made to the extraction form were the addition of specific items relationg to the AEE assessed in each study (e.g., adaptation techniques, duration of each training session). Two review authors (T.M., M.-F.D.) validated the data extraction forms. For all studies, we extracted the following data items if possible:

- *the population and setting*: study setting, study population, inclusion criteria, exclusion criteria;
- *the methods*: study aim, study design, unit of allocation, study start date and end date, and duration of participation;
- *the participants*: study sample, withdrawals and exclusions, age, sex, level of instruction, number of years of experience as a health professional, practice setting, and previous experience using e-learning;
- *the interventions*: name of intervention, theoretical framework, statistical model/algorithm used to generate the learning path, clinical topic, number of training sessions, duration of each training session, total duration of the training, adaptation techniques within the AEE (content, navigation, presentation, multimedia, tools), mode of delivery, presence of other educational interventions and strategies;

- *the outcomes*: name, time-points measured, definition, person measuring, unit of measurement, scales, validation of measurement tool;
- *the results*: results according to our primary (knowledge) and secondary (competence, behavior) outcomes, comparison, time-point, baseline data, statistical methods used, and key conclusions.

We contacted all of the corresponding authors (N=12) of the 17 included primary research articles to validate the completed data extraction forms, and to provide us with missing data.

Assessment of the Risk of Bias

We worked independently and in duplicate (G.F. and T.M./M.-F.D.) to assess the risk of bias of included primary research articles using the EPOC risk of bias criteria, based upon the data extracted with the data collection form[27]. A study was deemed at high risk of bias if the individual criterion “random sequence generation” was scored at “high” or at “unclear” risk of bias.

Data Synthesis

First, we synthesized data qualitatively using tables to provide an overview of the included studies, and of the AEEs reported in these studies.

Second, using the Review Manager (RevMan) software V5.1, we first conducted a meta-analysis to quantitatively synthesize the effectiveness of AEEs versus other educational interventions in improving all learning outcomes. We included studies in the meta-analysis if the comparator wasn’t another AEE, if they were randomized, and if they reported outcome data. We then conducted meta-analyses with the same comparison for each outcome for which data from at least 2 studies were available (i.e., knowledge, competence). For randomized controlled trials (RCTs), we converted each post-test mean and standard deviation (SD) to a standardized mean difference ([SMD], also known as Hedges g effect size [ES]). For crossover RCTs, we used means pooled across each intervention. We pooled effect sizes using a random effects model. Statistical significance was defined by a two-sided alpha of .05.

We first assessed heterogeneity qualitatively by examining the characteristics of included studies, the similarities and disparities between the types of participants, the types of interventions, and the types of outcomes. We then used the I^2 statistic within the RevMan software to quantify how much the results varied across individual studies (i.e., between-study inconsistency, or heterogeneity). We interpreted the I^2 values as follows: 0%-40%: might not be important; 30%-60%: may represent moderate heterogeneity; 50%-90%: may represent substantial heterogeneity; and 75%-100%: considerable heterogeneity[28]. We performed sensitivity analysis to assess if the exclusion of studies at high risk of bias or with a small sample size (n<20) would have had an impact on statistical heterogeneity. The small number of studies included in each meta-analysis did not allow for sensitivity of subgroup analyses to be performed.

Since less then 10 studies were included in the meta-analysis, we did not assess reporting biases using a funnel plot, as suggested in the Cochrane Handbook[29].

Assessment of the Quality of Evidence

We worked independently and in duplicate (G.F. and M.-A.M.-C.) to assess the quality of evidence for each individual outcome. We used the Grading of Recommendations Assessment, Development, and Evaluation (GRADE) Web-based software, based upon the data extracted with the data collection checklist[30]. We considered 5 factors (risk of bias of included studies,

250 indirectness of evidence, unexplained heterogeneity or inconsistency of results, imprecision of
251 the results, probability of reporting bias) for downgrading the quality of the body of evidence for
252 each outcome[30].

253 Patient and Public Involvement

254 Patients and the public were not involved in the selection of the research question and outcome
255 measures, or in the design of this systematic review and meta-analysis. No patients were involved
256 in the interpretation or writing up of results. We are unable to disseminate the results of the
257 research to study participants directly since this meta-analysis used aggregated data from
258 previous trials.

259 RESULTS

260 Study Flow

261 From a pool of 5,580 potentially relevant articles, we found 17 quantitative, controlled studies
262 assessing an AEE with health professionals or students (see **Figure 2**).

263 Out of 17 included studies in the qualitative synthesis, 4 studies compared two AEEs with design
264 variations[31-34], 4 studies were not randomized[35-38], and 1 study had missing data[39]. Thus, these 9
265 studies could not be included in the meta-analysis and the remaining 8 studies were used to
266 calculate an ES on learning outcomes.

267 Study Characteristics

268 We summarized the key characteristics of included studies in table format (see **Table 1**). In terms
269 of study population, in the 17 studies we have found published between 2006 and 2017,
270 investigators have evaluated AEEs mostly in the medical field, that is medical students (n=7) [35 37]

[40-43], medical residents (n=7) [31-34 36 44 45], nursing students (n=1) [46], physicians in practice (n=1) [39], and health sciences students (n=1) [47]. The mean sample size was 56.53 participants (standard deviation [SD] 44.13). In terms of study design, 13 out of 17 studies (77%) were randomized, 7 studies of which were randomized crossover trials [32 33 41-45]. The mean number of training sessions was 2 (SD 1.07) and the mean training time was 4.33 hours (SD 3.79). Across the 17 studies, trainings with AEEs were spread over a mean period of time of 29.06 days (SD 44.91). In terms of comparators, it is possible to underline three types of comparisons. The first comparison is an AEE versus another AEE with design variations (n=4) [31-34], which implies that one of the AEEs assessed had variations in its adaptation techniques (e.g., feedback in one AEE is longer or more complex than in the other). The second comparison is an AEE versus a nonadaptive e-learning environment (n=8) [35-37 40 42-44 47]. The third and final comparison is an AEE versus another type of educational intervention, such as a paper-based educational intervention, including handouts, textbooks or images (n=3) [39 41 45], and a traditional educational intervention, such as a group lecture (n=1) [46]. As stated before, only the second and third types of comparisons were included in the meta-analysis since our aim was to synthesize quantitatively th effectiveness of AEEs versus other types of educational interventions. Finally, in terms of outcomes, investigators evaluated learners' knowledge (n=11) [31 32 34 35 37 41-46], satisfaction (n=9) [31 33 35 37 41-45], competence (including skills) (n=6) [33 36 38-40 47], and metacognitive processes (n=3) [31 32 34]. However, none of the studies reported the assessment of health professionals' and students' clinical behavior.

291 **Table 1. Characteristics of included studies.**

First author, year Country	Participants*	Study design†	No. and duration of training sessions	Duration of intervention	Comparison(s)‡	Outcome(s)§
Comparison: adaptive e-learning environments vs. other educational interventions						
Cook, 2008 USA	R; N = 122	RXT; posttest-only, 4 groups	4 sessions; 30 minutes each	126 days	NEE	S, K
Crowley, 2010 USA	PP; N = 15	RCT; pretest–posttest, 2 groups	4 sessions; 4 hours each	138 days	P	C Δ
Hayes-Roth, 2010 USA	MS, NS; N = 30	RCT; pretest–posttest–retention-test, 3 groups	NR; mean training time 2.36 hours	NR	1. NEE 2. NI	C Δ
Morente, 2013 Spain	NS; N = 73	RCT; pretest–posttest, 2 groups	1 session; 4 hours	1 day	L	K Δ
Munoz, 2010 Colombia	MS; N = 40	NRCT; pretest–posttest, 2 groups	NR; mean training time 5.97 hours	NR	NEE	S, K
Romito, 2016 USA	R; N = 24	NRCT; pretest–posttest–retention-test, 2 groups	1 session; 30 minutes	1 day	NEE & L	C Δ
Samulski, 2017 USA	MS, R, PP; N = 36	RXT; pretest–posttest, 2 groups	2 sessions; 20 minutes to 14 hours	30 days	P	S, K
Thai, 2015 USA	HSC; N = 87	RCT; pretest–posttest–retention-test, 3 groups	1 session; 45 minutes	1 day	1. AEE 2. NEE	C Δ
Van Es, 2015 Australia	R; N = 43	RXT; posttest-only, 2 groups	3 sessions; NR	50 days	P	S, K Δ
Van Es, 2016 Australia	MS; N = 46	RXT; posttest-only, 2 groups	3 sessions; 2 hours each	34 days	NEE	S, K
Wong, 2015 Australia	MS; N = 99	RXT; posttest-only, 2 groups	2 sessions; 1.5 hour each	14 days	NEE	S, K Δ
Wong, 2017 USA	MS; N = 178	NRCT; pretest–posttest–retention-test, 3 groups	1 session; NR	35 days	1. L 2. AEE & T	C Δ
Woo, 2006 USA	MS; N = 73	NRCT; pretest–posttest, 3 groups	1 session; 2 hours	1 day	1. NEE 2. NI	S, K
Comparison: adaptive e-learning vs. adaptive e-learning (two AEEs with design variations)						
Crowley, 2007 USA	R; N = 21	RCT; pretest–posttest–retention-test, 2 groups	1 session; 4.5 hours	1 day	AEE	S, M, K
El Saadawi, 2008	R; N = 20	RXT; pretest–posttest, 2 groups	2 sessions; 2 hours each	1 day	AEE	S, C

USA						
El Saadawi, 2010 USA	R; N = 23	RXT; pretest–posttest, 2 groups	2 sessions; 2.25 hours each	2 days	AEE	M, K
Feyzi-Begnagh, 2014 USA	R; N = 31	RCT; pretest–posttest, 2 groups	2 sessions; 2 & 3 hours	1 day	AEE	M, K

292
293 * Participants: MS indicates medical students; NS, nursing students; R, residents (physicians in postgraduate training); PP, physicians in practice; HSC, health sciences students.
294 † Study design: RCT indicates randomized controlled trial; RXT, randomized crossover trial; NRCT, non-randomized controlled trial.
295 ‡ Comparison: AEE indicates adaptive e-learning environment; NEE, nonadaptive e-learning environment; NI, no-intervention control group; L, large-group classroom instruction; P,
296 paper-based instruction (handout, textbook, or latent image cases).
297 § Outcomes: S indicates satisfaction; M, metacognitive processes; K, knowledge; C, competence (includes skills); B, behavior. Moreover, ∆ indicates a statistically significant
298 improvement regarding this outcome in the experimental group in comparison with the control group for studies comparing an AEE with other educational interventions..
299 **Included in the meta-analysis**

Characteristics of Adaptive E-learning Environments

We summarized the key characteristics of AEEs assessed in the 17 studies in table format (see **Table 2**). In terms of the clinical topics of the AEEs, the majority of AEEs focused on training medical students and residents in executing and/or interpreting diagnostic tests. Indeed, the AEEs assessed focused on dermopathology and cytopathology microscopy [31-34 39 41 42 45] (n=8), on diagnostic imaging [36 43] (n=2), on chronic disease management [44] (n=1), on pressure ulcer evaluation [46] (n=1), on the management of childhood illness [35] (n=1), on brief intervention for alcohol consumption [40] (n=1), on electrocardiography [47] (n=1), on fetal heart rate interpretation [38] (n=1), and on hemodynamics [37] (n=1). Four out of 17 AEEs focused on developing the knowledge or skills of health professionals and students with regard to performing interventions in clinical practice [35 40 44 46]. Investigators adopted a wide variety of theoretical frameworks in the 17 studies. The most frequently used framework was cognitive tutoring, adopted in 5 studies [31-34 39], which implies the use of a cognitive model. The integration of a cognitive model in an AEE implies the representation of all the knowledge in the field of interest in a way that is similar to the human mind for the purpose of understanding and predicting the cognitive processes of learners [48]. The second most used framework was perceptual learning, adopted in 3 studies [36 38 47]. Perceptual learning aims at improving information extraction skills of the environment and the development of automaticity in this respect in learners [36]. Theoretical frameworks relating to self-regulated learning [34], learning styles [35], guided mastery [40], and cognitive load [43] were also used.

We propose 4 subdomains that emerged from the review to characterize the adaptation process of AEEs reported in the 17 studies: the goals of adaptation, the variables targeted by the adaptation process, the adaptation techniques, and the timing of the adaptation.

First Subdomain: Goals of the Adaptation Process

This subdomain relates to the purpose of the adaptation process within the AEE. For most AEEs, the adaptation process aims primarily to increase the effectiveness and/or efficiency of knowledge acquisition and competence development relative to other training methods [31 34 35 37 40-47]. For instance, several AEEs aimed to increase the diagnostic accuracy and reporting performance of medical students and residents [31-33 36 38 39]. In cases where two adaptive AEEs with certain variations in their techno-pedagogical design are compared with each other, the adaptation process generally aims at improving the metacognitive and cognitive processes related to learning [31 32 34].

Second Subdomain: Variables Targeted by the Adaptation Process

This subdomain relates to the user-related data (variables) upon which the adaptation process is based. The most frequently targeted variable is the user's scores after an assessment or a question within the AEE (e.g., knowledge/skills scores, response accuracy scores) [35-38 40-47]. Other frequently targeted variables include the user's actions during its use of the AEE (e.g., results of problem-solving tasks, results of reporting tasks, requests for help) [31-34 39], and the user's response time regarding a specific question or task [36 38 47].

Third Subdomain: Adaptation Techniques

The third subdomain relates to which adaptation techniques are mobilized in the AEE. In the context of this review, the adaptation techniques are based upon the work of Knutov and colleagues [8]. *Content adaptation* was the most used adaptation technique; it was implemented in all AEEs reviewed (n=17). Content adaptation aims to adapt the textual information (curriculum content) to the learner's profile through different mechanisms and to different degrees [8].

Navigation adaptation was the second most used adaptation technique (n=13). Navigation can be adapted in two ways; it can be enforced or suggested. When enforced, an optimal personalized learning path is determined for the user by the algorithms within the AEE. When suggested, there are several personalized learning paths available to each user, who can determine the path he prefers himself [8]. Most reviewed studies included AEEs with enforced navigation, with one optimal personalized learning path being determined through various algorithms. *Multimedia adaptation* was the third most used adaptation technique (n=10). This adaptation technique, much like content adaptation which relates to textual information, implies the adaptation of the multimedia elements of the training such as videos, pictures, models, to the user's profile. *Presentation adaptation* was the fourth most used adaptation technique (n=8). It implies the adaptation of the layout of the page to the digital device used, or to the user's profile. *Tools adaptation* was the least used adaptation technique (n=7). This technique results in providing a different set of features or learning strategies for different types of users, such as different interfaces for problem solving, and knowledge representation.

Fourth Subdomain: Timing of the Adaptation

This last subdomain relates to *when* the adaptation occurs during the learning process with the AEE. In 16 out of 17 studies, the adaptation occurred throughout the training with AEE, usually after an answer to a question or during intermediate problem-solving steps. In one study, adaptation techniques were only implemented at the beginning of the training with the AEE [35].

Table 2. Characteristics of adaptive e-learning environments

First author, year	Adaptive e-learning environment design			Adaptation process: four subdomains							
	Clinical Topic(s)	Theoretical framework(s)	Platform	*First subdomain:* Adaptation for which goals or objectives?	*Second subdomain:* Adaptation to which user-related variables?	*Third subdomain:* Adaptation techniques: Content	Navigation	Presentation	Multimedia	Tools	*Fourth subdomain:* Timing of adaptation
Cook, 2008	Diabetes, hyperlipidemia, asthma, depression	NR	NR	LEF	User knowledge	✓	✓				After each case-based question in each module (17 to 21 times/module).
Crowley, 2007	Dermopathology; subepidermal vesicular dermatitis	Cognitive Tutoring	SlideTutor	LE, MC, DX.	User actions: results of problem-solving tasks; requests for help	✓	✓	✓	✓	✓	At the beginning of each case.
Crowley, 2010	Dermopathology; melanoma	Cognitive Tutoring	SlideTutor	DX, RP.	User actions: results of problem-solving tasks; reporting tasks; requests for help	✓	✓	✓	✓	✓	At the beginning of each case.
El Saadawi, 2008	Dermopathology; melanoma	Cognitive Tutoring	ReportTutor	DX, RP.	User actions, report features	✓	✓	✓	✓		At the beginning of each case.
El Saadawi, 2010	Dermopathology	Cognitive Tutoring	SlideTutor	DX, MC.	User actions: results of problem-solving tasks; reporting tasks; requests for help	✓	✓	✓	✓		During intermediate problem-solving steps.
Feyzi-Begnagh, 2014	Dermopathology; nodular and diffuse dermatitides	Cognitive Tutoring, Theories of Self-Regulated Learning	SlideTutor	LE, MC	User actions: results of problem-solving tasks; reporting tasks; requests for help	✓	✓	✓	✓	✓	During each case or immediately after ech case.

Hayes-Roth, 2010	Brief intervention training in alcohol abuse	Guided Mastery	STAR Workshop	LE	User scores, user-generated dialogue	✓	✓				During clinical cases
Morente, 2013	Pressure ulcer evaluation	NR	ePULab	LE	User skills	✓					Each pressure ulcer evaluation.
Munoz, 2010	Management of childhood illness	Learning Styles Framework	SIAS-ITS	LE, LEF	User knowledge, user learning style	✓				✓	At the beginning of the training.
Romito, 2016	Transoesophageal echocardiography	Perceptual Learning	TOE PALM	DX	User response accuracy, user response time	✓	✓		✓		After each clinical case.
Samulski, 2017	Cytopathology; pap test, squamous lesions, glandular lesions	NR	SmartSparrow	LE	User knowledge	✓	✓				During intermediate problem-solving steps.
Thai, 2015	Electrocardiography	Perceptual Learing Theory; Adaptive response-time	PALM	LE, LEF	User response accuracy, user response time	✓		✓	✓	✓	After each user response.
Van Es, 2015	Diagnostic cytopathology; gynecology, fine needle aspiration, exfoliative fluid	NR	SmartSparrow	LE	User responses	✓	✓	✓	✓		During intermediate problem-solving steps.
Van Es, 2016	Diagnostic cytopathology; gynecology, fine needle aspiration, exfoliative fluid	NR	SmartSparrow	LE	User responses	✓	✓	✓	✓	✓	During intermediate problem-solving steps.
Wong, 2015	Diagnostic imaging; chest X-rays, CT scans	Cognitive Load Theory	SmartSparrow	LE	User responses	✓					During intermediate problem-solving steps.

Wong, 2017	Fetal heart rate interpretation	Perceptual Learning	PALM	DX	User response accuracy, user response time	✓	✓	✓		After each clinical case.
Woo, 2006	Hemodynamics; baroreceptor reflex	NR	CIRCSIM-Tutor	LE	User knowledge, user responses	✓	✓		✓	After each user response.

Goals/Objectives : LE indicates learning effectiveness; LEF learning efficiency; DX diagnostic accuracy; MC metacognitive gains; RP reporting performance.
NR indicates not reported.

Risk of Bias Assessment

Results of included studies for the risk of bias assessment are presented in **Figure 3** and **Figure 4**. In ≥ 75% of studies, biases related to random sequence generation, similarity of baseline outcome measurements, and selective reporting of outcomes were low. Moreover, in ≥ 50% of studies, biases related to the blinding of outcome assessment and contamination were low. Regarding the blinding of outcome assessment, in most studies, review authors judged that the outcome and the outcome measurement were not likely to be influenced by the lack of blinding, since studies had objective measures, i.e. an evaluative test of knowledge or competence. Regarding contamination bias, review authors scored studies at high risk if they had a crossover design.

However, in ≥ 50% of studies, biases related to allocation concealment, similarity of baseline characteristics, blinding of participants and personnel, and incomplete outcome data were unclear or high. Review authors, by consensus, decided that the cut-off criterion in terms of risk of bias to be included in the meta-analysis was randomization of study participants. Thus, the four studies[35-38] that presented high or unclear risk of bias regarding random sequence generation were not included in the meta-analysis.

Quantitative Results

Effectiveness of AEEs versus other educational interventions in improving all learning outcomes

As we considered effect sizes larger than 0.8 to be large [49], the pooled effect size (SMD 1.32; 95% confidence interval [CI] 0.20-2.43; Z =2.32, *P* 0.02) of AEEs compared to other educational interventions in improving all learning outcomes suggests a significantly large effect (see **Figure 5**). However, significant statistical heterogeneity was observed among studies (I^2 =96%, P <.00001), and individual effect sizes ranged from -1.10 to 3.05.

Effectiveness of AEEs versus other educational interventions in improving knowledge

The pooled effect size (SMD 1.04; 95% CI -0.86-2.94; Z =1.08, *P* 0.28) of AEEs compared to other educational interventions in improving knowledge suggests a large, but nonsignificant effect (see **Figure 6**). Significant statistical heterogeneity was observed among studies (I^2 =98%, P <.00001), and individual effect sizes ranged from -1.10 to 3.05. One study in particular[44] reported a negative effect size, but the difference between groups in knowledge scores was statistically nonsignificant. Moreover, while participants using the AEE in the experimental group reported the same knowledge scores than participants in the control group at the end of study, time spent on instruction was reduced by 18% with the AEE compared to the nonadaptive e-learning environment, thus improving learning efficiency [44].

Effectiveness of AEEs versus other educational interventions in improving competence

The pooled effect size (SMD 1.55; 95% CI 0.50-2.60; Z =2.90, *P* 0.004) of AEEs compared to other educational interventions in improving competence suggests a significantly large effect (see **Figure 7**). Statistical heterogeneity was lower than in previous analyses, but was still significant (I^2 =84%, P <.00001). Individual effect sizes ranged from 0.60 to 2.87.

Quality of the Evidence

The quality of evidence table produced with GRADE, as well as the justifications for each decision, is presented in **Supplementary File 3** (GRADE quality of evidence levels: very low, low, moderate, high). For knowledge, the quality of evidence was deemed to be very low. More precisely, risk of bias was deemed serious, inconsistency serious, indirectness not serious, and imprecision serious. For competence, the quality of evidence was deemed to be low. More precisely, risk of bias was deemed serious, inconsistency serious, indirectness not serious, and imprecision serious.

DISCUSSION

Principal Findings

This is the first systematic review and meta-analysis to evaluate the effectiveness of AEEs in health professionals and students. We identified 17 relevant studies published since 2006, 13 of which assessed an AEE versus another educational intervention (large-group classroom instruction, nonadaptive e-learning environment or paper-based learning), and 4 of which assessed 2 AEEs with design variations head-to-head. When compared with other educational interventions, AEEs were associated with statistically significant improvements in learning outcomes in 9 out of 13 studies. Pooled ES were large for knowledge and competence, but only the latter was associated with a statistically significant effect. Statistical heterogeneity was high in all analyses. However, this finding is consistent with other meta-analyses in the field of medical education that also reported high heterogeneity across studies[50-52]. A small number of eligible studies prohibited us from performing subgroup analyses which could have helped in explaining the source of the heterogeneity. The quality of evidence for all comparisons was either low or very low. Therefore, while we believe the results support the potential of AEEs for the education of health professionals and students, we recommend interpreting the ES with caution.

Comparison with Other Studies

To our knowledge, no previous systematic review and meta-analysis has specifically assessed the effectiveness of AEEs in improving learning outcomes in health professionals and students, or any other population. However, interestingly, since the 1990's there has been a strong research interest in the field of AEEs that integrate artificial intelligence (also known as intelligent e-learning environments [IEEs] and intelligent tutoring systems [ITSs], **Type B2**) into elementary, high school and postsecondary education for multiple subjects.[15]. Thus, multiple meta-analyses have been conducted with regard to AEEs in that setting.

Steenbergen-Hu and Cooper [13] reported a mean ES of 0.35 of AEEs integrating artificial intelligence on learning outcomes in college students when compared to all other types of educational interventions. The mean ES was 0.37 when the comparator was large-group classroom instruction, 0.35 when the comparator was nonadaptive e-learning, and 0.47 when the comparator was textbooks or workbooks[13].

Ma, et al. [16] reported a mean ES of 0.42 of AEEs integrating artificial intelligence on learning outcomes in elementary, high school and postsecondary students when compared to large-group classroom instruction. The mean ES was 0.57 when the comparator was nonadaptive e-learning, and 0.35 when the comparator was textbooks or workbooks. Interestingly, the mean ES was higher for studies which assessed an AEE in biology and physiology (0.59) and in humanities and social science (0.63) than in studies which assessed an AEE in mathematics (0.35) and physics (0.38)[16].

Kulik and Fletcher [15] reported a mean ES of 0.65 of AEEs integrating artificial intelligence on learning outcomes in elementary, high school, and postsecondary students when compared to large-group classroom instruction. Education areas in this review were diverse (e.g., mathematics, computer science, physics), but none were related to health sciences. Interestingly, the mean ES was 0.78 for studies up to 80 participants, and 0.30 for studies with more than 250 participants. Moreover, the mean ES for studies conducted with elementary and high school students was 0.44, compared to 0.75 for studies conducted with postsecondary students[15].

Thus, in light of the results of these meta-analyses, the ES reported in our review may appear high. However, our review looked more specifically into the effectiveness of AEEs in improving learning outcomes in health professionals and students. This is significant since, in the meta-analyses of Steenbergen-Hu and Cooper [13], Ma, et al. [16], and Kulik and Fletcher [15], AEEs seem to be more effective in postsecondary students [15 16] and for learning subjects related to biology, physiology and social science [16]. Moreover, previous meta-analyses focused on the effectiveness of AEEs in improving procedural and declarative knowledge, and did not report on the effectiveness on AEEs in improving skills or competence. This is important since AEEs may be more effective for providing tailored guidance and coaching for developing skills and competence regarding complex clinical interventions, rather than learning factual knowledge, as the results of our review suggest.

Strengths and Limitations

Strengths of this systematic review and meta-analysis include the prospective registration and publication of a protocol based on rigorous methods in accordance with Cochrane and PRISMA guidelines; the exhaustive search in all relevant databases; the independent screening of the titles, abstracts and full-text of studies; the assessment of each included studies' risk of bias using EPOC Cochrane guidelines; and the assessment of the quality of evidence for each individual outcome using the GRADE methodology.

Our review also has limitations to consider. First, outcome measures varied widely across studies. To address this issue, we conducted the meta-analysis using the SMD. Using the SMD allowed us to standardize the results of studies to a uniform scale before pooling them. However, the SMD also has drawbacks, since this method assumes that the differences in SDs reflect differences in outcome measures, and not differences attributable to variability among study populations[29]. Nevertheless, review authors judged that using the SMD was the best option for this review, as it is the current practice in the field of knowledge synthesis in medical education[12] [50].

Second, there was high inconsistency among study results, which we can mostly attribute to differences in populations, AEE design, research methods, and outcomes. This resulted in sometimes widely differing estimates of effect. To partly address this issue, we used a random-effects model for the meta-analysis, which assumes that the effects estimated in the studies are different and follow a distribution[29]. However, since a random-effects model awards more weight to smaller studies to learn about the distribution of effects, it could potentially exacerbate the effects of the bias in these studies[29].

Third, we made the decision to limit our search from the year 2005 onwards. This decision was based on the fact that studies published before 2005 seem to have a bias toward more positive results [15]. This could be explained by the novelty of e-learning in earlier studies, which could have positively affected student motivation and learning outcomes. Moreover, educational technology has significantly evolved since the early 2000s.

Finally, publication bias could not be assessed by the means of a funnel plot since there were less than 10 studies included in the meta-analysis.

CONCLUSIONS

We found low and very low quality evidence that AEEs are associated with improved learning outcomes in health professionals and students in comparison with other educational interventions, such as nonadaptive e-learning environments and large-group classroom learning, across a range of topics. Heterogeneity was high across populations, interventions, comparators, outcomes and study designs.

In terms of *population*, future research should focus on assessing AEEs with health professionals in practice, such as registered nurses and physicians, rather than students in these disciplines. This could provide key insights into how AEEs can impact clinical behavior and, ultimately, patient outcomes. In terms of *interventions*, researchers should report more clearly on the goals of adaptation, the targeted variables by the adaptation process, the techniques of adaptation, and the timing of adaptation. Moreover, researchers should provide additional details regarding the underlining algorithms allowing the adaptation process in order to ensure replicability of findings. Regarding *comparators*, this review suggests there is a need for additional research using traditional comparators (i.e., large group classroom instruction) and more specific comparators (i.e., adaptive e-learning environment with design variations). Regarding *outcomes* and outcome measures, researchers should use validated measurement tools of knowledge, competence, and clinical behavior to facilitate knowledge synthesis. Moreover, the absence of studies assessing the impact of AEEs on health professionals' and students' clinical behavior demonstrates the need for further research with higher-level outcomes. Finally, in terms of *study designs*, researchers should focus on research designs allowing the assessment of the impact of multiple educational design variations and adaptation techniques within one study, such as factorial experiments.

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CONTRIBUTORSHIP STATEMENT

All review authors contributed to at least one aspect of each of the four criteria for authorship defined by the International Committee for Medical Journal Editors (ICJME).

G.F. contributed to the conception and design of the review, to the acquisition and analysis of data, and to the interpretation of results. Moreover, G.F. drafted the initial manuscript. S.C. contributed to the conception and design of the review, and to the interpretation of results. M.-A.M.-C. contributed to the conception and design of the review, to the acquisition of data, and interpretation of results. T.M. contributed to the conception and design of the review, to the acquisition of data, and to the interpretation of results. M.-F.D. contributed to the conception and design of the review, to the acquisition of data, and to the interpretation of results. G.M.-D. contributed to the conception and design of the review, and to the interpretation of results. J.C. contributed to the interpretation of results. M.-P.G. contributed to the interpretation of results. V.D. contributed to the interpretation of results.

All review authors contributed to manuscript writing, critically revised the manuscript, gave final approval, and agreed to be accountable for all aspects of work, ensuring integrity and accuracy.

COMPETING INTERESTS

All authors have completed the ICMJE uniform disclosure form at www.icmje.org/coi_disclosure.pdf and declare: no support from any organisation for the submitted work; no financial relationships with any organisation that might have an interest in the submitted work in the previous three years; no other relationships or activities that could appear to have influenced the submitted work.

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DATA SHARING STATEMENT

No additional data are available.

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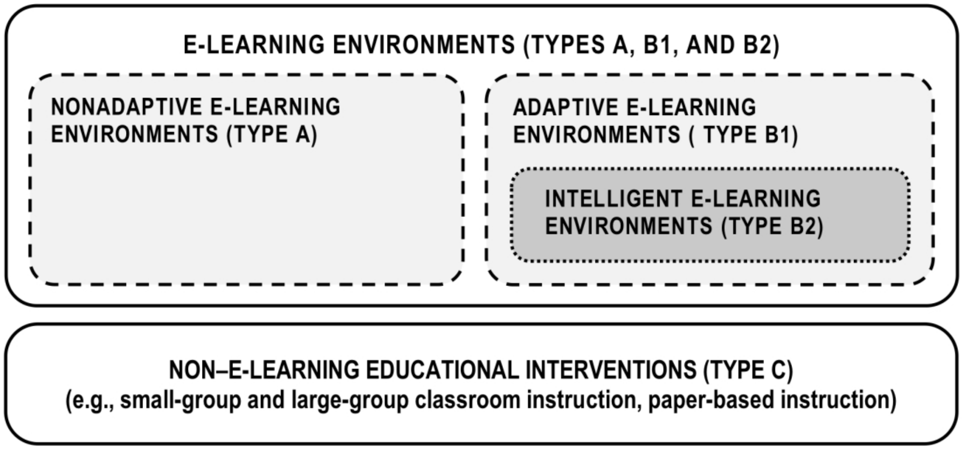

Figure 1. Types of educational interventions examined in the context of this review.

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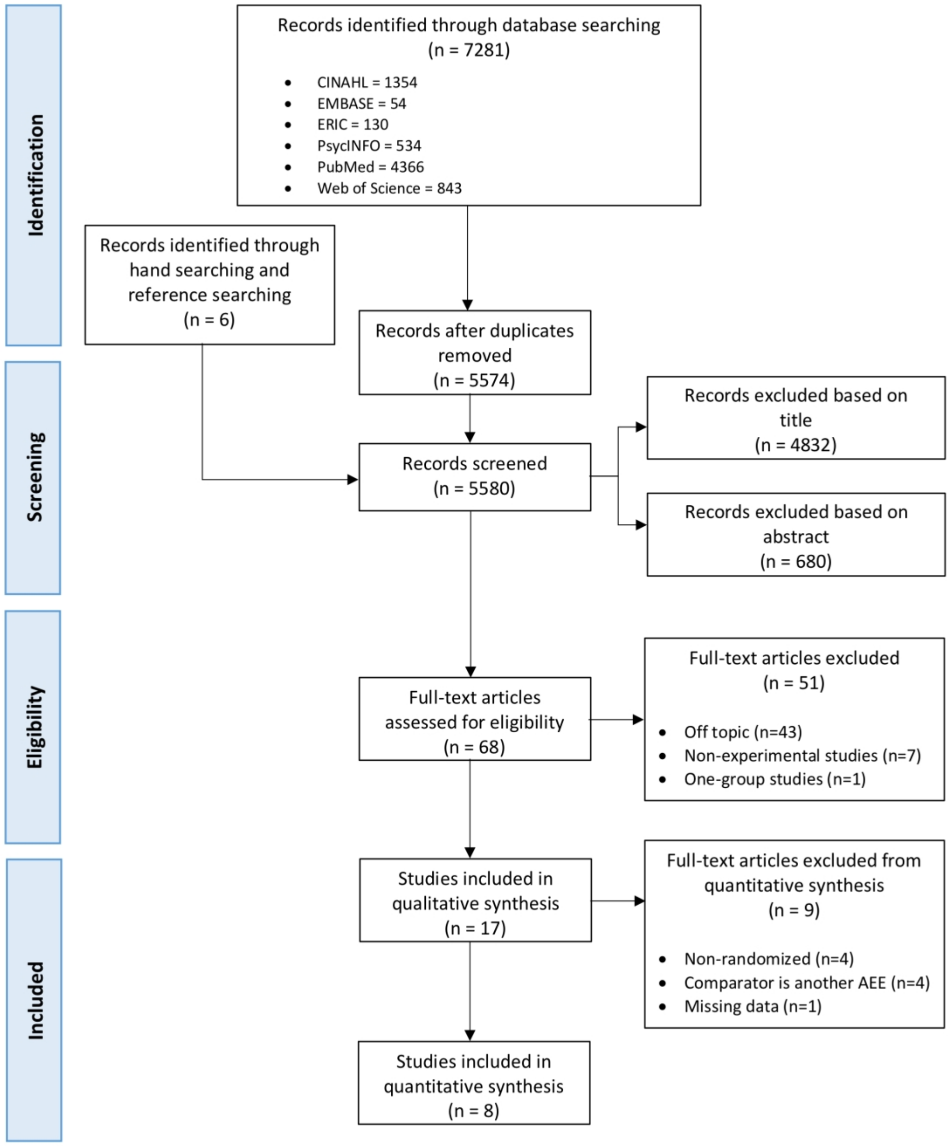

Figure 2. PRISMA study flow diagram.

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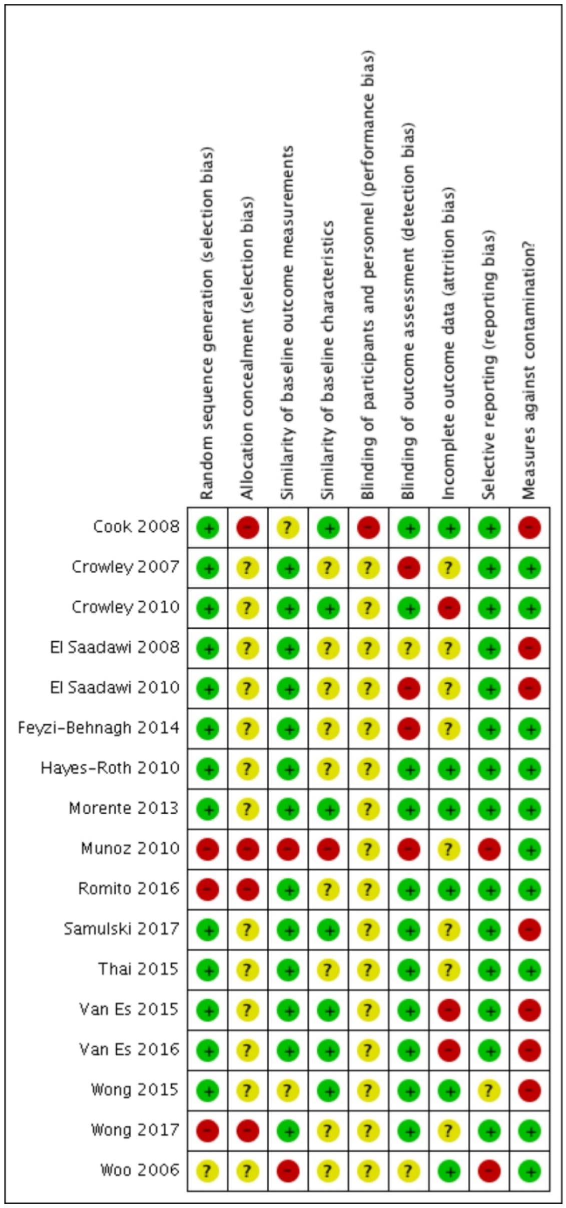

Figure 3. Risk of bias summary: review authors' judgements about each risk of bias item for each included study.

106x228mm (300 x 300 DPI)

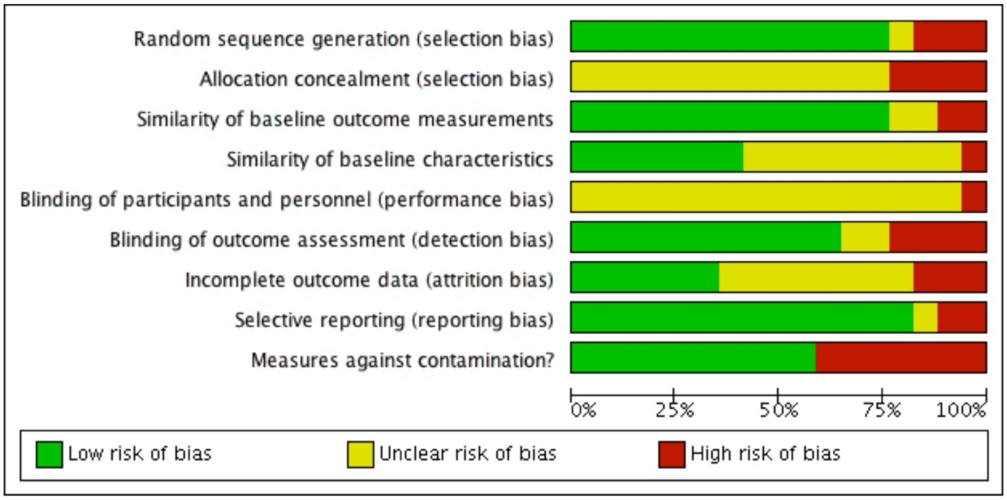

Figure 4. Risk of bias graph: review authors' judgements about each risk of bias item presented as percentages across all included studies.

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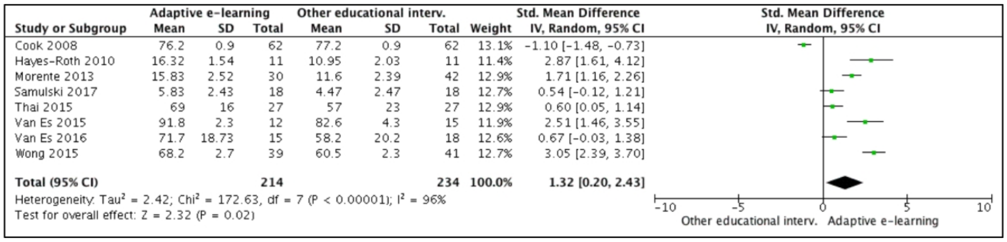

Study or Subgroup	Adaptive e-learning Mean	SD	Total	Other educational interv. Mean	SD	Total	Weight	Std. Mean Difference IV, Random, 95% CI
Cook 2008	76.2	0.9	62	77.2	0.9	62	13.1%	-1.10 [-1.48, -0.73]
Hayes-Roth 2010	16.32	1.54	11	10.95	2.03	11	11.4%	2.87 [1.61, 4.12]
Morente 2013	15.83	2.52	30	11.6	2.39	42	12.9%	1.71 [1.16, 2.26]
Samulski 2017	5.83	2.43	18	4.47	2.47	18	12.7%	0.54 [-0.12, 1.21]
Thai 2015	69	16	27	57	23	27	12.9%	0.60 [0.05, 1.14]
Van Es 2015	91.8	2.3	12	82.6	4.3	15	11.9%	2.51 [1.46, 3.55]
Van Es 2016	71.7	18.73	15	58.2	20.2	18	12.6%	0.67 [-0.03, 1.38]
Wong 2015	68.2	2.7	39	60.5	2.3	41	12.7%	3.05 [2.39, 3.70]
Total (95% CI)			**214**			**234**	**100.0%**	**1.32 [0.20, 2.43]**

Heterogeneity: $Tau^2 = 2.42$; $Chi^2 = 172.63$, df = 7 ($P < 0.00001$); $I^2 = 96\%$
Test for overall effect: Z = 2.32 (P = 0.02)

Figure 5. Forest plot #1: meta-analysis of the effectiveness of adaptive e-learning environments versus other educational interventions in improving all learning outcomes.

242x56mm (300 x 300 DPI)

	Adaptive e-learning			Other educational interv.				Std. Mean Difference
Study or Subgroup	Mean	SD	Total	Mean	SD	Total	Weight	IV, Random, 95% CI
Cook 2008	76.2	0.9	62	77.2	0.9	62	25.3%	-1.10 [-1.48, -0.73]
Morente 2013	15.83	2.52	30	11.6	2.39	42	25.0%	1.71 [1.16, 2.26]
Samulski 2017	5.83	2.43	18	4.47	2.47	18	24.8%	0.54 [-0.12, 1.21]
Wong 2015	68.2	2.7	39	60.5	2.3	41	24.8%	3.05 [2.39, 3.70]
Total (95% CI)			**149**			**163**	**100.0%**	**1.04 [-0.86, 2.94]**

Heterogeneity: $Tau^2 = 3.66$; $Chi^2 = 145.70$, df = 3 ($P < 0.00001$); $I^2 = 98\%$

Test for overall effect: Z = 1.08 (P = 0.28)

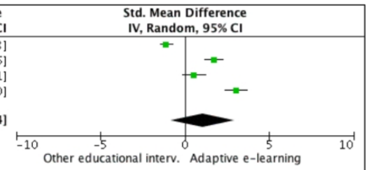

Figure 6. Forest plot #2: meta-analysis of the effectiveness of adaptive e-learning environments versus other educational interventions in improving knowledge.

247x42mm (300 x 300 DPI)

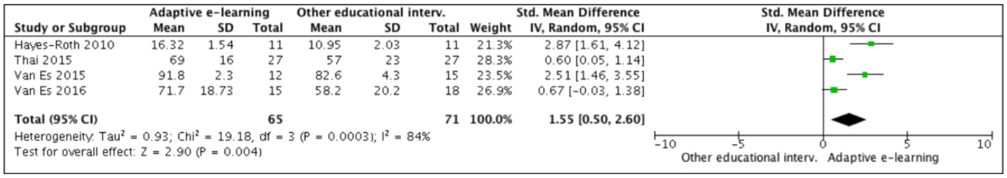

Figure 7. Forest plot #3: meta-analysis of the effectiveness of adaptive e-learning environments versus other educational interventions in improving competence.

242x41mm (300 x 300 DPI)

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	1
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	4-5
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	7-9
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	9-10
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	10
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	10-11
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	11
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	Supplementary File 2
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	11
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	11-12
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	12
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	13
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	13-14
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	13-14

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	13
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	14
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	15
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	18
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	27
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	28-30
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	28-30
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	28
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	N/A
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	30
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	N/A

From: Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med 6(7): e1000097. doi:10.1371/journal.pmed1000097

For more information, visit: www.prisma-statement.org.

Supplementary File 2 – Search Strategy for PubMed

PubMed – 17 avril 2017

1. ((Adaptive[TIAB] OR individualized [TIAB] OR personalized[TIAB] OR Tailored[TIAB]) AND (elearning[TIAB] OR learning[TIAB] OR Instruction[TIAB] OR "web-based instruction"[TIAB] OR computer-based instruction[TIAB] OR computer-based tutoring[TIAB] OR education[TIAB] OR tutorial[TIAB] OR tutorials[TIAB])) OR Intelligent tutoring system[TIAB] OR Intelligent tutoring systems[TIAB]
2. "Computer-Assisted Instruction"[MH]
3. #1 OR #2
4. Health Personnel*[TIAB] OR Health professional*[TIAB] OR Health care profession*[TIAB] OR Healthcare profession*[TIAB] OR Medical student*[TIAB] OR Medical assistant*[TIAB] OR health worker*[TIAB] OR Audiologist*[TIAB] OR Chiropractor*[TIAB] OR Dentist[TIAB] OR Dentists[TIAB] OR Dietitian*[TIAB] OR Dermatolog*[TIAB] OR endocrinologist*[TIAB] OR Gastroenterolog*[TIAB]OR Gynecolog*[TIAB]OR Radiolog*[TIAB] OR Medical Staff[TIAB] OR Midwife*[TIAB] OR nutritionist*[TIAB] OR Nurse[TIAB] OR Nurses[TIAB] OR Optometrist*[TIAB] OR Occupational Therapist*[TIAB] OR Patholog*[TIAB] OR Paramedic[TIAB] OR Paediatric[TIAB] OR pediatrician*[TIAB] OR Paediatrician*[TIAB] OR pediatrist*[TIAB] OR pediatric[TIAB] OR Pharmacist*[TIAB] OR Pharmaconomist*[TIAB] OR Pharmacologist*[TIAB] OR Pharmacy technician*[TIAB] OR Phlebotomist*[TIAB] OR Physician OR Podiatrist*[TIAB] OR Psychologist*[TIAB] OR Psychotherapist*[TIAB] OR psychiatrist*[TIAB] OR Physical therapist*[TIAB] OR physiotherapist*[TIAB] OR Respiratory therapist*[TIAB] OR Surgeon*[TIAB] OR Clinician*[TIAB] OR Cardiologist*[TIAB] OR Emergency medical technician*[TIAB] OR emergency doctor*[TIAB] OR emergentologist*[TIAB] OR clinical officer*[TIAB] OR Community health worker*[TIAB] OR Radiographer*[TIAB] OR Surgical technologist*[TIAB] OR Radiotherapist*[TIAB] OR Anesthetist*[TIAB] OR Resident[TIAB] OR residents[TIAB]
5. "Health Personnel"[MH] OR "Students, Premedical"[MH] OR "Students, Medical"[MH] OR "Students, Nursing"[Mesh]
6. "Education, Premedical"[MH] OR "Education, Medical"[MH] OR "Education, Nursing"[MH] OR "Education, Pharmacy"[MH] OR "Education, Public Health Professional"[MH] OR "Clinical Clerkship"[MH]
7. #4 OR #5 OR 6
8. knowledge*[TIAB] OR Aptitude*[TIAB] OR accuracy[TIAB] OR impact*[TIAB] OR skill*[TIAB] OR performance*[TIAB] OR Learning outcome*[TIAB] OR effectiveness[TIAB] OR efficacy[TIAB] OR improvement*[TIAB] OR Innovative*[TIAB] OR innovation*[TIAB] OR randomised controlled trial[TIAB] OR randomized controlled trial[TIAB]
9. "Clinical Competence"[MH] "Quality Improvement"[MH] OR "Learning Curve"[MH] OR Knowledge [MH] OR "randomized controlled trial"[PT]
10. #8 OR 9
11. #3 AND #7 AND #10
12. (english[LA] OR french[LA]) AND 2005:2017[DP]
13. #11 AND #12

Résultats: 4 375

Supplementary File 3 – Summary of the quality of evidence

Certainty assessment							№ of patients		Effect	Certainty	Importance
№ of studies	Study design	Risk of bias	Inconsistency	Indirectness	Imprecision	Other considerations	Adaptive e-Learning Intervention	Other educational interventions	Absolute (95% CI)		
Knowledge											
4	randomised trials	serious [a,b]	serious [c]	not serious	serious [d]	none	149	163	SMD **1.04 SD higher** (0.86 lower to 2.94 higher)	⊕◯◯◯ VERY LOW	IMPORTANT
Competence											
4	randomised trials	serious [e]	not serious	not serious	serious [f]	none	65	71	SMD **1.55 SD higher** (0.5 higher to 2.6 higher)	⊕⊕◯◯ LOW	CRITICAL

CI: Confidence interval; **SMD:** Standardised mean difference

Explanations

a. The four studies were scored at unclear or high risk of bias regarding allocation concealment. Thus, there is no guarantee that participants' allocation to each group didn't influence the delivery of the intervention.

b. The risk of bias for similarity of baseline measurements was unclear for 2 studies. Thus, groups in these studies could be disproportionate and the distribution may not be normal since sample size is generally small.

c. The individual confidence intervals of the four studies almost do not touch.

d. No author mentioned in these four studies that the measurement instrument for knowledge was validated, and no single instrument is used multiple times. According to sample size calculations, sample size was sufficient in 3 studies.

e. There was a high risk of contamination bias in 2 studies. Incomplete outcome data for 2, potentially 3 studies. Participants that were more motivated that completed the studies may have induced a bias in the results.

f. One underpowered study, according to authors, and 2 studies for which the sample size calculation is not mentioned. It is not mentioned in the measurement instruments were validated in the 4 studies, and no single instrument is used multiple times.

BMJ Open

Efficacy of adaptive e-learning for health professionals and students: a systematic review and meta-analysis

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Complete List of Authors:	Fontaine, Guillaume; University of Montreal, Faculty of Nursing; Montreal Heart Institute, Research Center Cossette, Sylvie ; University of Montreal, Faculty of Nursing; Montreal Heart Institute, Research Center Maheu-Cadotte, Marc-André; University of Montreal, Faculty of Nursing; Montreal Heart Institute, Research Center Mailhot, Tanya; Northeastern University, Bouve College of Health Sciences; Montreal Heart Institute, Research Center Deschênes, Marie-France; University of Montreal, Faculty of Nursing; Center for Innovation in Nursing Education Mathieu-Dupuis, Gabrielle; University of Montreal, School of Librarianship and Information Science Côté, José; University of Montreal, Faculty of Nursing; University of Montreal Hospital Centre, Research Center Gagnon, Marie-Pierre; Laval University, Faculty of Nursing; CHU de Québec-Université Laval, Research Center Dubé, Veronique; University of Montreal, Faculty of Nursing; University of Montreal Hospital Centre, Research Center
Primary Subject Heading:	Medical education and training
Secondary Subject Heading:	Health services research
Keywords:	MEDICAL EDUCATION & TRAINING, COMPUTER-ASSISTED INSTRUCTION, ADAPTIVE E-LEARNING ENVIRONMENTS, META-ANALYSIS, SYSTEMATIC REVIEW

Efficacy of adaptive e-learning for health professionals and students: a systematic review and meta-analysis

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DECLARATION OF COMPETING INTERESTS

All authors have completed the ICMJE uniform disclosure form at www.icmje.org/coi_disclosure.pdf and declare: no support from any organisation for the submitted work; no financial relationships with any organisation that might have an interest in the submitted work in the previous three years; no other relationships or activities that could appear to have influenced the submitted work

TRANSPARENCY DECLARATION

The lead author (the manuscript's guarantor) affirms that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

FUNDING STATEMENT

This study received no funding.

ABSTRACT (300 WORDS)

Objective: Although adaptive e-learning environments (AEEs) can provide personalized instruction to health professional and students, their efficacy remains unclear. Therefore, this review aimed to identify, appraise, and synthesize the evidence regarding the efficacy of AEEs in improving knowledge, skills, and clinical behavior in health professionals and students.

Design: Systematic review and meta-analysis.

Data Sources: CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science from the first year of records to February 2019.

Eligibility Criteria: Controlled studies that evaluated the effect of an AEE on knowledge, skills or clinical behavior in health professionals or students.

Screening, Data Extraction and Synthesis: AEEs were reviewed with regard to their topic, theoretical framework, and adaptivity process. Studies were included in the meta-analysis if they had a non-AEE control group and had no missing data. Effect sizes (ES) were pooled using a random effects model. Two authors screened studies, extracted data, assessed risk of bias, and coded quality of evidence independently.

Results: From a pool of 10,569 articles, we included 21 eligible studies enrolling 3,684 health professionals and students. Clinical topics were mostly related to diagnostic testing, theoretical frameworks were heterogeneous, and the adaptivity process was characterized by 5 subdomains: method, goals, timing, factors, and types. The pooled ES was 0.70 for knowledge (95% CI, -0.08-1.49; *P* .08), and 1.19 for skills (95% CI, 0.59-1.79; *P* < .00001). Risk of bias was generally high. Heterogeneity was large in all analyses.

Conclusions: AEEs appear particularly effective in improving skills in health professionals and students. The adaptivity process within AEEs may be more beneficial for learning skills rather than factual knowledge, which generates less cognitive load. Future research should report more clearly on the design and adaptivity process of AEEs, and target higher-level outcomes, such as clinical behavior.

PROSPERO registration number: CRD42017065585

Keywords: Computer-assisted instruction; medical education; nursing education; e-learning, meta-analysis

ARTICLE SUMMARY

Strengths and Limitations of the Study

- This is the first systematic review and meta-analysis examining the efficacy of adaptive e-learning environments in improving knowledge, skills, and clinical behavior in health professionals and students.
- Strengths of this review include the broad search strategy, and in-depth assessments of the risk of bias and the quality of evidence.
- High statistical heterogeneity resulting from clinical and methodological diversity limits the interpretation of findings.
- Quantitative results should be treated with caution, given the small number and risk of bias of studies included in the meta-analysis.

INTRODUCTION

The use of information and communication technologies (ICTs) in the education of health professionals and students has become ubiquitous. Indeed, e-learning, defined as the use of ITCs to access educational curriculum and support learning[1], is increasingly present in clinical settings for the continuing education of health professionals[2 3], and in academic settings for the education of health professions students[4]. E-learning environments integrate information, in the form of text and multimedia (e.g., illustrations, animations, videos). They can include both asynchronous (i.e., designed for self-study) and synchronous (i.e., a class taught by an educator in real time) components[1]. *Nonadaptive* e-learning environments, the most widespread type of e-learning environment today, provide a standardized training for all learners[5 6]. While they can include instructional design variations (e.g., interactivity, feedback, practice exercises), they *do not* consider learners' characteristics and the data generated during the learning process to provide a personalized training[6-8]. This is problematic, since the interaction of health professionals and students with e-learning environments during the learning process generates a significant amount of data[9]. However, designers of e-learning environments and educators rarely make use of this data to optimize learning efficacy and efficiency[9].

In recent years, educational researchers have strived to develop e-learning environments that take a data-driven and personalized approach to education[10-13]. E-learning environments that take into account each learner's interactions and performance level could anticipate what types of content and resources meet the learner's needs, potentially increasing learning efficacy and efficiency[13]. Adaptive e-learning environments (AEEs) were developed for this purpose. AEEs collect data to build each learner's profile (e.g., navigation behavior, preferences, knowledge), and use simple techniques (e.g., adaptive information filtering, adaptive hypermedia) to implement different types of adaptivity targeting the content, navigation, presentation, multimedia, or strategies of the training to provide a personalized learning experience [11 12]. In the fields of computer science and educational technology, the term *adaptivity* refers to the process executed by a system based on ICTs of adapting educational curriculum content, structure or delivery to the profile of a learner[14]. Two main methods of adaptivity can be implemented within an AEE. The first method, *designed adaptivity*, is expert-based and refers to an educator who designs the optimal instructional sequence to guide learners to learning content mastery. The educator determines how the curriculum will adapt to learners based on a variety of factors, such as knowledge or response time to a question. This method of adaptivity is thus based on the expertise of the educator who specifies how technology will react in a particular situation on the basis of the "if THIS, then THAT" approach. The second method, *algorithmic adaptivity*, refers to use of algorithms to determine, for instance, the extent of the learner's knowledge and the optimal instructional sequence. Algorithmic adaptivity requires more advanced adaptivity techniques and learner-modelling techniques derived from the fields of computer science and artificial intelligence (e.g. Bayesian knowledge tracing, rule-based machine learning, natural language processing) [10 15-18].

The variability in the degree and the complexity of adaptivity within AEEs mirrors the adaptivity that can be observed in non–e-learning educational interventions. Some interventions, like one-on-one human instruction and small-group classroom instruction, generally have a high degree of adaptivity since the instructor can adapt his teaching to the individual profiles of learners and consider their feedback [19]. Other interventions, like large-group classroom instruction, generally have a low degree of adaptivity to individual learners. In some interventions, like paper-based instruction (e.g., handouts, textbooks), there is no adaptivity at all.

AEEs have been developed and evaluated primarily in academic settings for students in mathematics, physics and related disciplines, for the acquisition of knowledge and development of cognitive skills (e.g., arithmetic calculation). Four meta-analyses reported on the efficacy of AEEs among high school and university students in in these fields of study [15-17 20]. The results are promising: AEEs are in almost all cases more effective than large-group classroom instruction. In addition, Nesbit, et al. [21] point out that AEEs are more effective than nonadaptive e-learning environments. However, despite evidence of the efficacy of AEEs for knowledge acquisition and skill development in areas such as mathematics in high school and university students, their efficacy in improving learning outcomes in health professionals and students has not yet been established. To address this need, we conducted a systematic review and meta-analysis to identify and quantitatively synthesize all comparative studies of AEEs involving health professionals and students.

Systematic Review and Meta-Analysis Objective

To systematically identify, appraise, and synthesize the best available evidence regarding the efficacy of AEEs in improving knowledge, skills, and clinical behavior in health professionals and students.

Systematic Review and Meta-Analysis Questions

We sought to answer the following questions with the systematic review:

1. What are the characteristics of studies assessing an AEE designed for health professionals' and students' education?
2. What are the characteristics of AEEs designed for health professionals' or students' education?

We sought to answer the following question with the meta-analysis:

3. What is the efficacy of AEEs in improving knowledge, skills, and clinical behavior in health professionals and students in comparison with nonadaptive e-learning environments, and non–e-learning educational interventions?

METHODS

We planned and conducted this systematic review following the Effective Practice and Organization of Care (EPOC) Cochrane Group guidelines[22], and reported it according to the Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) standards[23] (see **Supplementary File 1**). We prospectively registered (International Prospective Register of Systematic Reviews #CRD42017065585) and published the protocol of this systematic review[24]. Thus, in this paper, we present an abridged version of the methods with an emphasis on changes made to the methods since the publication of the protocol.

Study Eligibility

We included primary research articles that assessed an AEE with licensed health professionals, students, trainees, and residents in any discipline. We defined an AEE as a computer-based learning environment which collects data to build each learner's profile (e.g., navigation behavior, individual objectives, knowledge), interprets these data through algorithms, and adapts in real-time the content (e.g., showing/hiding information), navigation (e.g., specific links and paths), presentation (e.g., page layout), multimedia presentation (e.g., images, videos), or tools (e.g., different set of strategies for different types of learners) to provide a dynamic and evolutionary learning path for each learner[10 14]. We used the definitions of each type of adaptivity proposed by Knutov and colleagues[12]. We considered for inclusion studies in which AEEs had designed or algorithmic adaptivity, and studies including a co-intervention in addition to adaptive e-learning (e.g. paper-based instruction). We considered for inclusion primary research articles in which the comparator was: 1) a nonadaptive e-learning environment; 2) a non–e-learning educational intervention; 3) another AEE with design variations. While included in the qualitative synthesis of the evidence for descriptive purposes, the third comparator was excluded from the meta-analysis. Outcomes of interest were knowledge, skills, and behavior[25 26], and were defined as follows: 1) knowledge: subjective (e.g., learner self-report) or objective (e.g., multiple-choice question knowledge test) assessments of factual or conceptual understanding; 2) skills: subjective (eg, learner self-report) or objective (eg, faculty ratings) assessments of procedural skills (e.g. taking a blood sample, performing CPR) or cognitive skills (e.g. problem-solving, interpreting radiographs) in learners; 3) behavior: subjective (eg, learner self-report) or objective (eg, chart audit) assessments of behaviors in clinical practice (such as test ordering) [6]. In terms of study design, we considered for inclusion all controlled, quantitative studies in accordaSsnce with the EPOC Cochrane Review Group guidelines[27].

We excluded studies that: 1) were not published in English or French; 2) were non-experimental; 3) were not controlled; 4) did not report on at least one of the outcomes of interest in this review; 5) did not have a topic related to the clinical aspects of health.

Study Identification

We previously published our search strategy[24]. Briefly, we designed a strategy in consultation with a librarian to search CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science for primary research articles published since the inception of each database up to February 2019. The search strategy revolved around 3 key concepts: “adaptive e-learning environments”, “health professionals/students", and "effects on knowledge/competence (skills)/behavior" (see **Supplementary file 2**). To identify additional articles, we hand-searched 6 key journals (e.g., *British Journal of Educational Technology*, *Computers and Education*) and the reference lists of included primary research articles.

Study Selection

We worked independently and in duplicate (G.F. and M.-A.M.-C./T.M.) to screen all titles and abstracts for inclusion using the EndNote software V8.0 (Clarivate Analytics). We resolved disagreements by consensus. We then performed the full-text assessment of potentially eligible articles using the same methodology. Studies were included in the meta-analysis if they had a non-AEE control group and had no missing data.

Data Extraction

One review author (G.F.) extracted data from included primary research articles using a modified version of the data collection form developed by the EPOC Cochrane Review Group [28]. The main changes made to the extraction form were the addition of specific items relating to the AEE assessed in each study. Two review authors (T.M., M.-F.D.) validated the data extraction forms by reviewed the contents of each form against the data in the original article, adding comments when changes were needed. For all studies, we extracted the following data items if possible:

- *the population and setting*: study setting, study population, inclusion criteria, exclusion criteria;
- *the methods*: study aim, study design, unit of allocation, study start date and end date, and duration of participation;

- *the participants*: study sample, withdrawals and exclusions, age, sex, level of instruction, number of years of experience as a health professional, practice setting, and previous experience using e-learning;
- *the interventions*: name of intervention, theoretical framework, statistical model/algorithm used to generate the learning path, clinical topic, number of training sessions, duration of each training session, total duration of the training, adaptivity subdomains (method, goals, timing, factors, types), mode of delivery, presence of other educational interventions and strategies;
- *the outcomes*: name, time-points measured, definition, person measuring, unit of measurement, scales, validation of measurement tool;
- *the results*: results according to our primary (knowledge) and secondary (skills, behavior) outcomes, comparison, time-point, baseline data, statistical methods used, and key conclusions.

We contacted the corresponding authors of included primary research articles to provide us with missing data.

Assessment of the Risk of Bias

We worked independently and in duplicate (G.F. and T.M./M.-F.D.) to assess the risk of bias of included primary research articles using the EPOC risk of bias criteria, based upon the data extracted with the data collection form[28]. A study was deemed at high risk of bias if the individual criterion "random sequence generation" was scored at "high" or at "unclear" risk of bias.

Data Synthesis

First, we synthesized data qualitatively using tables to provide an overview of the included studies, and of the AEEs reported in these studies.

Second, using the Review Manager (RevMan) software V5.1, we first conducted a meta-analysis to quantitatively synthesize the efficacy of AEEs versus other educational interventions in improving all learning outcomes. We included studies in the meta-analysis if the comparator wasn't another AEE, if they were randomized, and if they reported outcome data. We then conducted meta-analyses with the same comparison for each outcome for which data from at least 2 studies were available (i.e., knowledge, skills). For randomized controlled trials (RCTs), we converted each post-test mean and standard deviation (SD) to a standardized mean difference ([SMD], also known as Hedges g effect size [ES]). For crossover RCTs, we used means pooled across each intervention. We pooled ESs using a random effects model. Statistical significance was defined by a two-sided alpha of .05.

We first assessed heterogeneity qualitatively by examining the characteristics of included studies, the similarities and disparities between the types of participants, the types of interventions, and the types of outcomes. We then used the I^2 statistic within the RevMan software to quantify how much the results varied across individual studies (i.e., between-study inconsistency, or heterogeneity). We interpreted the I^2 values as follows: 0%-40%: might not be important; 30%-60%: may represent moderate heterogeneity; 50%-90%: may represent substantial heterogeneity; and 75%-100%: considerable heterogeneity[29]. We performed sensitivity analysis to assess if the exclusion of studies at high risk of bias or with a small sample size (n<20) would have had an impact on statistical heterogeneity. The small number of studies included in each meta-analysis did not allow for subgroup analyses to be performed.

Since less then 10 studies were included in the meta-analysis for each outcome, we did not assess reporting biases using a funnel plot, as suggested in the Cochrane Handbook[30].

Assessment of the Quality of Evidence

We worked independently and in duplicate (G.F. and M.-A.M.-C.) to assess the quality of evidence for each individual outcome. We used the Grading of Recommendations Assessment, Development, and Evaluation (GRADE) Web-based software, based upon the data extracted with the data collection checklist [31]. We considered 5 factors (risk of bias of included studies, indirectness of evidence, unexplained heterogeneity or inconsistency of results, imprecision of the results, probability of reporting bias) for downgrading the quality of the body of evidence for each outcome [31].

Patient and Public Involvement

Patients and the public were not involved in setting the research question, the outcome measures, the design or conduct of this systematic review. Patients and the public were not asked to advise on interpretation of results or to contribute to the writing or editing of this document.

RESULTS

Study Flow

From a pool of 10,569 potentially relevant articles, we found 21 quantitative, controlled studies assessing an AEE with health professionals or students (see **Figure 1**).

[Insert Figure 1]

Out of 21 included studies in the qualitative synthesis, 4 studies compared two AEEs with design variations[32-35], and 4 studies had missing data[36-39]. Thus, these 8 studies could not be included in the meta-analysis and the remaining 13 studies were used to calculate an ES on learning outcomes.

Study Characteristics

We summarized the key characteristics of included studies in table format (see **Table 1**). In terms of study population, in the 21 studies examined published between 2003 and 2018, investigators have evaluated AEEs mostly in the medical field. Studies focused on medical students (n=8) [38-44], medical residents (n=8) [32-35 41 45-47], physicians in practice (n=4) [36 37 41 48], nursing students (n=2) [40 49], nurses in practice (n=2) [48 50] and health sciences students (n=1) [51]. Three studies focused on multiple populations [40 41 48]. The median sample size was 46 participants (interquartile range [IQR] 123). In terms of study design, 15 out of 21 studies (71%) were randomized, 7 studies of which were randomized crossover trials [33 34 41-43 45 47]. The median number of training sessions was 2 (IQR 2.5 sessions), the median training time was 2.13 hours (IQR 2.88 hours), and the median training period was 14 days (IQR 45 days). In terms of comparators, it is possible to underline three types of comparisons. The first comparison is an AEE versus another AEE with design variations (n=4) [32-35], which implies that one of the AEEs assessed had variations in its design, such as different types of adaptivity (e.g., feedback in one AEE is longer or more complex than in the other). The second comparison is an AEE versus a nonadaptive e-learning environment (n=11) [38-40 42-46 48 50 51]. The third and final comparison is an AEE versus another type of educational intervention, such as a paper-based educational intervention, including

305 handouts, textbooks or images (n=3) [37 41 47], or a traditional educational intervention, such as a
306 group lecture (n=2) [49 52]. In one study, the comparator was not clearly reported [36]. As stated
307 before, only the second and third types of comparisons were included in the meta-analysis since
308 our aim was to synthesize quantitatively the efficacy of AEEs versus other types of educational
309 interventions. Finally, in terms of outcomes, investigators evaluated learners' knowledge (n=15)
310 [32 33 35 36 38 39 41-45 47-50], satisfaction (n=9) [32 34 38 39 41-43 45 47], skills (n=8) [34 36 37 40 46 50-52],
311 metacognitive processes (n=3) [32 33 35], attitudes (n=2) [36 50], and behavior (n=1) [50].

Table 1. Characteristics of included studies.

First author, year Country	Participants*	Study design†	No. and duration of training sessions	Duration of intervention	Comparison(s)‡	Outcome(s)§
Comparison: adaptive e-learning environments vs. other educational interventions						
Casebeer, 2003 USA	PP; N = 181	RCT; posttest-only, 2 groups	4 sessions; 1 hour each	NR	NR	Knowledge Δ Attitudes Δ Skills Δ
Cook, 2008 USA	R; N = 122	RXT; posttest-only, 4 groups	4 sessions; 30 minutes each	126 days	NEE	Satisfaction Knowledge
Crowley, 2010 USA	PP; N = 15	RCT; pretest–posttest, 2 groups	4 sessions; 4 hours each	138 days	P	Skills Δ
de Ruijter, 2018 Netherlands	NP; N = 269	RCT; pretest-posttest, 2 groups	No fixed sessions	180 days	NEE	Knowledge Attitudes Behavior Δ
Hayes-Roth, 2010 USA	MS, NS; N = 30	RCT; pretest–posttest–retention-test, 3 groups	NR; mean training time 2.36 hours	NR	1. NEE 2. NI	Skills Δ
Lee, 2017 USA	MS; N = 1522	NRCT; pretest-posttest, 3 groups	5 sessions; NR	42 days	NEE	Knowledge Skills Δ Behavior Δ
Micheel, 2017 USA	PP, NP; N = 751	NRCT; pretest–posttest–retention-test, 2 groups	NR	NR	NEE	Knowledge Δ
Morente, 2013 Spain	NS; N = 73	RCT; pretest–posttest, 2 groups	1 session; 4 hours	1 day	T	Knowledge Δ
Munoz, 2010 Colombia	MS; N = 40	NRCT; pretest–posttest, 2 groups	NR; mean training time 5.97 hours	NR	NEE	Satisfaction Knowledge
Romito, 2016 USA	R; N = 24	NRCT; pretest–posttest–retention-test, 2 groups	1 session; 30 minutes	1 day	NEE & T	Skills Δ
Samulski, 2017 USA	MS, R, PP; N = 36	RXT; pretest–posttest, 2 groups	2 sessions; 20 minutes to 14 hours	1 month	P	Satisfaction Knowledge
Thai, 2015 USA	HSC; N = 87	RCT; pretest–posttest–retention-test, 3 groups	1 session; 45 minutes	1 day	1. AEE 2. NEE	Skills Δ
Van Es, 2015 Australia	R; N = 43	RXT; posttest-only, 2 groups	3 sessions; NR	50 days	P	Satisfaction Knowledge Δ
Van Es, 2016	MS; N = 46	RXT; posttest-only, 2 groups	3 sessions; 2 hours each	34 days	NEE	Satisfaction

Australia						Knowledge
Wong, 2015 Australia	MS; N = 99	RXT; posttest-only, 2 groups	2 sessions; 1.5 hour each	14 days	NEE	Satisfaction Knowledge Δ
Wong, 2017 USA	MS; N = 178	NRCT; pretest–posttest–retention-test, 3 groups	1 session; NR	35 days	1. T 2. AEE & T	Skills Δ
Woo, 2006 USA	MS; N = 73	NRCT; pretest–posttest, 3 groups	1 session; 2 hours	1 day	1. NEE 2. NI	Satisfaction Knowledge
Comparison: adaptive e-learning vs. adaptive e-learning (two AEEs with design variations)						
Crowley, 2007 USA	R; N = 21	RCT; pretest–posttest–retention-test, 2 groups	1 session; 4.5 hours	1 day	AEE	Satisfaction Metacognitive processes Knowledge
El Saadawi, 2008 USA	R; N = 20	RXT; pretest–posttest, 2 groups	2 sessions; 2 hours each	1 day	AEE	Satisfaction Skills
El Saadawi, 2010 USA	R; N = 23	RXT; pretest–posttest, 2 groups	2 sessions; 2.25 hours each	2 days	AEE	Metacognitive processes Knowledge
Feyzi-Begnagh, 2014 USA	R; N = 31	RCT; pretest–posttest, 2 groups	2 sessions; 2 & 3 hours	1 day	AEE	Metacognitive processes Knowledge

* Participants: MS indicates medical students; NS, nursing students; R, residents (physicians in postgraduate training); PP, physicians in practice; NP, nurses in practice; HSC, health sciences students.

† Study design: RCT indicates randomized controlled trial; RXT, randomized crossover trial; NRCT, non-randomized controlled trial.

‡ Comparison: AEE indicates adaptive e-learning environment; NEE, nonadaptive e-learning environment; NI, no-intervention control group; T, traditional (group lecture); P, paper (handout, textbook, or latent image cases).

§ Outcomes: Δ indicates a statistically significant improvement regarding this outcome in the experimental group in comparison with the control group for studies comparing an AEE with other educational interventions.

Characteristics of Adaptive E-Learning Environments

We summarized the key characteristics of AEEs assessed in the 21 studies in table format (see **Table 2**). In terms of the clinical topics of the AEEs, the majority of AEEs focused on training medical students and residents in executing and/or interpreting diagnostic tests. Indeed, a significant proportion of the AEEs assessed focused on dermopathology and cytopathology microscopy [32-35 37 41 42 47] (n=8). Other topics were diagnostic imaging [43 46] (n=2), behavior change counseling [40 50] (n=2), chronic disease management [45 48] (n=2), pressure ulcer evaluation [49] (n=1), childhood illness management [38] (n=1), electrocardiography [51] (n=1), fetal heart rate interpretation [52] (n=1), hemodynamics [39] (n=1), chlamydia screening (n=1) [36] and atrial fibrillation management (n=1) [44].

The 21 AEEs examined were based on a wide variety of theoretical frameworks. The most frequently used framework was cognitive tutoring, adopted in 5 studies [32-35 37], which refers to the use of a cognitive model. The integration of a cognitive model in an AEE implies the representation of all the knowledge in the field of interest in a way that is similar to the human mind for the purpose of understanding and predicting the cognitive processes of learners [53]. The second most used framework was perceptual learning, adopted in 3 studies [46 51 52]. Perceptual learning aims at improving information extraction skills of the environment and the development of automaticity in this respect in learners [46]. Interestingly, 2 studies used models from behavioral science, the Transtheoretical Model [36] and the I-Change Model [50], to tailor the AEE to the theoretical determinants of clinical behavior change in nurses and physicians in practice. Theoretical frameworks relating to self-regulated learning [35], learning styles [38 48], guided mastery [40], and cognitive load [43], problem-based-learning [36], and situated learning [36] were also used.

Three main adaptive e-learning platforms were used by investigators in studies examined: SlideTutor (n=4) [33 37 54 55], Smart Sparrow (n=4) [41-43 47], and the Perceptual Adaptive Learning Module (PALM, n=3) [51 52 56]. SlideTutor is an AEE with algorithmic adaptivity which provides cases to be solved by learners under supervision by the system. These cases incorporate dermopathology virtual slides that must be examined by learners to formulate a diagnosis. An expert knowledge base, consisting of evidence-diagnosis relationships, is used by SlideTutor to create a dynamic solution graph representing the current state of the learning process and to determine the optimal instructional sequence [55]. Smart Sparrow is an AEE with designed adaptivity which allows educators to determine adaptive factors, such as answers to questions, response time to a question, and learner actions, to specify how the system will adapt the instructional sequence or provide feedback. These custom learning paths can be more or less personalized [42]. PALM is an AEE with algorithmic adaptivity aiming to improve perceptual learning through adaptive response-time-based sequencing to determine dynamically the spacing between different learning items based on each learner's accuracy and speed in interactive learning trials [51]. Different custom adaptive e-learning platforms were used in other studies.

Table 2. Characteristics of adaptive e-learning environments.

First Author, Year	Clinical Topic(s)	Theoretical Framework(s)	Platform	Adaptivity Subdomains				
				Adaptivity Method	Adaptivity Goals	Adaptivity Timing	Adaptivity Factors	Adaptivity Types
Casebeer, 2003	Chlamydia screening	Transtheoretical model of change; Problem-based learning; Situated learning theory	NR	Designed Adaptivity	To increase learning effectiveness (knowledge, skills).	Throughout the training, after case-based and practice-based questions.	User answers to questions	• Content • Navigation
Cook, 2008	Diabetes, hyperlipidemia, asthma, depression	NR	NR	Designed Adaptivity	To increase learning efficiency (knowledge gain divided by learning time).	After each case-based question in each module (17 to 21 times/module).	User knowledge	• Content • Navigation
Crowley, 2007	Dermopathology; subepidermal vesicular dermatitis	Cognitive Tutoring	SlideTutor	Algorithmic Adaptivity	To increase learning gains, metacognitive gains, and diagnostic performance.	At the beginning of each case.	User actions: results of problem-solving tasks; requests for help	• Content • Navigation • Presentation • Multimedia • Tools
Crowley, 2010	Dermopathology; melanoma	Cognitive Tutoring	SlideTutor	Algorithmic Adaptivity	To improve reporting performance and diagnostic accuracy.	At the beginning of each case.	User actions: results of problem-solving tasks; reporting tasks; requests for help	• Content • Navigation • Presentation • Multimedia • Tools
de Ruijter, 2018	Smoking cessation counseling	I-Change Model	Computer-Tailored E-Learning Program	Designed Adaptivity	To modify behavioral predictors and behavior.	At the beginning of the training.	Demographics, behavioral predictors, behavior	• Content
El Saadawi, 2008	Dermopathology; melanoma	Cognitive Tutoring	ReportTutor	Algorithmic Adaptivity	To teach how to correctly identify and document all relevant	At the beginning of each case.	User actions, report features	• Content • Navigation • Presentation • Multimedia

					prognostic factors in the diagnostic report.			
El Saadawi, 2010	Dermopathology	Cognitive Tutoring	SlideTutor	Algorithmic Adaptivity	To facilitate transfer of performance gains to real-world tasks that do not provide direct feedback on intermediate steps.	During intermediate problem-solving steps.	User actions: results of problem-solving tasks; reporting tasks; requests for help	• Content • Navigation • Presentation • Multimedia
Feyzi-Begnagh, 2014	Dermopathology; nodular and diffuse dermatitis	Cognitive Tutoring, Theories of Self-Regulated Learning	SlideTutor	Algorithmic Adaptivity	To improve metacognitive and learning gains during problem solving.	During each case or immediately after each case.	User actions: results of problem-solving tasks; reporting tasks; requests for help	• Content • Navigation • Presentation • Multimedia • Tools
Hayes-Roth, 2010	Brief intervention training in alcohol abuse	Guided Mastery	STAR Workshop	NR	To improve attitudes and skills.	During clinical cases.	User scores, user-generated dialogue	• Content • Navigation
Lee, 2017	Treatment of atrial fibrillation	NR	Learning Assessment Platform	Designed Adaptivity	To increase learning effectiveness (knowledge, competence, confidence and practice).	After learning gaps identified in the first session.	Learning gaps in relation to objectives	• Content
Micheel, 2017	Oncology	Learning Style Frameworks	Learning-style tailored educational platform	Designed Adaptivity	To increase learning effectiveness (knowledge).	After assessing the learning style.	Learning style	• Presentation • Multimedia • Tools

Morente, 2013	Pressure ulcer evaluation	NR	ePULab	Designed Adaptivity	To increase learning effectiveness (knowledge, skills).	Each pressure ulcer evaluation.	User skills	• Content
Munoz, 2010	Management of childhood illness	Learning Styles Framework	SIAS-ITS	Designed Adaptivity	To increase learning effectiveness and efficiency.	At the beginning of the training.	User knowledge, user learning style	• Content • Tools
Romito, 2016	Transoesophageal echocardiography	Perceptual Learning	TOE PALM	Algorithmic Adaptivity	To improve response accuracy and response time.	After each clinical case.	User response accuracy, user response time	• Content • Navigation • Multimedia
Samulski, 2017	Cytopathology; pap test, squamous lesions, glandular lesions	NR	Smart Sparrow	Designed Adaptivity	To improve learning effectiveness.	During intermediate problem-solving steps.	User knowledge	• Content • Navigation
Thai, 2015	Electrocardiography	Perceptual Learing Theory; Adaptive response-time based algorithm	PALM	Algorithmic Adaptivity	To improve perceptual classification learning effectiveness and effiency.	After each user response.	User response accuracy, user response time	• Content • Presentation • Multimedia • Tools
Van Es, 2015	Diagnostic cytopathology; gynecology, fine needle aspiration, exfoliative fluid	NR	Smart Sparrow	Designed Adaptivity	To improve learning effectiveness.	During intermediate problem-solving steps.	User responses	• Content • Navigation • Presentation • Multimedia
Van Es, 2016	Diagnostic cytopathology; gynecology, fine needle aspiration, exfoliative fluid	NR	Smart Sparrow	Designed Adaptivity	To improve learning effectiveness.	During intermediate problem-solving steps.	User responses	• Content • Navigation • Presentation • Multimedia • Tools

Wong, 2015	Diagnostic imaging; chest X-rays, CT scans	Cognitive Load Theory	Smart Sparrow	Designed Adaptivity	To improve learning effectiveness.	During intermediate problem-solving steps.	User responses	• Content
Wong, 2017	Fetal heart rate interpretation	Perceptual Learning	PALM	Algorithmic Adaptivity	To improve response accuracy and response time.	After each clinical case.	User response accuracy, user response time	• Content • Navigation • Multimedia
Woo, 2006	Hemodynamics; baroreceptor reflex	NR	CIRCSIM-Tutor	Algorithmic Adaptivity	To improve knowledge related to problem-solving tasks.	After each user response.	User knowledge, user responses	• Content • Navigation • Tools

365 We propose 5 subdomains that emerged from the review to characterize the adaptivity process of AEEs reported in the 21 studies: adaptivity method, adaptivity goals, adaptivity timing, adaptivity factors and adaptivity types.

368 First Subdomain: Adaptivity Method

369 This subdomain relates to the method of adaptivity that dictates how the AEE adapts instruction to a learner. As we previously described, there are two main methods of adaptivity: *designed adaptivity* and *algorithmic adaptivity*. The first is based on the expertise of the educator who specifies how technology will react in a particular situation on the basis of the "if THIS, then THAT" approach. The second refers to use of algorithms that will determine, for instance, the extent of the learner's knowledge and the optimal instructional sequence. In this review, 11 AEEs employed designed adaptivity [36 38 41-44 47-50 57], and 9 AEEs employes algorithmic adaptivity [33 37 39 51 52 54-56 58]. The adaptivity method wasn't specified in one study [40].

377 Second Subdomain: Adaptivity Goals

378 This subdomain relates to the purpose of the adaptivity process within the AEE. For most AEEs, the adaptivity process aims primarily to increase the efficacy and/or efficiency of knowledge acquisition and skills development relative to other training methods [32 35 36 38-45 47-49 51]. For instance, several AEEs aimed to increase the diagnostic accuracy and reporting performance of medical students and residents [32-34 37 46 52]. In one study, the goal of adaptivity was to modify behavioral predictors and behavior in nurses [50]. In cases where two adaptive AEEs with certain variations in their techno-pedagogical design are compared with each other, the adaptivity process generally aims at improving the metacognitive and cognitive processes related to learning [32 33 35].

Third Subdomain: Adaptivity Timing

This subdomain relates to *when* the adaptivity occurs during the learning process with the AEE. In 19 out of 21 studies, the adaptivity occurred throughout the training with AEE, usually after an answer to a question or during intermediate problem-solving steps. However, in two studies, adaptivity was only implemented at the beginning of the training with the AEE following survey responses [38 50].

Fourth Subdomain: Adaptivity Factors

This subdomain relates to the learner-related data (variables) upon which the adaptivity process is based. The most frequently targeted variable is the learner's scores after an assessment or a question within the AEE (e.g., knowledge/skills scores, response accuracy scores) [38-43 45-47 49 51 52]. Other frequently targeted variables include the learner's actions during its use of the AEE (e.g., results of problem-solving tasks, results of reporting tasks, requests for help) [32-35 37], and the learner's response time regarding a specific question or task [46 51 52].

Fifth Subdomain: Adaptivity Types

The final subdomain relates to which types of adaptivity are mobilized in the AEE: content, navigation, multimedia, presentation and tools. In the context of this review, the adaptivity types are based upon the work of Knutov and colleagues [12]. Overall, 17 out of 21 (81%) AEEs examined integrated more than one type of adaptivity. *Content adaptivity* was the most used adaptivity type; it was implemented in all but one AEEs reviewed (n=20). Content adaptivity aims to adapt the textual information (curriculum content) to the learner's profile through different mechanisms and to different degrees [12]. *Navigation adaptivity* was the second most used adaptivity type (n=14). Navigation can be adapted in two ways; it can be enforced or suggested.

When enforced, an optimal personalized learning path is determined for the learner by an expert educator or by the algorithms within the AEE. When suggested, there are several personalized learning paths available to each learner, who can determine the path he prefers himself [12]. Most reviewed studies included AEEs with enforced navigation, with one optimal personalized learning path being determined by an expert educator or by the algorithm. *Multimedia adaptivity* was the third most used adaptivity type (n=11). This adaptivity type, much like content adaptivity which relates to textual information, implies the adaptivity of the multimedia elements of the training such as videos, pictures, models, to the learner's profile. *Presentation adaptivity* was the fourth most used adaptivity type (n=9). It implies the adaptivity of the layout of the page to the digital device used, or to the learner's profile. *Tools adaptivity* was the least used adaptivity type (n=8). This technique results in providing a different set of features or learning strategies for different types of learners, such as different interfaces for problem solving, and knowledge representation.

Risk of Bias Assessment

Results of included studies for the risk of bias assessment are presented in **Figure 2** and **Figure 3**. In ≥ 75% of studies, biases related to similarity of baseline outcome measurements, blinding of outcome assessment and selective reporting of outcomes were low. Moreover, in ≥ 50% of studies, biases related to contamination were low. Regarding the blinding of outcome assessment, in most studies, review authors judged that the outcomes of interest and the outcome measurement were not likely to be influenced by the lack of blinding, since studies had objective measures, i.e. an evaluative test of knowledge or skills. Regarding contamination bias, review authors scored studies at high risk if they had a crossover design.

However, in ≥ 50% of studies, biases related to random sequence generation, allocation concealment, similarity of baseline characteristics, similarity of baseline characteristics, blinding of participants and personnel, and incomplete outcome data were unclear or high. Regarding random sequence generation, an important number of studies did not report on the method of randomization used by investigators. As per Cochrane recommendations, all eligibile studies were incuded in the meta-analysis, regardless of the risk of bias assessment. Indeed, since almost all studies scored overall at unclear risk of bias, Cochrane suggests to present an estimated intervention effect based on all available studies, together with a description of the risk of bias in individual domains [30].

[Insert Figure 2]

[Insert Figure 3]

Quantitative Results

Efficacy of AEEs versus other educational interventions in improving knowledge

The pooled ES (standardized mean difference [SMD] 0.70; 95% confidence interval [CI] -0.08-1.49; Z =1.76, *P* 0.08) of AEEs compared to other educational interventions in improving knowledge suggests a medium to large effect (see **Figure 4**). However, this result is not statistically significant. Significant statistical heterogeneity was observed among studies (I^2 =97%, P <.00001), and individual ESs ranged from -1.10 to 3.05. One study in particular [45] reported a negative ES, but the difference between groups in knowledge scores was statistically nonsignificant. Moreover, while participants using the AEE in the experimental group reported the same knowledge scores as participants in the control group at the end of study, time spent on instruction was reduced by 18% with the AEE compared to the nonadaptive e-learning

453 environment, thus improving learning efficiency [45]. When that study [45] is removed from the meta-
454 analysis, the pooled ES becomes statistically significant (SMD 1.07; 95% CI 0.28-1.85; Z =2.67,
455 *P* 0.008).

456 [Insert Figure 4]

457 ### Efficacy of AEEs versus other educational interventions in improving skills

458 As we considered ESs larger than 0.8 to be large [59], the pooled ES (SMD 1.19; 95% CI 0.59-
459 1.79; Z =3.88, *P* 0.0001) of AEEs compared to other educational interventions in improving
460 skills suggests a significantly large effect (see **Figure 5**). Statistical heterogeneity was lower than
461 in previous analyses, but was still significant (I^2 =89%, P <.00001). Individual ESs ranged from
462 0.17 to 2.87.

463 [Insert Figure 5]

464 ## Quality of the Evidence

465 The quality of evidence table produced with GRADE, as well as the justifications for each
466 decision, is presented in **Supplementary File 3** (GRADE quality of evidence levels: very low, low,
467 moderate, high). For knowledge, the quality of evidence was deemed to be very low. More
468 precisely, risk of bias was deemed serious, inconsistency serious, indirectness not serious, and
469 imprecision serious. For skills, the quality of evidence was deemed to be low. More precisely,
470 risk of bias was deemed serious, inconsistency serious, indirectness not serious, and imprecision
471 serious.

DISCUSSION

Principal Findings

This is the first systematic review and meta-analysis to evaluate the efficacy of AEEs in health professionals and students. We identified 21 relevant studies published since 2003, 17 of which assessed an AEE versus another educational intervention (large-group classroom instruction, nonadaptive e-learning environment or paper-based learning), and 4 of which assessed 2 AEEs with design variations head-to-head. When compared with other educational interventions, AEEs were associated with statistically significant improvements in learning outcomes in 12 out of 17 studies. Pooled ESs were medium to large for knowledge and large for skills, but only the latter was associated with a statistically significant effect. Statistical heterogeneity was high in all analyses. However, this finding is consistent with other meta-analyses in the field of medical education that also reported high heterogeneity across studies [8,60,61]. A small number of eligible studies prohibited us from performing subgroup analyses which could have helped in explaining the source of the heterogeneity. The quality of evidence for all comparisons was either low or very low. Therefore, while we believe the results support the potential of AEEs for the education of health professionals and students, we recommend interpreting the ESs with caution.

Comparison with Other Studies

To our knowledge, no previous systematic review and meta-analysis has specifically assessed the efficacy of AEEs in improving learning outcomes in health professionals and students, or any other population. However, interestingly, since the 1990’s there has been a strong research interest in the field of AEEs with algorithmic adaptivity (also known as intelligent learning environments [IEEs] or intelligent tutoring systems [ITSs]) into elementary, high school and postsecondary education for multiple subjects [17]. Thus, multiple meta-analyses have been conducted with regard to AEEs in that setting.

Steenbergen-Hu and Cooper [15] reported a mean ES of 0.35 of AEEs with algorithmic adaptivity on learning outcomes in college students when compared to all other types of educational interventions. The mean ES was 0.37 when the comparator was large-group classroom instruction, 0.35 when the comparator was nonadaptive e-learning, and 0.47 when the comparator was textbooks or workbooks[15].

Ma, et al. [18] reported a mean ES of 0.42 of AEEs with algorithmic adaptivity on learning outcomes in elementary, high school and postsecondary students when compared to large-group classroom instruction. The mean ES was 0.57 when the comparator was nonadaptive e-learning, and 0.35 when the comparator was textbooks or workbooks. Interestingly, the mean ES was higher for studies which assessed an AEE in biology and physiology (0.59) and in humanities and social science (0.63) than in studies which assessed an AEE in mathematics (0.35) and physics (0.38)[18].

Kulik and Fletcher [17] reported a mean ES of 0.65 of AEEs with algorithmic adaptivity on learning outcomes in elementary, high school, and postsecondary students when compared to large-group classroom instruction. Education areas in this review were diverse (e.g., mathematics, computer science, physics), but none were related to health sciences. Interestingly, the mean ES was 0.78 for studies up to 80 participants, and 0.30 for studies with more than 250 participants. Moreover, the mean ES for studies conducted with elementary and high school students was 0.44, compared to 0.75 for studies conducted with postsecondary students[17].

Thus, in light of the results of these meta-analyses, the ES reported in our review may appear high. However, our review looked more specifically into the efficacy of AEEs in improving learning outcomes in health professionals and students. This is significant since, in the meta-analyses of Steenbergen-Hu and Cooper [15], Ma, et al. [18], and Kulik and Fletcher [17], AEEs seem to be more effective in postsecondary students [17 18] and for learning subjects related to biology, physiology and social science [18]. Moreover, previous meta-analyses focused on the efficacy of AEEs in improving procedural and declarative knowledge, and did not report on the efficacy on AEEs in improving skills. This is important since AEEs may be more effective for providing tailored guidance and coaching for developing skills regarding complex clinical interventions, rather than learning factual knowledge, which generates less cognitive load [62 63].

Implications for Practice and Research

This review provides important implications for the design and development of AEEs for health professionals and students. Table 3 presents 8 practical considerations for the design and development of adaptive e-learning environments based on the results of this systematic review for educators and educational researchers.

Table 3. Practical considerations for the design and development of adaptive e-learning environments.

Practical considerations	Explanations
Developing the Educational Content	• Given the adaptivity and the different learning pathways inherent to adaptive e-learning environments (AEEs), it is necessary to develop more pedagogical content (e.g. 60 minutes of learning) to reach the planned duration of each adaptive e-learning session (e.g. 30 minutes of learning).
Selecting a Theoretical Framework	• Selecting a theoretical framework coherent with the underlining principles of adaptivity of AEEs is crucial. These frameworks can be related to human cognition (e.g. Cognitive Load Theory, Cognitive Tutoring), behavior change (e.g. Transtheoretical model, I-Change Model) or learning (e.g. Perceptual Learning, Situated Learning).

Selecting the Adaptivity Method	• Selecting the adaptivity method refers to how the AEE will adapt its instructional sequence. There are two main adaptivity methods: ○ *Designed adaptivity* is based on the expertise of the educator who designs personalized pathways to guide learners to learning content mastery; ○ *Algorithmic adaptivity* is based on different algorithms to determine, for instance, the extent of the learner's knowledge and the optimal instructional pathway.
Selecting the Adaptivity Goal(s)	• Selecting the adaptivity goal(s) is important, since it will dictate how the instruction will be adapted in the AEE. The goal of adaptivity within an AEE may be to increase learning effectiveness, increase learning efficiency, modify behavioral predictors, or improve cognitive/metacognitive processes related to learning.
Selecting the Adaptivity Timing	• Selecting the timing of adaptivity within an AEE relates to *when* the adaptivity occurs during the learning process. Adaptivity can be implemented at the beginning of the training only, or throughout the training. Adaptivity timing is closely linked to which adaptivity factor(s) are targeted in learners.
Selecting the Adaptivity Factor(s)	• Adaptivity factors are essentially data upon which the adaptivity process is based. These data can be related to the learner's performance (e.g. knowledge, skills), his behavior / actions on the page (e.g. response time, requests for help), his overall learning path on the platform, or any other variables of interest in the learner.
Selecting the Adaptivity Type(s)	• Multiple types of adaptivity can be implemented in an AEE: ○ *Content adaptivity* refers to the adaptation of the textual information; ○ *Navigation adaptivity* refers to the adaptation of the curriculum sequence; ○ *Presentation adaptivity* refers to the adaptation of layout of the screen to the digital device used, or to the learner's profile; ○ *Multimedia adaptivity* refers to the adaptation of multimedia elements of the training such as videos, pictures, models; ○ *Tools adaptivity* refers to the adaptation of training features, learning strategies or learning assessment methods (e.g. interface for problem solving).
Determining your technical resources and selecting the adaptive e-learning platform	• After the content has been developed, the theoretical framework has been selected and the decisions related to the different subdomains adaptivity have been made, it is crucial to determine your technical resources and evaluate preexisting adaptive e-learning software to determine if it meets your needs and goals. If you plan to employ a specialist or team to develop the platform, estimate development cost and timeline.

This review also provides several key insights for future research. In terms of *population*, future research should focus on assessing AEEs with health professionals in practice, such as registered nurses and physicians, rather than students in these disciplines. This could provide key insights into how AEEs can impact clinical behavior and, ultimately, patient outcomes. In addition, invetsigators should target larger sample sizes. In terms of *interventions*, researchers should report more clearly on adaptivity methods, goals, timing, factors and types. Moreover, researchers should provide additional details regarding the underlining algorithms allowing the adaptivity process in order to ensure replicability of findings. Regarding *comparators*, this review suggests there is a need for additional research using traditional comparators (i.e., large group classroom instruction) and more specific comparators (i.e., adaptive e-learning environment with design variations). Regarding *outcomes* and outcome measures, researchers should use validated measurement tools of knowledge, skills, and clinical behavior to facilitate knowledge synthesis. Moreover, the very low number of studies assessing the impact of AEEs on health professionals' and students' clinical behavior demonstrates the need for further research with higher-level outcomes. Finally, in terms of *study designs*, researchers should focus on research designs allowing the assessment of the impact of multiple educational design variations and adaptivity types within one study, such as factorial experiments.

Strengths and Limitations

Strengths of this systematic review and meta-analysis include the prospective registration and publication of a protocol based on rigorous methods in accordance with Cochrane and PRISMA guidelines; the exhaustive search in all relevant databases; the independent screening of the titles, abstracts and full-text of studies; the assessment of each included studies' risk of bias using EPOC Cochrane guidelines; and the assessment of the quality of evidence for each individual outcome using the GRADE methodology.

Our review also has limitations to consider. First, outcome measures varied widely across studies. To address this issue, we conducted the meta-analysis using the SMD. Using the SMD allowed us to standardize the results of studies to a uniform scale before pooling them. Review authors judged that using the SMD was the best option for this review, as it is the current practice in the field of knowledge synthesis in medical education [6 60].

Second, there was high inconsistency among study results, which we can mostly attribute to differences in populations, AEE design, research methods, and outcomes. This resulted in sometimes widely differing estimates of effect. To partly address this issue, we used a random-effects model for the meta-analysis, which assumes that the effects estimated in the studies are different and follow a distribution [30]. However, since a random-effects model awards more weight to smaller studies to learn about the distribution of effects, it could potentially exacerbate the effects of the bias in these studies [30].

Finally, publication bias could not be assessed by the means of a funnel plot since there were less than 10 studies included in the meta-analysis.

CONCLUSIONS

Adaptive e-learning has significant potential to increase the effectiveness and efficiency of learning in health professionals and students. Through the different sub-domains of the adaptivity process (i.e. method, goals, timing, factors, types), AEEs can take into account the particularities inherent to each learner. This systematic review and meta-analysis underlines the potential of AEEs for improving knowledge and skills in health professionals and students in comparison with other educational interventions, such as nonadaptive e-learning environments and large-group classroom learning, across a range of topics. However, evidence was either of low or very low quality and heterogeneity was high across populations, interventions, comparators, and outcomes. Thus, additional comparative studies assessing the efficacy of AEEs in health professionals and students are needed to strengthen the quality of evidence .

AUTHOR CONTRIBUTIONS

All review authors contributed to at least one aspect of each of the four criteria for authorship defined by the International Committee for Medical Journal Editors (ICJME).

G.F. contributed to the conception and design of the review, to the acquisition and analysis of data, and to the interpretation of results. Moreover, G.F. drafted the initial manuscript. S.C. contributed to the conception and design of the review, and to the interpretation of results. M.-A.M.-C. contributed to the conception and design of the review, to the acquisition of data, and interpretation of results. T.M. contributed to the conception and design of the review, to the acquisition of data, and to the interpretation of results. M.-F.D. contributed to the conception and design of the review, to the acquisition of data, and to the interpretation of results. G.M.-D. contributed to the conception and design of the review, and to the interpretation of results. J.C. contributed to the interpretation of results. M.-P.G. contributed to the interpretation of results. V.D. contributed to the interpretation of results.

All review authors contributed to manuscript writing, critically revised the manuscript, gave final approval, and agreed to be accountable for all aspects of work, ensuring integrity and accuracy.

DATA SHARING STATEMENT

No additional data available.

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FIGURE LEGENDS

Figure 1. PRISMA Study Flow Diagram.

Figure 2. Risk of bias summary: review authors' judgements about each risk of bias item for each included study.

Figure 3. Risk of bias graph: review authors' judgements about each risk of bias item presented as percentages across all included studies.

Figure 4. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving knowledge.

Figure 5. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving skills.

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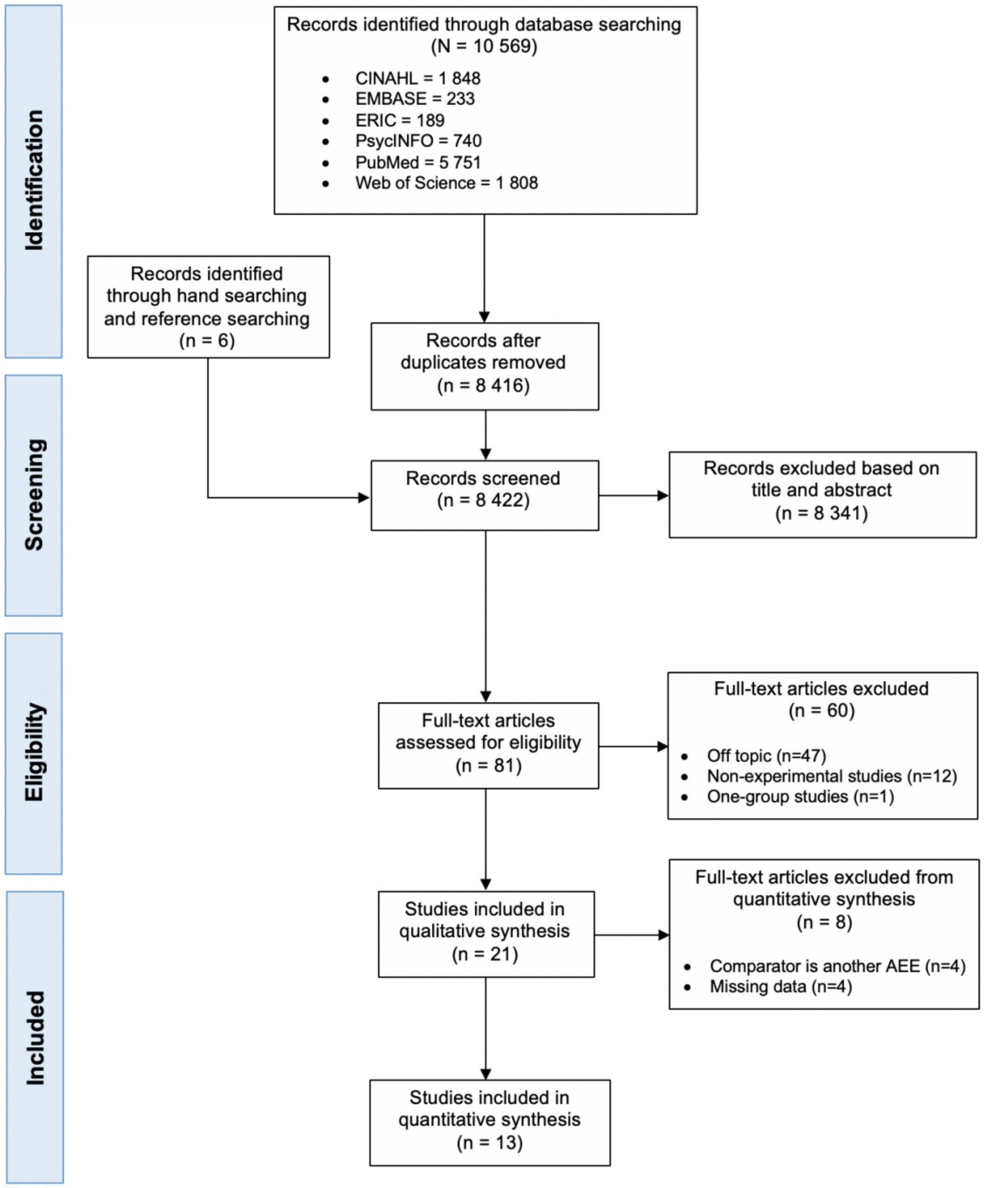

Figure 1. PRISMA study flow diagram.

242x292mm (144 x 144 DPI)

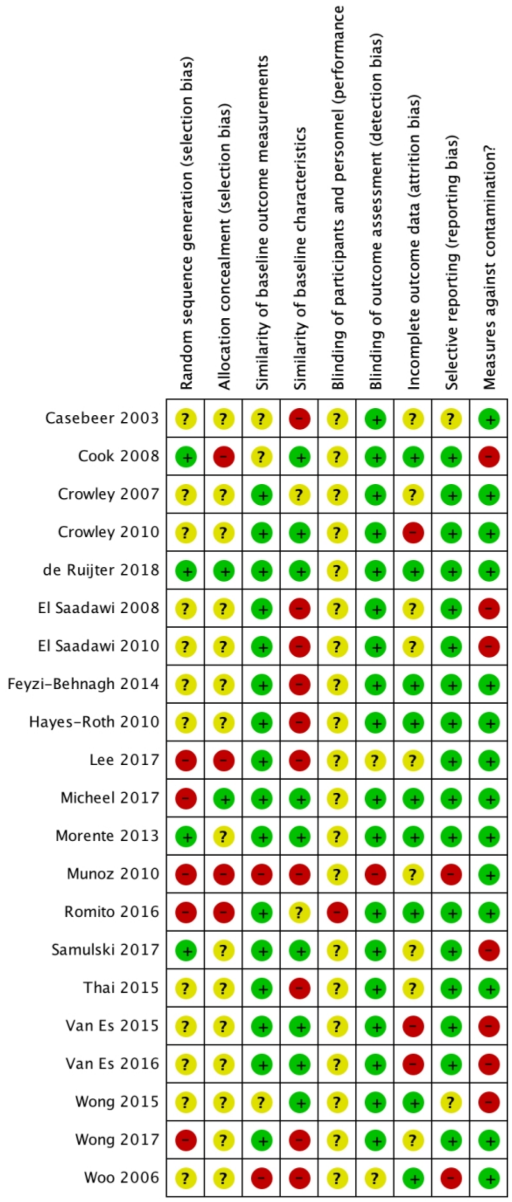

Figure 2. Risk of bias summary: review authors' judgements about each risk of bias item for each included study.

143x334mm (144 x 144 DPI)

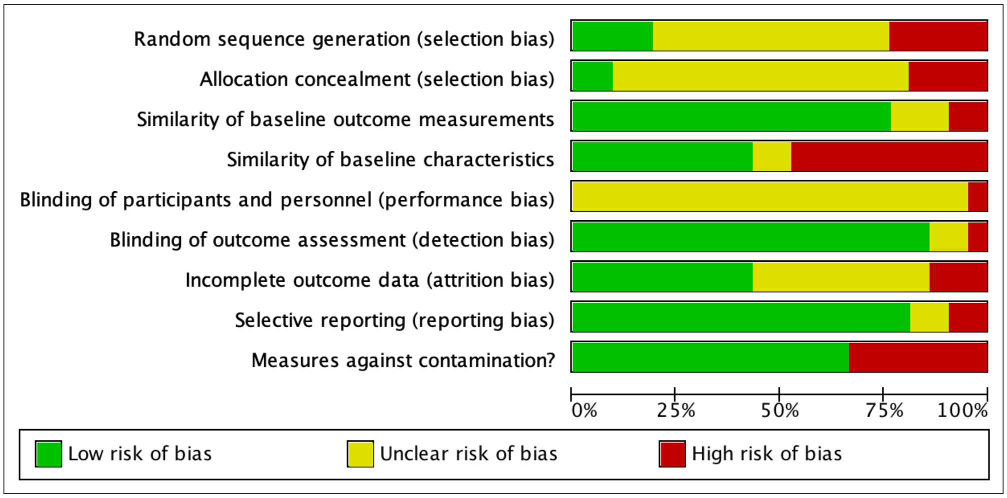

Figure 3. Risk of bias graph: review authors' judgements about each risk of bias item presented as percentages across all included studies.

219x107mm (144 x 144 DPI)

	Adaptive e-learning			Other educational interv.				Std. Mean Difference
Study or Subgroup	Mean	SD	Total	Mean	SD	Total	Weight	IV, Random, 95% CI
Cook 2008	76.2	0.9	62	77.2	0.9	62	17.1%	−1.10 [−1.48, −0.73]
de Ruijter 2018	14.876	1.242	121	14.8447	1.1093	103	17.4%	0.03 [−0.24, 0.29]
Micheel 2017	7.861	1.691	282	7.461	1.691	317	17.6%	0.24 [0.08, 0.40]
Morente 2013	15.83	2.52	30	11.6	2.39	42	16.3%	1.71 [1.16, 2.26]
Samulski 2017	5.83	2.43	18	4.47	2.47	18	15.7%	0.54 [−0.12, 1.21]
Wong 2015	68.2	2.7	39	60.5	2.3	41	15.8%	3.05 [2.39, 3.70]
Total (95% CI)			**552**			**583**	**100.0%**	**0.70 [−0.08, 1.49]**

Heterogeneity: $Tau^2 = 0.90$; $Chi^2 = 150.19$, $df = 5$ ($P < 0.00001$); $I^2 = 97\%$
Test for overall effect: $Z = 1.76$ ($P = 0.08$)

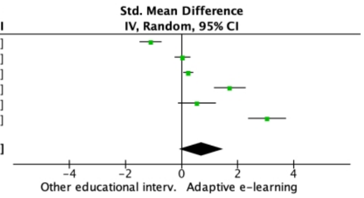

Figure 4. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving knowledge.

367x74mm (144 x 144 DPI)

Study or Subgroup	Adaptive e-learning Mean	SD	Total	Other educational interv. Mean	SD	Total	Weight	Std. Mean Difference IV, Random, 95% CI
Hayes-Roth 2010	16.32	1.54	11	10.95	2.03	11	10.3%	2.87 [1.61, 4.12]
Lee 2017	53	17	989	50	18	533	18.5%	0.17 [0.07, 0.28]
Romito 2016	67	4	12	53	6	12	11.1%	2.65 [1.51, 3.80]
Thai 2015	69	16	27	57	23	27	16.1%	0.60 [0.05, 1.14]
Van Es 2015	91.8	2.3	12	82.6	4.3	15	11.9%	2.51 [1.46, 3.55]
Van Es 2016	71.7	18.73	15	58.2	20.2	18	14.8%	0.67 [−0.03, 1.38]
Wong 2017	0.55	0.22	39	0.46	0.21	86	17.3%	0.42 [0.04, 0.80]
Total (95% CI)			**1105**			**702**	**100.0%**	**1.19 [0.59, 1.79]**

Heterogeneity: $Tau^2 = 0.50$; $Chi^2 = 57.00$, df = 6 ($P < 0.00001$); $I^2 = 89\%$
Test for overall effect: $Z = 3.88$ ($P = 0.0001$)

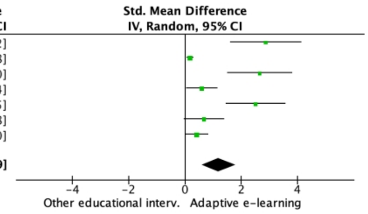

Figure 5. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving skills.

365x79mm (144 x 144 DPI)

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	1
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	4-5
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	7-9
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	9-10
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	10
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	10-11
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	11-12
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	Supplementary File 2
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	11-12
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	11-12
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	12-13
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	13
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	13-14
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	13-14

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	13
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	14
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	15
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	18
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	29-30
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	32-33
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	32-33
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	31
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	N/A
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	32-33
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	39
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	36-39
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	41

From: Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med 6(7): e1000097. doi:10.1371/journal.pmed1000097

For more information, visit: www.prisma-statement.org.

Supplementary File 2 – Search Strategy for PubMed

PubMed – 17 avril 2017

1. ((Adaptive[TIAB] OR individualized [TIAB] OR personalized[TIAB] OR Tailored[TIAB]) AND (elearning[TIAB] OR learning[TIAB] OR Instruction[TIAB] OR "web-based instruction"[TIAB] OR computer-based instruction[TIAB] OR computer-based tutoring[TIAB] OR education[TIAB] OR tutorial[TIAB] OR tutorials[TIAB])) OR Intelligent tutoring system[TIAB] OR Intelligent tutoring systems[TIAB]
2. "Computer-Assisted Instruction"[MH]
3. #1 OR #2
4. Health Personnel*[TIAB] OR Health professional*[TIAB] OR Health care profession*[TIAB] OR Healthcare profession*[TIAB] OR Medical student*[TIAB] OR Medical assistant*[TIAB] OR health worker*[TIAB] OR Audiologist*[TIAB] OR Chiropractor*[TIAB] OR Dentist[TIAB] OR Dentists[TIAB] OR Dietitian*[TIAB] OR Dermatolog*[TIAB] OR endocrinologist*[TIAB] OR Gastroenterolog*[TIAB]OR Gynecolog*[TIAB]OR Radiolog*[TIAB] OR Medical Staff[TIAB] OR Midwife*[TIAB] OR nutritionist*[TIAB] OR Nurse[TIAB] OR Nurses[TIAB] OR Optometrist*[TIAB] OR Occupational Therapist*[TIAB] OR Patholog*[TIAB] OR Paramedic[TIAB] OR Paediatric[TIAB] OR pediatrician*[TIAB] OR Paediatrician*[TIAB] OR pediatrist*[TIAB] OR pediatric[TIAB] OR Pharmacist*[TIAB] OR Pharmaconomist*[TIAB] OR Pharmacologist*[TIAB] OR Pharmacy technician*[TIAB] OR Phlebotomist*[TIAB] OR Physician OR Podiatrist*[TIAB] OR Psychologist*[TIAB] OR Psychotherapist*[TIAB] OR psychiatrist*[TIAB] OR Physical therapist*[TIAB] OR physiotherapist*[TIAB] OR Respiratory therapist*[TIAB] OR Surgeon*[TIAB] OR Clinician*[TIAB] OR Cardiologist*[TIAB] OR Emergency medical technician*[TIAB] OR emergency doctor*[TIAB] OR emergentologist*[TIAB] OR clinical officer*[TIAB] OR Community health worker*[TIAB] OR Radiographer*[TIAB] OR Surgical technologist*[TIAB] OR Radiotherapist*[TIAB] OR Anesthetist*[TIAB] OR Resident[TIAB] OR residents[TIAB]
5. "Health Personnel"[MH] OR "Students, Premedical"[MH] OR "Students, Medical"[MH] OR "Students, Nursing"[Mesh]
6. "Education, Premedical"[MH] OR "Education, Medical"[MH] OR "Education, Nursing"[MH] OR "Education, Pharmacy"[MH] OR "Education, Public Health Professional"[MH] OR "Clinical Clerkship"[MH]
7. #4 OR #5 OR 6
8. knowledge*[TIAB] OR Aptitude*[TIAB] OR accuracy[TIAB] OR impact*[TIAB] OR skill*[TIAB] OR performance*[TIAB] OR Learning outcome*[TIAB] OR effectiveness[TIAB] OR efficacy[TIAB] OR improvement*[TIAB] OR Innovative*[TIAB] OR innovation*[TIAB] OR randomised controlled trial[TIAB] OR randomized controlled trial[TIAB]
9. "Clinical Competence"[MH] "Quality Improvement"[MH] OR "Learning Curve"[MH] OR Knowledge [MH] OR "randomized controlled trial"[PT]
10. #8 OR 9
11. #3 AND #7 AND #10
12. (english[LA] OR french[LA]) AND 2005:2017[DP]
13. #11 AND #12

Résultats: 4 375

Supplementary File 3 – Summary of the quality of evidence

Certainty assessment							№ of patients		Effect		Certainty	Importance
№ of studies	Study design	Risk of bias	Inconsistency	Indirectness	Imprecision	Other considerations	adaptive and intelligent e-learning environments	other educational interventions	Relative (95% CI)	Absolute (95% CI)		
Knowledge												
6	randomised trials	serious [a]	serious [b]	not serious	serious [c]	none	552	583	-	SMD **0.7 SD higher** (0.08 lower to 1.49 higher)	⨁◯◯◯ VERY LOW	IMPORTANT
Competence												
7	randomised trials	serious [a]	not serious	not serious	serious [c]	none	1105	702	-	SMD **1.19 SD higher** (0.59 higher to 1.79 higher)	⨁⨁◯◯ LOW	CRITICAL

CI: Confidence interval; **SMD:** Standardised mean difference

Explanations

a. Most studies have unclear or high risk of bias with regard to random sequence generation and allocation concealment. The risk of bias for similarity of baseline measurements was unclear for some studies. Thus, groups in these studies could be disproportionate and the distribution may not be normal since sample size is generally small.

b. Studies yield widely differing estimates of effect (heterogeneity or variability in results). The individual confidence intervals of some studies almost do not touch.

c. Most studies include few participants and few events and have wide confidence intervals. Measurement instruments often not validated. Sample size often unsufficient.

BMJ Open

Efficacy of adaptive e-learning for health professionals and students: a systematic review and meta-analysis

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Efficacy of adaptive e-learning for health professionals and students: a systematic review and meta-analysis

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DECLARATION OF COMPETING INTERESTS

All authors have completed the ICMJE uniform disclosure form at www.icmje.org/coi_disclosure.pdf and declare: no support from any organisation for the submitted work; no financial relationships with any organisation that might have an interest in the submitted work in the previous three years; no other relationships or activities that could appear to have influenced the submitted work

TRANSPARENCY DECLARATION

The lead author (the manuscript's guarantor) affirms that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

FUNDING STATEMENT

This study received no funding.

ABSTRACT (300 WORDS)

Objective: Although adaptive e-learning environments (AEEs) can provide personalized instruction to health professional and students, their efficacy remains unclear. Therefore, this review aimed to identify, appraise, and synthesize the evidence regarding the efficacy of AEEs in improving knowledge, skills, and clinical behavior in health professionals and students.

Design: Systematic review and meta-analysis.

Data Sources: CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science from the first year of records to February 2019.

Eligibility Criteria: Controlled studies that evaluated the effect of an AEE on knowledge, skills or clinical behavior in health professionals or students.

Screening, Data Extraction and Synthesis: Two authors screened studies, extracted data, assessed risk of bias, and coded quality of evidence independently. AEEs were reviewed with regard to their topic, theoretical framework, and adaptivity process. Studies were included in the meta-analysis if they had a non-AEE control group and had no missing data. Effect sizes (ES) were pooled using a random effects model.

Results: From a pool of 10,569 articles, we included 21 eligible studies enrolling 3,684 health professionals and students. Clinical topics were mostly related to diagnostic testing, theoretical frameworks were varied, and the adaptivity process was characterized by 5 subdomains: method, goals, timing, factors, and types. The pooled ES was 0.70 for knowledge (95% CI, -0.08-1.49; P .08), and 1.19 for skills (95% CI, 0.59-1.79; $P < .00001$). Risk of bias was generally high. Heterogeneity was large in all analyses.

Conclusions: AEEs appear particularly effective in improving skills in health professionals and students. The adaptivity process within AEEs may be more beneficial for learning skills rather than factual knowledge, which generates less cognitive load. Future research should report more clearly on the design and adaptivity process of AEEs, and target higher-level outcomes, such as clinical behavior.

PROSPERO registration number: CRD42017065585

Keywords: Computer-assisted instruction; medical education; nursing education; e-learning, meta-analysis

ARTICLE SUMMARY

Strengths and Limitations of the Study

- This is the first systematic review and meta-analysis examining the efficacy of adaptive e-learning environments in improving knowledge, skills, and clinical behavior in health professionals and students.
- Strengths of this review include the broad search strategy, and in-depth assessments of the risk of bias and the quality of evidence.
- High statistical heterogeneity resulting from clinical and methodological diversity limits the interpretation of findings.
- Quantitative results should be treated with caution, given the small number and risk of bias of studies included in the meta-analysis.

INTRODUCTION

The use of information and communication technologies (ICTs) in the education of health professionals and students has become ubiquitous. Indeed, e-learning, defined as the use of ITCs to access educational curriculum and support learning[1], is increasingly present in clinical settings for the continuing education of health professionals[2 3], and in academic settings for the education of health professions students[4]. E-learning environments integrate information, in the form of text and multimedia (e.g., illustrations, animations, videos). They can include both asynchronous (i.e., designed for self-study) and synchronous (i.e., a class taught by an educator in real time) components[1]. *Nonadaptive* e-learning environments, the most widespread type of e-learning environment today, provide a standardized training for all learners[5 6]. While they can include instructional design variations (e.g., interactivity, feedback, practice exercises), they *do not* consider learners' characteristics and the data generated during the learning process to provide a personalized training[6-8]. This is problematic, since the interaction of health professionals and students with e-learning environments during the learning process generates a significant amount of data[9]. However, designers of e-learning environments and educators rarely make use of this data to optimize learning efficacy and efficiency[9].

In recent years, educational researchers have strived to develop e-learning environments that take a data-driven and personalized approach to education[10-13]. E-learning environments that take into account each learner's interactions and performance level could anticipate what types of content and resources meet the learner's needs, potentially increasing learning efficacy and efficiency[13]. Adaptive e-learning environments (AEEs) were developed for this purpose. AEEs collect data to build each learner's profile (e.g., navigation behavior, preferences, knowledge), and use simple techniques (e.g., adaptive information filtering, adaptive hypermedia) to implement different types of adaptivity targeting the content, navigation, presentation, multimedia, or strategies of the training to provide a personalized learning experience [11 12]. In the fields of computer science and educational technology, the term *adaptivity* refers to the process executed by a system based on ICTs of adapting educational curriculum content, structure or delivery to the profile of a learner[14]. Two main methods of adaptivity can be implemented within an AEE. The first method, *designed adaptivity*, is expert-based and refers to an educator who designs the optimal instructional sequence to guide learners to learning content mastery. The educator determines how the curriculum will adapt to learners based on a variety of factors, such as knowledge or response time to a question. This method of adaptivity is thus based on the expertise of the educator who specifies how technology will react in a particular situation on the basis of the "if THIS, then THAT" approach. The second method, *algorithmic adaptivity*, refers to use of algorithms to determine, for instance, the extent of the learner's knowledge and the optimal instructional sequence. Algorithmic adaptivity requires more advanced adaptivity techniques and learner-modelling techniques derived from the fields of computer science and artificial intelligence (e.g. Bayesian knowledge tracing, rule-based machine learning, natural language processing) [10 15-18].

The variability in the degree and the complexity of adaptivity within AEEs mirrors the adaptivity that can be observed in non–e-learning educational interventions. Some interventions, like one-on-one human instruction and small-group classroom instruction, generally have a high degree of adaptivity since the instructor can adapt his teaching to the individual profiles of learners and consider their feedback [19]. Other interventions, like large-group classroom instruction, generally have a low degree of adaptivity to individual learners. In some interventions, like paper-based instruction (e.g., handouts, textbooks), there is no adaptivity at all.

AEEs have been developed and evaluated primarily in academic settings for students in mathematics, physics and related disciplines, for the acquisition of knowledge and development of cognitive skills (e.g., arithmetic calculation). Four meta-analyses reported on the efficacy of AEEs among high school and university students in in these fields of study [15-17 20]. The results are promising: AEEs are in almost all cases more effective than large-group classroom instruction. In addition, Nesbit, et al. [21] point out that AEEs are more effective than nonadaptive e-learning environments. However, despite evidence of the efficacy of AEEs for knowledge acquisition and skill development in areas such as mathematics in high school and university students, their efficacy in improving learning outcomes in health professionals and students has not yet been established. To address this need, we conducted a systematic review and meta-analysis to identify and quantitatively synthesize all comparative studies of AEEs involving health professionals and students.

Systematic Review and Meta-Analysis Objective

To systematically identify, appraise, and synthesize the best available evidence regarding the efficacy of AEEs in improving knowledge, skills, and clinical behavior in health professionals and students.

Systematic Review and Meta-Analysis Questions

We sought to answer the following questions with the systematic review:

1. What are the characteristics of studies assessing an AEE designed for health professionals' and students' education?
2. What are the characteristics of AEEs designed for health professionals' or students' education?

We sought to answer the following question with the meta-analysis:

3. What is the efficacy of AEEs in improving knowledge, skills, and clinical behavior in health professionals and students in comparison with nonadaptive e-learning environments, and non–e-learning educational interventions?

METHODS

We planned and conducted this systematic review following the Effective Practice and Organization of Care (EPOC) Cochrane Group guidelines[22], and reported it according to the Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) standards[23] (see **Supplementary File 1**). We prospectively registered (International Prospective Register of Systematic Reviews #CRD42017065585) and published the protocol of this systematic review[24]. Thus, in this paper, we present an abridged version of the methods with an emphasis on changes made to the methods since the publication of the protocol.

Study Eligibility

We included primary research articles that assessed an AEE with licensed health professionals, students, trainees, and residents in any discipline. We defined an AEE as a computer-based learning environment which collects data to build each learner's profile (e.g., navigation behavior, individual objectives, knowledge), interprets these data through algorithms, and adapts in real-time the content (e.g., showing/hiding information), navigation (e.g., specific links and paths), presentation (e.g., page layout), multimedia presentation (e.g., images, videos), or tools (e.g., different set of strategies for different types of learners) to provide a dynamic and evolutionary learning path for each learner[10 14]. We used the definitions of each type of adaptivity proposed by Knutov and colleagues[12]. We considered for inclusion studies in which AEEs had designed or algorithmic adaptivity, and studies including a co-intervention in addition to adaptive e-learning (e.g. paper-based instruction). We considered for inclusion primary research articles in which the comparator was: 1) a nonadaptive e-learning environment; 2) a non–e-learning educational intervention; 3) another AEE with design variations. While included in the qualitative synthesis of the evidence for descriptive purposes, the third comparator was excluded from the meta-analysis. Outcomes of interest were knowledge, skills, and behavior[25 26], and were defined as follows: 1) knowledge: subjective (e.g., learner self-report) or objective (e.g., multiple-choice question knowledge test) assessments of factual or conceptual understanding; 2) skills: subjective (eg, learner self-report) or objective (eg, faculty ratings) assessments of procedural skills (e.g. taking a blood sample, performing CPR) or cognitive skills (e.g. problem-solving, interpreting radiographs) in learners; 3) behavior: subjective (eg, learner self-report) or objective (eg, chart audit) assessments of behaviors in clinical practice (such as test ordering) [6]. In terms of study design, we considered for inclusion all controlled, quantitative studies in accordaSsnce with the EPOC Cochrane Review Group guidelines[27].

We excluded studies that: 1) were not published in English or French; 2) were non-experimental; 3) were not controlled; 4) did not report on at least one of the outcomes of interest in this review; 5) did not have a topic related to the clinical aspects of health.

Study Identification

We previously published our search strategy[24]. Briefly, we designed a strategy in consultation with a librarian to search CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science for primary research articles published since the inception of each database up to February 2019. The search strategy revolved around 3 key concepts: “adaptive e-learning environments”, “health professionals/students", and "effects on knowledge/competence (skills)/behavior" (see **Supplementary file 2**). To identify additional articles, we hand-searched 6 key journals (e.g., *British Journal of Educational Technology*, *Computers and Education*) and the reference lists of included primary research articles.

Study Selection

We worked independently and in duplicate (G.F. and M.-A.M.-C./T.M.) to screen all titles and abstracts for inclusion using the EndNote software V8.0 (Clarivate Analytics). We resolved disagreements by consensus. We then performed the full-text assessment of potentially eligible articles using the same methodology. Studies were included in the meta-analysis if they had a non-AEE control group and had no missing data.

Data Extraction

One review author (G.F.) extracted data from included primary research articles using a modified version of the data collection form developed by the EPOC Cochrane Review Group [28]. The main changes made to the extraction form were the addition of specific items relating to the AEE assessed in each study. Two review authors (T.M., M.-F.D.) validated the data extraction forms by reviewed the contents of each form against the data in the original article, adding comments when changes were needed. For all studies, we extracted the following data items if possible:

- *the population and setting*: study setting, study population, inclusion criteria, exclusion criteria;
- *the methods*: study aim, study design, unit of allocation, study start date and end date, and duration of participation;

- *the participants*: study sample, withdrawals and exclusions, age, sex, level of instruction, number of years of experience as a health professional, practice setting, and previous experience using e-learning;
- *the interventions*: name of intervention, theoretical framework, statistical model/algorithm used to generate the learning path, clinical topic, number of training sessions, duration of each training session, total duration of the training, adaptivity subdomains (method, goals, timing, factors, types), mode of delivery, presence of other educational interventions and strategies;
- *the outcomes*: name, time-points measured, definition, person measuring, unit of measurement, scales, validation of measurement tool;
- *the results*: results according to our primary (knowledge) and secondary (skills, behavior) outcomes, comparison, time-point, baseline data, statistical methods used, and key conclusions.

We contacted the corresponding authors of included primary research articles to provide us with missing data.

Assessment of the Risk of Bias

We worked independently and in duplicate (G.F. and T.M./M.-F.D.) to assess the risk of bias of included primary research articles using the EPOC risk of bias criteria, based upon the data extracted with the data collection form[28]. A study was deemed at high risk of bias if the individual criterion "random sequence generation" was scored at "high" or at "unclear" risk of bias.

Data Synthesis

First, we synthesized data qualitatively using tables to provide an overview of the included studies, and of the AEEs reported in these studies.

Second, using the Review Manager (RevMan) software V5.1, we first conducted a meta-analysis to quantitatively synthesize the efficacy of AEEs versus other educational interventions in improving all learning outcomes. We included studies in the meta-analysis if the comparator wasn't another AEE, if they were randomized, and if they reported outcome data. We then conducted meta-analyses with the same comparison for each outcome for which data from at least 2 studies were available (i.e., knowledge, skills). For randomized controlled trials (RCTs), we converted each post-test mean and standard deviation (SD) to a standardized mean difference ([SMD], also known as Hedges g effect size [ES]). For crossover RCTs, we used means pooled across each intervention. We pooled ESs using a random effects model. Statistical significance was defined by a two-sided alpha of .05.

We first assessed heterogeneity qualitatively by examining the characteristics of included studies, the similarities and disparities between the types of participants, the types of interventions, and the types of outcomes. We then used the I^2 statistic within the RevMan software to quantify how much the results varied across individual studies (i.e., between-study inconsistency, or heterogeneity). We interpreted the I^2 values as follows: 0%-40%: might not be important; 30%-60%: may represent moderate heterogeneity; 50%-90%: may represent substantial heterogeneity; and 75%-100%: considerable heterogeneity[29]. We performed sensitivity analysis to assess if the exclusion of studies at high risk of bias or with a small sample size (n<20) would have had an impact on statistical heterogeneity. Subgroup analyses were performed to examine if study population and study comparators were potential effect modifiers.

Since less then 10 studies were included in the meta-analysis for each outcome, we did not assess reporting biases using a funnel plot, as suggested in the Cochrane Handbook[30].

Assessment of the Quality of Evidence

We worked independently and in duplicate (G.F. and M.-A.M.-C.) to assess the quality of evidence for each individual outcome. We used the Grading of Recommendations Assessment, Development, and Evaluation (GRADE) Web-based software, based upon the data extracted with the data collection checklist [31]. We considered 5 factors (risk of bias of included studies, indirectness of evidence, unexplained heterogeneity or inconsistency of results, imprecision of the results, probability of reporting bias) for downgrading the quality of the body of evidence for each outcome [31].

Patient and Public Involvement

Patients and the public were not involved in setting the research question, the outcome measures, the design or conduct of this systematic review. Patients and the public were not asked to advise on interpretation of results or to contribute to the writing or editing of this document.

RESULTS

Study Flow

From a pool of 10,569 potentially relevant articles, we found 21 quantitative, controlled studies assessing an AEE with health professionals or students (see **Figure 1**).

[Insert Figure 1]

Out of 21 included studies in the qualitative synthesis, 4 studies compared two AEEs with design variations[32-35], and 4 studies had missing data[36-39]. The 4 studies with missing data did not report properly data regarding the results, i.e. mean scores and standard deviations in both study groups at post-test, regarding the outcomes of interest in this review (i.e., knowledge, skills or clinical behavior). Thus, 13 studies were included in the meta-analysis and used to calculate an ES on learning outcomes.

Study Characteristics

We summarized the key characteristics of included studies in table format (see **Table 1**). In terms of study population, in the 21 studies examined published between 2003 and 2018, investigators have evaluated AEEs mostly in the medical field. Studies focused on medical students (n=8) [38-44], medical residents (n=8) [32-35 41 45-47], physicians in practice (n=4) [36 37 41 48], nursing students (n=2) [40 49], nurses in practice (n=2) [48 50] and health sciences students (n=1) [51]. Three studies focused on multiple populations [40 41 48]. The median sample size was 46 participants (interquartile range [IQR] 123). In terms of study design, 15 out of 21 studies (71%) were randomized, 7 studies of which were randomized crossover trials [33 34 41-43 45 47]. The median number of training sessions was 2 (IQR 2.5 sessions), the median training time was 2.13 hours (IQR 2.88 hours), and the median training period was 14 days (IQR 45 days). In terms of comparators, it is possible to underline three types of comparisons. The first comparison is an AEE versus another AEE with design variations (n=4) [32-35], which implies that one of the AEEs assessed had variations in its design, such as different types of adaptivity (e.g., feedback in one AEE is longer or more complex than in the other). The second comparison is an AEE versus a nonadaptive e-learning environment (n=11) [38-40 42-46 48 50 51]. The third and final comparison is an AEE versus another type of educational intervention, such as a paper-based educational intervention, including handouts, textbooks or images (n=3) [37 41 47], or a traditional educational intervention, such as a group lecture (n=2) [49 52]. In one study, the comparator was not clearly reported [36]. As stated before, only the second and third types of comparisons were included in the meta-analysis since our aim was to synthesize quantitatively the efficacy of AEEs versus other types of educational interventions.

Finally, regarding the outcomes, knowledge was assessed in 14 out of 21 studies (66.7%) [32 35 36 38 39 41-45 47-50], skills in 9 studies (42.9%) [33 34 36 37 40 46 50-52], and clinical behavior in 2 studies (9.5%) [44 50]. Outcome measures for knowledge were similar across studies: in 9 out of 14 studies measuring knowledge, investigators employed multiple-choice questionnaires developed by the research team with input from content experts that were tailored to training content to ensure specificity. Knowledge was also assessed using true-false questions in two studies, and the type of questionnaire was not specified in three studies. Outcome measures for skills were also similar across the 9 studies reporting this outcome, since in all studies investigators measured *cognitive* skills rather than *procedural* skills. Indeed, all outcomes measures for skills were related to clinical reasoning. In 6 studies, skills were measured through tests that included a series of diagnostic tests (eg electrocardiograms, x-rays, miscroscopy images) that learners had to interpret. In 3 studies, skills wre measured through questions based on clinical situations in which learners had to specify how they would react in these particular situations. We were not able to describe the similarity between the outcome measures for clinical behaviour no details were provided in one of the two studies reporting this outcome.

Table 1. Characteristics of Included Studies.

First Author, Year Country	Participants*	Study Design†	No. and Duration of Training Sessions	Duration of Intervention	Comparison(s)‡	Type of Outcome(s) of Interest§	Outcome Measures
Comparison: adaptive e-learning environments vs. other educational interventions							
Casebeer, 2003 USA	PP; N = 181	RCT; posttest-only, 2 groups	4 sessions; 1 hour each	NR	NR	Knowledge	21-item multiple-choice questionnaire
						Skills	
Cook, 2008 USA	R; N = 122	RXT; posttest-only, 4 groups	4 sessions; 30 minutes each	126 days	NEE	Knowledge	69-item case-based multiple-choice questionnaire
Crowley, 2010 USA	PP; N = 15	RCT; pretest–posttest, 2 groups	4 sessions; 4 hours each	138 days	P	Skills	Virtual slide test to examine diagnostic accurary
de Ruijter, 2018 Netherlands	NP; N = 269	RCT; pretest-posttest, 2 groups	No fixed sessions	180 days	NEE	Knowledge	18-item true-false questionnaire (range 0–18)
						Behavior	9-item self-reported questionnaire (range 0–9)
Hayes-Roth, 2010 USA	MS, NS; N = 30	RCT; pretest–posttest–retention-test, 3 groups	NR; mean training time 2.36 hours	NR	1. NEE 2. NI	Skills	6-item written skill probe (range -6–18)
Lee, 2017 USA	MS; N = 1522	NRCT; pretest-posttest, 3 groups	5 sessions; NR	42 days	NEE	Knowledge	Unclear
						Skills	Multidimensional situation-based questions –RealIndex (range 0–100%)
						Behavior	Unclear
Micheel, 2017 USA	PP, NP; N = 751	NRCT; pretest–posttest–retention-test, 2 groups	NR	NR	NEE	Knowledge	10-item true-false questionnaire (range 0–10)
Morente, 2013 Spain	NS; N = 73	RCT; pretest–posttest, 2 groups	1 session; 4 hours	1 day	T	Knowledge	22-item multiple-choice questionnaire (range 0–22)

Munoz, 2010 Colombia	MS; N = 40	NRCT; pretest–posttest, 2 groups	NR; mean training time 5.97 hours	NR	NEE	Knowledge	10-item multiple-choice questionnaire (range 0–10)
Romito, 2016 USA	R; N = 24	NRCT; pretest–posttest–retention-test, 2 groups	1 session; 30 minutes	1 day	NEE & T	Skills	22-item videoclip-based test
Samulski, 2017 USA	MS, R, PP; N = 36	RXT; pretest–posttest, 2 groups	2 sessions; 20 minutes to 14 hours	1 month	P	Knowledge	28-item multiple-choice questionnaire (range 0–100%)
Thai, 2015 USA	HSC; N = 87	RCT; pretest–posttest–retention-test, 3 groups	1 session; 45 minutes	1 day	1. AEE 2. NEE	Skills	14-item case-based test (range 0–100%)
Van Es, 2015 Australia	R; N = 43	RXT; posttest-only, 2 groups	3 sessions; NR	50 days	P	Knowledge	7 to 21-item multiple-choice questionnaire (range 0–100%)
Van Es, 2016 Australia	MS; N = 46	RXT; posttest-only, 2 groups	3 sessions; 2 hours each	34 days	NEE	Knowledge	Multiple-choice questionnaire
Wong, 2015 Australia	MS; N = 99	RXT; posttest-only, 2 groups	2 sessions; 1.5 hour each	14 days	NEE	Knowledge	8-item multiple-choice and interactive questions (range 0–100%)
Wong, 2017 USA	MS; N = 178	NRCT; pretest–posttest–retention-test, 3 groups	1 session; NR	35 days	1. T 2. AEE & T	Skills	Test to examine diagnostic accuracy
Woo, 2006 USA	MS; N = 73	NRCT; pretest–posttest, 3 groups	1 session; 2 hours	1 day	1. NEE 2. NI	Knowledge	Short-response questionnaire
Comparison: adaptive e-learning vs. adaptive e-learning (two AEEs with design variations)							
Crowley, 2007 USA	R; N = 21	RCT; pretest–posttest–retention-test, 2 groups	1 session; 4.5 hours	1 day	AEE	Knowledge	51-item multiple-choice questionnaire (range 0–100%)
El Saadawi, 2008 USA	R; N = 20	RXT; pretest–posttest, 2 groups	2 sessions; 2 hours each	1 day	AEE	Skills	Virtual slide test to examine diagnostic accuracy

1

El Saadawi, 2010 USA	R; N = 23	RXT; pretest–posttest, 2 groups	2 sessions; 2.25 hours each	2 days	AEE	Skills	Virtual slide test to examine diagnostic accuracy
Feyzi-Begnagh, 2014 USA	R; N = 31	RCT; pretest–posttest, 2 groups	2 sessions; 2 & 3 hours	1 day	AEE	Knowledge	Unspecified test

* Participants: MS indicates medical students; NS, nursing students; R, residents (physicians in postgraduate training); PP, physicians in practice; NP, nurses in practice; HSC, health sciences students.

† Study design: RCT indicates randomized controlled trial; RXT, randomized crossover trial; NRCT, non-randomized controlled trial.

‡ Comparison: AEE indicates adaptive e-learning environment; NEE, nonadaptive e-learning environment; NI, no-intervention control group; T, traditional (group lecture); P, paper (handout, textbook, or latent image cases).

Characteristics of Adaptive E-Learning Environments

We summarized the key characteristics of AEEs assessed in the 21 studies in table format (see **Table 2**). In terms of the clinical topics of the AEEs, the majority of AEEs focused on training medical students and residents in executing and/or interpreting diagnostic tests. Indeed, a significant proportion of the AEEs assessed focused on dermopathology and cytopathology microscopy [32-35 37 41 42 47] (n=8). Other topics were diagnostic imaging [43 46] (n=2), behavior change counseling [40 50] (n=2), chronic disease management [45 48] (n=2), pressure ulcer evaluation [49] (n=1), childhood illness management [38] (n=1), electrocardiography [51] (n=1), fetal heart rate interpretation [52] (n=1), hemodynamics [39] (n=1), chlamydia screening (n=1) [36] and atrial fibrillation management (n=1) [44].

The 21 AEEs examined were based on a wide variety of theoretical frameworks. The most frequently used framework was cognitive tutoring, adopted in 5 studies [32-35 37], which refers to the use of a cognitive model. The integration of a cognitive model in an AEE implies the representation of all the knowledge in the field of interest in a way that is similar to the human mind for the purpose of understanding and predicting the cognitive processes of learners [53]. The second most used framework was perceptual learning, adopted in 3 studies [46 51 52]. Perceptual learning aims at improving information extraction skills of the environment and the development of automaticity in this respect in learners [46]. Interestingly, 2 studies used models from behavioral science, the Transtheoretical Model [36] and the I-Change Model [50], to tailor the AEE to the theoretical determinants of clinical behavior change in nurses and physicians in practice. Theoretical frameworks relating to self-regulated learning [35], learning styles [38 48], guided mastery [40], and cognitive load [43], problem-based-learning [36], and situated learning [36] were also used.

Three main adaptive e-learning platforms were used by investigators in studies examined: SlideTutor (n=4) [33 37 54 55], Smart Sparrow (n=4) [41-43 47], and the Perceptual Adaptive Learning Module (PALM, n=3) [51 52 56]. SlideTutor is an AEE with algorithmic adaptivity which provides cases to be solved by learners under supervision by the system. These cases incorporate dermopathology virtual slides that must be examined by learners to formulate a diagnosis. An expert knowledge base, consisting of evidence-diagnosis relationships, is used by SlideTutor to create a dynamic solution graph representing the current state of the learning process and to determine the optimal instructional sequence [55]. Smart Sparrow is an AEE with designed adaptivity which allows educators to determine adaptive factors, such as answers to questions, response time to a question, and learner actions, to specify how the system will adapt the instructional sequence or provide feedback. These custom learning paths can be more or less personalized [42]. PALM is an AEE with algorithmic adaptivity aiming to improve perceptual learning through adaptive response-time-based sequencing to determine dynamically the spacing between different learning items based on each learner's accuracy and speed in interactive learning trials [51]. Different custom adaptive e-learning platforms were used in other studies.

Table 2. Characteristics of adaptive e-learning environments.

First Author, Year	Clinical Topic(s)	Theoretical Framework(s)	Platform	Adaptivity Subdomains				
				Adaptivity Method	Adaptivity Goals	Adaptivity Timing	Adaptivity Factors	Adaptivity Types
Casebeer, 2003	Chlamydia screening	Transtheoretical model of change; Problem-based learning; Situated learning theory	NR	Designed Adaptivity	To increase learning effectiveness (knowledge, skills).	Throughout the training, after case-based and practice-based questions.	User answers to questions	• Content • Navigation
Cook, 2008	Diabetes, hyperlipidemia, asthma, depression	NR	NR	Designed Adaptivity	To increase learning efficiency (knowledge gain divided by learning time).	After each case-based question in each module (17 to 21 times/module).	User knowledge	• Content • Navigation
Crowley, 2007	Dermopathology; subepidermal vesicular dermatitis	Cognitive Tutoring	SlideTutor	Algorithmic Adaptivity	To increase learning gains, metacognitive gains, and diagnostic performance.	At the beginning of each case.	User actions: results of problem-solving tasks; requests for help	• Content • Navigation • Presentation • Multimedia • Tools
Crowley, 2010	Dermopathology; melanoma	Cognitive Tutoring	SlideTutor	Algorithmic Adaptivity	To improve reporting performance and diagnostic accuracy.	At the beginning of each case.	User actions: results of problem-solving tasks; reporting tasks; requests for help	• Content • Navigation • Presentation • Multimedia • Tools
de Ruijter, 2018	Smoking cessation counseling	I-Change Model	Computer-Tailored E-Learning Program	Designed Adaptivity	To modify behavioral predictors and behavior.	At the beginning of the training.	Demographics, behavioral predictors, behavior	• Content
El Saadawi, 2008	Dermopathology; melanoma	Cognitive Tutoring	ReportTutor	Algorithmic Adaptivity	To teach how to correctly identify and document all relevant	At the beginning of each case.	User actions, report features	• Content • Navigation • Presentation • Multimedia

					prognostic factors in the diagnostic report.			
El Saadawi, 2010	Dermopathology	Cognitive Tutoring	SlideTutor	Algorithmic Adaptivity	To facilitate transfer of performance gains to real-world tasks that do not provide direct feedback on intermediate steps.	During intermediate problem-solving steps.	User actions: results of problem-solving tasks; reporting tasks; requests for help	• Content • Navigation • Presentation • Multimedia
Feyzi-Begnagh, 2014	Dermopathology; nodular and diffuse dermatitis	Cognitive Tutoring, Theories of Self-Regulated Learning	SlideTutor	Algorithmic Adaptivity	To improve metacognitive and learning gains during problem solving.	During each case or immediately after each case.	User actions: results of problem-solving tasks; reporting tasks; requests for help	• Content • Navigation • Presentation • Multimedia • Tools
Hayes-Roth, 2010	Brief intervention training in alcohol abuse	Guided Mastery	STAR Workshop	NR	To improve attitudes and skills.	During clinical cases.	User scores, user-generated dialogue	• Content • Navigation
Lee, 2017	Treatment of atrial fibrillation	NR	Learning Assessment Platform	Designed Adaptivity	To increase learning effectiveness (knowledge, competence, confidence and practice).	After learning gaps identified in the first session.	Learning gaps in relation to objectives	• Content
Micheel, 2017	Oncology	Learning Style Frameworks	Learning-style tailored educational platform	Designed Adaptivity	To increase learning effectiveness (knowledge).	After assessing the learning style.	Learning style	• Presentation • Multimedia • Tools

Morente, 2013	Pressure ulcer evaluation	NR	ePULab	Designed Adaptivity	To increase learning effectiveness (knowledge, skills).	Each pressure ulcer evaluation.	User skills	• Content
Munoz, 2010	Management of childhood illness	Learning Styles Framework	SIAS-ITS	Designed Adaptivity	To increase learning effectiveness and efficiency.	At the beginning of the training.	User knowledge, user learning style	• Content • Tools
Romito, 2016	Transoesophageal echocardiography	Perceptual Learning	TOE PALM	Algorithmic Adaptivity	To improve response accuracy and response time.	After each clinical case.	User response accuracy, user response time	• Content • Navigation • Multimedia
Samulski, 2017	Cytopathology; pap test, squamous lesions, glandular lesions	NR	Smart Sparrow	Designed Adaptivity	To improve learning effectiveness.	During intermediate problem-solving steps.	User knowledge	• Content • Navigation
Thai, 2015	Electrocardiography	Perceptual Learing Theory; Adaptive response-time based algorithm	PALM	Algorithmic Adaptivity	To improve perceptual classification learning effectiveness and effiency.	After each user response.	User response accuracy, user response time	• Content • Presentation • Multimedia • Tools
Van Es, 2015	Diagnostic cytopathology; gynecology, fine needle aspiration, exfoliative fluid	NR	Smart Sparrow	Designed Adaptivity	To improve learning effectiveness.	During intermediate problem-solving steps.	User responses	• Content • Navigation • Presentation • Multimedia
Van Es, 2016	Diagnostic cytopathology; gynecology, fine needle aspiration, exfoliative fluid	NR	Smart Sparrow	Designed Adaptivity	To improve learning effectiveness.	During intermediate problem-solving steps.	User responses	• Content • Navigation • Presentation • Multimedia • Tools

Wong, 2015	Diagnostic imaging; chest X-rays, CT scans	Cognitive Load Theory	Smart Sparrow	Designed Adaptivity	To improve learning effectiveness.	During intermediate problem-solving steps.	User responses	• Content
Wong, 2017	Fetal heart rate interpretation	Perceptual Learning	PALM	Algorithmic Adaptivity	To improve response accuracy and response time.	After each clinical case.	User response accuracy, user response time	• Content • Navigation • Multimedia
Woo, 2006	Hemodynamics; baroreceptor reflex	NR	CIRCSIM-Tutor	Algorithmic Adaptivity	To improve knowledge related to problem-solving tasks.	After each user response.	User knowledge, user responses	• Content • Navigation • Tools

We propose 5 subdomains that emerged from the review to characterize the adaptivity process of AEEs reported in the 21 studies: adaptivity method, adaptivity goals, adaptivity timing, adaptivity factors and adaptivity types.

First Subdomain: Adaptivity Method

This subdomain relates to the method of adaptivity that dictates how the AEE adapts instruction to a learner. As we previously described, there are two main methods of adaptivity: *designed adaptivity* and *algorithmic adaptivity*. The first is based on the expertise of the educator who specifies how technology will react in a particular situation on the basis of the "if THIS, then THAT" approach. The second refers to use of algorithms that will determine, for instance, the extent of the learner's knowledge and the optimal instructional sequence. In this review, 11 AEEs employed designed adaptivity [36 38 41-44 47-50 57], and 9 AEEs employes algorithmic adaptivity [33 37 39 51 52 54-56 58]. The adaptivity method wasn't specified in one study [40].

Second Subdomain: Adaptivity Goals

This subdomain relates to the purpose of the adaptivity process within the AEE. For most AEEs, the adaptivity process aims primarily to increase the efficacy and/or efficiency of knowledge acquisition and skills development relative to other training methods [32 35 36 38-45 47-49 51]. For instance, several AEEs aimed to increase the diagnostic accuracy and reporting performance of medical students and residents [32-34 37 46 52]. In one study, the goal of adaptivity was to modify behavioral predictors and behavior in nurses [50]. In cases where two adaptive AEEs with certain variations in their techno-pedagogical design are compared with each other, the adaptivity process generally aims at improving the metacognitive and cognitive processes related to learning [32 33 35].

399 ### Third Subdomain: Adaptivity Timing

400 This subdomain relates to *when* the adaptivity occurs during the learning process with the AEE.
401 In 19 out of 21 studies, the adaptivity occurred throughout the training with AEE, usually after an
402 answer to a question or during intermediate problem-solving steps. However, in two studies,
403 adaptivity was only implemented at the beginning of the training with the AEE following survey
404 responses [38 50].

405 ### Fourth Subdomain: Adaptivity Factors

406 This subdomain relates to the learner-related data (variables) upon which the adaptivity process is
407 based. The most frequently targeted variable is the learner's scores after an assessment or a
408 question within the AEE (e.g., knowledge/skills scores, response accuracy scores) [38-43 45-47 49 51 52].
409 Other frequently targeted variables include the learner's actions during its use of the AEE (e.g.,
410 results of problem-solving tasks, results of reporting tasks, requests for help) [32-35 37], and the
411 learner's response time regarding a specific question or task [46 51 52].

412 ### Fifth Subdomain: Adaptivity Types

413 The final subdomain relates to which types of adaptivity are mobilized in the AEE: content,
414 navigation, multimedia, presentation and tools. In the context of this review, the adaptivity types
415 are based upon the work of Knutov and colleagues [12]. Overall, 17 out of 21 (81%) AEEs
416 examined integrated more than one type of adaptivity. *Content adaptivity* was the most used
417 adaptivity type; it was implemented in all but one AEEs reviewed (n=20). Content adaptivity
418 aims to adapt the textual information (curriculum content) to the learner's profile through
419 different mechanisms and to different degrees [12]. *Navigation adaptivity* was the second most used
420 adaptivity type (n=14). Navigation can be adapted in two ways; it can be enforced or suggested.

When enforced, an optimal personalized learning path is determined for the learner by an expert educator or by the algorithms within the AEE. When suggested, there are several personalized learning paths available to each learner, who can determine the path he prefers himself [12]. Most reviewed studies included AEEs with enforced navigation, with one optimal personalized learning path being determined by an expert educator or by the algorithm. *Multimedia adaptivity* was the third most used adaptivity type (n=11). This adaptivity type, much like content adaptivity which relates to textual information, implies the adaptivity of the multimedia elements of the training such as videos, pictures, models, to the learner's profile. *Presentation adaptivity* was the fourth most used adaptivity type (n=9). It implies the adaptivity of the layout of the page to the digital device used, or to the learner's profile. *Tools adaptivity* was the least used adaptivity type (n=8). This technique results in providing a different set of features or learning strategies for different types of learners, such as different interfaces for problem solving, and knowledge representation.

Risk of Bias Assessment

Results of included studies for the risk of bias assessment are presented in **Figure 2** and **Figure 3**. In ≥ 75% of studies, biases related to similarity of baseline outcome measurements, blinding of outcome assessment and selective reporting of outcomes were low. Moreover, in ≥ 50% of studies, biases related to contamination were low. Regarding the blinding of outcome assessment, in most studies, review authors judged that the outcomes of interest and the outcome measurement were not likely to be influenced by the lack of blinding, since studies had objective measures, i.e. an evaluative test of knowledge or skills. Regarding contamination bias, review authors scored studies at high risk if they had a crossover design.

However, in ≥ 50% of studies, biases related to random sequence generation, allocation concealment, similarity of baseline characteristics, similarity of baseline characteristics, blinding of participants and personnel, and incomplete outcome data were unclear or high. Regarding random sequence generation, an important number of studies did not report on the method of randomization used by investigators. As per Cochrane recommendations, all eligibile studies were incuded in the meta-analysis, regardless of the risk of bias assessment. Indeed, since almost all studies scored overall at unclear risk of bias, Cochrane suggests to present an estimated intervention effect based on all available studies, together with a description of the risk of bias in individual domains [30].

[Insert Figure 2]

[Insert Figure 3]

Quantitative Results

Efficacy of AEEs versus other educational interventions in improving knowledge

The pooled ES (standardized mean difference [SMD] 0.70; 95% confidence interval [CI] -0.08-1.49; Z =1.76, *P* 0.08) of AEEs compared to other educational interventions in improving knowledge suggests a medium to large effect (see **Figure 4**). However, this result is not statistically significant. Significant statistical heterogeneity was observed among studies (I^2 =97%, P <.00001), and individual ESs ranged from -1.10 to 3.05. One study in particular [45] reported a negative ES, but the difference between groups in knowledge scores was statistically nonsignificant. Moreover, while participants using the AEE in the experimental group reported the same knowledge scores as participants in the control group at the end of study, time spent on instruction was reduced by 18% with the AEE compared to the nonadaptive e-learning environment, thus improving learning efficiency [45]. When that study [45] is removed from the meta-analysis, the pooled ES becomes statistically significant (SMD 1.07; 95% CI 0.28-1.85; Z =2.67, *P* 0.008).

[Insert Figure 4]

Efficacy of AEEs versus other educational interventions in improving skills

As we considered ESs larger than 0.8 to be large [59], the pooled ES (SMD 1.19; 95% CI 0.59-1.79; Z =3.88, *P* 0.0001) of AEEs compared to other educational interventions in improving skills suggests a significantly large effect (see **Figure 5**). Statistical heterogeneity was lower than in previous analyses, but was still significant (I^2 =89%, P <.00001). Individual ESs ranged from 0.17 to 2.87.

[Insert Figure 5]

For both knowledge and skills, we conducted subgroup analyses according to population (health professionals versus students) and comparator (adaptive e-learning versus nonadaptive e-learning, adaptive e-learning versus paper-based instruction, adaptive e-learning versus classroom-based instruction). No statistically significant differences between subgroups were found regarding the effect sizes.

Quality of the Evidence

The quality of evidence table produced with GRADE, as well as the justifications for each decision, is presented in **Supplementary File 3** (GRADE quality of evidence levels: very low, low, moderate, high). For knowledge, the quality of evidence was deemed to be very low. More precisely, risk of bias was deemed serious, inconsistency serious, indirectness not serious, and

486 imprecision serious. For skills, the quality of evidence was deemed to be low. More precisely,
487 risk of bias was deemed serious, inconsistency serious, indirectness not serious, and imprecision
488 serious.

489 **DISCUSSION**

490 **Principal Findings**

491 This is the first systematic review and meta-analysis to evaluate the efficacy of AEEs in health
492 professionals and students. We identified 21 relevant studies published since 2003, 17 of which
493 assessed an AEE versus another educational intervention (large-group classroom instruction,
494 nonadaptive e-learning environment or paper-based learning), and 4 of which assessed 2 AEEs
495 with design variations head-to-head. When compared with other educational interventions, AEEs
496 were associated with statistically significant improvements in learning outcomes in 12 out of 17
497 studies. Pooled ESs were medium to large for knowledge and large for skills, but only the latter
498 was associated with a statistically significant effect. Statistical heterogeneity was high in all
499 analyses. However, this finding is consistent with other meta-analyses in the field of medical
500 education that also reported high heterogeneity across studies [8 60 61]. No potential effect modifiers
501 were found during subgroup analyses, and these did not help in explaining the source of the
502 heterogeneity. The quality of evidence for all comparisons was either low or very low. Therefore,
503 while we believe the results support the potential of AEEs for the education of health
504 professionals and students, we recommend interpreting the ESs with caution.

505 **Comparison with Other Studies**

506 To our knowledge, no previous systematic review and meta-analysis has specifically assessed the
507 efficacy of AEEs in improving learning outcomes in health professionals and students, or any

other population. However, interestingly, since the 1990’s there has been a strong research interest in the field of AEEs with algorithmic adaptivity (also known as intelligent learning environments [IEEs] or intelligent tutoring systems [ITSs]) into elementary, high school and postsecondary education for multiple subjects [17]. Thus, multiple meta-analyses have been conducted with regard to AEEs in that setting.

Steenbergen-Hu and Cooper [15] reported a mean ES of 0.35 of AEEs with algorithmic adaptivity on learning outcomes in college students when compared to all other types of educational interventions. The mean ES was 0.37 when the comparator was large-group classroom instruction, 0.35 when the comparator was nonadaptive e-learning, and 0.47 when the comparator was textbooks or workbooks[15].

Ma, et al. [18] reported a mean ES of 0.42 of AEEs with algorithmic adaptivity on learning outcomes in elementary, high school and postsecondary students when compared to large-group classroom instruction. The mean ES was 0.57 when the comparator was nonadaptive e-learning, and 0.35 when the comparator was textbooks or workbooks. Interestingly, the mean ES was higher for studies which assessed an AEE in biology and physiology (0.59) and in humanities and social science (0.63) than in studies which assessed an AEE in mathematics (0.35) and physics (0.38)[18].

Kulik and Fletcher [17] reported a mean ES of 0.65 of AEEs with algorithmic adaptivity on learning outcomes in elementary, high school, and postsecondary students when compared to large-group classroom instruction. Education areas in this review were diverse (e.g., mathematics, computer science, physics), but none were related to health sciences. Interestingly, the mean ES was 0.78 for studies up to 80 participants, and 0.30 for studies with more than 250 participants. Moreover, the mean ES for studies conducted with elementary and high school students was 0.44, compared to 0.75 for studies conducted with postsecondary students[17].

Thus, in light of the results of these meta-analyses, the ES reported in our review may appear high. However, our review looked more specifically into the efficacy of AEEs in improving learning outcomes in health professionals and students. This is significant since, in the meta-analyses of Steenbergen-Hu and Cooper [15], Ma, et al. [18], and Kulik and Fletcher [17], AEEs seem to be more effective in postsecondary students [17 18] and for learning subjects related to biology, physiology and social science [18]. Moreover, previous meta-analyses focused on the efficacy of AEEs in improving procedural and declarative knowledge, and did not report on the efficacy on AEEs in improving skills. This is important since AEEs may be more effective for providing tailored guidance and coaching for developing skills regarding complex clinical interventions, rather than learning factual knowledge, which generates less cognitive load [62 63].

Implications for Practice and Research

This review provides important implications for the design and development of AEEs for health professionals and students. Table 3 presents 8 practical considerations for the design and development of adaptive e-learning environments based on the results of this systematic review for educators and educational researchers.

Table 3. Practical considerations for the design and development of adaptive e-learning environments.

Practical considerations	Explanations
Developing the Educational Content	• Given the adaptivity and the different learning pathways inherent to adaptive e-learning environments (AEEs), it is necessary to develop more pedagogical content (e.g. 60 minutes of learning) to reach the planned duration of each adaptive e-learning session (e.g. 30 minutes of learning).

Selecting a Theoretical Framework	• Selecting a theoretical framework coherent with the underlining principles of adaptivity of AEEs is crucial. These frameworks can be related to human cognition (e.g. Cognitive Load Theory, Cognitive Tutoring), behavior change (e.g. Transtheoretical model, I-Change Model) or learning (e.g. Perceptual Learning, Situated Learning).
Selecting the Adaptivity Method	• Selecting the adaptivity method refers to how the AEE will adapt its instructional sequence. There are two main adaptivity methods: ○ *Designed adaptivity* is based on the expertise of the educator who designs personalized pathways to guide learners to learning content mastery; ○ *Algorithmic adaptivity* is based on different algorithms to determine, for instance, the extent of the learner's knowledge and the optimal instructional pathway.
Selecting the Adaptivity Goal(s)	• Selecting the adaptivity goal(s) is important, since it will dictate how the instruction will be adapted in the AEE. The goal of adaptivity within an AEE may be to increase learning effectiveness, increase learning efficiency, modify behavioral predictors, or improve cognitive/metacognitive processes related to learning.
Selecting the Adaptivity Timing	• Selecting the timing of adaptivity within an AEE relates to *when* the adaptivity occurs during the learning process. Adaptivity can be implemented at the beginning of the training only, or throughout the training. Adaptivity timing is closely linked to which adaptivity factor(s) are targeted in learners.
Selecting the Adaptivity Factor(s)	• Adaptivity factors are essentially data upon which the adaptivity process is based. These data can be related to the learner's performance (e.g. knowledge, skills), his behavior / actions on the page (e.g. response time, requests for help), his overall learning path on the platform, or any other variables of interest in the learner.
Selecting the Adaptivity Type(s)	• Multiple types of adaptivity can be implemented in an AEE: ○ *Content adaptivity* refers to the adaptation of the textual information; ○ *Navigation adaptivity* refers to the adaptation of the curriculum sequence; ○ *Presentation adaptivity* refers to the adaptation of layout of the screen to the digital device used, or to the learner's profile; ○ *Multimedia adaptivity* refers to the adaptation of multimedia elements of the training such as videos, pictures, models; ○ *Tools adaptivity* refers to the adaptation of training features, learning strategies or learning assessment methods (e.g. interface for problem solving).
Determining your technical resources and selecting the adaptive e-learning platform	• After the content has been developed, the theoretical framework has been selected and the decisions related to the different subdomains adaptivity have been made, it is crucial to determine your technical resources and evaluate preexisting adaptive e-learning software to determine if it meets your needs and goals. If you plan to employ a specialist or team to develop the platform, estimate development cost and timeline.

This review also provides several key insights for future research. In terms of *population*, future research should focus on assessing AEEs with health professionals in practice, such as registered nurses and physicians, rather than students in these disciplines. This could provide key insights into how AEEs can impact clinical behavior and, ultimately, patient outcomes. In addition, invetsigators should target larger sample sizes. In terms of *interventions*, researchers should report more clearly on adaptivity methods, goals, timing, factors and types. Moreover, researchers should provide additional details regarding the underlining algorithms allowing the adaptivity process in order to ensure replicability of findings. Regarding *comparators*, this review suggests there is a need for additional research using traditional comparators (i.e., large group classroom instruction) and more specific comparators (i.e., adaptive e-learning environment with design variations). Regarding *outcomes* and outcome measures, researchers should use validated measurement tools of knowledge, skills, and clinical behavior to facilitate knowledge synthesis. Moreover, the very low number of studies assessing the impact of AEEs on health professionals' and students' clinical behavior demonstrates the need for further research with higher-level outcomes. Finally, in terms of *study designs*, researchers should focus on research designs allowing the assessment of the impact of multiple educational design variations and adaptivity types within one study, such as factorial experiments.

Strengths and Limitations

Strengths of this systematic review and meta-analysis include the prospective registration and publication of a protocol based on rigorous methods in accordance with Cochrane and PRISMA guidelines; the exhaustive search in all relevant databases; the independent screening of the titles, abstracts and full-text of studies; the assessment of each included studies' risk of bias using EPOC Cochrane guidelines; and the assessment of the quality of evidence for each individual outcome using the GRADE methodology.

Our review also has limitations to consider. First, outcome measures varied widely across studies. To address this issue, we conducted the meta-analysis using the SMD. Using the SMD allowed us to standardize the results of studies to a uniform scale before pooling them. Review authors judged that using the SMD was the best option for this review, as it is the current practice in the field of knowledge synthesis in medical education [6 60].

Second, there was high inconsistency among study results, which we can mostly attribute to differences in populations, AEE design, research methods, and outcomes. This resulted in sometimes widely differing estimates of effect. To partly address this issue, we used a random-effects model for the meta-analysis, which assumes that the effects estimated in the studies are different and follow a distribution [30]. However, since a random-effects model awards more weight to smaller studies to learn about the distribution of effects, it could potentially exacerbate the effects of the bias in these studies [30].

Finally, publication bias could not be assessed by the means of a funnel plot since there were less than 10 studies included in the meta-analysis.

CONCLUSIONS

Adaptive e-learning has significant potential to increase the effectiveness and efficiency of learning in health professionals and students. Through the different sub-domains of the adaptivity process (i.e. method, goals, timing, factors, types), AEEs can take into account the particularities inherent to each learner. This systematic review and meta-analysis underlines the potential of AEEs for improving knowledge and skills in health professionals and students in comparison with other educational interventions, such as nonadaptive e-learning environments and large-group classroom learning, across a range of topics. However, evidence was either of low or very low quality and heterogeneity was high across populations, interventions, comparators, and outcomes. Thus, additional comparative studies assessing the efficacy of AEEs in health professionals and students are needed to strengthen the quality of evidence .

AUTHOR CONTRIBUTIONS

All review authors contributed to at least one aspect of each of the four criteria for authorship defined by the International Committee for Medical Journal Editors (ICJME).

G.F. contributed to the conception and design of the review, to the acquisition and analysis of data, and to the interpretation of results. Moreover, G.F. drafted the initial manuscript. S.C. contributed to the conception and design of the review, and to the interpretation of results. M.-A.M.-C. contributed to the conception and design of the review, to the acquisition of data, and interpretation of results. T.M. contributed to the conception and design of the review, to the acquisition of data, and to the interpretation of results. M.-F.D. contributed to the conception and design of the review, to the acquisition of data, and to the interpretation of results. G.M.-D. contributed to the conception and design of the review, and to the interpretation of results. J.C. contributed to the interpretation of results. M.-P.G. contributed to the interpretation of results. V.D. contributed to the interpretation of results.

All review authors contributed to manuscript writing, critically revised the manuscript, gave final approval, and agreed to be accountable for all aspects of work, ensuring integrity and accuracy.

DATA SHARING STATEMENT

All data relevant to the study are included in the article or uploaded as supplementary information.

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FIGURE LEGENDS

Figure 1. PRISMA Study Flow Diagram.

Figure 2. Risk of bias summary: review authors' judgements about each risk of bias item for each included study.

Figure 3. Risk of bias graph: review authors' judgements about each risk of bias item presented as percentages across all included studies.

Figure 4. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving knowledge.

Figure 5. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving skills.

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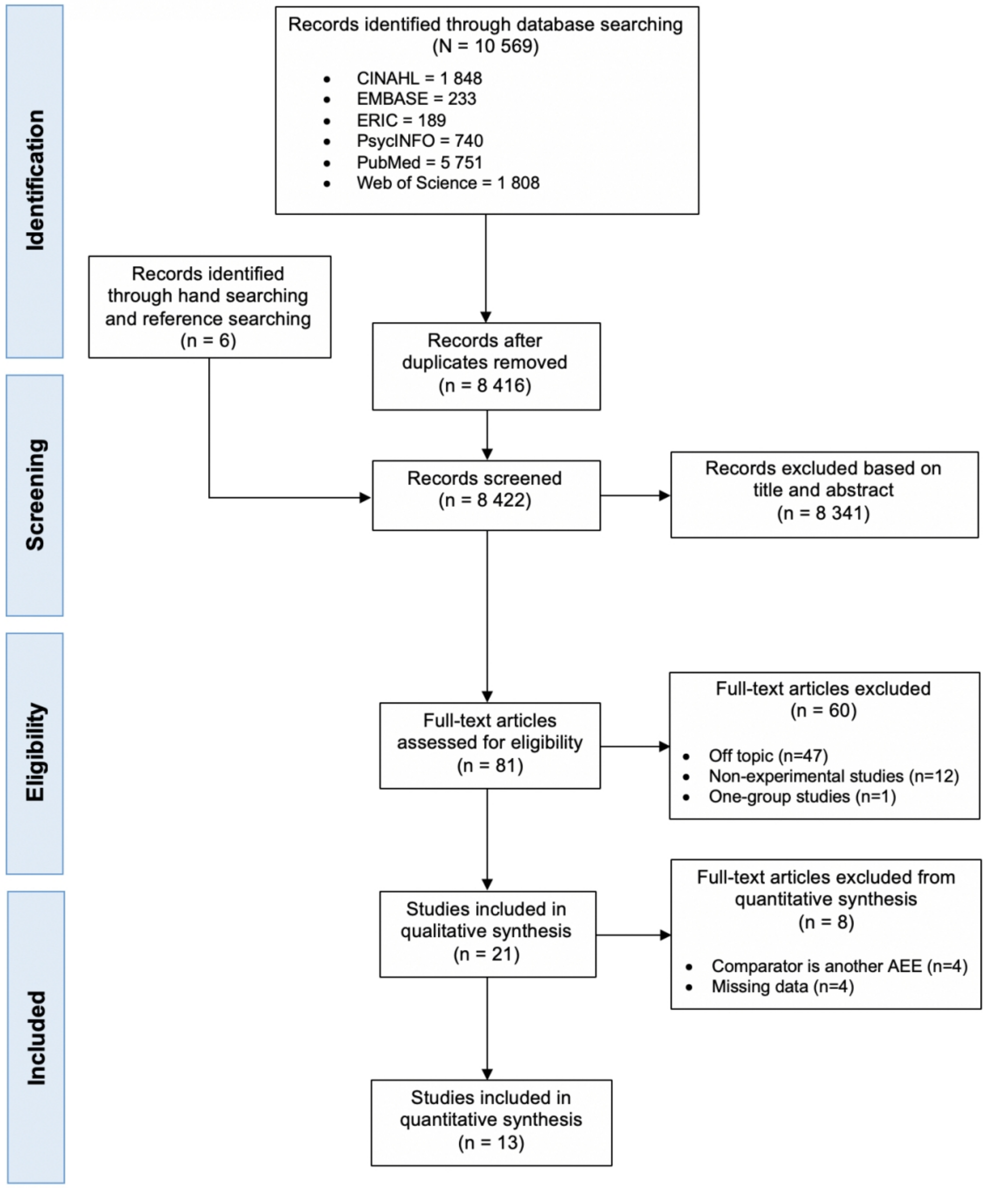

Figure 1. PRISMA study flow diagram.

242x292mm (144 x 144 DPI)

	Random sequence generation (selection bias)	Allocation concealment (selection bias)	Similarity of baseline outcome measurements	Similarity of baseline characteristics	Blinding of participants and personnel (performance	Blinding of outcome assessment (detection bias)	Incomplete outcome data (attrition bias)	Selective reporting (reporting bias)	Measures against contamination?
Casebeer 2003	?	?	?	−	?	+	?	?	+
Cook 2008	+	−	?	+	?	+	+	+	−
Crowley 2007	?	?	+	?	?	+	?	+	+
Crowley 2010	?	?	+	+	?	+	−	+	+
de Ruijter 2018	+	+	+	+	?	+	+	+	+
El Saadawi 2008	?	?	+	−	?	+	?	+	−
El Saadawi 2010	?	?	+	−	?	+	?	+	−
Feyzi-Behnagh 2014	?	?	+	−	?	+	+	+	+
Hayes-Roth 2010	?	?	+	−	?	+	+	+	+
Lee 2017	−	−	+	−	?	?	?	+	+
Micheel 2017	−	+	+	+	?	+	+	+	+
Morente 2013	+	?	+	+	?	+	+	+	+
Munoz 2010	−	−	−	−	?	−	?	−	+
Romito 2016	−	−	+	?	−	+	+	+	+
Samulski 2017	+	?	+	+	?	+	?	+	−
Thai 2015	?	?	+	−	?	+	?	+	+
Van Es 2015	?	?	+	+	?	+	−	+	−
Van Es 2016	?	?	+	+	?	+	−	+	−
Wong 2015	?	?	?	+	?	+	+	?	−
Wong 2017	−	?	+	−	?	+	?	+	+
Woo 2006	?	?	−	−	?	?	+	−	+

Figure 2. Risk of bias summary: review authors' judgements about each risk of bias item for each included study.

143x334mm (144 x 144 DPI)

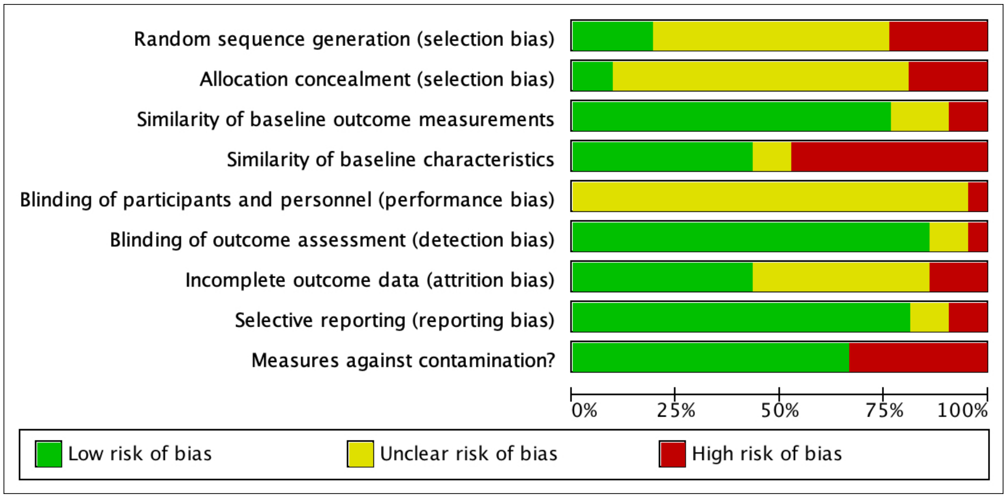

Figure 3. Risk of bias graph: review authors' judgements about each risk of bias item presented as percentages across all included studies.

219x107mm (144 x 144 DPI)

	Adaptive e-learning			Other educational interv.				Std. Mean Difference
Study or Subgroup	**Mean**	**SD**	**Total**	**Mean**	**SD**	**Total**	**Weight**	**IV, Random, 95% CI**
Cook 2008	76.2	0.9	62	77.2	0.9	62	17.1%	−1.10 [−1.48, −0.73]
de Ruijter 2018	14.876	1.242	121	14.8447	1.1093	103	17.4%	0.03 [−0.24, 0.29]
Micheel 2017	7.861	1.691	282	7.461	1.691	317	17.6%	0.24 [0.08, 0.40]
Morente 2013	15.83	2.52	30	11.6	2.39	42	16.3%	1.71 [1.16, 2.26]
Samulski 2017	5.83	2.43	18	4.47	2.47	18	15.7%	0.54 [−0.12, 1.21]
Wong 2015	68.2	2.7	39	60.5	2.3	41	15.8%	3.05 [2.39, 3.70]
Total (95% CI)			**552**			**583**	**100.0%**	**0.70 [−0.08, 1.49]**

Heterogeneity: $Tau^2 = 0.90$; $Chi^2 = 150.19$, $df = 5$ ($P < 0.00001$); $I^2 = 97\%$
Test for overall effect: $Z = 1.76$ ($P = 0.08$)

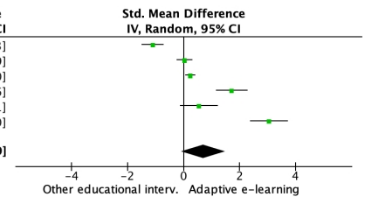

Figure 4. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving knowledge.

367x74mm (144 x 144 DPI)

	Adaptive e-learning			Other educational interv.				Std. Mean Difference
Study or Subgroup	**Mean**	**SD**	**Total**	**Mean**	**SD**	**Total**	**Weight**	**IV, Random, 95% CI**
Hayes-Roth 2010	16.32	1.54	11	10.95	2.03	11	10.3%	2.87 [1.61, 4.12]
Lee 2017	53	17	989	50	18	533	18.5%	0.17 [0.07, 0.28]
Romito 2016	67	4	12	53	6	12	11.1%	2.65 [1.51, 3.80]
Thai 2015	69	16	27	57	23	27	16.1%	0.60 [0.05, 1.14]
Van Es 2015	91.8	2.3	12	82.6	4.3	15	11.9%	2.51 [1.46, 3.55]
Van Es 2016	71.7	18.73	15	58.2	20.2	18	14.8%	0.67 [-0.03, 1.38]
Wong 2017	0.55	0.22	39	0.46	0.21	86	17.3%	0.42 [0.04, 0.80]
Total (95% CI)			**1105**			**702**	**100.0%**	**1.19 [0.59, 1.79]**

Heterogeneity: $Tau^2 = 0.50$; $Chi^2 = 57.00$, df = 6 ($P < 0.00001$); $I^2 = 89\%$
Test for overall effect: Z = 3.88 (P = 0.0001)

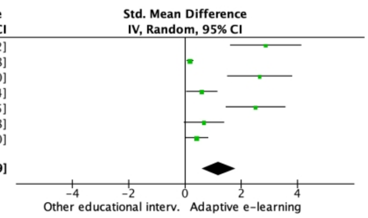

Figure 5. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving skills.

365x79mm (144 x 144 DPI)

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	1
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	4-5
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	7-9
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	9-10
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	10
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	10-11
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	11-12
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	Supplementary File 2
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	11-12
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	11-12
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	12-13
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	13
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	13-14
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	13-14

PRISMA 2009 Checklist

Section/topic	#	Checklist item	Reported on page #
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	13
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	14
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	15
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	18
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	29-30
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	32-33
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	32-33
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	31
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	N/A
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	32-33
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	39
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	36-39
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	41

From: Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. PLoS Med 6(7): e1000097. doi:10.1371/journal.pmed1000097

For more information, visit: **www.prisma-statement.org**.

Supplementary File 2 – Search Strategy for PubMed

PubMed – 17 avril 2017

1. ((Adaptive[TIAB] OR individualized [TIAB] OR personalized[TIAB] OR Tailored[TIAB]) AND (elearning[TIAB] OR learning[TIAB] OR Instruction[TIAB] OR "web-based instruction"[TIAB] OR computer-based instruction[TIAB] OR computer-based tutoring[TIAB] OR education[TIAB] OR tutorial[TIAB] OR tutorials[TIAB])) OR Intelligent tutoring system[TIAB] OR Intelligent tutoring systems[TIAB]
2. "Computer-Assisted Instruction"[MH]
3. #1 OR #2
4. Health Personnel*[TIAB] OR Health professional*[TIAB] OR Health care profession*[TIAB] OR Healthcare profession*[TIAB] OR Medical student*[TIAB] OR Medical assistant*[TIAB] OR health worker*[TIAB] OR Audiologist*[TIAB] OR Chiropractor*[TIAB] OR Dentist[TIAB] OR Dentists[TIAB] OR Dietitian*[TIAB] OR Dermatolog*[TIAB] OR endocrinologist*[TIAB] OR Gastroenterolog*[TIAB]OR Gynecolog*[TIAB]OR Radiolog*[TIAB] OR Medical Staff[TIAB] OR Midwife*[TIAB] OR nutritionist*[TIAB] OR Nurse[TIAB] OR Nurses[TIAB] OR Optometrist*[TIAB] OR Occupational Therapist*[TIAB] OR Patholog*[TIAB] OR Paramedic[TIAB] OR Paediatric[TIAB] OR pediatrician*[TIAB] OR Paediatrician*[TIAB] OR pediatrist*[TIAB] OR pediatric[TIAB] OR Pharmacist*[TIAB] OR Pharmaconomist*[TIAB] OR Pharmacologist*[TIAB] OR Pharmacy technician*[TIAB] OR Phlebotomist*[TIAB] OR Physician OR Podiatrist*[TIAB] OR Psychologist*[TIAB] OR Psychotherapist*[TIAB] OR psychiatrist*[TIAB] OR Physical therapist*[TIAB] OR physiotherapist*[TIAB] OR Respiratory therapist*[TIAB] OR Surgeon*[TIAB] OR Clinician*[TIAB] OR Cardiologist*[TIAB] OR Emergency medical technician*[TIAB] OR emergency doctor*[TIAB] OR emergentologist*[TIAB] OR clinical officer*[TIAB] OR Community health worker*[TIAB] OR Radiographer*[TIAB] OR Surgical technologist*[TIAB] OR Radiotherapist*[TIAB] OR Anesthetist*[TIAB] OR Resident[TIAB] OR residents[TIAB]
5. "Health Personnel"[MH] OR "Students, Premedical"[MH] OR "Students, Medical"[MH] OR "Students, Nursing"[Mesh]
6. "Education, Premedical"[MH] OR "Education, Medical"[MH] OR "Education, Nursing"[MH] OR "Education, Pharmacy"[MH] OR "Education, Public Health Professional"[MH] OR "Clinical Clerkship"[MH]
7. #4 OR #5 OR 6
8. knowledge*[TIAB] OR Aptitude*[TIAB] OR accuracy[TIAB] OR impact*[TIAB] OR skill*[TIAB] OR performance*[TIAB] OR Learning outcome*[TIAB] OR effectiveness[TIAB] OR efficacy[TIAB] OR improvement*[TIAB] OR Innovative*[TIAB] OR innovation*[TIAB] OR randomised controlled trial[TIAB] OR randomized controlled trial[TIAB]
9. "Clinical Competence"[MH] "Quality Improvement"[MH] OR "Learning Curve"[MH] OR Knowledge [MH] OR "randomized controlled trial"[PT]
10. #8 OR 9
11. #3 AND #7 AND #10
12. (english[LA] OR french[LA]) AND 2005:2017[DP]
13. #11 AND #12

Résultats: 4 375

Supplementary File 3 – Summary of the quality of evidence

Certainty assessment							№ of patients		Effect		Certainty	Importance
№ of studies	Study design	Risk of bias	Inconsistency	Indirectness	Imprecision	Other considerations	adaptive and intelligent e-learning environments	other educational interventions	Relative (95% CI)	Absolute (95% CI)		
Knowledge												
6	randomised trials	serious [a]	serious [b]	not serious	serious [c]	none	552	583	-	SMD **0.7 SD higher** (0.08 lower to 1.49 higher)	⨁◯◯◯ VERY LOW	IMPORTANT
Competence												
7	randomised trials	serious [a]	not serious	not serious	serious [c]	none	1105	702	-	SMD **1.19 SD higher** (0.59 higher to 1.79 higher)	⨁⨁◯◯ LOW	CRITICAL

CI: Confidence interval; **SMD:** Standardised mean difference

Explanations

a. Most studies have unclear or high risk of bias with regard to random sequence generation and allocation concealment. The risk of bias for similarity of baseline measurements was unclear for some studies. Thus, groups in these studies could be disproportionate and the distribution may not be normal since sample size is generally small.

b. Studies yield widely differing estimates of effect (heterogeneity or variability in results). The individual confidence intervals of some studies almost do not touch.

c. Most studies include few participants and few events and have wide confidence intervals. Measurement instruments often not validated. Sample size often unsufficient.