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

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1 **Adaptive e-learning environments for health professionals** 2 **and students: a systematic review and meta-analysis**

3
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34 The lead author (the manuscript's guarantor) affirms that the manuscript is an honest,
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36 study have been omitted; and that any discrepancies from the study as planned (and, if relevant,
37 registered) have been explained.

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2
3 38 **ABSTRACT (300 WORDS)**
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6 39 **Objective:** To systematically identify, appraise, and synthesize the evidence regarding the
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8
9 40 effectiveness of adaptive e-learning environments (AEEs) in improving knowledge, competence,
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11 41 and clinical behavior in health professionals and students.
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14 42 **Design:** Systematic review and meta-analysis.
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17 43 **Methods:** A search for studies published between January 2005 and April 2017 was performed in
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19 44 CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science. Studies were eligible if
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21 45 they were controlled, and evaluated the effect of an AEE on knowledge, competence or clinical
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23 46 behavior in health professionals or students. AEEs were reviewed with regard to their clinical
24
25 47 topic, theoretical framework, and adaptation process. Studies were included in the meta-analysis
26
27 48 if they were randomized, and had a non-AEE control group. Effect sizes (ES) were pooled using
28
29 49 a random effects model. Two authors screened studies, extracted data, assessed risk of bias, and
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31 50 coded quality of evidence independently.
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36 51 **Results:** From a pool of 5,580 articles, we included 17 eligible studies enrolling 333 health
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38 52 professionals and 628 students. Risk of bias was generally high due to issues related to allocation
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40 53 concealment, similarity of baseline characteristics, blinding, and outcome data. Clinical topics
41
42 54 were mostly related to diagnostic testing, theoretical frameworks were heterogeneous, and the
43
44 55 adaptation process was characterized by 4 subdomains: goals, targeted variables, techniques, and
45
46 56 timing. The pooled ES was 1.04 for knowledge (95% CI, -0.86-2.94; *P* .28), and 1.55 for
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48 57 competence (95% CI, 0.50-2.60; *P* .004). Statistical heterogeneity was high in all analyses.
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53 58 **Conclusions:** AEEs may improve only competence, not knowledge, in health professionals and
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55 59 students. The adaptation process within AEEs may be more beneficial more learning
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3 60 competencies since they are complex in nature, rather than learning knowledge, which generates
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5 61 less cognitive load. Future research should report more clearly on the design and adaptation
6
7 62 process of AEEs, and target higher-level outcomes, such as clinical behavior.
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11 63 **PROSPERO registration number:** CRD42017065585
12

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14 64 **Keywords:** Computer-assisted instruction; medical education; nursing education; e-learning,
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16 65 meta-analysis
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For peer review only

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

77 INTRODUCTION

78 The use of information and communication technologies (ICTs) in the education of health
79 professionals and students has become ubiquitous. Indeed, e-learning, defined as the use of ICTs
80 to access educational curriculum and support learning¹, is increasingly present in clinical settings
81 for the continuing education of health professionals^{2,3}, and in academic settings for the education
82 of health professions students⁴. The interaction of health professionals and students with e-
83 learning environments during the learning process generates a significant amount of data⁵.
84 However, designers of e-learning environments and educators rarely make use of this data to
85 optimize learning effectiveness and efficiency. Thus, in recent years, educational researchers
86 have strived to develop e-learning environments that take a data-driven and personalized
87 approach to education⁶⁻⁹. E-learning environments that take into account each user's interactions
88 and performance level could anticipate what types of content and resources meet the user's needs,
89 potentially increasing learning effectiveness and efficiency⁹.

90 E-learning environments integrate information, in the form of text and multimedia (e.g.,
91 illustrations, animations, videos). They can include both asynchronous (i.e., designed for self-
92 study) and synchronous (i.e., a class taught by an educator in real time) components¹. E-learning
93 environments can be either *nonadaptive*, *adaptive*, or *intelligent*¹⁰ (see **Figure 1**). In the fields of
94 computer science and educational technology, the term *adaptation* refers to the process executed
95 by a system based on ICTs of adapting educational curriculum content, structure or delivery to
96 the profile of a user¹⁰.

97 Nonadaptive e-learning environments (**Type A**) provide a standardized training for all users.
98 While they can include instructional design variations (e.g., interactivity, feedback, practice

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3 99 exercises), they *do not* consider users' characteristics to provide a personalized training. They are
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5 100 generally considered to be as effective as non-e-learning educational interventions, such as large-
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7 101 group classroom instruction and printed text, in improving learning outcomes^{11 12}. Adaptive e-
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10 102 learning environments (AEEs; **Type B1**) collect data to build each user's profile (e.g., navigation
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12 103 behavior, preferences, knowledge), and use simple techniques (e.g., adaptive information
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14 104 filtering, adaptive hypermedia) to adapt the content, navigation, presentation, multimedia, or
15
16 105 strategies to provide personalized training^{7 8}. Intelligent e-learning environments (IEEs; **Type**
17
18 106 **B2**) are a subtype of AEEs that use advanced adaptation techniques and user-modelling
19
20 107 techniques derived from artificial intelligence (e.g., machine learning, rule-based systems, natural
21
22 108 language processing) to provide a more personalized training for each user^{6 13-16}. In the context of
23
24 109 this review, our use of the term "AEEs" includes IEEs.
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29 110 In recent years, AEEs have been developed and evaluated primarily in academic settings for
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31 111 students in mathematics, physics and related disciplines, for the acquisition of knowledge and
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33 112 development of cognitive skills (e.g., arithmetic calculation). Four meta-analyses reported on the
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35 113 effectiveness of AEEs among high school and university students in in these fields of study¹³⁻¹⁵
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37 114 ¹⁷. The results are promising: AEEs are in almost all cases more effective than large-group
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39 115 classroom instruction. In addition, Nesbit, et al.¹⁸ point out that AEEs are more effective than
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41 116 nonadaptive e-learning environments.
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46 117 The variability in the degree and the complexity of adaptation within AEEs mirrors the
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48 118 adaptation that can be observed in non-e-learning educational interventions (**Type C**). Some
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50 119 interventions, like one-on-one human instruction and small-group classroom instruction,
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52 120 generally have a high degree of adaptation since the instructor can adapt his teaching to the
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54 121 individual profiles of learners and consider their feedback¹⁹. Other interventions, like large-
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3 122 group classroom instruction, generally have a low degree of adaptation to individual learners. In
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5 123 some interventions, like paper-based instruction (e.g., handouts, textbooks), there is no adaptation
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8 124 at all.

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11 125 Despite evidence of the effectiveness of AEEs for knowledge acquisition and skill development
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13 126 in areas such as mathematics in high school and university students, their effectiveness in
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15 127 improving learning outcomes in health professionals and students has not yet been established.
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18 128 To address this need, we conducted a systematic review and meta-analysis to identify and
19
20 129 quantitatively synthesize all comparative studies of AEEs involving health professionals and
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22 130 students.

23 24 25 131 **Systematic Review and Meta-Analysis Objective**

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28 132 To systematically identify, appraise, and synthesize the best available evidence regarding the use
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31 133 and the effectiveness of AEEs in improving knowledge, competence, and clinical behavior in
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33 134 health professionals and students.

34 35 36 135 **Systematic Review and Meta-Analysis Questions**

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39 136 We sought to answer the following questions with the systematic review:

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43 137 1. What are the characteristics of studies assessing an AEE designed for health
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45 138 professionals' and students' education?
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47 139 2. What are the characteristics of AEEs designed for health professionals' or students'
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49 140 education?

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53 141 We sought to answer the following question with the meta-analysis:
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3 142 3. What is the effectiveness of AEEs in improving knowledge, competence, and clinical
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5 143 behavior in health professionals and students in comparison with nonadaptive e-learning
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7 144 environments, and non–e-learning educational interventions?
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10 11 145 **METHODS**

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14 146 We planned and conducted this systematic review following the Effective Practice and
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16 147 Organization of Care (EPOC) Cochrane Group guidelines²⁰, and reported it according to the
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18 148 Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) standards²¹ (see
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21 149 **Supplementary File 1**). We prospectively registered (International Prospective Register of
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23 150 Systematic Reviews #CRD42017065585) and published the protocol of this systematic review²²
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25 151 ²³. Thus, in this paper, we present an abridged version of the methods with an emphasis on
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28 152 changes made to the methods since the publication of the protocol.
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31 153 **Study Eligibility**

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34 154 We included primary research articles that assessed an AEE with licensed health professionals,
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36 155 students, trainees, and residents in any discipline. We defined an AEE as a computer-based
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38 156 learning environment which collects data to build each user's profile (e.g., navigation behavior,
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40 157 individual objectives, knowledge), interprets these data through algorithms, and adapts in real-
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42 158 time the content (e.g., showing/hiding information), navigation (e.g., specific links and paths),
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44 159 presentation (e.g., page layout), multimedia presentation (e.g., images, videos), or tools (e.g.,
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46 160 different set of strategies for different types of users) to provide a dynamic and evolutionary
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48 161 learning path for each user^{6 10}. We used the definitions of each type of adaptation proposed by
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51 162 Knutov and colleagues⁸. We included AEEs with variable levels of technological complexity,
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54 163 ranging from simple adaptive functionality (**Type B1**) to the use of artificial intelligence (IEEs,
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3 164 **Type B2**). We considered for inclusion primary research articles in which the comparator was: 1)
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5 165 a nonadaptive e-learning environment; 2) a non-e-learning educational intervention; 3) another
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7 166 AEE with design variations. While included in the qualitative synthesis of the evidence for
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9 167 descriptive purposes, the third comparator was excluded from the meta-analysis. Outcomes of
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11 168 interest were knowledge, competence (including skills), and clinical behavior^{24 25}. Finally, in
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13 169 terms of study design, we considered for inclusion all controlled, quantitative studies in
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15 170 accordance with the EPOC Cochrane Review Group guidelines²⁶.
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20 171 **Study Identification**

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23 172 We previously published our search strategy²². Briefly, we designed a strategy in consultation
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25 173 with a librarian to search CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science
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27 174 for primary research articles published between January 2005 and April 2017. We limited our
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29 175 search to articles published after 2005 since earlier studies seem to have a bias toward more
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31 176 positive results¹⁵, which could be explained by the effect of the novelty of e-learning on student
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33 177 motivation and learning outcomes. The search strategy revolved around 3 key concepts:
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35 178 “adaptive e-learning environments”, “health professionals/students”, and “effects on
36
37 179 knowledge/competence/behavior” (see **Supplementary file 2**). To identify additional articles, we
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39 180 hand-searched 6 key journals (e.g., *British Journal of Educational Technology*, *Computers and*
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41 181 *Education*) and the reference lists of included primary research articles. We sought relevant
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43 182 articles published in English or French.
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49 183 **Study Selection**

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52 184 We worked independently and in duplicate (G.F. and M.-A.M.-C./T.M.) to screen all titles and
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54 185 abstracts for inclusion using the EndNote software V8.0 (Clarivate Analytics). We resolved
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186 disagreements by consensus. We then performed the full-text assessment of potentially eligible
187 articles using the same methodology.

188 **Data Extraction**

189 One review author (G.F.) extracted data from included primary research articles using a modified
190 version of the data collection form developed by the EPOC Cochrane Review Group²⁷. The main
191 changes made to the extraction form were the addition of specific items relating to the AEE
192 assessed in each study (e.g., adaptation techniques, duration of each training session). Two
193 review authors (T.M., M.-F.D.) validated the data extraction forms. For all studies, we extracted
194 the following data items if possible:

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

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3 207 • *the outcomes*: name, time-points measured, definition, person measuring, unit of
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5 208 measurement, scales, validation of measurement tool;
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8 209 • *the results*: results according to our primary (knowledge) and secondary (competence,
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10 210 behavior) outcomes, comparison, time-point, baseline data, statistical methods used, and
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12 211 key conclusions.

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15 212 We contacted all of the corresponding authors (N=12) of the 17 included primary research
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17 213 articles to validate the completed data extraction forms, and to provide us with missing data.

21 214 **Assessment of the Risk of Bias**

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24 215 We worked independently and in duplicate (G.F. and T.M./M.-F.D.) to assess the risk of bias of
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26 216 included primary research articles using the EPOC risk of bias criteria, based upon the data
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28 217 extracted with the data collection form²⁷. A study was deemed at high risk of bias if the
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30 218 individual criterion “random sequence generation” was scored at “high” or at “unclear” risk of
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32 219 bias.

33 34 35 36 220 **Data Synthesis**

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39 221 First, we synthesized data qualitatively using tables to provide an overview of the included
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41 222 studies, and of the AEEs reported in these studies.

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45 223 Second, using the Review Manager (RevMan) software V5.1, we first conducted a meta-analysis
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47 224 to quantitatively synthesize the effectiveness of AEEs versus other educational interventions in
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49 225 improving all learning outcomes. We included studies in the meta-analysis if the comparator
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51 226 wasn't another AEE, if they were randomized, and if they reported outcome data. We then
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53 227 conducted meta-analyses with the same comparison for each outcome for which data from at

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3 228 least 2 studies were available (i.e., knowledge, competence). For randomized controlled trials
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5 229 (RCTs), we converted each post-test mean and standard deviation (SD) to a standardized mean
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7 230 difference ([SMD], also known as Hedges g effect size [ES]). For crossover RCTs, we used
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10 231 means pooled across each intervention. We pooled effect sizes using a random effects model.
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12 232 Statistical significance was defined by a two-sided alpha of .05.
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15 233 We first assessed heterogeneity qualitatively by examining the characteristics of included studies,
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17 234 the similarities and disparities between the types of participants, the types of interventions, and
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20 235 the types of outcomes. We then used the I^2 statistic within the RevMan software to quantify how
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22 236 much the results varied across individual studies (i.e., between-study inconsistency, or
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24 237 heterogeneity). We interpreted the I^2 values as follows: 0%-40%: might not be important; 30%-
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26 238 60%: may represent moderate heterogeneity; 50%-90%: may represent substantial heterogeneity;
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28 239 and 75%-100%: considerable heterogeneity²⁸. We performed sensitivity analysis to assess if the
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30 240 exclusion of studies at high risk of bias or with a small sample size ($n < 20$) would have had an
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32 241 impact on statistical heterogeneity. The small number of studies included in each meta-analysis
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34 242 did not allow for sensitivity of subgroup analyses to be performed.
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39 243 Since less than 10 studies were included in the meta-analysis, we did not assess reporting biases
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41 244 using a funnel plot, as suggested in the Cochrane Handbook²⁹.
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45 245 **Assessment of the Quality of Evidence**

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48 246 We worked independently and in duplicate (G.F. and M.-A.M.-C.) to assess the quality of
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50 247 evidence for each individual outcome. We used the Grading of Recommendations Assessment,
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52 248 Development, and Evaluation (GRADE) Web-based software, based upon the data extracted with
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54 249 the data collection checklist³⁰. We considered 5 factors (risk of bias of included studies,
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3 250 indirectness of evidence, unexplained heterogeneity or inconsistency of results, imprecision of
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5 251 the results, probability of reporting bias) for downgrading the quality of the body of evidence for
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7 252 each outcome³⁰.

11 253 **Patient and Public Involvement**

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14 254 Patients and the public were not involved in the selection of the research question and outcome
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16 255 measures, or in the design of this systematic review and meta-analysis. No patients were involved
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18 256 in the interpretation or writing up of results. We are unable to disseminate the results of the
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20 257 research to study participants directly since this meta-analysis used aggregated data from
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23 258 previous trials.

26 259 **RESULTS**

29 260 **Study Flow**

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33 261 From a pool of 5,580 potentially relevant articles, we found 17 quantitative, controlled studies
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35 262 assessing an AEE with health professionals or students (see **Figure 2**).

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38 263 Out of 17 included studies in the qualitative synthesis, 4 studies compared two AEEs with design
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40 264 variations³¹⁻³⁴, 4 studies were not randomized³⁵⁻³⁸, and 1 study had missing data³⁹. Thus, these 9
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42 265 studies could not be included in the meta-analysis and the remaining 8 studies were used to
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45 266 calculate an ES on learning outcomes.

48 267 **Study Characteristics**

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51 268 We summarized the key characteristics of included studies in table format (see **Table 1**). In terms
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53 269 of study population, in the 17 studies we have found published between 2006 and 2017,
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56 270 investigators have evaluated AEEs mostly in the medical field, that is medical students (n=7)^{35 37}

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3 271 ⁴⁰⁻⁴³, medical residents (n=7) ^{31-34 36 44 45}, nursing students (n=1) ⁴⁶, physicians in practice (n=1) ³⁹,
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5 272 and health sciences students (n=1) ⁴⁷. The mean sample size was 56.53 participants (standard
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7 273 deviation [SD] 44.13). In terms of study design, 13 out of 17 studies (77%) were randomized, 7
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9 274 studies of which were randomized crossover trials ^{32 33 41-45}. The mean number of training
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11 275 sessions was 2 (SD 1.07) and the mean training time was 4.33 hours (SD 3.79). Across the 17
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13 276 studies, trainings with AEEs were spread over a mean period of time of 29.06 days (SD 44.91).
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15 277 In terms of comparators, it is possible to underline three types of comparisons. The first
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17 278 comparison is an AEE versus another AEE with design variations (n=4) ³¹⁻³⁴, which implies that
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19 279 one of the AEEs assessed had variations in its adaptation techniques (e.g., feedback in one AEE
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21 280 is longer or more complex than in the other). The second comparison is an AEE versus a
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23 281 nonadaptive e-learning environment (n=8) ^{35-37 40 42-44 47}. The third and final comparison is an
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25 282 AEE versus another type of educational intervention, such as a paper-based educational
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27 283 intervention, including handouts, textbooks or images (n=3) ^{39 41 45}, and a traditional educational
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29 284 intervention, such as a group lecture (n=1) ⁴⁶. As stated before, only the second and third types of
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31 285 comparisons were included in the meta-analysis since our aim was to synthesize quantitatively th
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33 286 effectiveness of AEEs versus other types of educational interventions. Finally, in terms of
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35 287 outcomes, investigators evaluated learners' knowledge (n=11) ^{31 32 34 35 37 41-46}, satisfaction (n=9)
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37 288 ^{31 33 35 37 41-45}, competence (including skills) (n=6) ^{33 36 38-40 47}, and metacognitive processes (n=3)
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39 289 ^{31 32 34}. However, none of the studies reported the assessment of health professionals' and
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41 290 students' clinical behavior.
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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

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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

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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, Δ 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**

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300 **Characteristics of Adaptive E-learning Environments**

301 We summarized the key characteristics of AEEs assessed in the 17 studies in table format (see
302 **Table 2**). In terms of the clinical topics of the AEEs, the majority of AEEs focused on training
303 medical students and residents in executing and/or interpreting diagnostic tests. Indeed, the AEEs
304 assessed focused on dermatopathology and cytopathology microscopy^{31-34 39 41 42 45} (n=8), on
305 diagnostic imaging^{36 43} (n=2), on chronic disease management⁴⁴ (n=1), on pressure ulcer
306 evaluation⁴⁶ (n=1), on the management of childhood illness³⁵ (n=1), on brief intervention for
307 alcohol consumption⁴⁰ (n=1), on electrocardiography⁴⁷ (n=1), on fetal heart rate interpretation³⁸
308 (n=1), and on hemodynamics³⁷ (n=1). Four out of 17 AEEs focused on developing the
309 knowledge or skills of health professionals and students with regard to performing interventions
310 in clinical practice^{35 40 44 46}. Investigators adopted a wide variety of theoretical frameworks in the
311 17 studies. The most frequently used framework was cognitive tutoring, adopted in 5 studies³¹⁻³⁴
312³⁹, which implies the use of a cognitive model. The integration of a cognitive model in an AEE
313 implies the representation of all the knowledge in the field of interest in a way that is similar to
314 the human mind for the purpose of understanding and predicting the cognitive processes of
315 learners⁴⁸. The second most used framework was perceptual learning, adopted in 3 studies^{36 38 47}.
316 Perceptual learning aims at improving information extraction skills of the environment and the
317 development of automaticity in this respect in learners³⁶. Theoretical frameworks relating to self-
318 regulated learning³⁴, learning styles³⁵, guided mastery⁴⁰, and cognitive load⁴³ were also used.

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

322 First Subdomain: Goals of the Adaptation Process

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

331 Second Subdomain: Variables Targeted by the Adaptation Process

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

338 Third Subdomain: Adaptation Techniques

339 The third subdomain relates to which adaptation techniques are mobilized in the AEE. In the
340 context of this review, the adaptation techniques are based upon the work of Knutov and
341 colleagues⁸. *Content adaptation* was the most used adaptation technique; it was implemented in
342 all AEEs reviewed (n=17). Content adaptation aims to adapt the textual information (curriculum
343 content) to the learner's profile through different mechanisms and to different degrees⁸.

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3 344 *Navigation adaptation* was the second most used adaptation technique (n=13). Navigation can be
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5 345 adapted in two ways; it can be enforced or suggested. When enforced, an optimal personalized
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7 346 learning path is determined for the user by the algorithms within the AEE. When suggested, there
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10 347 are several personalized learning paths available to each user, who can determine the path he
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12 348 prefers himself⁸. Most reviewed studies included AEEs with enforced navigation, with one
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14 349 optimal personalized learning path being determined through various algorithms. *Multimedia*
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16 350 *adaptation* was the third most used adaptation technique (n=10). This adaptation technique, much
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19 351 like content adaptation which relates to textual information, implies the adaptation of the
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21 352 multimedia elements of the training such as videos, pictures, models, to the user's profile.
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23 353 *Presentation adaptation* was the fourth most used adaptation technique (n=8). It implies the
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25 354 adaptation of the layout of the page to the digital device used, or to the user's profile. *Tools*
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27 355 *adaptation* was the least used adaptation technique (n=7). This technique results in providing a
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30 356 different set of features or learning strategies for different types of users, such as different
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32 357 interfaces for problem solving, and knowledge representation.

36 358 **Fourth Subdomain: Timing of the Adaptation**

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39 359 This last subdomain relates to *when* the adaptation occurs during the learning process with the
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41 360 AEE. In 16 out of 17 studies, the adaptation occurred throughout the training with AEE, usually
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43 361 after an answer to a question or during intermediate problem-solving steps. In one study,
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45 362 adaptation techniques were only implemented at the beginning of the training with the AEE³⁵.

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365 **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					Fourth subdomain: Timing of adaptation
						Content	Navigation	Personalisation	Interactivity	Tools	
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 each case.

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4	Hayes-Roth, 2010	Brief intervention training in alcohol abuse	Guided Mastery	STAR Workshop	LE	User scores, user-generated dialogue	✓	✓		During clinical cases		
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8	Morente, 2013	Pressure ulcer evaluation	NR	ePULab	LE	User skills	✓			Each pressure ulcer evaluation.		
9												
10												
11	Munoz, 2010	Management of childhood illness	Learning Styles Framework	SIAS-ITS	LE, LEF	User knowledge, user learning style	✓		✓	At the beginning of the training.		
12												
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16	Romito, 2016	Transoesophageal echocardiography	Perceptual Learning	TOE PALM	DX	User response accuracy, user response time	✓	✓	✓	After each clinical case.		
17												
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20	Samulski, 2017	Cytopathology; pap test, squamous lesions, glandular lesions	NR	SmartSparrow	LE	User knowledge	✓	✓		During intermediate problem-solving steps.		
21												
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24	Thai, 2015	Electrocardiography	Perceptual Learning Theory; Adaptive response-time	PALM	LE, LEF	User response accuracy, user response time	✓		✓	✓	✓	After each user response.
25												
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28	Van Es, 2015	Diagnostic cytopathology; gynecology, fine needle aspiration, exfoliative fluid	NR	SmartSparrow	LE	User responses	✓	✓	✓	✓	During intermediate problem-solving steps.	
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33	Van Es, 2016	Diagnostic cytopathology; gynecology, fine needle aspiration, exfoliative fluid	NR	SmartSparrow	LE	User responses	✓	✓	✓	✓	✓	During intermediate problem-solving steps.
34												
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38	Wong, 2015	Diagnostic imaging; chest X-rays, CT scans	Cognitive Load Theory	SmartSparrow	LE	User responses	✓				During intermediate problem-solving steps.	
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4	Wong, 2017	Fetal heart rate interpretation	Perceptual Learning	PALM	DX	User response accuracy, user response time	✓	✓	✓	After each clinical case.
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8	Woo, 2006	Hemodynamics; baroreceptor reflex	NR	CIRCSIM-Tutor	LE	User knowledge, user responses	✓	✓	✓	After each user response.
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Goals/Objectives : LE indicates learning effectiveness; LEF learning efficiency; DX diagnostic accuracy; MC metacognitive gains; RP reporting performance.
 NR indicates not reported.

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377 Risk of Bias Assessment

378 Results of included studies for the risk of bias assessment are presented in **Figure 3** and **Figure 4**.

379 In $\geq 75\%$ of studies, biases related to random sequence generation, similarity of baseline outcome
380 measurements, and selective reporting of outcomes were low. Moreover, in $\geq 50\%$ of studies,
381 biases related to the blinding of outcome assessment and contamination were low. Regarding the
382 blinding of outcome assessment, in most studies, review authors judged that the outcome and the
383 outcome measurement were not likely to be influenced by the lack of blinding, since studies had
384 objective measures, i.e. an evaluative test of knowledge or competence. Regarding contamination
385 bias, review authors scored studies at high risk if they had a crossover design.

386 However, in $\geq 50\%$ of studies, biases related to allocation concealment, similarity of baseline
387 characteristics, blinding of participants and personnel, and incomplete outcome data were unclear
388 or high. Review authors, by consensus, decided that the cut-off criterion in terms of risk of bias to
389 be included in the meta-analysis was randomization of study participants. Thus, the four
390 studies³⁵⁻³⁸ that presented high or unclear risk of bias regarding random sequence generation
391 were not included in the meta-analysis.

392 Quantitative Results

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

394 As we considered effect sizes larger than 0.8 to be large⁴⁹, the pooled effect size (SMD 1.32;
395 95% confidence interval [CI] 0.20-2.43; $Z = 2.32$, $P = 0.02$) of AEEs compared to other educational
396 interventions in improving all learning outcomes suggests a significantly large effect (see **Figure**
397 **5**). However, significant statistical heterogeneity was observed among studies ($I^2 = 96\%$, P
398 $< .00001$), and individual effect sizes ranged from -1.10 to 3.05.

399 Effectiveness of AEEs versus other educational interventions in improving knowledge

400 The pooled effect size (SMD 1.04; 95% CI -0.86-2.94; $Z = 1.08$, $P 0.28$) of AEEs compared to
401 other educational interventions in improving knowledge suggests a large, but nonsignificant
402 effect (see **Figure 6**). Significant statistical heterogeneity was observed among studies ($I^2 = 98\%$, P
403 $<.00001$), and individual effect sizes ranged from -1.10 to 3.05. One study in particular⁴⁴ reported
404 a negative effect size, but the difference between groups in knowledge scores was statistically
405 nonsignificant. Moreover, while participants using the AEE in the experimental group reported
406 the same knowledge scores than participants in the control group at the end of study, time spent
407 on instruction was reduced by 18% with the AEE compared to the nonadaptive e-learning
408 environment, thus improving learning efficiency⁴⁴.

409 Effectiveness of AEEs versus other educational interventions in improving competence

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

414 Quality of the Evidence

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

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3 420 precisely, risk of bias was deemed serious, inconsistency serious, indirectness not serious, and
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5 421 imprecision serious.
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8 422 **DISCUSSION**

9 423 **Principal Findings**

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12 424 This is the first systematic review and meta-analysis to evaluate the effectiveness of AEEs in
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15 425 health professionals and students. We identified 17 relevant studies published since 2006, 13 of
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18 426 which assessed an AEE versus another educational intervention (large-group classroom
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21 427 instruction, nonadaptive e-learning environment or paper-based learning), and 4 of which
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24 428 assessed 2 AEEs with design variations head-to-head. When compared with other educational
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27 429 interventions, AEEs were associated with statistically significant improvements in learning
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29 430 outcomes in 9 out of 13 studies. Pooled ES were large for knowledge and competence, but only
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31 431 the latter was associated with a statistically significant effect. Statistical heterogeneity was high
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33 432 in all analyses. However, this finding is consistent with other meta-analyses in the field of
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35 433 medical education that also reported high heterogeneity across studies⁵⁰⁻⁵². A small number of
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37 434 eligible studies prohibited us from performing subgroup analyses which could have helped in
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40 435 explaining the source of the heterogeneity. The quality of evidence for all comparisons was
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43 436 either low or very low. Therefore, while we believe the results support the potential of AEEs for
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45 437 the education of health professionals and students, we recommend interpreting the ES with
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47 438 caution.
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50 439 **Comparison with Other Studies**

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53 440 To our knowledge, no previous systematic review and meta-analysis has specifically assessed the
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56 441 effectiveness of AEEs in improving learning outcomes in health professionals and students, or
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3 442 any other population. However, interestingly, since the 1990's there has been a strong research
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5 443 interest in the field of AEEs that integrate artificial intelligence (also known as intelligent e-
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7 444 learning environments [IEEs] and intelligent tutoring systems [ITSs], **Type B2**) into elementary,
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10 445 high school and postsecondary education for multiple subjects.¹⁵ Thus, multiple meta-analyses
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12 446 have been conducted with regard to AEEs in that setting.
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15 447 Steenbergen-Hu and Cooper¹³ reported a mean ES of 0.35 of AEEs integrating artificial
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17 448 intelligence on learning outcomes in college students when compared to all other types of
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19 449 educational interventions. The mean ES was 0.37 when the comparator was large-group
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21 450 classroom instruction, 0.35 when the comparator was nonadaptive e-learning, and 0.47 when the
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23 451 comparator was textbooks or workbooks¹³.
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27 452 Ma, et al.¹⁶ reported a mean ES of 0.42 of AEEs integrating artificial intelligence on learning
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29 453 outcomes in elementary, high school and postsecondary students when compared to large-group
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31 454 classroom instruction. The mean ES was 0.57 when the comparator was nonadaptive e-learning,
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33 455 and 0.35 when the comparator was textbooks or workbooks. Interestingly, the mean ES was
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35 456 higher for studies which assessed an AEE in biology and physiology (0.59) and in humanities and
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37 457 social science (0.63) than in studies which assessed an AEE in mathematics (0.35) and physics
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39 458 (0.38)¹⁶.
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44 459 Kulik and Fletcher¹⁵ reported a mean ES of 0.65 of AEEs integrating artificial intelligence on
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46 460 learning outcomes in elementary, high school, and postsecondary students when compared to
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48 461 large-group classroom instruction. Education areas in this review were diverse (e.g.,
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50 462 mathematics, computer science, physics), but none were related to health sciences. Interestingly,
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52 463 the mean ES was 0.78 for studies up to 80 participants, and 0.30 for studies with more than 250
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3 464 participants. Moreover, the mean ES for studies conducted with elementary and high school
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5 465 students was 0.44, compared to 0.75 for studies conducted with postsecondary students¹⁵.
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8 466 Thus, in light of the results of these meta-analyses, the ES reported in our review may appear
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10 467 high. However, our review looked more specifically into the effectiveness of AEEs in improving
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12 468 learning outcomes in health professionals and students. This is significant since, in the meta-
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14 469 analyses of Steenbergen-Hu and Cooper¹³, Ma, et al.¹⁶, and Kulik and Fletcher¹⁵, AEEs seem to
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17 470 be more effective in postsecondary students^{15 16} and for learning subjects related to biology,
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19 471 physiology and social science¹⁶. Moreover, previous meta-analyses focused on the effectiveness
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21 472 of AEEs in improving procedural and declarative knowledge, and did not report on the
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23 473 effectiveness on AEEs in improving skills or competence. This is important since AEEs may be
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25 474 more effective for providing tailored guidance and coaching for developing skills and
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27 475 competence regarding complex clinical interventions, rather than learning factual knowledge, as
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29 476 the results of our review suggest.
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34 477 **Strengths and Limitations**

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37 478 Strengths of this systematic review and meta-analysis include the prospective registration and
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39 479 publication of a protocol based on rigorous methods in accordance with Cochrane and PRISMA
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41 480 guidelines; the exhaustive search in all relevant databases; the independent screening of the titles,
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43 481 abstracts and full-text of studies; the assessment of each included studies' risk of bias using
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45 482 EPOC Cochrane guidelines; and the assessment of the quality of evidence for each individual
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47 483 outcome using the GRADE methodology.
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52 484 Our review also has limitations to consider. First, outcome measures varied widely across
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54 485 studies. To address this issue, we conducted the meta-analysis using the SMD. Using the SMD
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3 486 allowed us to standardize the results of studies to a uniform scale before pooling them. However,
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5 487 the SMD also has drawbacks, since this method assumes that the differences in SDs reflect
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7 488 differences in outcome measures, and not differences attributable to variability among study
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10 489 populations²⁹. Nevertheless, review authors judged that using the SMD was the best option for
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12 490 this review, as it is the current practice in the field of knowledge synthesis in medical education¹²
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18 492 Second, there was high inconsistency among study results, which we can mostly attribute to
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20 493 differences in populations, AEE design, research methods, and outcomes. This resulted in
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22 494 sometimes widely differing estimates of effect. To partly address this issue, we used a random-
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24 495 effects model for the meta-analysis, which assumes that the effects estimated in the studies are
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26 496 different and follow a distribution²⁹. However, since a random-effects model awards more weight
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29 497 to smaller studies to learn about the distribution of effects, it could potentially exacerbate the
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31 498 effects of the bias in these studies²⁹.

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35 499 Third, we made the decision to limit our search from the year 2005 onwards. This decision was
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37 500 based on the fact that studies published before 2005 seem to have a bias toward more positive
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39 501 results¹⁵. This could be explained by the novelty of e-learning in earlier studies, which could
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41 502 have positively affected student motivation and learning outcomes. Moreover, educational
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44 503 technology has significantly evolved since the early 2000s.

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47 504 Finally, publication bias could not be assessed by the means of a funnel plot since there were less
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49 505 than 10 studies included in the meta-analysis.
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506 CONCLUSIONS

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

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

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545 All review authors contributed to at least one aspect of each of the four criteria for authorship
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547 G.F. contributed to the conception and design of the review, to the acquisition and analysis of
548 data, and to the interpretation of results. Moreover, G.F. drafted the initial manuscript. S.C.
549 contributed to the conception and design of the review, and to the interpretation of results. M.-
550 A.M.-C. contributed to the conception and design of the review, to the acquisition of data, and

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3 551 interpretation of results. T.M. contributed to the conception and design of the review, to the
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5 552 acquisition of data, and to the interpretation of results. M.-F.D. contributed to the conception and
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7 553 design of the review, to the acquisition of data, and to the interpretation of results. G.M.-D.
8
9 554 contributed to the conception and design of the review, and to the interpretation of results. J.C.
10
11 555 contributed to the interpretation of results. M.-P.G. contributed to the interpretation of results.
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13 556 V.D. contributed to the interpretation of results.
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18 557 All review authors contributed to manuscript writing, critically revised the manuscript, gave final
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20 558 approval, and agreed to be accountable for all aspects of work, ensuring integrity and accuracy.
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23 559 **COMPETING INTERESTS**

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26 560 All authors have completed the ICMJE uniform disclosure form at
27
28 561 www.icmje.org/coi_disclosure.pdf and declare: no support from any organisation for the
29
30 562 submitted work; no financial relationships with any organisation that might have an interest in the
31
32 563 submitted work in the previous three years; no other relationships or activities that could appear
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34 564 to have influenced the submitted work.
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42 566 This study received no funding.
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45 567 **DATA SHARING STATEMENT**

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48 568 No additional data are available.
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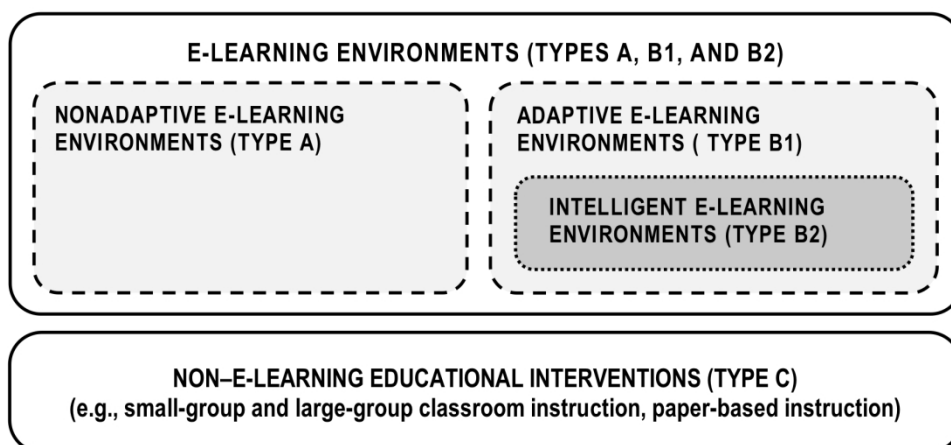


Figure 1. Types of educational interventions examined in the context of this review.

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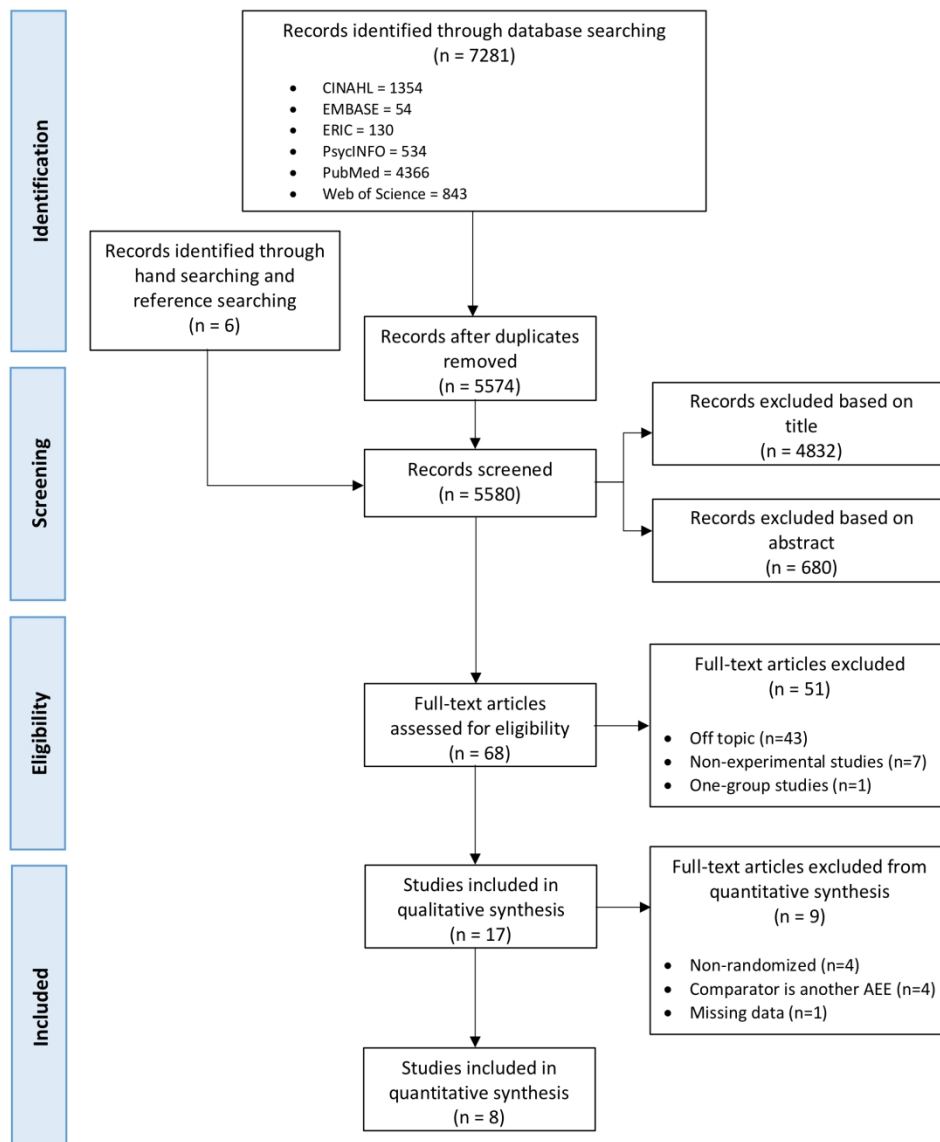


Figure 2. PRISMA study flow diagram.

190x229mm (300 x 300 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 bias)	Blinding of outcome assessment (detection bias)	Incomplete outcome data (attrition bias)	Selective reporting (reporting bias)	Measures against contamination?
Cook 2008	+	+	?	+	+	+	+	+	+
Crowley 2007	+	?	+	?	?	+	+	+	+
Crowley 2010	+	?	+	+	?	+	+	+	+
El Saadawi 2008	+	?	+	?	?	?	?	+	+
El Saadawi 2010	+	?	+	?	?	+	?	+	+
Feyzi-Behnagh 2014	+	?	+	?	?	+	?	+	+
Hayes-Roth 2010	+	?	+	?	?	+	+	+	+
Morente 2013	+	?	+	+	?	+	+	+	+
Munoz 2010	+	+	+	+	?	+	?	+	+
Romito 2016	+	+	+	?	?	+	+	+	+
Samulski 2017	+	?	+	+	?	+	?	+	+
Thai 2015	+	?	+	?	?	+	?	+	+
Van Es 2015	+	?	+	+	?	+	+	+	+
Van Es 2016	+	?	+	+	?	+	+	+	+
Wong 2015	+	?	?	+	?	+	+	?	+
Wong 2017	+	+	+	?	?	+	?	+	+
Woo 2006	?	?	+	?	?	?	+	+	+

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

106x228mm (300 x 300 DPI)

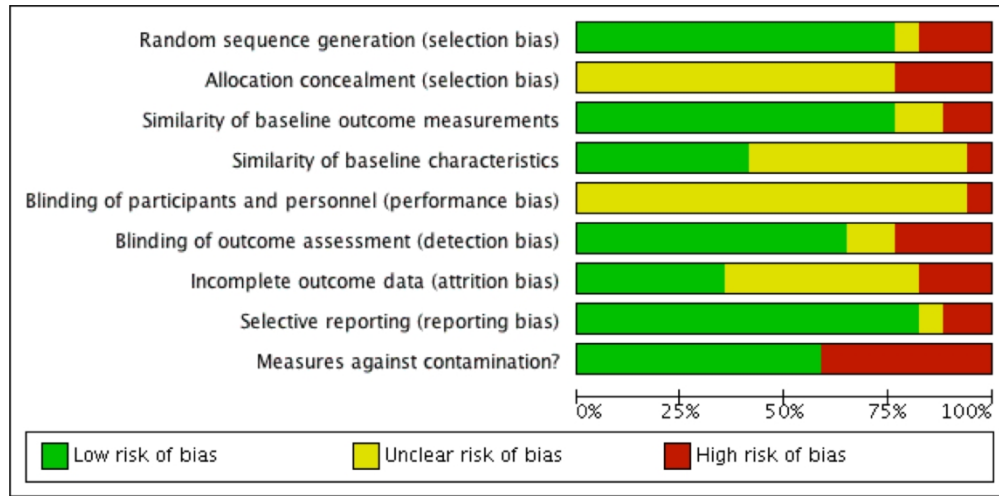


Figure 4. Risk of bias graph: review authors' judgements about each risk of bias item presented as percentages across all included studies.

205x101mm (300 x 300 DPI)

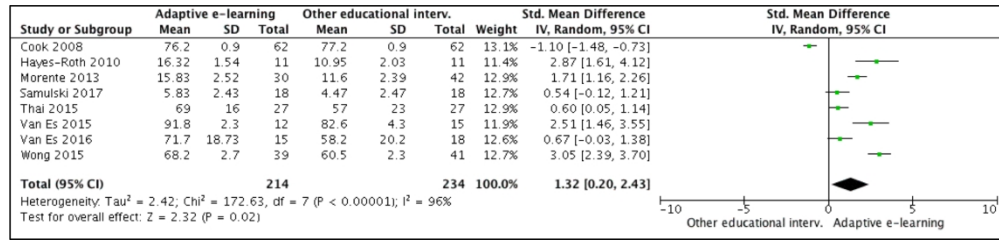


Figure 5. Forest plot #1: meta-analysis of the effectiveness of adaptive e-learning environments versus other educational interventions in improving all learning outcomes.

242x56mm (300 x 300 DPI)

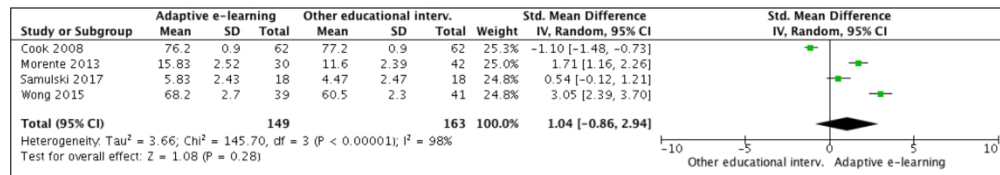


Figure 6. Forest plot #2: meta-analysis of the effectiveness of adaptive e-learning environments versus other educational interventions in improving knowledge.

247x42mm (300 x 300 DPI)

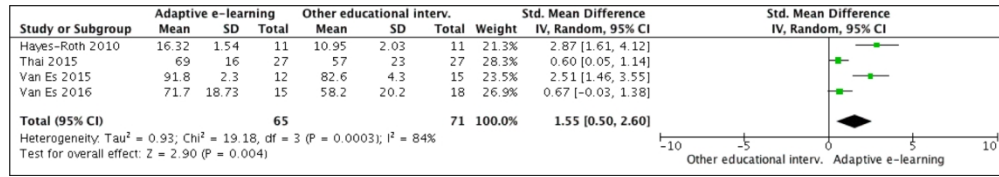


Figure 7. Forest plot #3: meta-analysis of the effectiveness of adaptive e-learning environments versus other educational interventions in improving competence.

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 pediatricist*[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							No of patients		Effect	Certainty	Importance
No 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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Manuscripts

1 Efficacy of adaptive e-learning for health professionals and 2 students: a systematic review and meta-analysis

3
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30 34 **DECLARATION OF COMPETING INTERESTS**
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35 36 www.icmje.org/coi_disclosure.pdf and declare: no support from any organisation for the
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37 37 submitted work; no financial relationships with any organisation that might have an interest in the
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39 38 submitted work in the previous three years; no other relationships or activities that could appear
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41 39 to have influenced the submitted work
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45 40 **TRANSPARENCY DECLARATION**
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49 41 The lead author (the manuscript's guarantor) affirms that the manuscript is an honest,
50
51 42 accurate, and transparent account of the study being reported; that no important aspects of the
52
53 43 study have been omitted; and that any discrepancies from the study as planned (and, if relevant,
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55 44 registered) have been explained.
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46 This study received no funding.

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48 **ABSTRACT (300 WORDS)**

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

53 **Design:** Systematic review and meta-analysis.

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

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

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

63 **Results:** From a pool of 10,569 articles, we included 21 eligible studies enrolling 3,684 health
64 professionals and students. Clinical topics were mostly related to diagnostic testing, theoretical
65 frameworks were heterogeneous, and the adaptivity process was characterized by 5 subdomains:
66 method, goals, timing, factors, and types. The pooled ES was 0.70 for knowledge (95% CI, -0.08-
67 1.49; P .08), and 1.19 for skills (95% CI, 0.59-1.79; P < .00001). Risk of bias was generally high.
68 Heterogeneity was large in all analyses.

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3 69 **Conclusions:** AEEs appear particularly effective in improving skills in health professionals and
4
5 70 students. The adaptivity process within AEEs may be more beneficial for learning skills rather
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7 71 than factual knowledge, which generates less cognitive load. Future research should report more
8
9 72 clearly on the design and adaptivity process of AEEs, and target higher-level outcomes, such as
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11 73 clinical behavior.
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15 74 **PROSPERO registration number:** CRD42017065585
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18 75 **Keywords:** Computer-assisted instruction; medical education; nursing education; e-learning,
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20 76 meta-analysis
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77 **ARTICLE SUMMARY**

78 **Strengths and Limitations of the Study**

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

88 INTRODUCTION

89 The use of information and communication technologies (ICTs) in the education of health
90 professionals and students has become ubiquitous. Indeed, e-learning, defined as the use of ITCs
91 to access educational curriculum and support learning¹, is increasingly present in clinical settings
92 for the continuing education of health professionals^{2,3}, and in academic settings for the education
93 of health professions students⁴. E-learning environments integrate information, in the form of text
94 and multimedia (e.g., illustrations, animations, videos). They can include both asynchronous (i.e.,
95 designed for self-study) and synchronous (i.e., a class taught by an educator in real time)
96 components¹. *Nonadaptive* e-learning environments, the most widespread type of e-learning
97 environment today, provide a standardized training for all learners^{5,6}. While they can include
98 instructional design variations (e.g., interactivity, feedback, practice exercises), they *do not*
99 consider learners' characteristics and the data generated during the learning process to provide a
100 personalized training⁶⁻⁸. This is problematic, since the interaction of health professionals and
101 students with e-learning environments during the learning process generates a significant amount
102 of data⁹. However, designers of e-learning environments and educators rarely make use of this
103 data to optimize learning efficacy and efficiency⁹.

104 In recent years, educational researchers have strived to develop e-learning environments that take
105 a data-driven and personalized approach to education¹⁰⁻¹³. E-learning environments that take into
106 account each learner's interactions and performance level could anticipate what types of content
107 and resources meet the learner's needs, potentially increasing learning efficacy and efficiency¹³.

108 Adaptive e-learning environments (AEEs) were developed for this purpose. AEEs collect data to
109 build each learner's profile (e.g., navigation behavior, preferences, knowledge), and use simple
110 techniques (e.g., adaptive information filtering, adaptive hypermedia) to implement different

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3 111 types of adaptivity targeting the content, navigation, presentation, multimedia, or strategies of the
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5 112 training to provide a personalized learning experience^{11 12}. In the fields of computer science and
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7 113 educational technology, the term *adaptivity* refers to the process executed by a system based on
8
9 114 ICTs of adapting educational curriculum content, structure or delivery to the profile of a
10
11 115 learner¹⁴. Two main methods of adaptivity can be implemented within an AEE. The first method,
12
13 116 *designed adaptivity*, is expert-based and refers to an educator who designs the optimal
14
15 117 instructional sequence to guide learners to learning content mastery. The educator determines
16
17 118 how the curriculum will adapt to learners based on a variety of factors, such as knowledge or
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19 119 response time to a question. This method of adaptivity is thus based on the expertise of the
20
21 120 educator who specifies how technology will react in a particular situation on the basis of the “if
22
23 121 THIS, then THAT” approach. The second method, *algorithmic adaptivity*, refers to use of
24
25 122 algorithms to determine, for instance, the extent of the learner’s knowledge and the optimal
26
27 123 instructional sequence. Algorithmic adaptivity requires more advanced adaptivity techniques and
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29 124 learner-modelling techniques derived from the fields of computer science and artificial
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31 125 intelligence (e.g. Bayesian knowledge tracing, rule-based machine learning, natural language
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33 126 processing)^{10 15-18}.

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41 127 The variability in the degree and the complexity of adaptivity within AEEs mirrors the adaptivity
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43 128 that can be observed in non-e-learning educational interventions. Some interventions, like one-
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45 129 on-one human instruction and small-group classroom instruction, generally have a high degree of
46
47 130 adaptivity since the instructor can adapt his teaching to the individual profiles of learners and
48
49 131 consider their feedback¹⁹. Other interventions, like large-group classroom instruction, generally
50
51 132 have a low degree of adaptivity to individual learners. In some interventions, like paper-based
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53 133 instruction (e.g., handouts, textbooks), there is no adaptivity at all.
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3 134 AEEs have been developed and evaluated primarily in academic settings for students in
4
5 135 mathematics, physics and related disciplines, for the acquisition of knowledge and development
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7 136 of cognitive skills (e.g., arithmetic calculation). Four meta-analyses reported on the efficacy of
8
9 137 AEEs among high school and university students in in these fields of study^{15-17 20}. The results are
10
11 138 promising: AEEs are in almost all cases more effective than large-group classroom instruction. In
12
13 139 addition, Nesbit, et al.²¹ point out that AEEs are more effective than nonadaptive e-learning
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15 140 environments. However, despite evidence of the efficacy of AEEs for knowledge acquisition and
16
17 141 skill development in areas such as mathematics in high school and university students, their
18
19 142 efficacy in improving learning outcomes in health professionals and students has not yet been
20
21 143 established. To address this need, we conducted a systematic review and meta-analysis to identify
22
23 144 and quantitatively synthesize all comparative studies of AEEs involving health professionals and
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25 145 students.

146 **Systematic Review and Meta-Analysis Objective**

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

150 **Systematic Review and Meta-Analysis Questions**

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

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

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3 156 We sought to answer the following question with the meta-analysis:
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6 157 3. What is the efficacy of AEEs in improving knowledge, skills, and clinical behavior in
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8 158 health professionals and students in comparison with nonadaptive e-learning
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10 159 environments, and non-e-learning educational interventions?
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14 160 **METHODS**

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17 161 We planned and conducted this systematic review following the Effective Practice and
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19 162 Organization of Care (EPOC) Cochrane Group guidelines²², and reported it according to the
20
21 163 Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) standards²³ (see
22
23 164 **Supplementary File 1**). We prospectively registered (International Prospective Register of
24
25 165 Systematic Reviews #CRD42017065585) and published the protocol of this systematic review²⁴.
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27 166 Thus, in this paper, we present an abridged version of the methods with an emphasis on changes
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29 167 made to the methods since the publication of the protocol.
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34 168 **Study Eligibility**

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37 169 We included primary research articles that assessed an AEE with licensed health professionals,
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39 170 students, trainees, and residents in any discipline. We defined an AEE as a computer-based
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41 171 learning environment which collects data to build each learner's profile (e.g., navigation
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43 172 behavior, individual objectives, knowledge), interprets these data through algorithms, and adapts
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45 173 in real-time the content (e.g., showing/hiding information), navigation (e.g., specific links and
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47 174 paths), presentation (e.g., page layout), multimedia presentation (e.g., images, videos), or tools
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49 175 (e.g., different set of strategies for different types of learners) to provide a dynamic and
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51 176 evolutionary learning path for each learner^{10 14}. We used the definitions of each type of adaptivity
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54 177 proposed by Knutov and colleagues¹². We considered for inclusion studies in which AEEs had
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3 178 designed or algorithmic adaptivity, and studies including a co-intervention in addition to adaptive
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5 179 e-learning (e.g. paper-based instruction). We considered for inclusion primary research articles
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7 180 in which the comparator was: 1) a nonadaptive e-learning environment; 2) a non-e-learning
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9 181 educational intervention; 3) another AEE with design variations. While included in the qualitative
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11 182 synthesis of the evidence for descriptive purposes, the third comparator was excluded from the
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13 183 meta-analysis. Outcomes of interest were knowledge, skills, and behavior^{25 26}, and were defined
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15 184 as follows: 1) knowledge: subjective (e.g., learner self-report) or objective (e.g., multiple-choice
16
17 185 question knowledge test) assessments of factual or conceptual understanding; 2) skills: subjective
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19 186 (eg, learner self-report) or objective (eg, faculty ratings) assessments of procedural skills (e.g.
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21 187 taking a blood sample, performing CPR) or cognitive skills (e.g. problem-solving, interpreting
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23 188 radiographs) in learners; 3) behavior: subjective (eg, learner self-report) or objective (eg, chart
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25 189 audit) assessments of behaviors in clinical practice (such as test ordering)⁶. In terms of study
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27 190 design, we considered for inclusion all controlled, quantitative studies in accordance with the
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29 191 EPOC Cochrane Review Group guidelines²⁷.

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36 192 We excluded studies that: 1) were not published in English or French; 2) were non-experimental;
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38 193 3) were not controlled; 4) did not report on at least one of the outcomes of interest in this review;
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40 194 5) did not have a topic related to the clinical aspects of health.

41 42 43 195 **Study Identification**

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47 196 We previously published our search strategy²⁴. Briefly, we designed a strategy in consultation
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49 197 with a librarian to search CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science
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51 198 for primary research articles published since the inception of each database up to February 2019.
52
53 199 The search strategy revolved around 3 key concepts: “adaptive e-learning environments”, “health

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3 200 professionals/students”, and “effects on knowledge/competence (skills)/behavior” (see
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5 201 **Supplementary file 2**). To identify additional articles, we hand-searched 6 key journals (e.g.,
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7 202 *British Journal of Educational Technology, Computers and Education*) and the reference lists of
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9
10 203 included primary research articles.

13 204 **Study Selection**

16 205 We worked independently and in duplicate (G.F. and M.-A.M.-C./T.M.) to screen all titles and
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18 206 abstracts for inclusion using the EndNote software V8.0 (Clarivate Analytics). We resolved
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21 207 disagreements by consensus. We then performed the full-text assessment of potentially eligible
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23 208 articles using the same methodology. Studies were included in the meta-analysis if they had a
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25 209 non-AEE control group and had no missing data.

28 210 **Data Extraction**

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32 211 One review author (G.F.) extracted data from included primary research articles using a modified
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34 212 version of the data collection form developed by the EPOC Cochrane Review Group²⁸. The main
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36 213 changes made to the extraction form were the addition of specific items relating to the AEE
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38 214 assessed in each study. Two review authors (T.M., M.-F.D.) validated the data extraction forms
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40 215 by reviewed the contents of each form against the data in the original article, adding comments
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43 216 when changes were needed. For all studies, we extracted the following data items if possible:

- 46 217 • *the population and setting*: study setting, study population, inclusion criteria, exclusion
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48 218 criteria;
- 51 219 • *the methods*: study aim, study design, unit of allocation, study start date and end date, and
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53 220 duration of participation;

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3 221 • *the participants*: study sample, withdrawals and exclusions, age, sex, level of instruction,
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5 222 number of years of experience as a health professional, practice setting, and previous
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7 223 experience using e-learning;
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10 224 • *the interventions*: name of intervention, theoretical framework, statistical model/algorithm
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12 225 used to generate the learning path, clinical topic, number of training sessions, duration of
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14 226 each training session, total duration of the training, adaptivity subdomains (method, goals,
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16 227 timing, factors, types), mode of delivery, presence of other educational interventions and
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18 228 strategies;
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20 229 • *the outcomes*: name, time-points measured, definition, person measuring, unit of
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22 230 measurement, scales, validation of measurement tool;
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24 231 • *the results*: results according to our primary (knowledge) and secondary (skills, behavior)
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26 232 outcomes, comparison, time-point, baseline data, statistical methods used, and key
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28 233 conclusions.

29 234 We contacted the corresponding authors of included primary research articles to provide us with
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31 235 missing data.

32 236 **Assessment of the Risk of Bias**

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34 237 We worked independently and in duplicate (G.F. and T.M./M.-F.D.) to assess the risk of bias of
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36 238 included primary research articles using the EPOC risk of bias criteria, based upon the data
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38 239 extracted with the data collection form²⁸. A study was deemed at high risk of bias if the
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40 240 individual criterion “random sequence generation” was scored at “high” or at “unclear” risk of
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42 241 bias.

242 Data Synthesis

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

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

255 We first assessed heterogeneity qualitatively by examining the characteristics of included studies,
256 the similarities and disparities between the types of participants, the types of interventions, and
257 the types of outcomes. We then used the I^2 statistic within the RevMan software to quantify how
258 much the results varied across individual studies (i.e., between-study inconsistency, or
259 heterogeneity). We interpreted the I^2 values as follows: 0%-40%: might not be important; 30%-
260 60%: may represent moderate heterogeneity; 50%-90%: may represent substantial heterogeneity;
261 and 75%-100%: considerable heterogeneity²⁹. We performed sensitivity analysis to assess if the
262 exclusion of studies at high risk of bias or with a small sample size ($n < 20$) would have had an

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3 263 impact on statistical heterogeneity. The small number of studies included in each meta-analysis
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5 264 did not allow for subgroup analyses to be performed.
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8 265 Since less than 10 studies were included in the meta-analysis for each outcome, we did not assess
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10 266 reporting biases using a funnel plot, as suggested in the Cochrane Handbook³⁰.
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14 267 **Assessment of the Quality of Evidence**

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17 268 We worked independently and in duplicate (G.F. and M.-A.M.-C.) to assess the quality of
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19 269 evidence for each individual outcome. We used the Grading of Recommendations Assessment,
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21 270 Development, and Evaluation (GRADE) Web-based software, based upon the data extracted with
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23 271 the data collection checklist³¹. We considered 5 factors (risk of bias of included studies,
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25 272 indirectness of evidence, unexplained heterogeneity or inconsistency of results, imprecision of
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27 273 the results, probability of reporting bias) for downgrading the quality of the body of evidence for
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29 274 each outcome³¹.
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34 275 **Patient and Public Involvement**

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37 276 Patients and the public were not involved in setting the research question, the outcome measures,
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39 277 the design or conduct of this systematic review. Patients and the public were not asked to advise
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41 278 on interpretation of results or to contribute to the writing or editing of this document.
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45 279 **RESULTS**

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48 280 **Study Flow**

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51 281 From a pool of 10,569 potentially relevant articles, we found 21 quantitative, controlled studies
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53 282 assessing an AEE with health professionals or students (see **Figure 1**).
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3 283 [Insert Figure 1]
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6 284 Out of 21 included studies in the qualitative synthesis, 4 studies compared two AEEs with design
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8 285 variations³²⁻³⁵, and 4 studies had missing data³⁶⁻³⁹. Thus, these 8 studies could not be included in
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10 286 the meta-analysis and the remaining 13 studies were used to calculate an ES on learning
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13 287 outcomes.
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16 288 **Study Characteristics**

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19 289 We summarized the key characteristics of included studies in table format (see **Table 1**). In terms
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21 290 of study population, in the 21 studies examined published between 2003 and 2018, investigators
22
23 291 have evaluated AEEs mostly in the medical field. Studies focused on medical students (n=8)³⁸⁻⁴⁴,
24
25 292 medical residents (n=8)^{32-35 41 45-47}, physicians in practice (n=4)^{36 37 41 48}, nursing students (n=2)
26
27 293 ^{40 49}, nurses in practice (n=2)^{48 50} and health sciences students (n=1)⁵¹. Three studies focused on
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29 294 multiple populations^{40 41 48}. The median sample size was 46 participants (interquartile range
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31 295 [IQR] 123). In terms of study design, 15 out of 21 studies (71%) were randomized, 7 studies of
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33 296 which were randomized crossover trials^{33 34 41-43 45 47}. The median number of training sessions
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35 297 was 2 (IQR 2.5 sessions), the median training time was 2.13 hours (IQR 2.88 hours), and the
36
37 298 median training period was 14 days (IQR 45 days). In terms of comparators, it is possible to
38
39 299 underline three types of comparisons. The first comparison is an AEE versus another AEE with
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41 300 design variations (n=4)³²⁻³⁵, which implies that one of the AEEs assessed had variations in its
42
43 301 design, such as different types of adaptivity (e.g., feedback in one AEE is longer or more
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45 302 complex than in the other). The second comparison is an AEE versus a nonadaptive e-learning
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47 303 environment (n=11)^{38-40 42-46 48 50 51}. The third and final comparison is an AEE versus another
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49 304 type of educational intervention, such as a paper-based educational intervention, including
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3 305 handouts, textbooks or images (n=3)^{37 41 47}, or a traditional educational intervention, such as a
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5 306 group lecture (n=2)^{49 52}. In one study, the comparator was not clearly reported³⁶. As stated
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7 307 before, only the second and third types of comparisons were included in the meta-analysis since
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10 308 our aim was to synthesize quantitatively the efficacy of AEEs versus other types of educational
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12 309 interventions. Finally, in terms of outcomes, investigators evaluated learners' knowledge (n=15)
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14 310^{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},
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17 311 metacognitive processes (n=3)^{32 33 35}, attitudes (n=2)^{36 50}, and behavior (n=1)⁵⁰.
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312 **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

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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.

322 **Characteristics of Adaptive E-Learning Environments**

323 We summarized the key characteristics of AEEs assessed in the 21 studies in table format (see
324 **Table 2**). In terms of the clinical topics of the AEEs, the majority of AEEs focused on training
325 medical students and residents in executing and/or interpreting diagnostic tests. Indeed, a
326 significant proportion of the AEEs assessed focused on dermatopathology and cytopathology
327 microscopy^{32-35 37 41 42 47} (n=8). Other topics were diagnostic imaging^{43 46} (n=2), behavior change
328 counseling^{40 50} (n=2), chronic disease management^{45 48} (n=2), pressure ulcer evaluation⁴⁹ (n=1),
329 childhood illness management³⁸ (n=1), electrocardiography⁵¹ (n=1), fetal heart rate
330 interpretation⁵² (n=1), hemodynamics³⁹ (n=1), chlamydia screening (n=1)³⁶ and atrial
331 fibrillation management (n=1)⁴⁴.

332 The 21 AEEs examined were based on a wide variety of theoretical frameworks. The most
333 frequently used framework was cognitive tutoring, adopted in 5 studies^{32-35 37}, which refers to the
334 use of a cognitive model. The integration of a cognitive model in an AEE implies the
335 representation of all the knowledge in the field of interest in a way that is similar to the human
336 mind for the purpose of understanding and predicting the cognitive processes of learners⁵³. The
337 second most used framework was perceptual learning, adopted in 3 studies^{46 51 52}. Perceptual
338 learning aims at improving information extraction skills of the environment and the development
339 of automaticity in this respect in learners⁴⁶. Interestingly, 2 studies used models from behavioral
340 science, the Transtheoretical Model³⁶ and the I-Change Model⁵⁰, to tailor the AEE to the
341 theoretical determinants of clinical behavior change in nurses and physicians in practice.
342 Theoretical frameworks relating to self-regulated learning³⁵, learning styles^{38 48}, guided mastery
343⁴⁰, and cognitive load⁴³, problem-based-learning³⁶, and situated learning³⁶ were also used.

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3 344 Three main adaptive e-learning platforms were used by investigators in studies examined:
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5 345 SlideTutor (n=4)^{33 37 54 55}, Smart Sparrow (n=4)^{41-43 47}, and the Perceptual Adaptive Learning
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7 346 Module (PALM, n=3)^{51 52 56}. SlideTutor is an AEE with algorithmic adaptivity which provides
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10 347 cases to be solved by learners under supervision by the system. These cases incorporate
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12 348 dermatology virtual slides that must be examined by learners to formulate a diagnosis. An
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14 349 expert knowledge base, consisting of evidence-diagnosis relationships, is used by SlideTutor to
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16 350 create a dynamic solution graph representing the current state of the learning process and to
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18 351 determine the optimal instructional sequence⁵⁵. Smart Sparrow is an AEE with designed
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20 352 adaptivity which allows educators to determine adaptive factors, such as answers to questions,
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22 353 response time to a question, and learner actions, to specify how the system will adapt the
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24 354 instructional sequence or provide feedback. These custom learning paths can be more or less
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26 355 personalized⁴². PALM is an AEE with algorithmic adaptivity aiming to improve perceptual
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28 356 learning through adaptive response-time-based sequencing to determine dynamically the spacing
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31 357 between different learning items based on each learner's accuracy and speed in interactive
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33 358 learning trials⁵¹. Different custom adaptive e-learning platforms were used in other studies.
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361 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Presentation • Multimedia • Tools

Morente, 2013	Pressure ulcer evaluation	NR	ePULab	Designed Adaptivity	To increase learning effectiveness (knowledge, skills).	Each pressure ulcer evaluation.	User skills	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Content • Navigation
Thai, 2015	Electrocardiography	Perceptual Learning Theory; Adaptive response-time based algorithm	PALM	Algorithmic Adaptivity	To improve perceptual classification learning effectiveness and efficiency.	After each user response.	User response accuracy, user response time	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Content • Navigation • Presentation • Multimedia • Tools

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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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Content • Navigation • Tools

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3 365 We propose 5 subdomains that emerged from the review to characterize the adaptivity process of
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5 366 AEEs reported in the 21 studies: adaptivity method, adaptivity goals, adaptivity timing,
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7 367 adaptivity factors and adaptivity types.
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10 368 **First Subdomain: Adaptivity Method**

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13 369 This subdomain relates to the method of adaptivity that dictates how the AEE adapts instruction
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15 370 to a learner. As we previously described, there are two main methods of adaptivity: *designed*
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17 371 *adaptivity* and *algorithmic adaptivity*. The first is based on the expertise of the educator who
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19 372 specifies how technology will react in a particular situation on the basis of the “if THIS, then
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21 373 THAT” approach. The second refers to use of algorithms that will determine, for instance, the
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23 374 extent of the learner’s knowledge and the optimal instructional sequence. In this review, 11 AEEs
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25 375 employed designed adaptivity^{36 38 41-44 47-50 57}, and 9 AEEs employes algorithmic adaptivity^{33 37 39}
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27 376 ^{51 52 54-56 58}. The adaptivity method wasn’t specified in one study⁴⁰.
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32 377 **Second Subdomain: Adaptivity Goals**

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35 378 This subdomain relates to the purpose of the adaptivity process within the AEE. For most AEEs,
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37 379 the adaptivity process aims primarily to increase the efficacy and/or efficiency of knowledge
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39 380 acquisition and skills development relative to other training methods^{32 35 36 38-45 47-49 51}. For
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41 381 instance, several AEEs aimed to increase the diagnostic accuracy and reporting performance of
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43 382 medical students and residents^{32-34 37 46 52}. In one study, the goal of adaptivity was to modify
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45 383 behavioral predictors and behavior in nurses⁵⁰. In cases where two adaptive AEEs with certain
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47 384 variations in their techno-pedagogical design are compared with each other, the adaptivity
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49 385 process generally aims at improving the metacognitive and cognitive processes related to learning
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387 Third Subdomain: Adaptivity Timing

388 This subdomain relates to *when* the adaptivity occurs during the learning process with the AEE.

389 In 19 out of 21 studies, the adaptivity occurred throughout the training with AEE, usually after an
390 answer to a question or during intermediate problem-solving steps. However, in two studies,
391 adaptivity was only implemented at the beginning of the training with the AEE following survey
392 responses^{38 50}.

393 Fourth Subdomain: Adaptivity Factors

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

400 Fifth Subdomain: Adaptivity Types

401 The final subdomain relates to which types of adaptivity are mobilized in the AEE: content,
402 navigation, multimedia, presentation and tools. In the context of this review, the adaptivity types
403 are based upon the work of Knutov and colleagues¹². Overall, 17 out of 21 (81%) AEEs
404 examined integrated more than one type of adaptivity. *Content adaptivity* was the most used
405 adaptivity type; it was implemented in all but one AEEs reviewed (n=20). Content adaptivity
406 aims to adapt the textual information (curriculum content) to the learner's profile through
407 different mechanisms and to different degrees¹². *Navigation adaptivity* was the second most used
408 adaptivity type (n=14). Navigation can be adapted in two ways; it can be enforced or suggested.

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3 409 When enforced, an optimal personalized learning path is determined for the learner by an expert
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5 410 educator or by the algorithms within the AEE. When suggested, there are several personalized
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7 411 learning paths available to each learner, who can determine the path he prefers himself¹². Most
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9 412 reviewed studies included AEEs with enforced navigation, with one optimal personalized
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11 413 learning path being determined by an expert educator or by the algorithm. *Multimedia adaptivity*
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13 414 was the third most used adaptivity type (n=11). This adaptivity type, much like content adaptivity
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15 415 which relates to textual information, implies the adaptivity of the multimedia elements of the
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17 416 training such as videos, pictures, models, to the learner's profile. *Presentation adaptivity* was the
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19 417 fourth most used adaptivity type (n=9). It implies the adaptivity of the layout of the page to the
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21 418 digital device used, or to the learner's profile. *Tools adaptivity* was the least used adaptivity type
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23 419 (n=8). This technique results in providing a different set of features or learning strategies for
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25 420 different types of learners, such as different interfaces for problem solving, and knowledge
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27 421 representation.

422 **Risk of Bias Assessment**

37 423 Results of included studies for the risk of bias assessment are presented in **Figure 2** and **Figure 3**.
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39 424 In $\geq 75\%$ of studies, biases related to similarity of baseline outcome measurements, blinding of
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41 425 outcome assessment and selective reporting of outcomes were low. Moreover, in $\geq 50\%$ of
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43 426 studies, biases related to contamination were low. Regarding the blinding of outcome assessment,
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45 427 in most studies, review authors judged that the outcomes of interest and the outcome
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47 428 measurement were not likely to be influenced by the lack of blinding, since studies had objective
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49 429 measures, i.e. an evaluative test of knowledge or skills. Regarding contamination bias, review
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51 430 authors scored studies at high risk if they had a crossover design.

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3 431 However, in $\geq 50\%$ of studies, biases related to random sequence generation, allocation
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5 432 concealment, similarity of baseline characteristics, similarity of baseline characteristics, blinding
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7 433 of participants and personnel, and incomplete outcome data were unclear or high. Regarding
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9 434 random sequence generation, an important number of studies did not report on the method of
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11 435 randomization used by investigators. As per Cochrane recommendations, all eligible studies
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13 436 were included in the meta-analysis, regardless of the risk of bias assessment. Indeed, since almost
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15 437 all studies scored overall at unclear risk of bias, Cochrane suggests to present an estimated
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17 438 intervention effect based on all available studies, together with a description of the risk of bias in
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19 439 individual domains ³⁰.

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25 440 [Insert Figure 2]

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29 30 31 442 **Quantitative Results**

32 33 34 443 **Efficacy of AEEs versus other educational interventions in improving knowledge**

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37 444 The pooled ES (standardized mean difference [SMD] 0.70; 95% confidence interval [CI] -0.08-
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39 445 1.49; $Z = 1.76$, $P = 0.08$) of AEEs compared to other educational interventions in improving
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41 446 knowledge suggests a medium to large effect (see **Figure 4**). However, this result is not
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43 447 statistically significant. Significant statistical heterogeneity was observed among studies (I^2
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45 448 =97%, $P < .00001$), and individual ESs ranged from -1.10 to 3.05. One study in particular ⁴⁵
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47 449 reported a negative ES, but the difference between groups in knowledge scores was statistically
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49 450 nonsignificant. Moreover, while participants using the AEE in the experimental group reported
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51 451 the same knowledge scores as participants in the control group at the end of study, time spent on
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53 452 instruction was reduced by 18% with the AEE compared to the nonadaptive e-learning
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3 453 environment, thus improving learning efficiency⁴⁵. When that study⁴⁵ is removed from the meta-
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5 454 analysis, the pooled ES becomes statistically significant (SMD 1.07; 95% CI 0.28-1.85; Z =2.67,
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7 455 *P* 0.008).

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14 457 Efficacy of AEEs versus other educational interventions in improving skills

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17 458 As we considered ESs larger than 0.8 to be large⁵⁹, the pooled ES (SMD 1.19; 95% CI 0.59-
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19 459 1.79; Z =3.88, *P* 0.0001) of AEEs compared to other educational interventions in improving
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21 460 skills suggests a significantly large effect (see **Figure 5**). Statistical heterogeneity was lower than
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23 461 in previous analyses, but was still significant (I^2 =89%, *P* <.00001). Individual ESs ranged from
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25 462 0.17 to 2.87.

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29 463 [Insert Figure 5]
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32 464 Quality of the Evidence

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35 465 The quality of evidence table produced with GRADE, as well as the justifications for each
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37 466 decision, is presented in **Supplementary File 3** (GRADE quality of evidence levels: very low, low,
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39 467 moderate, high). For knowledge, the quality of evidence was deemed to be very low. More
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41 468 precisely, risk of bias was deemed serious, inconsistency serious, indirectness not serious, and
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43 469 imprecision serious. For skills, the quality of evidence was deemed to be low. More precisely,
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45 470 risk of bias was deemed serious, inconsistency serious, indirectness not serious, and imprecision
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472 DISCUSSION

473 Principal Findings

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

488 Comparison with Other Studies

489 To our knowledge, no previous systematic review and meta-analysis has specifically assessed the
490 efficacy of AEEs in improving learning outcomes in health professionals and students, or any
491 other population. However, interestingly, since the 1990's there has been a strong research
492 interest in the field of AEEs with algorithmic adaptivity (also known as intelligent learning
493 environments [IEEs] or intelligent tutoring systems [ITSs]) into elementary, high school and

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3 494 postsecondary education for multiple subjects¹⁷. Thus, multiple meta-analyses have been
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5 495 conducted with regard to AEEs in that setting.
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8 496 Steenbergen-Hu and Cooper¹⁵ reported a mean ES of 0.35 of AEEs with algorithmic adaptivity
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10 497 on learning outcomes in college students when compared to all other types of educational
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12 498 interventions. The mean ES was 0.37 when the comparator was large-group classroom
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14 499 instruction, 0.35 when the comparator was nonadaptive e-learning, and 0.47 when the comparator
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16 500 was textbooks or workbooks¹⁵.
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20 501 Ma, et al.¹⁸ reported a mean ES of 0.42 of AEEs with algorithmic adaptivity on learning
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22 502 outcomes in elementary, high school and postsecondary students when compared to large-group
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24 503 classroom instruction. The mean ES was 0.57 when the comparator was nonadaptive e-learning,
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26 504 and 0.35 when the comparator was textbooks or workbooks. Interestingly, the mean ES was
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28 505 higher for studies which assessed an AEE in biology and physiology (0.59) and in humanities and
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30 506 social science (0.63) than in studies which assessed an AEE in mathematics (0.35) and physics
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32 507 (0.38)¹⁸.
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38 508 Kulik and Fletcher¹⁷ reported a mean ES of 0.65 of AEEs with algorithmic adaptivity on
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40 509 learning outcomes in elementary, high school, and postsecondary students when compared to
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42 510 large-group classroom instruction. Education areas in this review were diverse (e.g.,
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44 511 mathematics, computer science, physics), but none were related to health sciences. Interestingly,
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46 512 the mean ES was 0.78 for studies up to 80 participants, and 0.30 for studies with more than 250
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48 513 participants. Moreover, the mean ES for studies conducted with elementary and high school
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50 514 students was 0.44, compared to 0.75 for studies conducted with postsecondary students¹⁷.
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3 515 Thus, in light of the results of these meta-analyses, the ES reported in our review may appear
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5 516 high. However, our review looked more specifically into the efficacy of AEEs in improving
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7 517 learning outcomes in health professionals and students. This is significant since, in the meta-
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9 518 analyses of Steenbergen-Hu and Cooper ¹⁵, Ma, et al. ¹⁸, and Kulik and Fletcher ¹⁷, AEEs seem to
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11 519 be more effective in postsecondary students ^{17 18} and for learning subjects related to biology,
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13 520 physiology and social science ¹⁸. Moreover, previous meta-analyses focused on the efficacy of
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15 521 AEEs in improving procedural and declarative knowledge, and did not report on the efficacy on
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17 522 AEEs in improving skills. This is important since AEEs may be more effective for providing
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19 523 tailored guidance and coaching for developing skills regarding complex clinical interventions,
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21 524 rather than learning factual knowledge, which generates less cognitive load ^{62 63}.

27 525 **Implications for Practice and Research**

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30 526 This review provides important implications for the design and development of AEEs for health
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32 527 professionals and students. Table 3 presents 8 practical considerations for the design and
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34 528 development of adaptive e-learning environments based on the results of this systematic review
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36 529 for educators and educational researchers.

40 530 **Table 3. Practical considerations for the design and development of adaptive e-learning**
41 531 **environments.**

Practical considerations	Explanations
Developing the Educational Content	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> • Selecting the adaptivity method refers to how the AEE will adapt its instructional sequence. There are two main adaptivity methods: <ul style="list-style-type: none"> ○ <i>Designed adaptivity</i> is based on the expertise of the educator who designs personalized pathways to guide learners to learning content mastery; ○ <i>Algorithmic adaptivity</i> 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)	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Selecting the timing of adaptivity within an AEE relates to <i>when</i> 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)	<ul style="list-style-type: none"> • 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)	<ul style="list-style-type: none"> • Multiple types of adaptivity can be implemented in an AEE: <ul style="list-style-type: none"> ○ <i>Content adaptivity</i> refers to the adaptation of the textual information; ○ <i>Navigation adaptivity</i> refers to the adaptation of the curriculum sequence; ○ <i>Presentation adaptivity</i> refers to the adaptation of layout of the screen to the digital device used, or to the learner's profile; ○ <i>Multimedia adaptivity</i> refers to the adaptation of multimedia elements of the training such as videos, pictures, models; ○ <i>Tools adaptivity</i> 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	<ul style="list-style-type: none"> • 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.

532 This review also provides several key insights for future research. In terms of *population*, future
 533 research should focus on assessing AEEs with health professionals in practice, such as registered
 534 nurses and physicians, rather than students in these disciplines. This could provide key insights
 535 into how AEEs can impact clinical behavior and, ultimately, patient outcomes. In addition,
 536 investigators should target larger sample sizes. In terms of *interventions*, researchers should
 537 report more clearly on adaptivity methods, goals, timing, factors and types. Moreover,
 538 researchers should provide additional details regarding the underlining algorithms allowing the

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3 539 adaptivity process in order to ensure replicability of findings. Regarding *comparators*, this review
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5 540 suggests there is a need for additional research using traditional comparators (i.e., large group
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7 541 classroom instruction) and more specific comparators (i.e., adaptive e-learning environment with
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9 542 design variations). Regarding *outcomes* and outcome measures, researchers should use validated
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11 543 measurement tools of knowledge, skills, and clinical behavior to facilitate knowledge synthesis.
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14 544 Moreover, the very low number of studies assessing the impact of AEEs on health professionals'
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16 545 and students' clinical behavior demonstrates the need for further research with higher-level
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18 546 outcomes. Finally, in terms of *study designs*, researchers should focus on research designs
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20 547 allowing the assessment of the impact of multiple educational design variations and adaptivity
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22 548 types within one study, such as factorial experiments.
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27 549 **Strengths and Limitations**

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30 550 Strengths of this systematic review and meta-analysis include the prospective registration and
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32 551 publication of a protocol based on rigorous methods in accordance with Cochrane and PRISMA
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34 552 guidelines; the exhaustive search in all relevant databases; the independent screening of the titles,
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36 553 abstracts and full-text of studies; the assessment of each included studies' risk of bias using
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38 554 EPOC Cochrane guidelines; and the assessment of the quality of evidence for each individual
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40 555 outcome using the GRADE methodology.
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45 556 Our review also has limitations to consider. First, outcome measures varied widely across
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47 557 studies. To address this issue, we conducted the meta-analysis using the SMD. Using the SMD
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49 558 allowed us to standardize the results of studies to a uniform scale before pooling them. Review
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51 559 authors judged that using the SMD was the best option for this review, as it is the current practice
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53 560 in the field of knowledge synthesis in medical education^{6 60}.
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3 561 Second, there was high inconsistency among study results, which we can mostly attribute to
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5 562 differences in populations, AEE design, research methods, and outcomes. This resulted in
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7 563 sometimes widely differing estimates of effect. To partly address this issue, we used a random-
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9 564 effects model for the meta-analysis, which assumes that the effects estimated in the studies are
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11 565 different and follow a distribution³⁰. However, since a random-effects model awards more
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13 566 weight to smaller studies to learn about the distribution of effects, it could potentially exacerbate
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15 567 the effects of the bias in these studies³⁰.
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20 568 Finally, publication bias could not be assessed by the means of a funnel plot since there were less
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22 569 than 10 studies included in the meta-analysis.
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25 570 **CONCLUSIONS**

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29 571 Adaptive e-learning has significant potential to increase the effectiveness and efficiency of
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31 572 learning in health professionals and students. Through the different sub-domains of the adaptivity
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33 573 process (i.e. method, goals, timing, factors, types), AEEs can take into account the particularities
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35 574 inherent to each learner. This systematic review and meta-analysis underlines the potential of
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37 575 AEEs for improving knowledge and skills in health professionals and students in comparison
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39 576 with other educational interventions, such as nonadaptive e-learning environments and large-
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41 577 group classroom learning, across a range of topics. However, evidence was either of low or very
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43 578 low quality and heterogeneity was high across populations, interventions, comparators, and
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45 579 outcomes. Thus, additional comparative studies assessing the efficacy of AEEs in health
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49 580 professionals and students are needed to strengthen the quality of evidence .
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581 AUTHOR CONTRIBUTIONS

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

584 G.F. contributed to the conception and design of the review, to the acquisition and analysis of
585 data, and to the interpretation of results. Moreover, G.F. drafted the initial manuscript. S.C.
586 contributed to the conception and design of the review, and to the interpretation of results. M.-
587 A.M.-C. contributed to the conception and design of the review, to the acquisition of data, and
588 interpretation of results. T.M. contributed to the conception and design of the review, to the
589 acquisition of data, and to the interpretation of results. M.-F.D. contributed to the conception and
590 design of the review, to the acquisition of data, and to the interpretation of results. G.M.-D.
591 contributed to the conception and design of the review, and to the interpretation of results. J.C.
592 contributed to the interpretation of results. M.-P.G. contributed to the interpretation of results.
593 V.D. contributed to the interpretation of results.

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

596 DATA SHARING STATEMENT

597 No additional data available.

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21 611 for Innovation in Nursing Education.
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27 612 **FIGURE LEGENDS**

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30 613 Figure 1. PRISMA Study Flow Diagram.
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33 614 Figure 2. Risk of bias summary: review authors' judgements about each risk of bias item for each
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35 615 included study.
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39 616 Figure 3. Risk of bias graph: review authors' judgements about each risk of bias item presented as
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41 617 percentages across all included studies.
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44 618 Figure 4. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus
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46 619 other educational interventions in improving knowledge.
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49 620 Figure 5. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus
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51 621 other educational interventions in improving skills.
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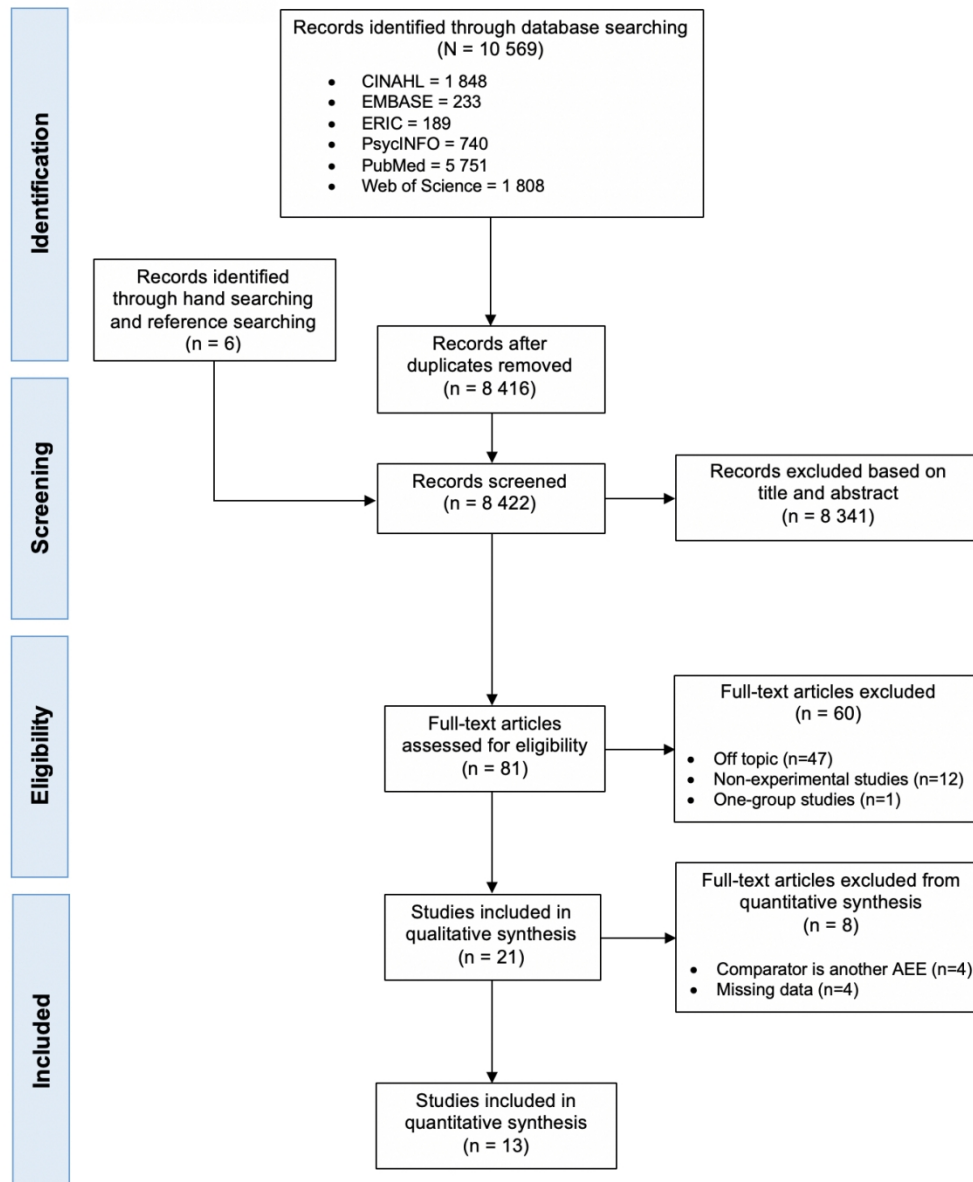


Figure 1. PRISMA study flow diagram.

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)

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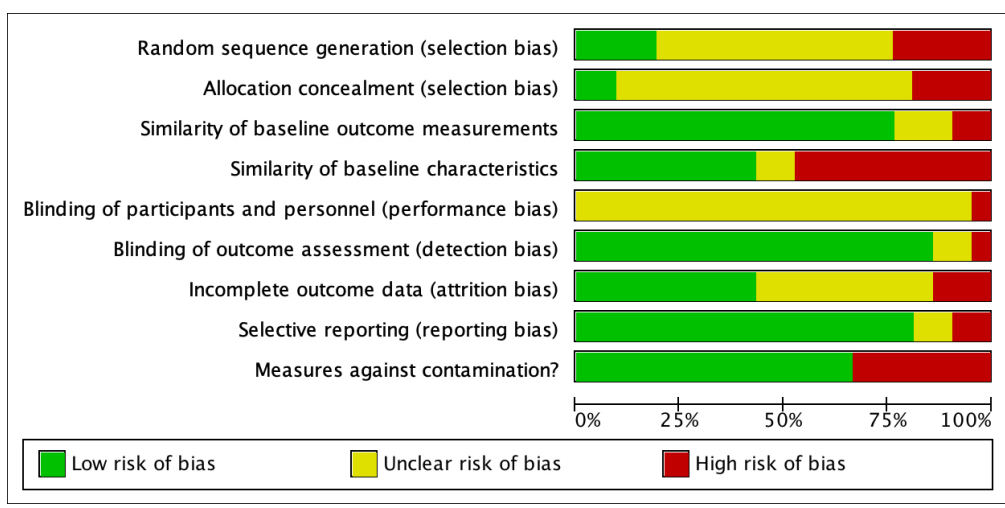


Figure 3. Risk of bias graph: review authors' judgements about each risk of bias item presented as percentages across all included studies.

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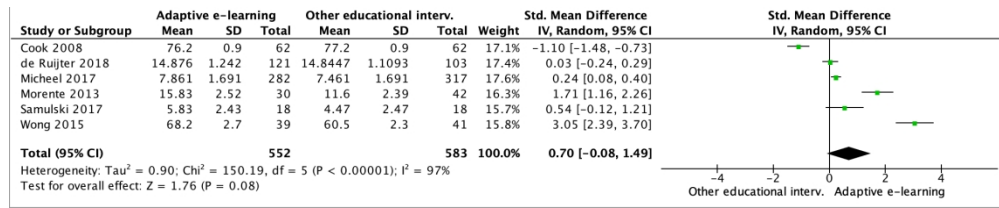


Figure 4. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving knowledge.

367x74mm (144 x 144 DPI)

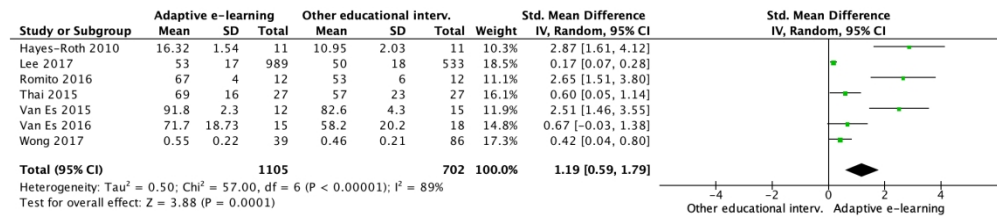


Figure 5. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving skills.

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 pediatricist*[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							No of patients		Effect		Certainty	Importance
No 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 insufficient.

BMJ Open

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

Journal:	<i>BMJ Open</i>
Manuscript ID	bmjopen-2018-025252.R2
Article Type:	Research
Date Submitted by the Author:	10-Jun-2019
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 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

SCHOLARONE™
Manuscripts

1 **Efficacy of adaptive e-learning for health professionals and** 2 **students: a systematic review and meta-analysis**

3
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30 34 **DECLARATION OF COMPETING INTERESTS**
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33 35 All authors have completed the ICMJE uniform disclosure form at
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35 36 www.icmje.org/coi_disclosure.pdf and declare: no support from any organisation for the
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37 37 submitted work; no financial relationships with any organisation that might have an interest in the
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39 38 submitted work in the previous three years; no other relationships or activities that could appear
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45 40 **TRANSPARENCY DECLARATION**
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49 41 The lead author (the manuscript's guarantor) affirms that the manuscript is an honest,
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51 42 accurate, and transparent account of the study being reported; that no important aspects of the
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53 43 study have been omitted; and that any discrepancies from the study as planned (and, if relevant,
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55 44 registered) have been explained.
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45 **FUNDING STATEMENT**

46 This study received no funding.

47

For peer review only

48 ABSTRACT (300 WORDS)

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

53 **Design:** Systematic review and meta-analysis.

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

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

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

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

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3 69 **Conclusions:** AEEs appear particularly effective in improving skills in health professionals and
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5 70 students. The adaptivity process within AEEs may be more beneficial for learning skills rather
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7 71 than factual knowledge, which generates less cognitive load. Future research should report more
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9 72 clearly on the design and adaptivity process of AEEs, and target higher-level outcomes, such as
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11 73 clinical behavior.
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15 74 **PROSPERO registration number:** CRD42017065585
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18 75 **Keywords:** Computer-assisted instruction; medical education; nursing education; e-learning,
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77 **ARTICLE SUMMARY**

78 **Strengths and Limitations of the Study**

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

88 INTRODUCTION

89 The use of information and communication technologies (ICTs) in the education of health
90 professionals and students has become ubiquitous. Indeed, e-learning, defined as the use of ITCs
91 to access educational curriculum and support learning¹, is increasingly present in clinical settings
92 for the continuing education of health professionals^{2,3}, and in academic settings for the education
93 of health professions students⁴. E-learning environments integrate information, in the form of text
94 and multimedia (e.g., illustrations, animations, videos). They can include both asynchronous (i.e.,
95 designed for self-study) and synchronous (i.e., a class taught by an educator in real time)
96 components¹. *Nonadaptive* e-learning environments, the most widespread type of e-learning
97 environment today, provide a standardized training for all learners^{5,6}. While they can include
98 instructional design variations (e.g., interactivity, feedback, practice exercises), they *do not*
99 consider learners' characteristics and the data generated during the learning process to provide a
100 personalized training⁶⁻⁸. This is problematic, since the interaction of health professionals and
101 students with e-learning environments during the learning process generates a significant amount
102 of data⁹. However, designers of e-learning environments and educators rarely make use of this
103 data to optimize learning efficacy and efficiency⁹.

104 In recent years, educational researchers have strived to develop e-learning environments that take
105 a data-driven and personalized approach to education¹⁰⁻¹³. E-learning environments that take into
106 account each learner's interactions and performance level could anticipate what types of content
107 and resources meet the learner's needs, potentially increasing learning efficacy and efficiency¹³.
108 Adaptive e-learning environments (AEEs) were developed for this purpose. AEEs collect data to
109 build each learner's profile (e.g., navigation behavior, preferences, knowledge), and use simple
110 techniques (e.g., adaptive information filtering, adaptive hypermedia) to implement different

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3 111 types of adaptivity targeting the content, navigation, presentation, multimedia, or strategies of the
4
5 112 training to provide a personalized learning experience^{11 12}. In the fields of computer science and
6
7 113 educational technology, the term *adaptivity* refers to the process executed by a system based on
8
9 114 ICTs of adapting educational curriculum content, structure or delivery to the profile of a
10
11 115 learner¹⁴. Two main methods of adaptivity can be implemented within an AEE. The first method,
12
13 116 *designed adaptivity*, is expert-based and refers to an educator who designs the optimal
14
15 117 instructional sequence to guide learners to learning content mastery. The educator determines
16
17 118 how the curriculum will adapt to learners based on a variety of factors, such as knowledge or
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19 119 response time to a question. This method of adaptivity is thus based on the expertise of the
20
21 120 educator who specifies how technology will react in a particular situation on the basis of the “if
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23 121 THIS, then THAT” approach. The second method, *algorithmic adaptivity*, refers to use of
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25 122 algorithms to determine, for instance, the extent of the learner’s knowledge and the optimal
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27 123 instructional sequence. Algorithmic adaptivity requires more advanced adaptivity techniques and
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29 124 learner-modelling techniques derived from the fields of computer science and artificial
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31 125 intelligence (e.g. Bayesian knowledge tracing, rule-based machine learning, natural language
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33 126 processing)^{10 15-18}.

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40 127 The variability in the degree and the complexity of adaptivity within AEEs mirrors the adaptivity
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42 128 that can be observed in non-e-learning educational interventions. Some interventions, like one-
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44 129 on-one human instruction and small-group classroom instruction, generally have a high degree of
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46 130 adaptivity since the instructor can adapt his teaching to the individual profiles of learners and
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48 131 consider their feedback¹⁹. Other interventions, like large-group classroom instruction, generally
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50 132 have a low degree of adaptivity to individual learners. In some interventions, like paper-based
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52 133 instruction (e.g., handouts, textbooks), there is no adaptivity at all.
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3 134 AEEs have been developed and evaluated primarily in academic settings for students in
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5 135 mathematics, physics and related disciplines, for the acquisition of knowledge and development
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7 136 of cognitive skills (e.g., arithmetic calculation). Four meta-analyses reported on the efficacy of
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10 137 AEEs among high school and university students in in these fields of study^{15-17 20}. The results are
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12 138 promising: AEEs are in almost all cases more effective than large-group classroom instruction. In
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14 139 addition, Nesbit, et al.²¹ point out that AEEs are more effective than nonadaptive e-learning
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16 140 environments. However, despite evidence of the efficacy of AEEs for knowledge acquisition and
17
18 141 skill development in areas such as mathematics in high school and university students, their
19
20 142 efficacy in improving learning outcomes in health professionals and students has not yet been
21
22 143 established. To address this need, we conducted a systematic review and meta-analysis to identify
23
24 144 and quantitatively synthesize all comparative studies of AEEs involving health professionals and
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26 145 students.

146 **Systematic Review and Meta-Analysis Objective**

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

150 **Systematic Review and Meta-Analysis Questions**

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

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

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3 156 We sought to answer the following question with the meta-analysis:
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6 157 3. What is the efficacy of AEEs in improving knowledge, skills, and clinical behavior in
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8 158 health professionals and students in comparison with nonadaptive e-learning
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10 159 environments, and non-e-learning educational interventions?
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14 160 **METHODS**

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17 161 We planned and conducted this systematic review following the Effective Practice and
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19 162 Organization of Care (EPOC) Cochrane Group guidelines²², and reported it according to the
20
21 163 Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) standards²³ (see
22
23 164 **Supplementary File 1**). We prospectively registered (International Prospective Register of
24
25 165 Systematic Reviews #CRD42017065585) and published the protocol of this systematic review²⁴.
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27 166 Thus, in this paper, we present an abridged version of the methods with an emphasis on changes
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29 167 made to the methods since the publication of the protocol.
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34 168 **Study Eligibility**

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37 169 We included primary research articles that assessed an AEE with licensed health professionals,
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39 170 students, trainees, and residents in any discipline. We defined an AEE as a computer-based
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41 171 learning environment which collects data to build each learner's profile (e.g., navigation
42
43 172 behavior, individual objectives, knowledge), interprets these data through algorithms, and adapts
44
45 173 in real-time the content (e.g., showing/hiding information), navigation (e.g., specific links and
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47 174 paths), presentation (e.g., page layout), multimedia presentation (e.g., images, videos), or tools
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49 175 (e.g., different set of strategies for different types of learners) to provide a dynamic and
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51 176 evolutionary learning path for each learner^{10 14}. We used the definitions of each type of adaptivity
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54 177 proposed by Knutov and colleagues¹². We considered for inclusion studies in which AEEs had
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3 178 designed or algorithmic adaptivity, and studies including a co-intervention in addition to adaptive
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5 179 e-learning (e.g. paper-based instruction). We considered for inclusion primary research articles
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7 180 in which the comparator was: 1) a nonadaptive e-learning environment; 2) a non-e-learning
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9 181 educational intervention; 3) another AEE with design variations. While included in the qualitative
10
11 182 synthesis of the evidence for descriptive purposes, the third comparator was excluded from the
12
13 183 meta-analysis. Outcomes of interest were knowledge, skills, and behavior^{25 26}, and were defined
14
15 184 as follows: 1) knowledge: subjective (e.g., learner self-report) or objective (e.g., multiple-choice
16
17 185 question knowledge test) assessments of factual or conceptual understanding; 2) skills: subjective
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19 186 (eg, learner self-report) or objective (eg, faculty ratings) assessments of procedural skills (e.g.
20
21 187 taking a blood sample, performing CPR) or cognitive skills (e.g. problem-solving, interpreting
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23 188 radiographs) in learners; 3) behavior: subjective (eg, learner self-report) or objective (eg, chart
24
25 189 audit) assessments of behaviors in clinical practice (such as test ordering)⁶. In terms of study
26
27 190 design, we considered for inclusion all controlled, quantitative studies in accordance with the
28
29 191 EPOC Cochrane Review Group guidelines²⁷.

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36 192 We excluded studies that: 1) were not published in English or French; 2) were non-experimental;
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38 193 3) were not controlled; 4) did not report on at least one of the outcomes of interest in this review;
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40 194 5) did not have a topic related to the clinical aspects of health.

41 42 43 195 **Study Identification**

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47 196 We previously published our search strategy²⁴. Briefly, we designed a strategy in consultation
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49 197 with a librarian to search CINAHL, EMBASE, ERIC, PsycINFO, PubMed and Web of Science
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51 198 for primary research articles published since the inception of each database up to February 2019.
52
53 199 The search strategy revolved around 3 key concepts: “adaptive e-learning environments”, “health

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3 200 professionals/students”, and “effects on knowledge/competence (skills)/behavior” (see
4
5 201 **Supplementary file 2**). To identify additional articles, we hand-searched 6 key journals (e.g.,
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7 202 *British Journal of Educational Technology, Computers and Education*) and the reference lists of
8
9 203 included primary research articles.
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13 204 **Study Selection**

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16 205 We worked independently and in duplicate (G.F. and M.-A.M.-C./T.M.) to screen all titles and
17
18 206 abstracts for inclusion using the EndNote software V8.0 (Clarivate Analytics). We resolved
19
20 207 disagreements by consensus. We then performed the full-text assessment of potentially eligible
21
22 208 articles using the same methodology. Studies were included in the meta-analysis if they had a
23
24 209 non-AEE control group and had no missing data.
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28 210 **Data Extraction**

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31 211 One review author (G.F.) extracted data from included primary research articles using a modified
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33 212 version of the data collection form developed by the EPOC Cochrane Review Group²⁸. The main
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35 213 changes made to the extraction form were the addition of specific items relating to the AEE
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37 214 assessed in each study. Two review authors (T.M., M.-F.D.) validated the data extraction forms
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39 215 by reviewed the contents of each form against the data in the original article, adding comments
40
41 216 when changes were needed. For all studies, we extracted the following data items if possible:
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- 46 217 • *the population and setting*: study setting, study population, inclusion criteria, exclusion
47
48 218 criteria;
- 49
50 219 • *the methods*: study aim, study design, unit of allocation, study start date and end date, and
51
52 220 duration of participation;
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3 221 • *the participants*: study sample, withdrawals and exclusions, age, sex, level of instruction,
4
5 222 number of years of experience as a health professional, practice setting, and previous
6
7 223 experience using e-learning;
8
9
10 224 • *the interventions*: name of intervention, theoretical framework, statistical model/algorithm
11
12 225 used to generate the learning path, clinical topic, number of training sessions, duration of
13
14 226 each training session, total duration of the training, adaptivity subdomains (method, goals,
15
16 227 timing, factors, types), mode of delivery, presence of other educational interventions and
17
18 228 strategies;
19
20 229 • *the outcomes*: name, time-points measured, definition, person measuring, unit of
21
22 230 measurement, scales, validation of measurement tool;
23
24 231 • *the results*: results according to our primary (knowledge) and secondary (skills, behavior)
25
26 232 outcomes, comparison, time-point, baseline data, statistical methods used, and key
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28 233 conclusions.
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34 234 We contacted the corresponding authors of included primary research articles to provide us with
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36 235 missing data.
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39 236 **Assessment of the Risk of Bias**

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42 237 We worked independently and in duplicate (G.F. and T.M./M.-F.D.) to assess the risk of bias of
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44 238 included primary research articles using the EPOC risk of bias criteria, based upon the data
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46 239 extracted with the data collection form²⁸. A study was deemed at high risk of bias if the
47
48 240 individual criterion “random sequence generation” was scored at “high” or at “unclear” risk of
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50 241 bias.
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242 Data Synthesis

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

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

255 We first assessed heterogeneity qualitatively by examining the characteristics of included studies,
256 the similarities and disparities between the types of participants, the types of interventions, and
257 the types of outcomes. We then used the I^2 statistic within the RevMan software to quantify how
258 much the results varied across individual studies (i.e., between-study inconsistency, or
259 heterogeneity). We interpreted the I^2 values as follows: 0%-40%: might not be important; 30%-
260 60%: may represent moderate heterogeneity; 50%-90%: may represent substantial heterogeneity;
261 and 75%-100%: considerable heterogeneity²⁹. We performed sensitivity analysis to assess if the
262 exclusion of studies at high risk of bias or with a small sample size ($n < 20$) would have had an

263 impact on statistical heterogeneity. Subgroup analyses were performed to examine if study
264 population and study comparators were potential effect modifiers.

265 Since less than 10 studies were included in the meta-analysis for each outcome, we did not assess
266 reporting biases using a funnel plot, as suggested in the Cochrane Handbook³⁰.

267 **Assessment of the Quality of Evidence**

268 We worked independently and in duplicate (G.F. and M.-A.M.-C.) to assess the quality of
269 evidence for each individual outcome. We used the Grading of Recommendations Assessment,
270 Development, and Evaluation (GRADE) Web-based software, based upon the data extracted with
271 the data collection checklist³¹. We considered 5 factors (risk of bias of included studies,
272 indirectness of evidence, unexplained heterogeneity or inconsistency of results, imprecision of
273 the results, probability of reporting bias) for downgrading the quality of the body of evidence for
274 each outcome³¹.

275 **Patient and Public Involvement**

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

279 **RESULTS**

280 **Study Flow**

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

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2
3 283 [Insert Figure 1]
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6 284 Out of 21 included studies in the qualitative synthesis, 4 studies compared two AEEs with design
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8 285 variations³²⁻³⁵, and 4 studies had missing data³⁶⁻³⁹. The 4 studies with missing data did not report
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10 286 properly data regarding the results, i.e. mean scores and standard deviations in both study groups
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12
13 287 at post-test, regarding the outcomes of interest in this review (i.e., knowledge, skills or clinical
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15 288 behavior). Thus, 13 studies were included in the meta-analysis and used to calculate an ES on
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17 289 learning outcomes.
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20 21 290 **Study Characteristics**

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24 291 We summarized the key characteristics of included studies in table format (see **Table 1**). In terms
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26 292 of study population, in the 21 studies examined published between 2003 and 2018, investigators
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28 293 have evaluated AEEs mostly in the medical field. Studies focused on medical students (n=8)³⁸⁻⁴⁴,
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30 294 medical residents (n=8)^{32-35 41 45-47}, physicians in practice (n=4)^{36 37 41 48}, nursing students (n=2)
31
32 295 ^{40 49}, nurses in practice (n=2)^{48 50} and health sciences students (n=1)⁵¹. Three studies focused on
33
34 296 multiple populations^{40 41 48}. The median sample size was 46 participants (interquartile range
35
36 297 [IQR] 123). In terms of study design, 15 out of 21 studies (71%) were randomized, 7 studies of
37
38 298 which were randomized crossover trials^{33 34 41-43 45 47}. The median number of training sessions
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40 299 was 2 (IQR 2.5 sessions), the median training time was 2.13 hours (IQR 2.88 hours), and the
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42 300 median training period was 14 days (IQR 45 days). In terms of comparators, it is possible to
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44 301 underline three types of comparisons. The first comparison is an AEE versus another AEE with
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46 302 design variations (n=4)³²⁻³⁵, which implies that one of the AEEs assessed had variations in its
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48 303 design, such as different types of adaptivity (e.g., feedback in one AEE is longer or more
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50 304 complex than in the other). The second comparison is an AEE versus a nonadaptive e-learning
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3 305 environment (n=11)^{38-40 42-46 48 50 51}. The third and final comparison is an AEE versus another
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5 306 type of educational intervention, such as a paper-based educational intervention, including
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7 307 handouts, textbooks or images (n=3)^{37 41 47}, or a traditional educational intervention, such as a
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9 308 group lecture (n=2)^{49 52}. In one study, the comparator was not clearly reported³⁶. As stated
10
11 309 before, only the second and third types of comparisons were included in the meta-analysis since
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13 310 our aim was to synthesize quantitatively the efficacy of AEEs versus other types of educational
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15 311 interventions.
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20 312 Finally, regarding the outcomes, knowledge was assessed in 14 out of 21 studies (66.7%)^{32 35 36 38}
21
22 313^{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%)
23
24 314^{44 50}. Outcome measures for knowledge were similar across studies: in 9 out of 14 studies
25
26 315 measuring knowledge, investigators employed multiple-choice questionnaires developed by the
27
28 316 research team with input from content experts that were tailored to training content to ensure
29
30 317 specificity. Knowledge was also assessed using true-false questions in two studies, and the type
31
32 318 of questionnaire was not specified in three studies. Outcome measures for skills were also similar
33
34 319 across the 9 studies reporting this outcome, since in all studies investigators measured *cognitive*
35
36 320 skills rather than *procedural* skills. Indeed, all outcomes measures for skills were related to
37
38 321 clinical reasoning. In 6 studies, skills were measured through tests that included a series of
39
40 322 diagnostic tests (eg electrocardiograms, x-rays, microscopy images) that learners had to
41
42 323 interpret. In 3 studies, skills were measured through questions based on clinical situations in which
43
44 324 learners had to specify how they would react in these particular situations. We were not able to
45
46 325 describe the similarity between the outcome measures for clinical behaviour no details were
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48 326 provided in one of the two studies reporting this outcome.
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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 Skills	21-item multiple-choice questionnaire
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 accuracy
de Ruijter, 2018 Netherlands	NP; N = 269	RCT; pretest-posttest, 2 groups	No fixed sessions	180 days	NEE	Knowledge Behavior	18-item true-false questionnaire (range 0–18) 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 Knowledge	6-item written skill probe (range 6–18) Unclear
Lee, 2017 USA	MS; N = 1522	NRCT; pretest-posttest, 3 groups	5 sessions; NR	42 days	NEE	Skills Behavior	Multidimensional situation-based questions –RealIndex (range 0–100%) 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								
2								
3	El Saadawi,							
4	2010	R; N = 23	RXT; pretest–posttest, 2 groups	2 sessions; 2.25 hours each	2 days	AEE	Skills	Virtual slide test to examine
5	USA							diagnostic accuracy
6								
7	Feyzi-							
8	Begnagh,	R; N = 31	RCT; pretest–posttest, 2 groups	2 sessions; 2 & 3 hours	1 day	AEE	Knowledge	Unspecified test
9	2014							
10	USA							

328
329 * 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
330 students.

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

332 ‡ 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,
333 or latent image cases).

334 **Characteristics of Adaptive E-Learning Environments**

335 We summarized the key characteristics of AEEs assessed in the 21 studies in table format (see
336 **Table 2**). In terms of the clinical topics of the AEEs, the majority of AEEs focused on training
337 medical students and residents in executing and/or interpreting diagnostic tests. Indeed, a
338 significant proportion of the AEEs assessed focused on dermatopathology and cytopathology
339 microscopy^{32-35 37 41 42 47} (n=8). Other topics were diagnostic imaging^{43 46} (n=2), behavior change
340 counseling^{40 50} (n=2), chronic disease management^{45 48} (n=2), pressure ulcer evaluation⁴⁹ (n=1),
341 childhood illness management³⁸ (n=1), electrocardiography⁵¹ (n=1), fetal heart rate
342 interpretation⁵² (n=1), hemodynamics³⁹ (n=1), chlamydia screening (n=1)³⁶ and atrial
343 fibrillation management (n=1)⁴⁴.

344 The 21 AEEs examined were based on a wide variety of theoretical frameworks. The most
345 frequently used framework was cognitive tutoring, adopted in 5 studies^{32-35 37}, which refers to the
346 use of a cognitive model. The integration of a cognitive model in an AEE implies the
347 representation of all the knowledge in the field of interest in a way that is similar to the human
348 mind for the purpose of understanding and predicting the cognitive processes of learners⁵³. The
349 second most used framework was perceptual learning, adopted in 3 studies^{46 51 52}. Perceptual
350 learning aims at improving information extraction skills of the environment and the development
351 of automaticity in this respect in learners⁴⁶. Interestingly, 2 studies used models from behavioral
352 science, the Transtheoretical Model³⁶ and the I-Change Model⁵⁰, to tailor the AEE to the
353 theoretical determinants of clinical behavior change in nurses and physicians in practice.
354 Theoretical frameworks relating to self-regulated learning³⁵, learning styles^{38 48}, guided mastery
355⁴⁰, and cognitive load⁴³, problem-based-learning³⁶, and situated learning³⁶ were also used.

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3 356 Three main adaptive e-learning platforms were used by investigators in studies examined:
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5 357 SlideTutor (n=4)^{33 37 54 55}, Smart Sparrow (n=4)^{41-43 47}, and the Perceptual Adaptive Learning
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7 358 Module (PALM, n=3)^{51 52 56}. SlideTutor is an AEE with algorithmic adaptivity which provides
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9
10 359 cases to be solved by learners under supervision by the system. These cases incorporate
11
12 360 dermatology virtual slides that must be examined by learners to formulate a diagnosis. An
13
14 361 expert knowledge base, consisting of evidence-diagnosis relationships, is used by SlideTutor to
15
16
17 362 create a dynamic solution graph representing the current state of the learning process and to
18
19 363 determine the optimal instructional sequence⁵⁵. Smart Sparrow is an AEE with designed
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21 364 adaptivity which allows educators to determine adaptive factors, such as answers to questions,
22
23 365 response time to a question, and learner actions, to specify how the system will adapt the
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25
26 366 instructional sequence or provide feedback. These custom learning paths can be more or less
27
28 367 personalized⁴². PALM is an AEE with algorithmic adaptivity aiming to improve perceptual
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30 368 learning through adaptive response-time-based sequencing to determine dynamically the spacing
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33 369 between different learning items based on each learner's accuracy and speed in interactive
34
35 370 learning trials⁵¹. Different custom adaptive e-learning platforms were used in other studies.

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372

373 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Presentation • Multimedia • Tools

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Morente, 2013	Pressure ulcer evaluation	NR	ePULab	Designed Adaptivity	To increase learning effectiveness (knowledge, skills).	Each pressure ulcer evaluation.	User skills	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Content • Navigation
Thai, 2015	Electrocardiography	Perceptual Learning Theory; Adaptive response-time based algorithm	PALM	Algorithmic Adaptivity	To improve perceptual classification learning effectiveness and efficiency.	After each user response.	User response accuracy, user response time	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Content • Navigation • Presentation • Multimedia • Tools

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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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Content • Navigation • Tools

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3 377 We propose 5 subdomains that emerged from the review to characterize the adaptivity process of
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5 378 AEEs reported in the 21 studies: adaptivity method, adaptivity goals, adaptivity timing,
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8 379 adaptivity factors and adaptivity types.
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10 380 **First Subdomain: Adaptivity Method**

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13 381 This subdomain relates to the method of adaptivity that dictates how the AEE adapts instruction
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15 382 to a learner. As we previously described, there are two main methods of adaptivity: *designed*
16
17 383 *adaptivity* and *algorithmic adaptivity*. The first is based on the expertise of the educator who
18
19 384 specifies how technology will react in a particular situation on the basis of the “if THIS, then
20
21 385 THAT” approach. The second refers to use of algorithms that will determine, for instance, the
22
23 386 extent of the learner’s knowledge and the optimal instructional sequence. In this review, 11 AEEs
24
25 387 employed designed adaptivity^{36 38 41-44 47-50 57}, and 9 AEEs employes algorithmic adaptivity^{33 37 39}
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27 388 ^{51 52 54-56 58}. The adaptivity method wasn’t specified in one study⁴⁰.
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32 389 **Second Subdomain: Adaptivity Goals**

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35 390 This subdomain relates to the purpose of the adaptivity process within the AEE. For most AEEs,
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37 391 the adaptivity process aims primarily to increase the efficacy and/or efficiency of knowledge
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39 392 acquisition and skills development relative to other training methods^{32 35 36 38-45 47-49 51}. For
40
41 393 instance, several AEEs aimed to increase the diagnostic accuracy and reporting performance of
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43 394 medical students and residents^{32-34 37 46 52}. In one study, the goal of adaptivity was to modify
44
45 395 behavioral predictors and behavior in nurses⁵⁰. In cases where two adaptive AEEs with certain
46
47 396 variations in their techno-pedagogical design are compared with each other, the adaptivity
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49 397 process generally aims at improving the metacognitive and cognitive processes related to learning
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52 398 ^{32 33 35}.
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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 colleagues¹². 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 degrees¹². *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.

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3 421 When enforced, an optimal personalized learning path is determined for the learner by an expert
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5 422 educator or by the algorithms within the AEE. When suggested, there are several personalized
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7 423 learning paths available to each learner, who can determine the path he prefers himself¹². Most
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9 424 reviewed studies included AEEs with enforced navigation, with one optimal personalized
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11 425 learning path being determined by an expert educator or by the algorithm. *Multimedia adaptivity*
12
13 426 was the third most used adaptivity type (n=11). This adaptivity type, much like content adaptivity
14
15 427 which relates to textual information, implies the adaptivity of the multimedia elements of the
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17 428 training such as videos, pictures, models, to the learner's profile. *Presentation adaptivity* was the
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19 429 fourth most used adaptivity type (n=9). It implies the adaptivity of the layout of the page to the
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21 430 digital device used, or to the learner's profile. *Tools adaptivity* was the least used adaptivity type
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23 431 (n=8). This technique results in providing a different set of features or learning strategies for
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25 432 different types of learners, such as different interfaces for problem solving, and knowledge
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27 433 representation.

434 Risk of Bias Assessment

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37 435 Results of included studies for the risk of bias assessment are presented in **Figure 2** and **Figure 3**.
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39 436 In $\geq 75\%$ of studies, biases related to similarity of baseline outcome measurements, blinding of
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41 437 outcome assessment and selective reporting of outcomes were low. Moreover, in $\geq 50\%$ of
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43 438 studies, biases related to contamination were low. Regarding the blinding of outcome assessment,
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45 439 in most studies, review authors judged that the outcomes of interest and the outcome
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47 440 measurement were not likely to be influenced by the lack of blinding, since studies had objective
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49 441 measures, i.e. an evaluative test of knowledge or skills. Regarding contamination bias, review
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51 442 authors scored studies at high risk if they had a crossover design.
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3 443 However, in $\geq 50\%$ of studies, biases related to random sequence generation, allocation
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5 444 concealment, similarity of baseline characteristics, similarity of baseline characteristics, blinding
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7 445 of participants and personnel, and incomplete outcome data were unclear or high. Regarding
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9 446 random sequence generation, an important number of studies did not report on the method of
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11 447 randomization used by investigators. As per Cochrane recommendations, all eligible studies
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13 448 were included in the meta-analysis, regardless of the risk of bias assessment. Indeed, since almost
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15 449 all studies scored overall at unclear risk of bias, Cochrane suggests to present an estimated
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17 450 intervention effect based on all available studies, together with a description of the risk of bias in
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19 451 individual domains ³⁰.

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25 452 [Insert Figure 2]

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28 453 [Insert Figure 3]

30 31 454 **Quantitative Results**

32 33 34 455 **Efficacy of AEEs versus other educational interventions in improving knowledge**

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37 456 The pooled ES (standardized mean difference [SMD] 0.70; 95% confidence interval [CI] -0.08-
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39 457 1.49; $Z = 1.76$, $P 0.08$) of AEEs compared to other educational interventions in improving
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41 458 knowledge suggests a medium to large effect (see **Figure 4**). However, this result is not
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43 459 statistically significant. Significant statistical heterogeneity was observed among studies (I^2
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45 460 =97%, $P < .00001$), and individual ESs ranged from -1.10 to 3.05. One study in particular ⁴⁵
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47 461 reported a negative ES, but the difference between groups in knowledge scores was statistically
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49 462 nonsignificant. Moreover, while participants using the AEE in the experimental group reported
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51 463 the same knowledge scores as participants in the control group at the end of study, time spent on
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53 464 instruction was reduced by 18% with the AEE compared to the nonadaptive e-learning
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3 465 environment, thus improving learning efficiency⁴⁵. When that study⁴⁵ is removed from the meta-
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5 466 analysis, the pooled ES becomes statistically significant (SMD 1.07; 95% CI 0.28-1.85; Z =2.67,
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7 467 *P* 0.008).

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11 468 [Insert Figure 4]
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14 469 Efficacy of AEEs versus other educational interventions in improving skills

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17 470 As we considered ESs larger than 0.8 to be large⁵⁹, the pooled ES (SMD 1.19; 95% CI 0.59-
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19 471 1.79; Z =3.88, *P* 0.0001) of AEEs compared to other educational interventions in improving
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21 472 skills suggests a significantly large effect (see **Figure 5**). Statistical heterogeneity was lower than
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23 473 in previous analyses, but was still significant (I^2 =89%, *P* <.00001). Individual ESs ranged from
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25 474 0.17 to 2.87.

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29 475 [Insert Figure 5]
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32 476 For both knowledge and skills, we conducted subgroup analyses according to population (health
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34 477 professionals versus students) and comparator (adaptive e-learning versus nonadaptive e-
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36 478 learning, adaptive e-learning versus paper-based instruction, adaptive e-learning versus
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38 479 classroom-based instruction). No statistically significant differences between subgroups were
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40 480 found regarding the effect sizes.
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44 481 Quality of the Evidence

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48 482 The quality of evidence table produced with GRADE, as well as the justifications for each
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50 483 decision, is presented in **Supplementary File 3** (GRADE quality of evidence levels: very low, low,
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52 484 moderate, high). For knowledge, the quality of evidence was deemed to be very low. More
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54 485 precisely, risk of bias was deemed serious, inconsistency serious, indirectness not serious, and
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3 486 imprecision serious. For skills, the quality of evidence was deemed to be low. More precisely,
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5 487 risk of bias was deemed serious, inconsistency serious, indirectness not serious, and imprecision
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7 488 serious.
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10 489 **DISCUSSION**

11 490 **Principal Findings**

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14 491 This is the first systematic review and meta-analysis to evaluate the efficacy of AEEs in health
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16 492 professionals and students. We identified 21 relevant studies published since 2003, 17 of which
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18 493 assessed an AEE versus another educational intervention (large-group classroom instruction,
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20 494 nonadaptive e-learning environment or paper-based learning), and 4 of which assessed 2 AEEs
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22 495 with design variations head-to-head. When compared with other educational interventions, AEEs
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24 496 were associated with statistically significant improvements in learning outcomes in 12 out of 17
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26 497 studies. Pooled ESs were medium to large for knowledge and large for skills, but only the latter
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28 498 was associated with a statistically significant effect. Statistical heterogeneity was high in all
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30 499 analyses. However, this finding is consistent with other meta-analyses in the field of medical
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32 500 education that also reported high heterogeneity across studies^{8 60 61}. No potential effect modifiers
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34 501 were found during subgroup analyses, and these did not help in explaining the source of the
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36 502 heterogeneity. The quality of evidence for all comparisons was either low or very low. Therefore,
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38 503 while we believe the results support the potential of AEEs for the education of health
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40 504 professionals and students, we recommend interpreting the ESs with caution.
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50 505 **Comparison with Other Studies**

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53 506 To our knowledge, no previous systematic review and meta-analysis has specifically assessed the
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55 507 efficacy of AEEs in improving learning outcomes in health professionals and students, or any
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3 508 other population. However, interestingly, since the 1990's there has been a strong research
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5 509 interest in the field of AEEs with algorithmic adaptivity (also known as intelligent learning
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7 510 environments [IEEs] or intelligent tutoring systems [ITSs]) into elementary, high school and
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10 511 postsecondary education for multiple subjects¹⁷. Thus, multiple meta-analyses have been
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12 512 conducted with regard to AEEs in that setting.
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15 513 Steenbergen-Hu and Cooper¹⁵ reported a mean ES of 0.35 of AEEs with algorithmic adaptivity
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17 514 on learning outcomes in college students when compared to all other types of educational
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19 515 interventions. The mean ES was 0.37 when the comparator was large-group classroom
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21 516 instruction, 0.35 when the comparator was nonadaptive e-learning, and 0.47 when the comparator
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23 517 was textbooks or workbooks¹⁵.
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28 518 Ma, et al.¹⁸ reported a mean ES of 0.42 of AEEs with algorithmic adaptivity on learning
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30 519 outcomes in elementary, high school and postsecondary students when compared to large-group
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32 520 classroom instruction. The mean ES was 0.57 when the comparator was nonadaptive e-learning,
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34 521 and 0.35 when the comparator was textbooks or workbooks. Interestingly, the mean ES was
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36 522 higher for studies which assessed an AEE in biology and physiology (0.59) and in humanities and
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38 523 social science (0.63) than in studies which assessed an AEE in mathematics (0.35) and physics
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40 524 (0.38)¹⁸.
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44 525 Kulik and Fletcher¹⁷ reported a mean ES of 0.65 of AEEs with algorithmic adaptivity on
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46 526 learning outcomes in elementary, high school, and postsecondary students when compared to
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48 527 large-group classroom instruction. Education areas in this review were diverse (e.g.,
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50 528 mathematics, computer science, physics), but none were related to health sciences. Interestingly,
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52 529 the mean ES was 0.78 for studies up to 80 participants, and 0.30 for studies with more than 250
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3 530 participants. Moreover, the mean ES for studies conducted with elementary and high school
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5 531 students was 0.44, compared to 0.75 for studies conducted with postsecondary students¹⁷.
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8 532 Thus, in light of the results of these meta-analyses, the ES reported in our review may appear
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10 533 high. However, our review looked more specifically into the efficacy of AEEs in improving
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12 534 learning outcomes in health professionals and students. This is significant since, in the meta-
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14 535 analyses of Steenbergen-Hu and Cooper¹⁵, Ma, et al.¹⁸, and Kulik and Fletcher¹⁷, AEEs seem to
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16 536 be more effective in postsecondary students^{17 18} and for learning subjects related to biology,
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18 537 physiology and social science¹⁸. Moreover, previous meta-analyses focused on the efficacy of
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20 538 AEEs in improving procedural and declarative knowledge, and did not report on the efficacy on
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22 539 AEEs in improving skills. This is important since AEEs may be more effective for providing
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24 540 tailored guidance and coaching for developing skills regarding complex clinical interventions,
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26 541 rather than learning factual knowledge, which generates less cognitive load^{62 63}.
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32 542 **Implications for Practice and Research**

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35 543 This review provides important implications for the design and development of AEEs for health
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37 544 professionals and students. Table 3 presents 8 practical considerations for the design and
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39 545 development of adaptive e-learning environments based on the results of this systematic review
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41 546 for educators and educational researchers.
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45 547 **Table 3. Practical considerations for the design and development of adaptive e-learning**
46 548 **environments.**

Practical considerations	Explanations
Developing the Educational Content	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> Selecting the adaptivity method refers to how the AEE will adapt its instructional sequence. There are two main adaptivity methods: <ul style="list-style-type: none"> <i>Designed adaptivity</i> is based on the expertise of the educator who designs personalized pathways to guide learners to learning content mastery; <i>Algorithmic adaptivity</i> 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)	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> Selecting the timing of adaptivity within an AEE relates to <i>when</i> 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)	<ul style="list-style-type: none"> 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)	<ul style="list-style-type: none"> Multiple types of adaptivity can be implemented in an AEE: <ul style="list-style-type: none"> <i>Content adaptivity</i> refers to the adaptation of the textual information; <i>Navigation adaptivity</i> refers to the adaptation of the curriculum sequence; <i>Presentation adaptivity</i> refers to the adaptation of layout of the screen to the digital device used, or to the learner's profile; <i>Multimedia adaptivity</i> refers to the adaptation of multimedia elements of the training such as videos, pictures, models; <i>Tools adaptivity</i> 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	<ul style="list-style-type: none"> 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.

549 This review also provides several key insights for future research. In terms of *population*, future
 550 research should focus on assessing AEEs with health professionals in practice, such as registered
 551 nurses and physicians, rather than students in these disciplines. This could provide key insights
 552 into how AEEs can impact clinical behavior and, ultimately, patient outcomes. In addition,
 553 investigators should target larger sample sizes. In terms of *interventions*, researchers should

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3 554 report more clearly on adaptivity methods, goals, timing, factors and types. Moreover,
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5 555 researchers should provide additional details regarding the underlining algorithms allowing the
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7 556 adaptivity process in order to ensure replicability of findings. Regarding *comparators*, this review
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10 557 suggests there is a need for additional research using traditional comparators (i.e., large group
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12 558 classroom instruction) and more specific comparators (i.e., adaptive e-learning environment with
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14 559 design variations). Regarding *outcomes* and outcome measures, researchers should use validated
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17 560 measurement tools of knowledge, skills, and clinical behavior to facilitate knowledge synthesis.
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19 561 Moreover, the very low number of studies assessing the impact of AEEs on health professionals'
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21 562 and students' clinical behavior demonstrates the need for further research with higher-level
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23 563 outcomes. Finally, in terms of *study designs*, researchers should focus on research designs
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26 564 allowing the assessment of the impact of multiple educational design variations and adaptivity
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28 565 types within one study, such as factorial experiments.

31 566 **Strengths and Limitations**

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34 567 Strengths of this systematic review and meta-analysis include the prospective registration and
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36 568 publication of a protocol based on rigorous methods in accordance with Cochrane and PRISMA
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38 569 guidelines; the exhaustive search in all relevant databases; the independent screening of the titles,
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41 570 abstracts and full-text of studies; the assessment of each included studies' risk of bias using
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43 571 EPOC Cochrane guidelines; and the assessment of the quality of evidence for each individual
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46 572 outcome using the GRADE methodology.

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49 573 Our review also has limitations to consider. First, outcome measures varied widely across
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51 574 studies. To address this issue, we conducted the meta-analysis using the SMD. Using the SMD
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54 575 allowed us to standardize the results of studies to a uniform scale before pooling them. Review

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3 576 authors judged that using the SMD was the best option for this review, as it is the current practice
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5 577 in the field of knowledge synthesis in medical education^{6 60}.

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8 578 Second, there was high inconsistency among study results, which we can mostly attribute to
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10 579 differences in populations, AEE design, research methods, and outcomes. This resulted in
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12 580 sometimes widely differing estimates of effect. To partly address this issue, we used a random-
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14 581 effects model for the meta-analysis, which assumes that the effects estimated in the studies are
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16 582 different and follow a distribution³⁰. However, since a random-effects model awards more
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18 583 weight to smaller studies to learn about the distribution of effects, it could potentially exacerbate
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20 584 the effects of the bias in these studies³⁰.

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22 585 Finally, publication bias could not be assessed by the means of a funnel plot since there were less
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24 586 than 10 studies included in the meta-analysis.

25 587 **CONCLUSIONS**

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27 588 Adaptive e-learning has significant potential to increase the effectiveness and efficiency of
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29 589 learning in health professionals and students. Through the different sub-domains of the adaptivity
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31 590 process (i.e. method, goals, timing, factors, types), AEEs can take into account the particularities
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33 591 inherent to each learner. This systematic review and meta-analysis underlines the potential of
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35 592 AEEs for improving knowledge and skills in health professionals and students in comparison
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37 593 with other educational interventions, such as nonadaptive e-learning environments and large-
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39 594 group classroom learning, across a range of topics. However, evidence was either of low or very
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41 595 low quality and heterogeneity was high across populations, interventions, comparators, and
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43 596 outcomes. Thus, additional comparative studies assessing the efficacy of AEEs in health
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45 597 professionals and students are needed to strengthen the quality of evidence .

598 AUTHOR CONTRIBUTIONS

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

601 G.F. contributed to the conception and design of the review, to the acquisition and analysis of
602 data, and to the interpretation of results. Moreover, G.F. drafted the initial manuscript. S.C.
603 contributed to the conception and design of the review, and to the interpretation of results. M.-
604 A.M.-C. contributed to the conception and design of the review, to the acquisition of data, and
605 interpretation of results. T.M. contributed to the conception and design of the review, to the
606 acquisition of data, and to the interpretation of results. M.-F.D. contributed to the conception and
607 design of the review, to the acquisition of data, and to the interpretation of results. G.M.-D.
608 contributed to the conception and design of the review, and to the interpretation of results. J.C.
609 contributed to the interpretation of results. M.-P.G. contributed to the interpretation of results.
610 V.D. contributed to the interpretation of results.

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

613 DATA SHARING STATEMENT

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

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1
2
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4
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6
7 621 Higher Education, and multiple scholarships from the Faculty of Nursing at the University of
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23 629 for Innovation in Nursing Education.
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29 630 **FIGURE LEGENDS**

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32 631 Figure 1. PRISMA Study Flow Diagram.
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36 632 Figure 2. Risk of bias summary: review authors' judgements about each risk of bias item for each
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38 633 included study.
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41 634 Figure 3. Risk of bias graph: review authors' judgements about each risk of bias item presented as
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43 635 percentages across all included studies.
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46 636 Figure 4. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus
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48 637 other educational interventions in improving knowledge.
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52 638 Figure 5. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus
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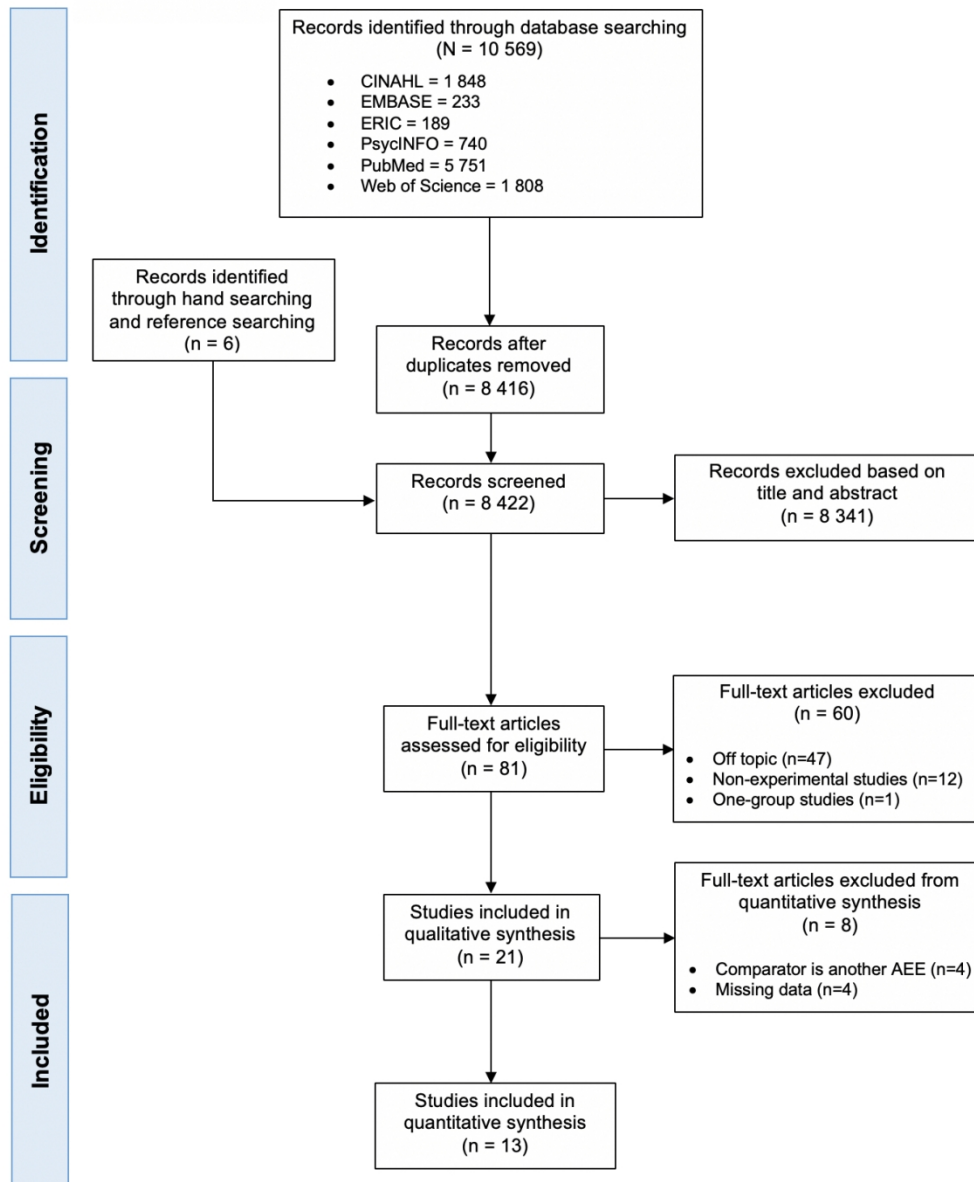


Figure 1. PRISMA study flow diagram.

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.

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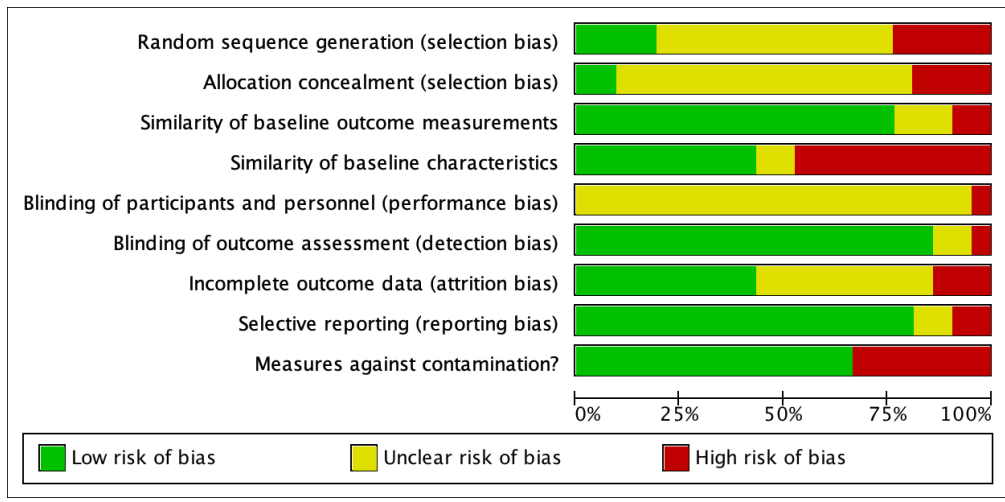


Figure 3. Risk of bias graph: review authors' judgements about each risk of bias item presented as percentages across all included studies.

219x107mm (144 x 144 DPI)

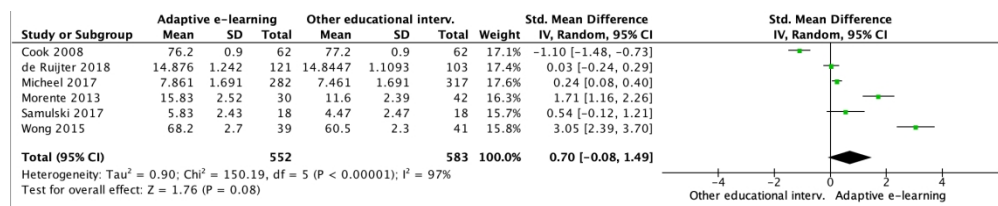


Figure 4. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving knowledge.

367x74mm (144 x 144 DPI)

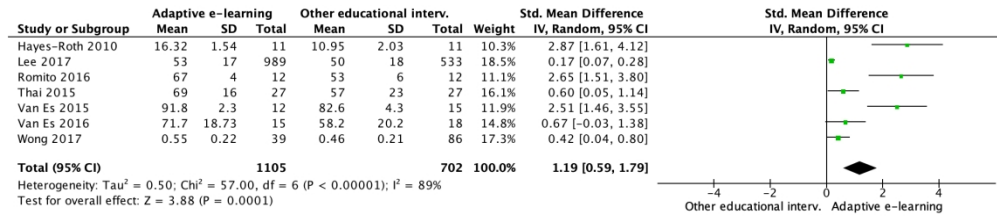


Figure 5. Forest plot representing the meta-analysis of the efficacy of adaptive e-learning versus other educational interventions in improving skills.

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 pediatricist*[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							No of patients		Effect		Certainty	Importance
No 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 insufficient.