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1

2 **A library of logic models to explain how interventions to reduce**
3 **diagnostic errors work**

4

5 Maartje Kletter, MSc, University of Warwick

6 G.J. Mendelez-Torres, PhD, Cardiff University

7 Richard Lilford, PhD, University of Warwick

8 Celia Taylor, PhD, University of Warwick

9

10 Corresponding author: Celia Taylor, Warwick Medical School, University of Warwick,
11 Coventry CV4 7AL.

12 Tel: 00442476524793, Email: celia.taylor@warwick.ac.uk

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17

18 Abstract

19 **Objectives:** We aimed to create a library of logic models for interventions to reduce diagnostic
20 error. This library can be used by those developing, implementing or evaluating an intervention
21 to improve patient care, in order to understand what needs to happen, and in what order, if the
22 intervention is to be effective.

23 **Methods:** To create the library we modified an existing method for generating logic models. Five
24 ordered activities to include in each model were defined: pre-intervention, implementation of the
25 intervention, post-implementation, but before the immediate outcome can occur, the immediate
26 outcome (usually behaviour change) and post-immediate outcome, but before a reduction in
27 diagnostic errors can occur. We also included reasons for lack of progress through the model.
28 Relevant information was extracted about existing evaluations of interventions to reduce
29 diagnostic error, identified by updating a previous systematic review.

30 **Results:** Data were synthesized to create logic models for four types of intervention, addressing
31 five causes of diagnostic error in seven stages in the diagnostic pathway. In total 46 interventions
32 from 43 studies were included and 24 different logic models were generated.

33 **Conclusions:** We used a novel approach to create a freely available library of logic models. The
34 models highlight the importance of attending to what needs to occur before and after
35 intervention delivery if the intervention is to be effective. Our work provides a useful starting
36 point for intervention developers, helps evaluators identify intermediate outcomes and provides a
37 method to enable others to generate libraries for interventions targeting other errors.

38 **Key words:** Diagnostic error, logic model, mechanistic theory, effectiveness

39 **Word count:** 3,981 (plus 1.044 in boxes)

40

41 Introduction

42 Any attempt to reduce the incidence of a particular error in healthcare must begin with an
43 exploration of the epidemiology of the error, including an understanding of its cause, i.e. of *why*
44 the particular error occurs [1]. It is then necessary to address the underlying cause by developing
45 and implementing an appropriate *intervention* that changes the existing structure and/or process
46 of care. In their review of methods for designing interventions intended to change the behaviour
47 of healthcare professionals – the change required to address many (but not all) causes of error -
48 Colquhoun and colleagues identified four tasks common to almost all methods: identification of
49 barriers, selection of intervention components, use of theory and engagement of end-users [2].
50 These are time-consuming tasks. However, in many cases, an intervention developer does not
51 have to start at square one because there are existing interventions that could be used (possibly
52 following adaptation) for many error/cause of error combinations. To help a developer use an
53 existing intervention with confidence, they need to know, amongst other things, how the
54 intervention should be implemented, i.e. what specific steps are required and in what order, to
55 make the intervention effective? This sequence of steps is known as the intervention's *logic model*
56 or mechanistic theory [3-5]. In constructing a logic model, it is important to identify steps that
57 need to occur *before* the intervention is implemented, as well as those that need to occur *after* the
58 implementation if the final desired outcome is to be realised. A logic model should also include
59 any specific facilitators and barriers that help or hinder progress at each step. By clearly
60 specifying all of these steps, facilitators and barriers, logic models can also enable the
61 identification of appropriate intermediate outcomes, such as fidelity, that should be measured
62 during an evaluation to help explain the quantitative effect of the intervention on the final
63 outcome (adverse events).

64 It has been argued that the use of logic models as part of theory-based intervention development
65 will increase the probability that the intervention is effective [5, 6]. It is therefore good practice to
66 describe an intervention's logic model in any report of its evaluation. However, including an
67 explicit logic model is not prescribed in either the TIDieR [7] or the CONSORT [8] checklists.

68 The former stipulates that a full description of the intervention should be provided (including any
69 essential theory), while the latter states that: “*Authors should ... suggest a plausible explanation for*
70 *how the intervention(s) might work, if this is not obvious*”. Even a study adhering to both may result in
71 the omission of important behavioural requirements, such as professionals’ willingness to engage
72 with the intervention. Therefore, although reports of evaluations of many existing interventions
73 to reduce error are widely available, logic models are rarely included [9]. This lack of readily-
74 accessible information makes it challenging for someone tasked with reducing a particular error
75 to use an “off the shelf” intervention with confidence, just as it is challenging to bake a cake
76 without a list of ingredients and recipe.

77 There are a number of systematic reviews that have considered the effectiveness of different
78 possible interventions that aim to address specific types of error (see, for example, McDonald et
79 al. on diagnostic errors [10], Royal et al. on prescribing errors in primary care [11] or Cottrell on
80 wrong blood in tube errors in transfusion [12]). Although there are a number of patient safety
81 practices with a strong evidence base [13], such practices do not yet exist for all errors.

82 McDonald et al., for example, report that: “*some interventions, ..., can reduce diagnostic errors in*
83 *certain situations*” ([10], p. 382, emphasis added). Our premise is that one reason for the
84 ineffectiveness of some interventions is that there is often insufficient attention afforded to the *full*
85 logic model of the intervention i.e. from the decision to design and implement an intervention
86 right through to a reduction in error at patient level [1, 6, 14, 15]. For example, while an effective
87 training programme may have been developed, the intervention developers do not consider how
88 to ensure all clinicians attend the training and subsequently apply their new knowledge once they
89 are back in practice. We therefore aimed to show how full logic models for a range of existing
90 interventions could be developed and compiled in a library, helping to broaden attention from
91 intervention implementation alone to the entire intervention pathway. To illustrate our
92 approach, we consider existing interventions that aim to address the causes of one specific error
93 in healthcare, diagnostic error. We selected diagnostic errors because these are fairly common
94 [16] and tend to have serious consequences [16-18]. Diagnostic errors have also been prioritised

95 as a key focus for primary care by the WHO [19]. Our library can be used by intervention
96 developers familiar with the specific type of diagnostic error they are aiming to address and its
97 cause(s), to help them choose, modify and implement an appropriate intervention that addresses
98 the cause of the error. By identifying the individual steps, the models should also “nudge”
99 developers to ensure they can provide a sufficient justification (or causal theory) as to why each
100 step in the model will lead to the next. The models in the library could also be used by
101 intervention evaluators who need to know which intermediate outcome variables need to be
102 measured. Our method for developing the models and synthesising them into a library can
103 subsequently be used by other researchers seeking to create libraries of logic models of
104 interventions addressing other types of error.

105 Methods

106 *Search strategy for existing interventions to reduce diagnostic error*

107 Our starting point was McDonald et al.’s systematic review of evaluations of interventions to
108 reduce diagnostic error [10], which included 109 studies. This review only contained studies
109 published before October 2012 and excluded studies in simulated settings. We therefore repeated
110 the original search, and extended it to July 2016.

111 All of the titles and abstracts of the studies identified in our search were independently screened
112 against a set of selection criteria (Box 1) by MK and CT. We used the inclusion criteria of
113 McDonald et al., adapted to incorporate simulation-based studies, and added additional
114 exclusion criteria designed to ensure the interventions included could be used in another setting
115 (i.e. were not over-specific) and had data on their effectiveness available. We also excluded
116 studies which increased the number of clinicians making an interpretation or changed the type of
117 professional making the diagnosis, because of the minimal change to the diagnostic pathway that
118 would result from implementing these interventions. The full text of all studies included by either
119 reviewer was obtained and independently screened against the selection criteria by MK and CT.

120 Any disagreements regarding inclusion at the full text-stage were resolved by discussion and the
121 reason for exclusion after full text screening was recorded.

122 **Box 1: Selection criteria**

123 Inclusion criteria specified by McDonald et al. [10]

124 Study evaluating any intervention to decrease diagnostic errors, the time to correct diagnosis or
125 to appropriate clinical action.

126 Study in any clinical setting.

127 Any study design.

128 Study addressing patient-related outcomes or proxy measures of patient-related outcomes.

129 Exclusion criteria specified by McDonald et al. [10]

130 No intervention.

131 No real patients: modified for this review to include studies in simulated clinical settings and
132 those with healthcare students as participants.

133 Additional exclusion criteria for this review

134 Studies where the intervention is a specific test used for a specific diagnosis.

135 Studies of interventions which increased the number of clinicians making an interpretation or
136 changed the type of professional making the diagnosis.

137 Studies of evaluations of response to treatment or the effect of taking action on signs of
138 deterioration.

139 Studies in which the intervention was designed primarily to reduce costs.

140 Studies not including an evaluation of the intervention.

141 Systematic (or other) reviews, case reports, letters, editorials, commentaries, opinion pieces,
142 audits or protocols.

143

144 *Generic library structure*

145 In designing the structure of the library we considered the following course of action: a particular
146 diagnostic error is identified, which could be due to one or more potential causes, each of which

147 could be addressed with a number of potential interventions. The first level of the library
148 therefore needed to describe the error itself, the second level the potential cause(s) of each error
149 and the third level the types of intervention that could be implemented (Figure 1). Each logic
150 model would then synthesize all of the specific interventions, of each type, that addressed each
151 cause of each error. In order to operationalise this, we needed to create appropriate categories of
152 errors (level 1), causes (level 2), and intervention types (level 3). For errors (level 1), we used the
153 seven temporal stages (and sub-stages) of the diagnostic pathway as outlined by Schiff and
154 colleagues [20]. For causes (level 2), we used an expanded version of the three-level
155 categorisation outlined by Gandhi et al. [21] and Singh et al. [22] (cognitive, system-related and
156 patient-related). We split cognitive causes into two categories, cognitive reasoning (akin to
157 “judgment” in Gandhi et al.) and lack of knowledge/skill/experience (“lack of knowledge” in
158 Gandhi et al.) because of the large number of interventions aiming to address cognitive-related
159 errors. Furthermore, enhancing cognitive reasoning requires a different type of intervention to
160 enhancing knowledge/ skill/experience. We added sub-optimal attention as a separate category,
161 although we acknowledge that this may not accord with “no blame” patient safety cultures. This
162 provided five “error cause” categories in total. For intervention type (level 3), we used a modified
163 version of the six categories outlined by McDonald et al. [10]. The educational and technology
164 intervention categories were retained unchanged. We amalgamated personnel and technique
165 changes into the process change category and added quality improvement interventions as a
166 separate category. Studies using only additional review methods were excluded (as discussed
167 above) to give four “intervention type” categories in total.

168 The seven diagnostic pathway stages, five causes of error and four types of intervention meant
169 that our library could theoretically contain up to $7 \times 5 \times 4 = 140$ logic models..

170 CT and MK subsequently independently coded each intervention using these three
171 categorisations; each intervention in studies including multiple interventions was coded
172 separately. Results were then compared and any disagreements resolved by discussion.

173 Information on the following additional aspects of each intervention was coded by MK, using

174 NVivo Pro v11: specific intervention description, setting (including whether a simulation),
175 participants and study design. In addition MK coded any *ex ante* explanation of why the
176 intervention was expected to work and any *ex post* explanation of why the intervention did or did
177 not work. All coding was subsequently verified by CT.

178 *Logic model structure and generation of synthesized logic models*

179 We applied a modified version of Kneale et al.'s procedure for logic model creation [9], as
180 described in Box 2, with the aim of identifying, in the most plausible temporal order, the
181 activities that would be included in intervention development and implementation. We decided
182 that the starting point for each model would be the *decision* to implement a specific intervention
183 and subsequently identified five key temporal activities to include in each model: pre-
184 intervention (intervention development and other requirements before the intervention can be
185 implemented on the ground), the implementation of the intervention itself, post-implementation
186 (what needs to happen before the immediate outcome of the intervention can occur), the
187 immediate outcome (which generally mitigated the underlying cause of the error) and post-
188 immediate outcome (before the effects can reach the patient and a reduction in diagnostic errors
189 can occur). Within each stage, there could be multiple steps (i.e. the individual requirements,
190 activities and/or changes). This meant that each logic model would show the full, ordered chain
191 by which intervention implementation leads to the desired outcome.

192 We modified Kneale et al.'s procedures in three ways. First, following examination of logic
193 models in existing studies and general frameworks (#1 in Box 2), we worked forwards from the
194 initial design of the intervention to the final (distal) outcome, rather than the other way round, as
195 this seems a better match to what an implementer would do in practice having chosen a specific
196 intervention. Second, we extended #8 (sharing initial logic models) to include the generation of a
197 single, synthesized model for each error/cause/type of intervention combination. Finally, we
198 excluded #10 (presenting the final logic model in the protocol for the review) as it was not
199 required for our work. We also wanted to include an indication of the effectiveness of each

200 intervention, to aid users of the library in selecting a potentially effective intervention. Our
201 method of doing so is described in Box 3.

202 **Box 2: Generation of synthesized logic models**

203 *#1: Examination of logic models in existing studies and general frameworks:* We gathered the coded
204 explanations for intervention (in)effectiveness from our NVivo database. Given that the majority
205 of interventions sought to achieve some form of professional behaviour change, we also
206 examined the COM-B framework [23], the Stages of Change model for behavioural change
207 interventions [24] and Kirkpatrick's hierarchy of outcomes for educational interventions [25].
208 These explanation, frameworks and models provided an overview of the individual steps that
209 needed to be included in our logic models in each of the five key activities we had already
210 identified.

211 [For #2 to #5, CT and MK worked independently, aggregating the information from #1 to
212 enable development of a draft logic model for each intervention in each study.]

213 *#2: Specification of intervention inputs (intervention development and other requirements before the
214 intervention can be implemented on the ground):* We identified two main types of input: suitable
215 intervention design and the intended subjects being able to attend to it. Drawing on the COM-B
216 framework [23] for example, the curriculum and pedagogy of a training programme (as an
217 example of a specific intervention) would need to be appropriate to enable the development of
218 the psychological capacity of the target audience and the intended "subjects" of the intervention
219 would need sufficient time (social opportunity) to attend to it.

220 *#3: Specification of intervention processes:* This is an explanation of how the intervention would be
221 provided (e.g. the nature of the training provided to clinicians) and what resources would be
222 required in order to do so (e.g. room space).

223 *#4: Identification of what needs to happen post-implementation, before the immediate outcome of the
224 intervention can occur:* We identified any requirements for those using the intervention in practice,

225 including Kneale et al.'s "proximal" outcomes [9]. Drawing on the Kirkpatrick model for
226 training evaluation [25], our exemplar training programme could only be effective if clinicians
227 were engaged during the course and learnt from it.

228 *#5: Identification of immediate outcome and steps from the immediate to the distal outcome:* Our
229 "immediate" outcome was equivalent to Kneale et al.'s "intermediate" outcome [9], the change
230 necessary to achieve the distal (final) outcome (usually behaviour change). Such behaviour
231 change is the "action" stage in the stages of change model [24], the third level in the Kirkpatrick
232 model [25] and the outcome of the COM-B framework [23].

233 *#6: Identification of distal outcome:* We had already identified a common distal outcome for all
234 interventions, a reduction in diagnostic errors impacting on patient-level outcomes. This would
235 be achieved when a clinician made a correct or timelier diagnosis that they would not have done
236 in the absence of the intervention.

237 *#7: Specification of intervention moderators including setting and population group:* To avoid over-
238 complication, we did not include these aspects within the logic models themselves but extracted
239 information on setting and participants, as described above and which are presented separately.

240 *#8: Share initial logic models, review and generate a single, synthesized model for each error/cause/type of*
241 *intervention combination:* MK and CT shared the logic models they had developed for each
242 intervention and discussed similarities and differences. We then agreed on a model for each
243 error/cause/type of intervention combination as shown in Figure 1. Within the "testing" error
244 category we developed one logic model for each sub-category to avoid over-complication.

245 *#9: Share synthesized models with the whole group, review and revise:* The synthesized models were
246 then shared with the remainder of the team and revised as required.

247

248

249 **Box 3: Determining intervention effectiveness**

250 The effectiveness of the interventions was assessed based on the size of the effect achieved and its
251 statistical significance. For an intervention's effect size (ES), we used results for total diagnostic
252 accuracy or for all errors combined (including all 'levels' of error from minor to major) and
253 across all participants (rather than for a specific type of error or a specific participant sub-group),
254 unless there was a clear indication in the study that the primary outcome was for a specific type
255 of error/sub-group. If studies included immediate and longitudinal effects, we used outcomes
256 measured immediately after the intervention, as not all studies included repeat measurements
257 and the time gaps where this was done were variable. The outcome we used (detailed in
258 Appendix 1) was not always that reported in the abstract of the paper. For some papers we used
259 the primary data presented to calculate effect size and statistical significance, using the Campbell
260 Collaboration's effect size calculator, using the logit method for 2x2 tables and pooled standard
261 deviations for paired t-tests [26]. Any effective intervention was shown as having a positive
262 effect size, regardless of whether the outcome related to diagnostic accuracy or error rates. It was
263 not always possible to determine effect size and statistical significance from the results or data
264 presented and in some cases we were unable to adjust for non-independence in pre/post studies
265 where the same participants contributed data in both time periods, albeit regarding different
266 (simulated) patients. Using Cohen's rules of thumb [27] and traditional frequentist approaches to
267 determining statistical significance, we classified the effectiveness of the intervention as negative
268 ($ES < 0$ and $p < 0.05$), none ($p > 0.05$), very small ($0 < ES < 0.2$ and $p < 0.05$), small ($0.2 < ES < 0.5$ and
269 $p < 0.05$), medium ($0.5 < ES < 0.8$ and $p < 0.05$) or large ($ES > 0.8$ and $p < 0.05$).

270

271

272 Results

273 We reviewed 2,638 titles and abstracts and 286 full text studies. A total of 43 studies met the
274 inclusion criteria (Figure 2) and proceeded to data extraction and coding. Of the 140 potential
275 logic models, there was at least one intervention in 19 (14%). A total of 58 active trial arms were
276 reported across the 43 studies. After grouping very similar interventions, a total of 46 unique
277 (specific) interventions were identified.

278 Table 1 summarises the studies included in the logic models in each combination; full details on
279 each are provided in Appendix 1. The most common errors addressed were errors in the testing
280 stage of the diagnostic pathway (N=26 interventions, 60%). The most common interventions
281 addressed errors caused by a lack of knowledge/skill/experience (N=18, 39%) or sub-optimal
282 cognitive reasoning (N=14, 30%). The most common types of interventions were those in the
283 process category (N=18, 39%) and the education and feedback category (N=16, 35%).

284 51 effect sizes could be calculated although some were for multi-component interventions as a
285 whole. While no interventions had a statistically significant negative effect, only seven (14%)
286 were classified as having “large” effect sizes and 16 (31%) were classified as having no effect.

287 An example of a logic model, for errors in diagnostic decision making caused by sub-optimal
288 cognitive reasoning and addressed with education and feedback interventions, is shown in Figure
289 3. The full library of the 24 generated logic models is shown in Appendix 2. All logic models use
290 the generic term “clinician” to denote any healthcare professional or staff member involved in
291 making a diagnosis at any stage in the diagnostic pathway. To generate the logic model shown in
292 Figure 3, we drew on two specific interventions in this error-cause-type combination, a training
293 programme in diagnostic coding for psychiatric disorders (ICD-10) trialled in a simulated setting
294 [28] and cognitive forcing strategy training trialled with medical students in a simulated
295 emergency medicine setting [29]. The use of a structured diagnostic system (i.e. ICD-10 codes)
296 was intended to help overcome the cultural biases known to affect diagnostic decision-making in

297 psychiatry [28]. The cognitive forcing training aimed to encourage participants to use analytic, or
298 System 2, thinking during diagnostic reasoning, which means that they would self-monitor
299 following an initial diagnosis and “force” themselves to consider any alternative, non-obvious
300 diagnoses [29]. At the pre-intervention stage each training programme needed to be designed
301 appropriately in terms of curriculum and pedagogy and participants needed to be given time to
302 attend the training. During the intervention stage training would be provided. Clinicians needed
303 to actually attend the training, engage in it (e.g. pay attention), learn from the training and retain
304 this learning. The immediate outcome would be that the participants change their existing
305 behaviour by applying the newly learnt knowledge/skills in diagnostic decision making. During
306 the post-immediate outcome stage the use of the learnt knowledge/skills would need to help the
307 clinician make a correct diagnosis (that they would not have done previously), if the intervention
308 is to reduce diagnostic error.

309 The effectiveness of both specific interventions included in Figure 3 was evaluated in simulations
310 of clinical practice using a test requiring participants to diagnose one or more cases, with one
311 showing a large effect [28] and the other no effect [29]. Sherbino and colleagues [29] suggested a
312 number of reasons why their intervention was ineffective, including insufficiently complex cases
313 that did not require System 2 thinking, a lack of transfer of learning to new cases and an
314 insufficiently strong training programme to counter existing cognitive biases. For the
315 intervention found to be effective [28], it would still be necessary to show longer-term retention
316 and transfer to real-life clinical practice if patient-level outcomes are to be improved.

Discussion

Summary of findings

We have generated 24 logic models which show the mechanistic theory of 46 different interventions designed to reduce the incidence of diagnostic error in healthcare. These models can be used by anyone seeking to develop and implement an intervention to reduce a specific diagnostic error in their own setting. The models provide a guide as to what needs to be done in what order if the desired final effects of a particular intervention are to be realised; as such they also help intervention evaluators choose appropriate intermediate outcomes. One prerequisite for using the library is that the intervention developer has a good idea of the main cause of the error they are trying to tackle; although of course many errors are multi-factorial [30]. Intervention developers also need to be cognisant of how any aspects of their own context may mean that the intervention has a different level of effectiveness to that in the evaluations included in this study. Thus, while a developer may need to adapt an existing intervention, they do not have to start with a blank piece of paper.

As with patient safety incidents, which are often followed-up with investigations using techniques such as Root Cause Analysis [31], we can learn from the unsuccessful interventions by examining the “leaks” from the logic models. For example, in Goodacre et al.’s study [32], computer-generated interpretations of ECG results were provided to clinicians but one reason for a lack of intervention effectiveness was that the results were ignored. In general, however, there was a lack of evidence in the included studies about potential “leaks”, as has also been noted by others [33]. An intervention developer wanting to implement a similar intervention in their own context should therefore be encouraged to discuss the proposed ECG reports with clinicians and determine whether they would be used and why/why not; and to consider any other leaks that may occur at other steps in the logic model. The final intervention design and implementation would also need to include a strategy to improve adherence, such as routine reminders or peer assistance.

Strengths

To our knowledge, this is the first attempt at creating and providing a library of logic models which enables a user to compare and contrast different interventions and to understand what needs to occur and in what order if an intervention is to be effective. Our task was more challenging than we had originally anticipated, as none of the included studies explicitly described the full logic model for the intervention being evaluated. By using the library, intervention developers should be able to develop and implement interventions that are more likely to be effective, as they can ensure that all steps in the logic model are considered at an early stage.

Limitations

We were only able to generate 24 logic models. There will be more potential models, because interventions for other meaningful error/cause combinations are yet to be developed and/or evaluated. The existing breakdown of interventions by type of diagnostic error may not match the prevalence or severity of different types of error in reality. The library should therefore be updated when evidence accumulates, although some of the cells in Table 1 may be empty because a particular error is unlikely to be due to a particular cause (e.g. missing information on samples is unlikely to be due to cognitive bias because the cognitive load of completing the information required is low). Nevertheless, the “gaps” in Table 1 could be combined with evidence on the epidemiology of error to identify priorities for intervention development. Although we followed a standardized procedure for generating the logic models, and based our model structure on existing work [10, 20-22], they remain subjective and could be challenged by others. In particular, many errors have multiple causes (as identified by Graber et al. [30]) but we assigned each intervention to only one overall cause category. However, some interventions address more than one possible cause of each error and we would encourage intervention developers to consider all possible causes and design multi-faceted interventions when required.

We also advocate greater adherence to the TIDieR checklist [7], as clearer intervention descriptions would have enabled us to provide more objective logic models.

We have not included causal theories in our logic models, as we discuss in more detail below. Our approach suggests that intervention implementation through the steps in the logic model is linear in time, when this is unlikely to be the case for all interventions in practice. Although we provided an indication of each study's effectiveness, it was outside our remit to determine which specific components of multi-faceted interventions were critical for overall effectiveness, however it is also plausible that the "effectiveness sum" of a multi-faceted intervention is greater than that of the sum of its parts and, indeed, multi-faceted interventions may well be essential [34]. Likewise, we do not yet know the relative importance of each step in a logic model or the impact of context on effectiveness; other authors have reported a paucity of evidence in this area across patient safety interventions more generally [33]. Furthermore, we did not undertake a quality appraisal of the included studies, so our estimates of effectiveness may be biased.

The sample of studies (and therefore interventions) included was limited by our inclusion criteria; for example we excluded studies of interventions that focused on reducing costs without increasing the error rate or in which the only intervention was to increase the number of clinicians reviewing test results prior to making a diagnosis. Our sample may also be limited by publication bias, which is likely to reduce the number of ineffective interventions included. While a user of the library may be less likely to choose an intervention previously found to be ineffective, their inclusion would help us to learn from previous mistakes.

Comparison with existing literature and future work

It is generally accepted that all interventions should be based on causal theory [6, 10, 14, 15], and knowing an intervention's logic model or mechanistic theory is a prerequisite for explaining its causal theory (i.e. we need to identify the steps in the logic model before we can explain the "why" of each; bearing in mind that different causal theories may be needed to link different pairs of steps). However, the superior effectiveness of theory-led over non-theory-led interventions is not

always borne out in practice [3]. Our work suggests that one reason for this is that while a theory-based intervention may make the “immediate” outcome of the intervention more likely (e.g. the knowledge level of the clinicians who attend an educational intervention increases), there are additional steps both before and after the intervention itself where various “leaks” from the logic model dilute effectiveness.

There are four possible extensions to the work presented here. The first is to apply our method to interventions designed to tackle different errors, such as prescribing errors, and subsequently, to synthesise results across these different errors in the context of patient safety in general. The second is to identify which steps in the logic model, context and intervention design features are critical for effectiveness, and which tend to lead to ineffectiveness, potentially using Qualitative Comparative Analysis [35]. This task will however be difficult given the large variety of interventions and types of error across the included studies. Third, we could identify plausible causal theories for each link in each logic model. Again this will not be a simple task; Michie and colleagues, for example have identified and described 83 theories of behaviour change [36]. Finally, we could consider the quantitative relationships between steps in the logic models. For example, the logic models could be presented as Bayesian networks, which would facilitate the synthesis of multiple sources of evidence to derive estimates of the effect on the intervention on health outcomes and costs [37].

Conclusion

We were able to generate logic models for all of the interventions to reduce diagnostic error identified in our search and the resulting library is freely available to all (Appendix 2). We had to rely on the published evaluation reports for information about each intervention, meaning that logic model development was partially subjective. However, we based our method on previously published work [9], although we worked in the opposite direction to Kneale and colleagues, from intervention design to distal outcome. The resulting library of logic models can be used by others in a variety of ways: the library gives intervention developers a useful starting point and encourages them to consider and publish their logic models and identify appropriate causal

theories, and helps intervention evaluators to identify and measure critical intermediate outcome measures. Furthermore the methods we have described will help researchers to generate libraries for interventions targeting other errors in healthcare.

Figure legends

Figure 1: Generic library structure

Figure 2: Flow diagram

Figure 3: Logic model for errors in diagnostic decision making caused by cognitive bias and addressed with education and feedback interventions [28, 29]

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Table 1: Summary of error, cause of error and intervention types

Stage in diagnostic process (Schiff)	Error (Schiff sub-category; only sub-categories with at least one intervention are included)	Cause of error				
		Sub-optimal cognitive reasoning	Lack of knowledge/ skill/ experience	Sub-optimal attention	System-related	Patient-related
Access/presentation	N/A					
History taking	Failure/delay in eliciting critical piece of history data					P: Patient-completed questionnaire [1-3]
Physical exam	Failure/delay in eliciting critical physical exam finding			EF: Patient feedback [4]		
	Sub-optimal weighting				P: Tertiary trauma survey [5, 6]	
Testing	Failure/delay in performing ordered tests			T: Computer test support [7]		
	Sample mix-up/mislabeled			P: Computer-aided double-signing [8] T: Computer test support [9]		
	Technical errors/poor processing of specimen/test		EF: Poster with most common errors [10]; Crash course about most common errors [10]; Leaflet explaining blood drawing procedure and explanation of procedure by senior nurse [7]; Training on sample management and standardized sample collection [8]; Reference materials on sample collection produced [8]; Training on blood sample collection [11, 12]		P: Improved storage facilities [8]; More delivery staff [8] QI: Participation in cross-institution benchmarking [13]	
	Failed/delayed transmission of result to clinician			P: Structured report template [14]	P: Quiet working environment [14]	

	Erroneous clinician interpretation of test	P: Verification stage added [15]; Checklists to correct mistakes in initial diagnosis [15, 16] T: Computer pattern recognition [17]	EF: Individual feedback on image interpretation [18, 19]; Meetings to discuss errors/missed cases [20, 21]; Technician report written at time of investigation and presented to clinicians [22]; Training including hands-on training and expert tutorial [23] T: Software to help trainees read capsule endoscopy images [19]; Computer test support [24]; Computer-interpretation of investigation results provided to clinicians [25, 26]		P: Structured reporting process [20] T: Computerised version of images [27]	
Assessment	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	EF: Specific training programme in diagnostic coding [28]; Cognitive forcing strategy training [29] P: Self-directed reflection [30]; Enhanced analytical reasoning using structured template [31]; Provision of additional data and querying initial hypothesis [32]; Structured reanalysis of case findings [33]; Checklists after collecting information without return to patient [34]; Checklists after collecting information with return to patient [34] T: Diagnostic reminder system [35, 36]; Computer diagnostic support system before testing [37, 38]; Computer diagnostic support system after testing [37, 38]	EF: Monthly feedback added to standardised data collection and computer support [39]; Education about atypical presentations [40]; Feedback about telephone follow-up of high risk patients [40] P: Standardised data collection forms [39] T: Computer-based decision support tool [39, 41, 42]			
Referral	Failure/delay in ordering needed referral			P: Reminders [43]		
Follow-up	N/A					

Type of intervention codes: Education/feedback (EF), Process (P), Technology (T), Quality improvement activities (QI).

Several interventions were sufficiently similar in multiple studies to group them as one intervention and the number of references specifies the number of studies, including two sets of two papers [35-38] in which the interventions were identical. Some studies included multiple interventions (range 1-5). Where the second and any subsequent interventions built on the first, the intervention is coded according to its incremental type. N/A: No interventions in this stage of the diagnostic process identified.

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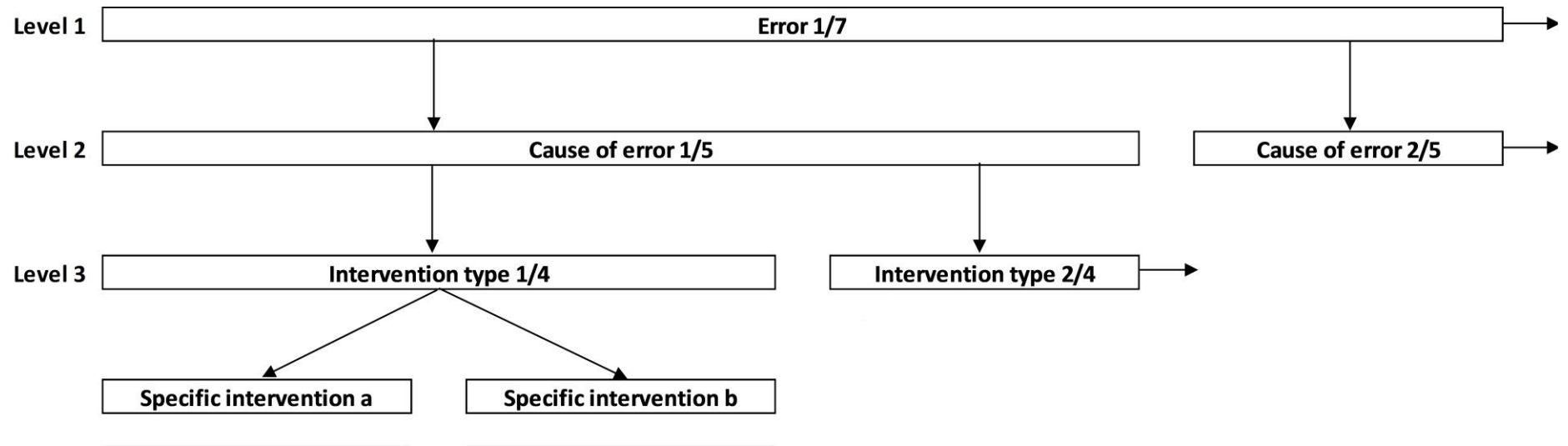


Figure 1

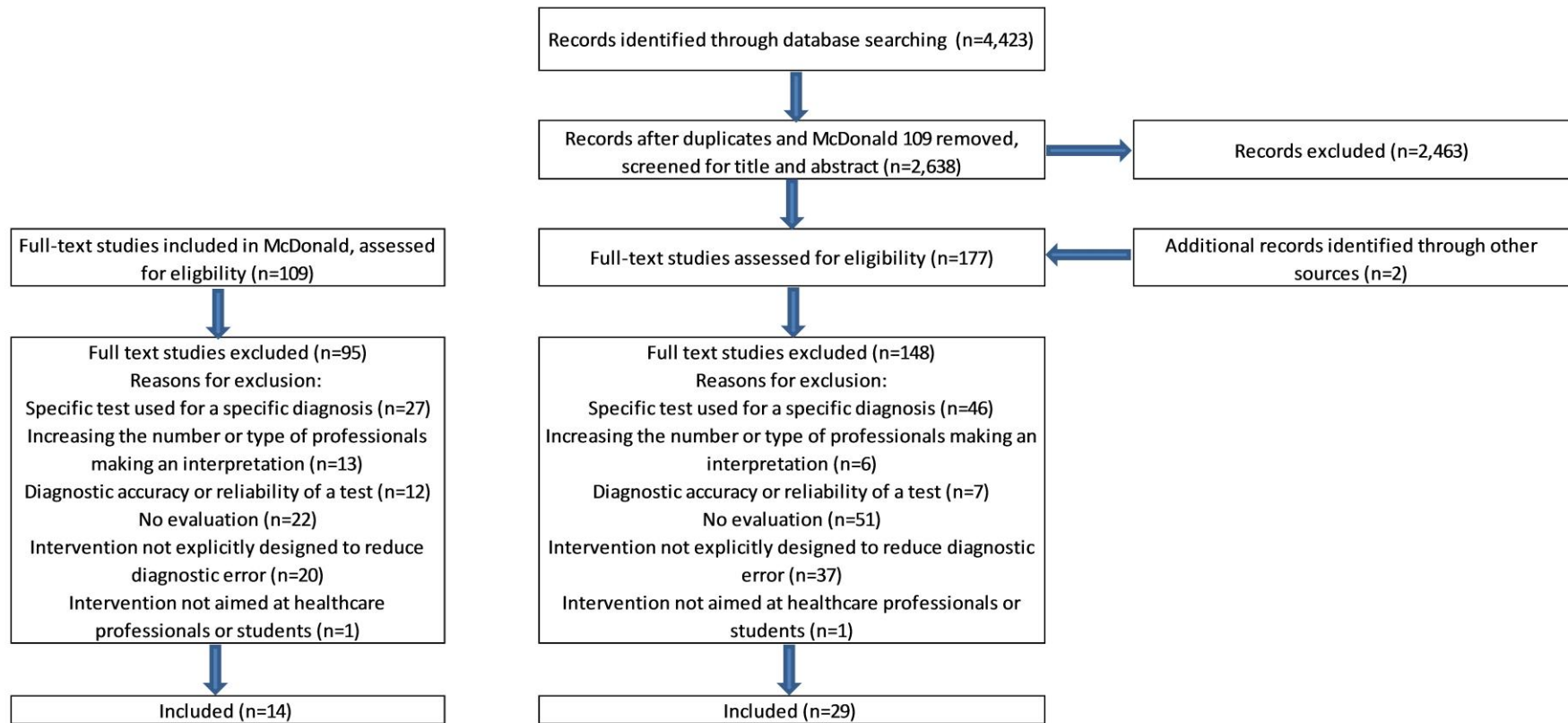


Figure 2

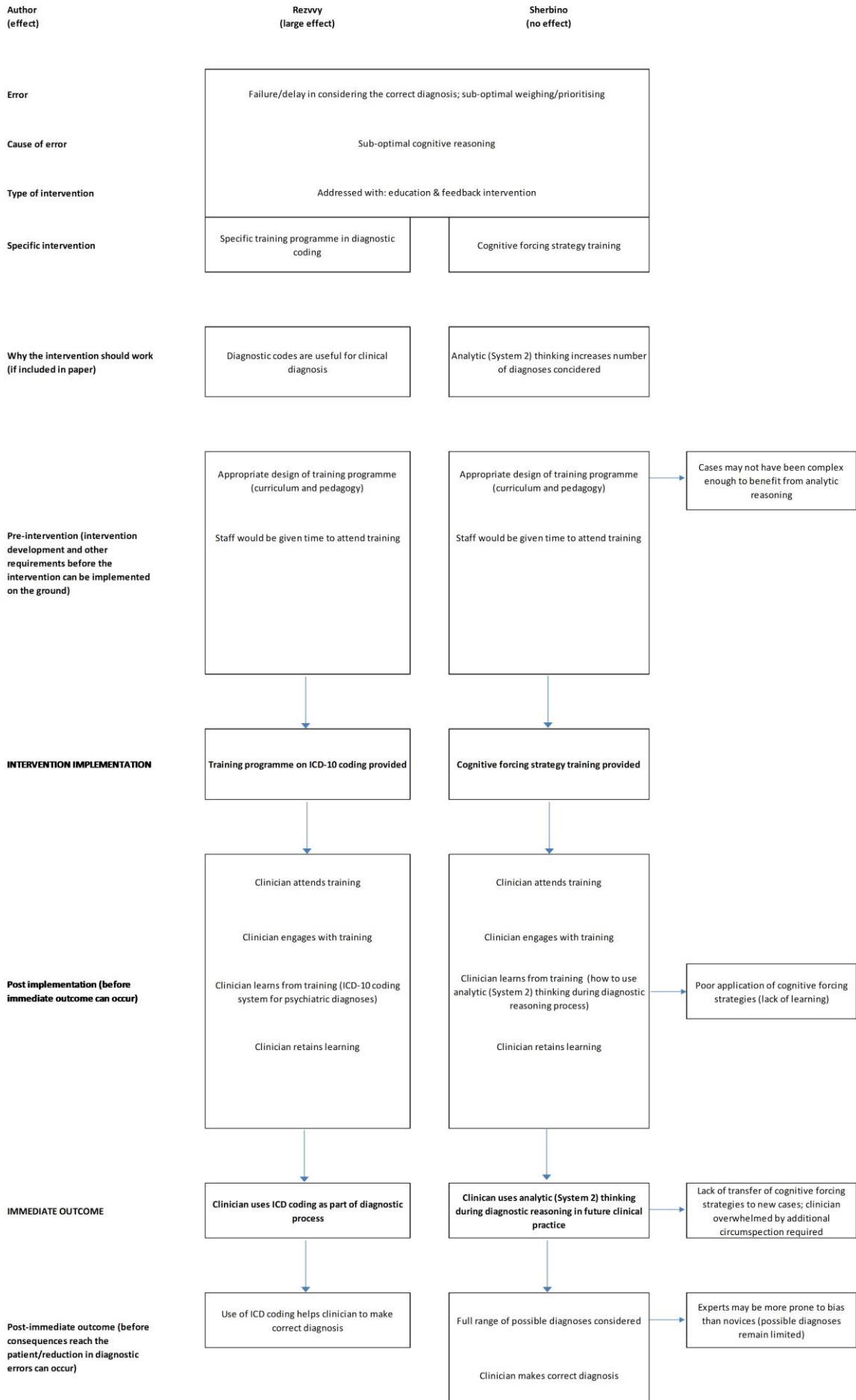


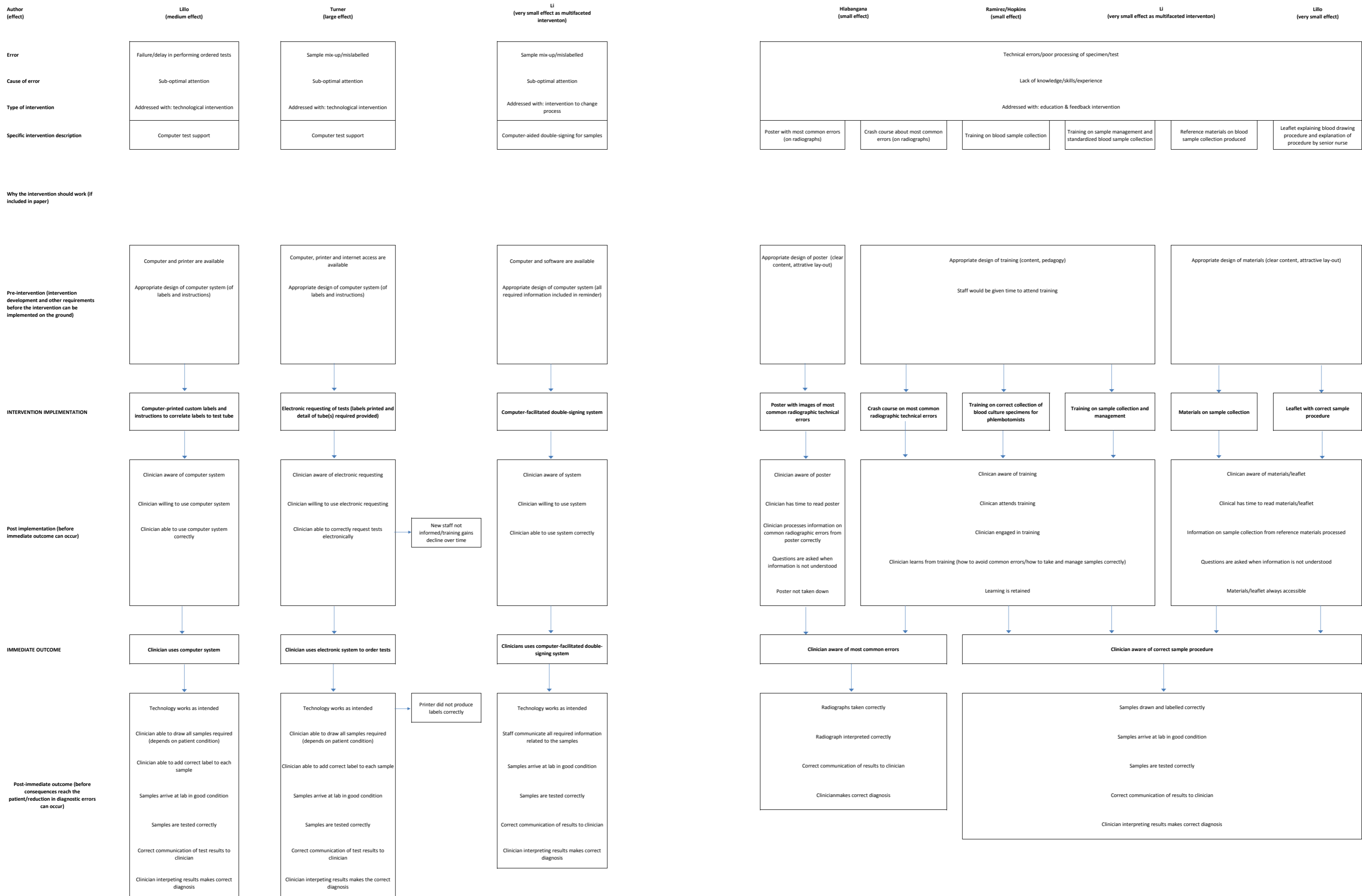
Figure 3

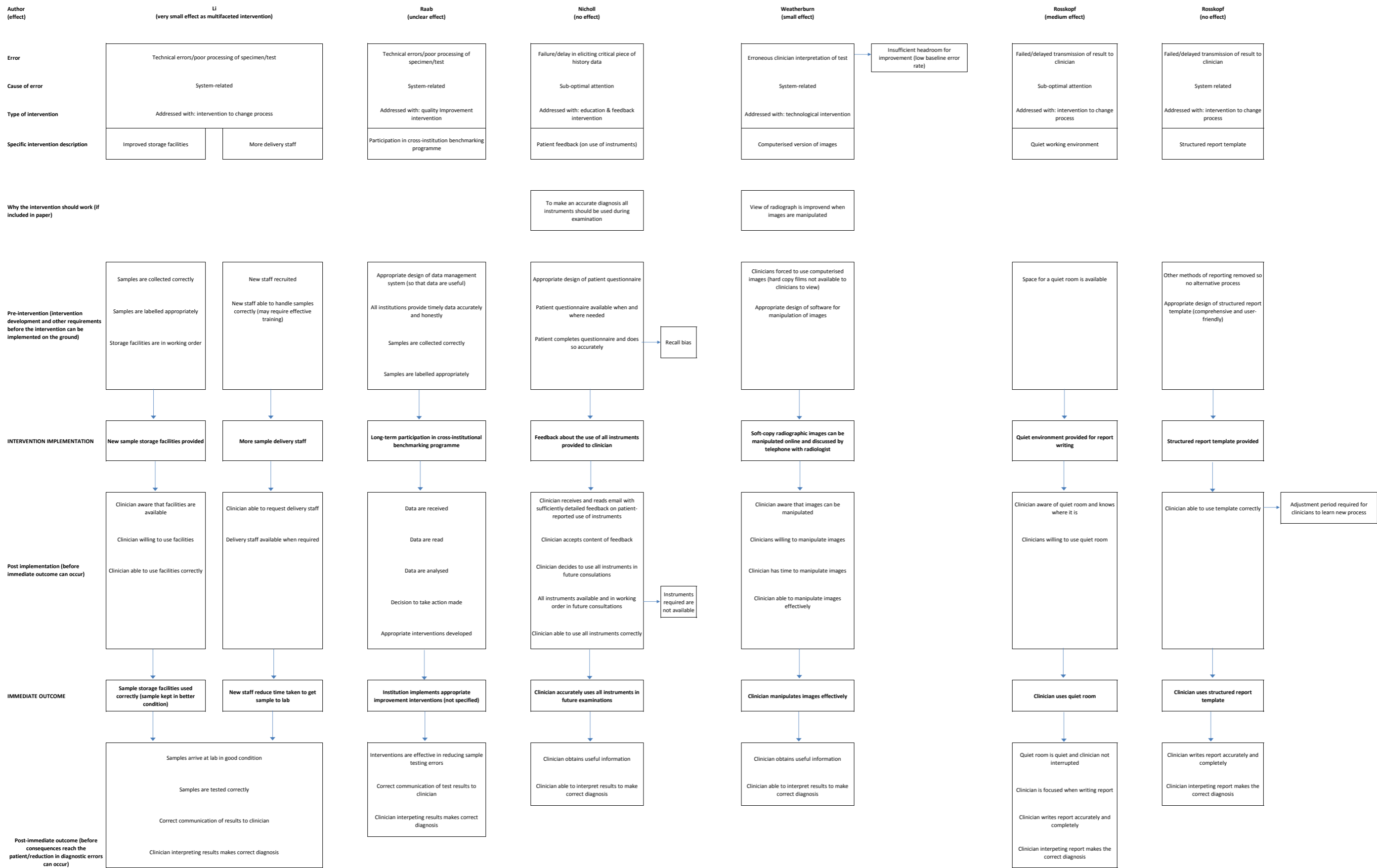
Appendix 1: Summary of included studies

Study	Source	Participants	Setting	Country	Design	Intervention description	Intervention category	Error	Cause of error	Definition of outcome/error used to calculate effect	Baseline or Control group outcome (grey=error; white=accuracy)	Post or Intervention group outcome (grey=error; white=accuracy)	Effect size (p-value)	Effect size group
Biffi	109	Physicians	Trauma ICU	USA	Pre-post	Tertiary trauma survey	Process	Sub-optimal weighing during physical examination	System-related	Percentage of patients with a missed injury	2.40%	1.50%	Chi-squared=6.71, p=0.001, Cohen's d=0.254	Small
Chern	109	Physicians	Hospital (Emergency Department)	Taiwan	Pre-post	Education about atypical presentations Feedback about telephone follow-up of high risk patients	Education and feedback	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Lack of knowledge/skill/experience	Percentage of patients with a clinically significant adverse event	0.94%	0.43%	Chi-squared=7.17, p=0.007; Cohen's d=0.438 (Combined)	Small
Coderre	Repeat	Medical students	Simulation	Canada	Pre-post (type of data randomised)	Provision of additional data and querying of initial diagnosis	Process	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal cognitive reasoning	Percentage of participants with correct diagnosis (combined across types of data provided)	45.4%	82.3%	Chi-squared=79.4, p<0.001, Cohen's d=0.953	Large
Dudley	109	Junior doctors	Hospital	UK	Controlled (not randomised)	Technician report written at time of investigation	Education and feedback	Erroneous clinician interpretation of test	Lack of knowledge/skill/experience	Percentage of reports containing an error (minor disagreement, disagreement or significant disagreement), A&E and medical SHOs combined	52.1%	42.3%	Chi-squared=2.74, p=0.098; Cohen's d=0.220	None
Espinosa	109	Emergency Physicians	Hospital (Emergency Department)	USA	Longitudinal	Review of clinically significant errors in blame-free environment	Education and feedback	Erroneous clinician interpretation of test	Lack of knowledge/skill/experience	Percentages of radiograph interpretations with a false negative finding	3.00%	1.20%	Chi-squared=174, p<0.001, Cohen's d=0.515	Medium
		System re-design				Process	System-related				1.20%	0.30%	Chi-squared=150, p<0.001, Cohen's d=0.771	Medium
Goodacre	Repeat	Senior house officers (Junior doctors)	Simulation of a Hospital Emergency Department	UK	RCT (reports randomised not participants)	Computer-interpretation of investigation results provided to clinicians	Technology	Erroneous clinician interpretation of test	Lack of knowledge/skill/experience	Percentage of ECG interpretations with an error (major or minor)	63.6%	58.4%	Chi-squared=1.42, p=0.233, Cohen's d=0.121	None
Hlabangana	Update	Radiographers	Hospital (Paediatric Department)	South Africa	Pre-post	Poster with most common errors Crash course about most common errors	Education and feedback	Technical errors/poor processing of specimen/test	Lack of knowledge/skill/experience	Mean number of errors per chest radiograph film (post = 1 month after intervention)	4.20	3.23	t=3.634, p<0.001, Cohen's d=0.466 (Combined)	Small
Hopkins	Update	Nurses	Hospital	USA	Pre-post	Training on blood sample collection	Education and feedback	Technical errors/poor processing of specimen/test	Lack of knowledge/skill/experience	Percentage of blood cultures that were contaminated (post = quarter following intervention)	3.11%	2.02%	Chi-squared=7.75, p=0.005, Cohen's d=0.245	Small
Hosoe	Repeat	Trainee Endoscopists	Simulation	Japan	Cross-over (random allocation of recordings)	Capsule Endoscopy software providing different methods of viewing recordings	Technology	Erroneous clinician interpretation of test	Lack of knowledge/skill/experience	Median number of missed lesions (false negatives) in capsule endoscopy interpretation	N/A	N/A	Median number of false negatives = 1 for each viewing method, p<0.01; impossible to determine effect size from data presented	None
					Longitudinal	Feedback on previous performance	Education and feedback				N/A	N/A	Mean number of false negatives with each step (approx.): 1.4, 2.5, 0.7, 1.0, 0.6. Impossible to determine effect size or statistical significance from data presented	Unclear
Itri	109	Residents and Fellows	Hospital	USA	Difference in differences (residents vs. fellows; pre-post)	Focused missed-Case Conferences for residents only (fellows act as non-random controls)	Education and feedback	Erroneous clinician interpretation of test	Lack of knowledge/skill/experience	Percentage of musculoskeletal radiograph interpretations (across 31 common injuries) with a major discrepancy	Residents (Int): 18.0%; Fellows (Ctrl): 17.9%	Residents (Int): 6.0%; Fellows (Ctrl): 20.6%	Difference in Differences estimator -0.112 (SE 0.054), t=-2.08, p=0.038; Cohen's d for post error rates only=0.644	Medium
Keijzers	Other	Physicians	Trauma Hospital	Australia	Pre-post	Tertiary trauma survey	Process	Sub-optimal weighing during physical examination	System-related	Percentage of injuries detected during hospital stay that were missed on initial examination (denominator is total patients, not total missed injuries)	3.80%	4.80%	Chi-squared=0.253, p=0.613; Cohen's d=0.126	None
Kostopoulou Greece	Update	GPs	Simulation of Primary Care	Greece	RCT	Computer diagnostic support system before testing	Technology	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal cognitive reasoning	Mean percentage of correct diagnoses across participants	60%	71%	t=3.19, p=0.002; Cohen's d=0.639	Medium
						Computer diagnostic support system after testing					60%	69%	t=2.75, p=0.007; Cohen's d=0.548	Medium
Kostopoulou UK	Other	GPs	Simulation of Primary Care	UK	RCT	Computer diagnostic support system before testing	Technology	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal cognitive reasoning	Mean percentage of correct diagnoses across participants	63%	69%	t=2.37, p=0.019; Cohen's d=0.337	Small
						Computer diagnostic support system after testing					63%	65%	t=0.74, p=0.462; Cohen's d=0.105	None
Kundel	109	Radiologists	Simulation	USA	Difference in differences (with vs. without feedback using cross-over; pre-post)	Computer pattern recognition	Technology	Erroneous clinician interpretation of test	Sub-optimal cognitive reasoning	Increase in accuracy from initial to second view (area under AFROC curve)	-0.04	0.16	Paired t=40.34, p<0.001; Cohen's d=2.270	Large
Lewis	109	GPs	Primary Care	UK	RCT (patients randomised)	Patient completed questionnaire (PROQSY)	Process	Failure/delay in eliciting critical piece of history data	System-related	Clinical outcomes of patients with possible mental disorder (mean General Household Questionnaire scores/36 at 6 weeks; lower scores are better)	26.6	25.7	t=1.43, p=0.155; Cohen's d=0.160	None
Li	Update	Various	Hospital	China	Pre-post	Computer aided double-signing for samples	Process	Sample mix-up/mislabeled	Sub-optimal attention	Percentage of disqualified samples (post = 1-3 months after intervention)	1.36%	1.19%	Chi-squared=23.8, p<0.001; Cohen's d=0.075 (Combined)	Very small
						Training on sample management and standardized blood sample collection	Education and feedback	Technical errors/poor processing of specimen/test	Lack of knowledge/skill/experience					
						Reference materials on sample collection produced	Education and feedback	Technical errors/poor processing of specimen/test	System-related					
						Improved storage facilities	Process	Technical errors/poor processing of specimen/test	System-related					
Lillo	Repeat	Nurses	Hospital	Spain	Longitudinal	Computer test support	Technology	Failure/delay in performing ordered tests	Sub-optimal attention	Percentage of samples with an error across hematology, coagulation, chemistry and urine samples	0.84%	0.70%	Chi-squared=7.12, p=0.008; Cohen's d=0.097	Very small
						Leaflet explaining blood drawing procedure and explanation of procedure by senior nurse	Education and feedback	Technical errors/poor processing of specimen/test	Lack of knowledge/skill/experience		0.70%	0.38%	Chi-squared=57.5, p<0.001; Cohen's d=0.336	Medium
Mamede	Repeat	Residents	Simulation of Internal Medicine	Netherlands	Pre-post	Structured reanalysis of case findings	Process	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal cognitive reasoning	Mean percentage diagnostic accuracy score on four cases subject to availability bias (previous experience of a similar case; Phase 2 to Phase 3 in the study), across participants, combined first and second years	44.8%	54.3%	t=-1.60, p=0.114; Cohen's d=0.377 (data to enable paired t-test to be undertaken not presented)	None
Monteiro	Update	Residents	Simulation of Medicine Department	Canada	Pre-post	Self-directed reflection	Process	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal cognitive reasoning	Mean percentage diagnostic accuracy score across participants	60.0%	61.0%	t=2.15, p=0.03; Cohen's d cannot be determined (data to verify t-test cannot be determined)	Unclear but possibly very small
Mueller	109	GPs	Primary Care	Germany	Post only with GP confirmation	Patient completed questionnaire	Process	Failure/delay in eliciting critical piece of history data	System-related	Number of health problems uncovered using questionnaire that were previously unknown by the GP	0	Median: 2 (IQR 1-4)	Cannot be determined from the data presented	Unclear
Murphy	Update	Primary Care Providers	Primary Care	USA	RCTs (PCPs randomised)	Reminders	Process	Failure/delay in ordering needed referral	Sub-optimal attention	Percentage of patients with abnormal findings followed-up for diagnostic evaluation by final review (7 months)	52.5%	73.4%	Chi-squared=35.4, p<0.001; Cohen's d=0.511	Medium
Myung	Update	Medical students	Simulation	South Korea	RCT	Enhanced analytical reasoning using structured template	Process	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal attention	Mean percentage diagnostic accuracy score across participants	76.3%	85.0%	t=2.46, p=0.015; Cohen's d=0.355	Small
Nicholl	Repeat	Doctors	Neurology out-patients	UK	Pre-post	Patient feedback	Education and feedback	Failure/delay in eliciting critical piece of history data	Sub-optimal attention	Percentage of missed examinations across all patients in both trusts (3 examinations per patient expected)	31.0%	25.2%	Chi-squared=1.072, p=0.301; Cohen's d=0.156	None
Nishikawa	Repeat	Radiologists	Simulation	USA	Pre-post	Computer test support	Technology	Erroneous clinician interpretation of test	Lack of knowledge/skill/experience	Mean percentage of true positive lesions detected on mammograms across readers	54.9%	60.3%	Paired t=3.91, p=0.006; Cohen's d=1.382	Large
Raab	109	Various/Not stated	Laboratories	USA	Longitudinal	Participation in cross-institution benchmarking programme	Quality improvement	Technical errors/poor processing of specimen/test	System-related	Mean reduction in discordant diagnosis rate for each number of years of participation in programme	N/A	N/A	Mean reductions: 1 year 0.84%, 2 years 0.93%, 3 years 0.97%, 4/5 years 0.99%, p=0.04; Cannot determine effect size from data presented	Unclear but possibly small
Ramirez	Update	Nurses	Intensive Care Unit	Spain	Controlled (not randomised)	Training on blood sample collection	Education and feedback	Technical errors/poor processing of specimen/test	Lack of knowledge/skill/experience	Percentage of blood cultures that were contaminated	23%	13%	Chi-squared=10.9, p=0.001; Cohen's d=0.381	Small
Ramnarayan - Paediatrics	109	Junior doctors	4 hospitals (Paediatric Department)	UK	Pre-post	Diagnostic reminder system	Technology	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal cognitive reasoning	Percentage of "unsafe" diagnostic workups (only of cases where system consulted)	45.2%	32.7%	McNemar Chi-squared=13.0, p<0.001; Not possible to calculate Cohen's d	Unclear but possibly small to medium
Ramnarayan - Simulation	Repeat	Various	Simulation	UK	Pre-post					Mean number of diagnostic errors of omission in 12 cases across participants	5.5	5.0	Repeated measures ANOVA p<0.001 (data to calculate F statistic not presented); Cohen's d=0.335	Small

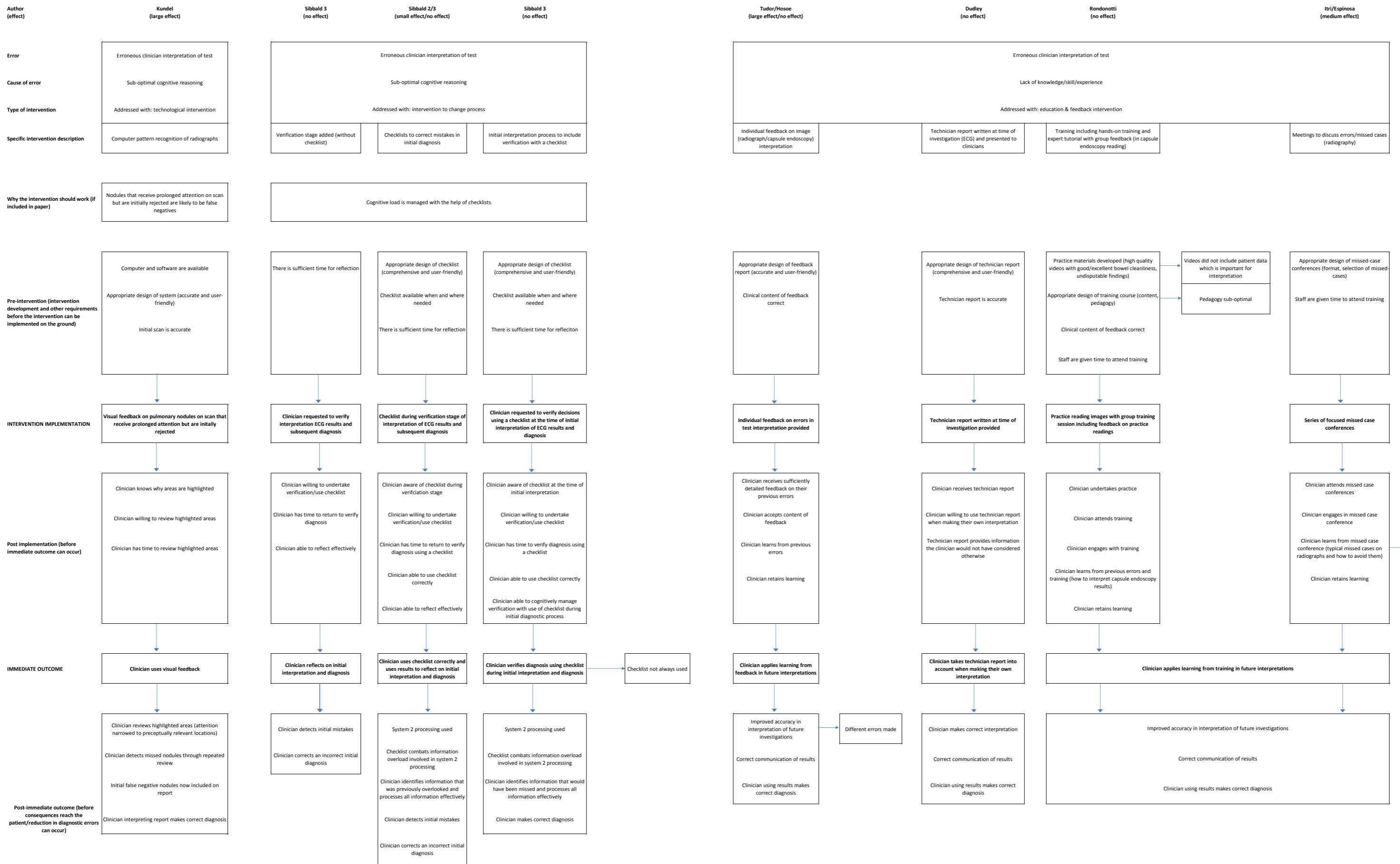
Appendix 1: Summary of included studies

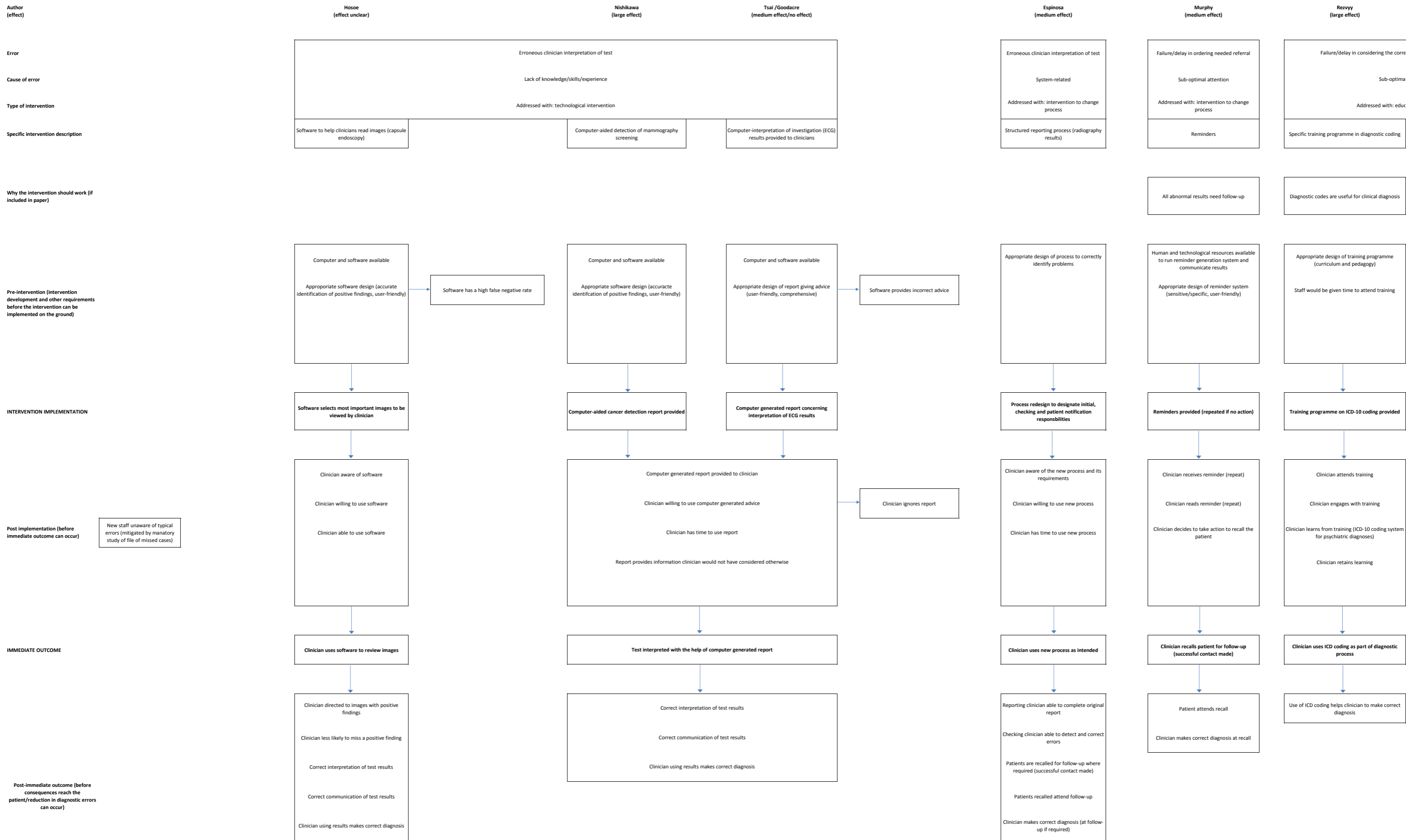
Study	Source	Participants	Setting	Country	Design	Intervention description	Intervention category	Error	Cause of error	Definition of outcome/error used to calculate effect	Baseline or Control group outcome (grey=error; white=accuracy)	Post or Intervention group outcome (grey=error; white=accuracy)	Effect size (p-value)	Effect size group
Rezvyv	Repeat	Psychiatrists	Simulation	Russia	Difference in differences (control vs. intervention; pre-post)	Specific training programme in diagnostic coding	Education and feedback	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal cognitive reasoning	Mean number of correct diagnoses for all cases across participants	Pre: 45.6% Post: 72.4%	Pre: 42.1% Post: 51.3%	p<0.001 for gain in intervention group and comparing post-test scores between groups (data to calculate test statistic not presented); Cohen's d (post-test scores)=1.196	Large
Rondonotti	Update	Capsule Endoscopy readers	Multiple hospitals	Italy	Pre-post	Training including hands-on training and expert tutorial with group feedback	Education and feedback	Erroneous clinician interpretation of test	Lack of knowledge/skill/experience	Percentage of findings detected	35.1%	37.3%	Paired t=0.57, p=0.575; Cohen's d=0.194	None
Roskopf	Update	Musculoskeletal radiologists	Hospital (Radiology Department)	Switzerland	RCT but comparisons pre-post	Quiet working environment	Process	Failed/delayed transmission of result to clinician	System-related	Percentage of reports with any level of discrepancy in diagnostic content	20.8%	8.8%	Chi-Squared=12.5, p<0.001; Cohen's d=0.550	Medium
						Structured report template	Process		Sub-optimal attention	20.8%	20.0%	Chi-Squared=0.05, p=0.824; Cohen's d=0.027	None	
Schriger	109	Physicians	Hospital (Emergency Department)	USA	RCT	Patient completed questionnaire	Process	Failure/delay in eliciting critical piece of history data	System-related	Percentage of patients who received a psychiatric diagnosis, consultation or referral (assumes that all should do so)	5.10%	7.61%	Chi-squared=0.50, p=0.478; Cohen's d=0.235	None
Segal	Update	Neurologists	Simulation	USA	Pre-post	Computer-based decision support tool	Technology	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Lack of knowledge/skill/experience	Percentage of cases with a diagnostic error	36%	15%	Chi-squared=48.6, p<0.001; Chi-squared=0.638	Medium
Sherbino Trial	Update	Medical students	Simulation	Canada	RCT	Cognitive forcing strategy training	Education and feedback	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal cognitive reasoning	Percentage of participants correctly identifying the second diagnosis on a "search satisficing bias" case	23.9%	31.0%	Chi-squared=0.86, p=0.355; Cohen's d=0.198	None
Sibbald1 - Cardiac	Update	Residents (Junior doctors)	Simulation	Canada	RCT but comparisons pre-post	Checklist after collecting information without return to patient	Process	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Sub-optimal cognitive reasoning	Percentage of doctors with correct diagnosis of cardiac case	44.8%	44.8%	McNemar Chi-squared=0, p=1; Cohen's d=0	None
						Checklist after collecting information with return to patient	Process			47.4%	56.8%	McNemar Chi-squared=7.4, p=0.007; Cohen's d=1.272	Large	
Sibbald2 - Experience	Update	Various clinicians	Simulation	Canada	Pre-post	Checklist to correct mistakes in initial diagnosis	Process	Erroneous clinician interpretation of test	Sub-optimal cognitive reasoning	Mean total number of errors (omitted and incorrect diagnoses) in all ECG cases across participants	26.5	24.9	Repeated measures ANOVA F=12.2, p=0.001; Cohen's d=0.201	Small
Sibbald3 - Experts	Update	Physicians (experts)	Simulation	Canada	Pre-post	Verification stage (no checklist)	Process	Erroneous clinician interpretation of test	Sub-optimal cognitive reasoning	Mean number of errors per ECG (omitted and incorrect diagnoses) across participants	1.66	1.63	t=0.13, p=0.896 (data to calculate paired t-test statistic not presented); Cohen's d=0.020	None
						Checklist to correct mistakes in initial diagnosis					1.51	1.21	t=1.41, p=0.160 (data to calculate paired t-test statistic not presented); Cohen's d=0.211	None
Tsai	Repeat	Residents	Simulation	USA	RCT (cross-over)	Computer-interpretation of investigation results provided to clinicians	Technology	Erroneous clinician interpretation of test	Lack of knowledge/skill/experience	Mean percentage of findings correctly interpreted across participants (regardless of accuracy of computer system)	48.9%	55.4%	Paired t cannot be determined from data presented, p<0.001; Cohen's d=0.628	Medium
Tudor	Repeat	Physicians	Simulation of Radiology Department	UK	Pre-post	Individual feedback on image interpretation	Education and feedback	Erroneous clinician interpretation of test	Lack of knowledge/skill/experience	Percentage accuracy of reporting across radiologists	82.2%	88.0%	Paired t=2.54, p=0.032; Cohen's d=0.803 Results for each radiologist had to be read from a graph	Large
Turner	Update	GPs	Primary Care	UK	Pre-post	Computer test support	Technology	Sample mix-up/mislabelled	Sub-optimal attention	Percentage of samples with any error	1.25%	0.21%	Chi-squared=1644, p<0.001; Cohen's d=0.981	Large
Weatherburn	109	Senior house officers (Junior doctors)	Hospital (Emergency Department)	UK	Pre-post	Computerised version of images	Technology	Erroneous clinician interpretation of test	System-related	Percentage of radiographed patients with any level of misdiagnosis	1.51%	0.65%	Chi-squared=13.7, p<0.001; Cohen's d=0.464	Small
Wellwood	109	Senior house officers (Junior doctors)	Hospital (Emergency Department)	UK	RCT	Standardised data collection forms	Process	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Lack of knowledge/skill/experience	Percentage of initial diagnoses that were incorrect	41%	35%	Unable to determine from data presented (percentages are approximate as read from a graph)	Unclear
					RCT of incremental effect (data for pre-post only)	+Computer-based decision support tool	Technology				35%	32%		
					Pre-post	+Monthly feedback	Education and feedback				32%	29%		
Wexler	109	Physicians	Hospital (Paediatric Department)	USA	Non-randomised controls (odd/even day admissions)	Computer-based decision support tool	Technology	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Lack of knowledge/skill/experience	Mean time to diagnosis (days)	2.8	1.9	p>0.05; test statistic and Cohen's d cannot be calculated from data presented	None

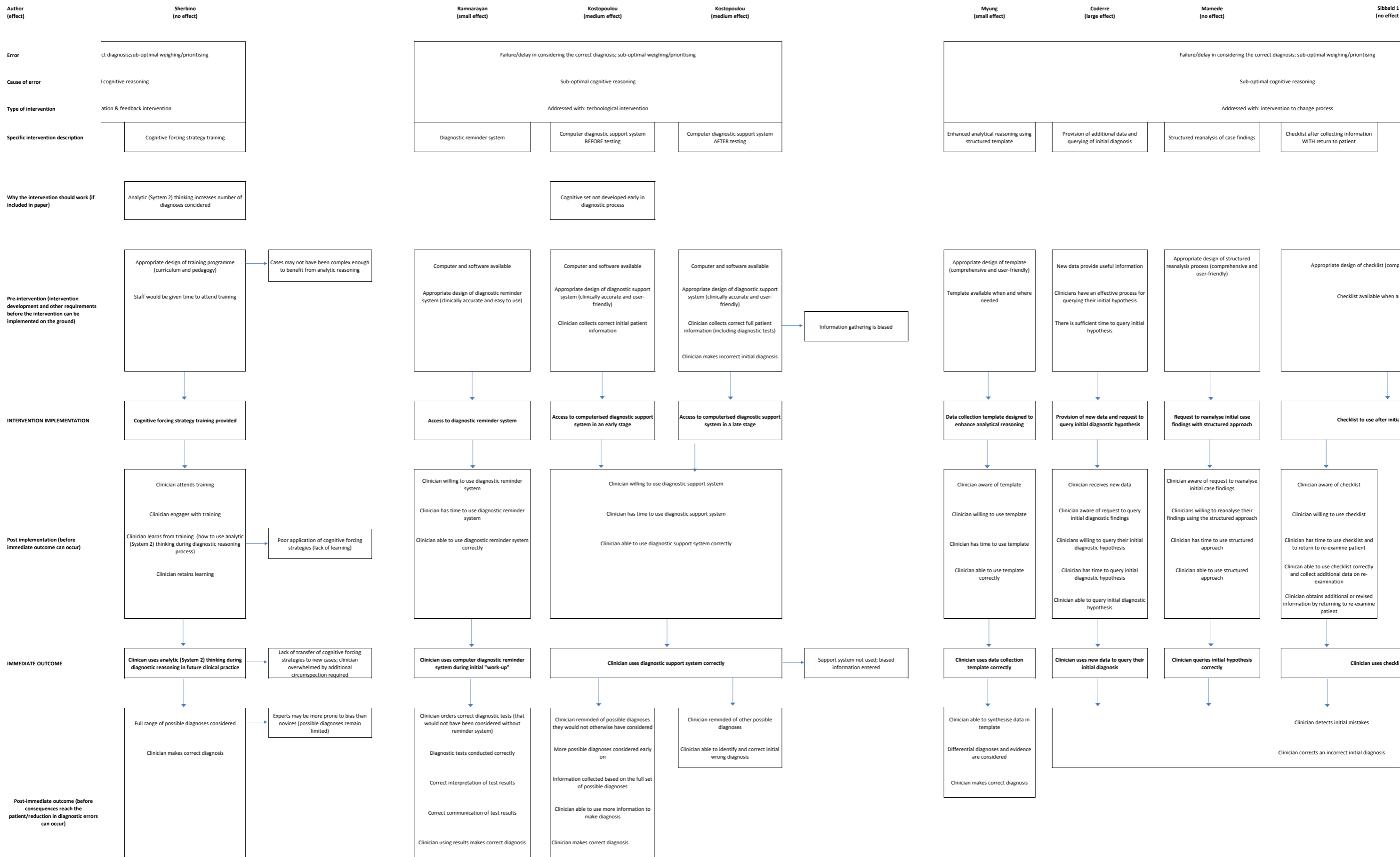




Appendix 2: Logic Models







Author (effect)	Monteiro (effect unclear)	Segal/Wellwood/Wexler (medium/unclear/small effect)	Wellwood (effect unclear)	Chern (large effect)	Wellwood (effect unclear)
Error		Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	Failure/delay in considering the correct diagnosis; sub-optimal weighing/prioritising	
Cause of error		Lack of knowledge/skills/experience	Lack of knowledge/skills/experience	Lack of knowledge/skills/experience	
Type of intervention		Addressed with: technological intervention	Addressed with: intervention to change process	Addressed with: education & feedback intervention	
Specific intervention description	<div style="display: flex; justify-content: space-between;"> <div style="border: 1px solid black; padding: 2px;">Checklist after collecting information WITHOUT return to patient</div> <div style="border: 1px solid black; padding: 2px;">Self-directed reflection</div> </div>	Computer-based decision support tool	Standardised data collection forms	<div style="display: flex; justify-content: space-between;"> <div style="border: 1px solid black; padding: 2px;">Education about atypical presentations</div> <div style="border: 1px solid black; padding: 2px;">Feedback about telephone follow-up of high risk patients</div> </div>	Monthly feedback added to standardised data collection and computer support

Why the intervention should work (if included in paper)



Appendix 2: Logic Models

Author (effect)	Lewis/Mueller/Schriger (no effect/effect unclear/no effect)	Biffi/Keijzers (small effect/no effect)
Error	Failure/delay in eliciting critical piece of history data	Sub-optimal weighing during physical examination
Cause of error	System-related	System-related
Type of intervention	Addressed with: intervention to change process	Addressed with: intervention to change process
Specific intervention description	Patient-completed questionnaire (about symptoms/problems)	Tertiary trauma survey

Why the intervention should work (if included in paper)

