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# Lessons Learned from the Usability Evaluation of a Simulated Patient Dialogue System

Q1 Leonardo Campillos-Llanos<sup>1,2</sup> · Catherine Thomas<sup>3</sup> · Éric Bilinski<sup>3</sup> · Antoine Neuraz<sup>3</sup> · Sophie Rosset<sup>3</sup> · Pierre Zweigenbaum<sup>3</sup>

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## Abstract

Simulated consultations through virtual patients allow medical students to practice history-taking skills. Ideally, applications should provide interactions in natural language and be multi-case, multi-specialty. Nevertheless, few systems handle or are tested on a large variety of cases. We present a virtual patient dialogue system in which a medical trainer types new cases and these are processed without human intervention. To develop it, we designed a patient record model, a knowledge model for the history-taking task, and a termino-ontological model for term variation and out-of-vocabulary words. We evaluated whether this system provided quality dialogue across medical specialities (n = 18), and with unseen cases (n = 29) compared to the cases used for development (n = 6). Medical evaluators (students, residents, practitioners, and researchers) conducted simulated history-taking with the system and assessed its performance through Likert-scale questionnaires. We analysed interaction logs and evaluated system correctness. The mean user evaluation score for the 29 unseen cases was 4.06 out of 5 (very good). The evaluation of correctness determined that, on average, 74.3% (sd = 9.5) of replies were correct, 14.9% (sd = 6.3) incorrect, and in 10.7% the system behaved cautiously by deferring a reply. In the user evaluation, all aspects scored higher in the 29 unseen cases than in the 6 seen cases. Although such a multi-case system has its limits, the evaluation showed that creating it is feasible; that it performs adequately; and that it is judged usable. We discuss some lessons learned and pivotal design choices affecting its performance and the end-users, who are primarily medical students.

**Keywords** Medical history taking · Natural language processing · Education · Medical · Virtual patient · Artificial intelligence

## 0 Introduction

1 Developing diagnosis and clinical reasoning skills is a  
 2 key element of medical education. In addition to clinical

This article is part of the Topical Collection on *Education & Training*

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3 practice, medical students and practitioners can enhance  
 4 these abilities by means of mannequins, role games and  
 5 simulation systems. These have shown beneficial results  
 6 [1–7] and are currently integrated in virtual patients [8–  
 7 15]. Virtual patients (VPs)<sup>1</sup> are software through which  
 8 students can train themselves by emulating the roles of  
 9 health providers [16].

Ideally, a VP simulation system should simulate a  
 10 patient in all consultation stages. The patient’s medical  
 11 history taking (*anamnesis*) is an essential but difficult-to-  
 12 master skill. Real consultations occur in time-restricted  
 13 settings and there is a language-level gap in doctor-  
 14 patient communication. Due to the health implications,  
 15 doctors need to receive training to acquire these skills so  
 16 that they assess patients’ conditions and make a correct  
 17 diagnosis. 18

<sup>1</sup>We refer with this term to *virtual standardised patients*.

19 Natural language dialogue systems (*chatbots* or *conver-*  
 20 *sational agents*) have been integrated in healthcare appli-  
 21 cations [17–19] and VP simulation environments. Inter-  
 22 action modules allow trainees to simulate history taking,  
 23 mostly through constrained input—e.g. lists of questions  
 24 and answers prepared for a specific case [11, 20–25]. Other  
 25 methods for processing user input use rules, ontologies and  
 26 knowledge bases [26, 27], statistical language models [28],  
 27 machine-learning classifiers [29], crowd-sourcing data [22]  
 28 and preliminary neural approaches [30, 31]. Some systems  
 29 feature automatic speech recognition [32–34]. However,  
 30 very few virtual patients feature dialogue through natural  
 31 language [34] (humans’ inherent mode of communication),  
 32 which might result in more natural interaction with a con-  
 33 versational agent [35, 36].  
 34 A successful interaction relies both on the type of  
 35 technology and the degree to which the VP helps users to  
 36 acquire clinical reasoning and history-taking skills. To do  
 37 so, interacting with a wide range of cases is beneficial [36].  
 38 Accordingly, a VP system should provide simulations with  
 39 a variety of clinical specialities. Most systems, nonetheless,  
 40 only deal with one or a few conditions [33, 34, 37–43]. Very  
 41 few systems cope with diverse pathologies [22, 44].

42 **Objectives**

43 Our objective was to overcome the limitation of the  
 44 scarce number of simulated cases by designing a dialogue-  
 45 enabled VP system that can cope with a variety of  
 46 clinical conditions. We hypothesise that a multi-case VP  
 47 can be achieved if medical trainers can create VPs  
 48 easily, through a graphical interface (Fig. 6, Appendix),  
 49 without programming anything nor the development team’s  
 50 intervention. The description of the clinical case, in the  
 51 form of a semi-structured record, is typed offline in natural  
 52 language; next, the dialogue system embodies a patient with  
 53 each clinical case.

54 Accordingly, a first requirement of the system is to  
 55 cope with new contents across medical specialities. The  
 56 second requirement is to provide unconstrained input,  
 57 because the system aims at improving medical students’  
 58 history-taking skills through the interaction with the VP.  
 59 Figure 1 is a sample dialogue and illustrates natural dialogue  
 60 phenomena. The system is integrated in a serious game  
 61 developed with partner companies and a medical team  
 62 [45]. The software features an animated avatar with text-to-  
 63 speech, lip-synch and minor gestures.

64 To make the system able to handle plenty of cases, we  
 65 gave it extensive conceptual and terminological coverage  
 66 of the domain [27, 46]. The system can also adapt to  
 67 new records dynamically. We provided it with components  
 68 to detect out-of-vocabulary words (OOV) and predict

morphological information of missing words. The system  
 with adaptation modules is available in French;<sup>2</sup> English  
 and Spanish versions are available but not well-supported.

This article reports a usability evaluation of the French  
 system, where we assessed, in a simulated history-taking  
 setting:

- Q1 Whether a multi-case system can provide quality  
 dialogue (with regard to grammar and on-topic and  
 realistic replies) through natural language across  
 clinical cases.
- Q2 Whether quality dialogue is maintained when process-  
 ing unseen records across medical specialities.

We evaluated these aspects through user experiments in  
 a real context. Study participants (n = 39) interacted in  
 French language with the dialogue system, then performed  
 a user evaluation of their dialogue.

**Material and methods**

**Dialogue system architecture**

To tackle the task, we first designed a patient record  
 model, which defines a virtual patient’s health state in  
 a semi-structured format. Table 9 (Appendix) shows an  
 example. Second, we conceived a knowledge model for  
 the task, i.e. a scheme of question types, dialogue acts  
 and entity types concerning the anamnesis. Third, we  
 created a termino-ontological model, which hosts structured  
 thesauri for managing the variation of terms [46, 47].  
 Figure 2 is a schema of the different stages (which  
 occur asynchronously): case creation by an instructor (1),  
 comparison and analysis of a new record (2), and dialogue  
 by a student (3).

We designed the system following a knowledge-based  
 and rule-frame-based approach [27]. The user—typically a  
 medical student or resident—types text. A natural language  
 understanding (NLU) module performs the linguistic and  
 semantic processing (e.g. *pain* is a SYMPTOM). A semantic  
 frame is fed to a dialogue manager, which keeps track of the  
 dialogue state and context information, queries the record,  
 selects the information and replies through a template-based  
 generation module (Fig. 3).

The termino-ontological model contains lexical  
 resources for processing linguistic variation: inflection (e.g.  
*lung* ↔ *lungs*), derivation (e.g. *face* ↔ *facial*), synonymy  
 (e.g. *operation* ↔ *surgery*) and mapping between full  
 words and affixes/roots (e.g. *heart* ↔ *cardio-*). The model  
 also defines domain relations and concepts for processing  
 and normalising the variety of terms in a case: e.g. *pain* and

<sup>2</sup><http://vps-9069f76a.vps.ovh.net>

**Fig. 1** Sample of an actual dialogue of a medical student (D for Doctor) with a virtual patient (P)—the transcript comes from a session with the English version of our system



D: What brings you here?  
 P: I am seeing you about persistent backache  
 D: When did it start?  
 P: I don't remember  
 D: Where is the pain exactly?  
 P: I have pain in the lower back, the pain is located in the lower back and sometimes down the legs  
 D: Can you sleep well?  
 P: The pain often makes it difficult to fall asleep  
 D: Do you suffer from any disease?  
 P: Chronic stomach ulcers  
 D: Do you follow any treatment for that?  
 P: Omeprazole for the chronic stomach ulcers. Maybe there is more information in my file

ache refer to the same concept. These resources support a key feature of the system: its ability to map doctor's language to patient's language to better simulate a real patient. We populated this model with large general and domain resources (e.g., the Unified Medical Language System® [48]). Our lexicons contain domain lists (over 161,000 terms in French, 116,000 in English, and 103,000 in Spanish) and dictionaries (over 959,000 word/concept entries in French, 1,886,000 in English, and 1,428,000 in Spanish).

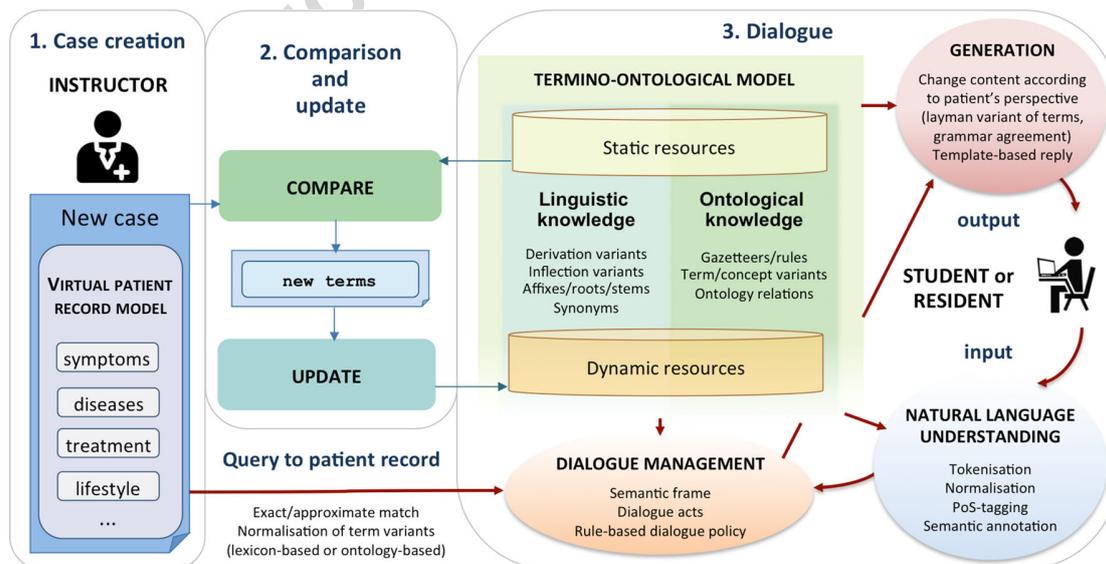
Although these resources allow the system to handle plenty of cases, the medical jargon evolves continually with neologisms. Not knowing out-of-vocabulary words (OOVs) might cause incorrectly generated replies, because the system lacks the linguistic information for morphological agreement of OOVs. We thus developed methods to predict the Part-of-Speech (PoS) and gender/number of OOVs (see Table 9 in the Appendix). Multiple approaches are run in parallel: dictionary-based, and inference from linguistic context or from the base form/affixes (Fig. 7 in the Appendix). They are combined using heuristic weights set during development. This prediction is executed offline

whenever an instructor creates or modifies a case. Figure 8 (Appendix) gives more technical details of the system components.

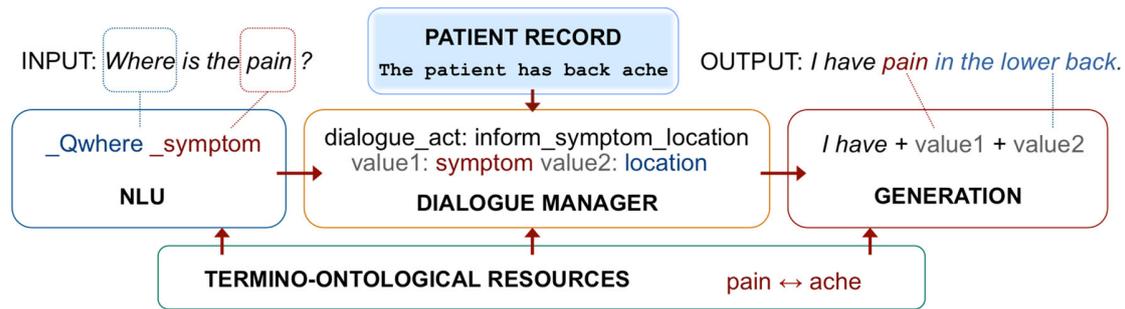
**Evaluation design**

To assess whether the system provides quality dialogue across clinical cases (Q1), potential end-users (n = 39) tested 35 different VPs. Medical students, interns and expert practitioners conducted medical history-taking in French language with a VP and evaluated the system performance in different evaluation rounds in two types of conditions (Table 1). Some sessions used unseen cases that were just created; we did not modify the system between creation and use. Other sessions used already seen cases, created earlier, for which we had fine-tuned the system manually. The system evolved over evaluation rounds and improved gradually by correcting the errors in interaction logs.

The medical evaluators had varied profiles (Table 2) and some participated in multiple evaluation rounds. Medical instructors created the content of 6 seen and 23 unseen cases. A co-author of this paper (LC) input the records of



**Fig. 2** Schema of the virtual patient dialogue system and update components



**Fig. 3** Example of functioning of the dialogue system from input to output. The patient record is simplified; Table 9 shows a full example

157 6 unseen cases using the wordings of the clinical cases of  
 158 French national classifying exams for medical students.<sup>3</sup>  
 159 Tables 10 and 11 (Appendix) provide a brief description of  
 160 each case.

161 We first conducted a user evaluation by means of 5-  
 162 point Likert-scale questionnaires ranging from 1 (Very  
 163 poor) to 5 (Very good). After each interaction, evaluators  
 164 assessed the system on nine aspects (Table 3), which come  
 165 from the evaluation framework of dialogue systems [49,  
 166 50]. Evaluators were given instructions on the types of  
 167 utterances the system can process, and an online link to the  
 168 questionnaire.

169 We also evaluated the dialogue system's correctness. We  
 170 gathered data from the dialogues with all the 35 VP cases.  
 171 We analysed dialogue logs and quantified the number of  
 172 correct replies. We considered correct those replies giving a  
 173 coherent answer (consistent according to the user input and  
 174 correct regarding the data in the record). Table 6 (Appendix)  
 175 describes some examples of correct, incorrect and deferred  
 176 replies. An author of this paper (LC) annotated all data;  
 177 another author (SR) checked the annotations of a subset of  
 178 84 (2%) turn-reply pairs that were unclear about how to  
 179 classify; finally, a consensus was reached. We computed the  
 180 kappa agreement between both annotators.

181 To evaluate whether quality dialogue is maintained with  
 182 new cases (Q2), we compared the evaluation scores given  
 183 to seen and unseen cases (Table 1). 26 of the 39 medical  
 184 evaluators assessed 6 seen VP cases (50 questionnaires),  
 185 and 23 of the 39 evaluators evaluated 29 unseen cases (67  
 186 questionnaires); some evaluators assessed both seen and  
 187 unseen cases. We conducted two-tailed t-tests and Mann-  
 188 Whitney tests, using the Prism 5 software, to determine if  
 189 the differences in scores were statistically significant.

190 To measure the diversity of the unseen cases, we counted  
 191 the word types (i.e. different word forms) appearing in  
 192 only one record, and the types shared across different  
 193 cases. The unseen cases belong to 14 specialities (Table 1).

<sup>3</sup><http://umvf.cerimes.fr/portail/ecn.php>

We analysed how scores varied according to evaluators' 194  
 profiles. 195

**Results** 196

**Quality of natural language dialogue** 197

Each case was tested by an average of 3.74 evaluators (±2.8; 198  
 minimum number of evaluators per case = 1; maximum = 199  
 13). Panels A and B of Fig. 4 display the average evaluator 200  
 scores for the seen and unseen cases respectively. Lower 201  
 scores are placed to the left of each Y axis; neutral scores, in 202  
 the middle; and higher scores, to the right. The bars show the 203  
 cumulated percentages of evaluator scores that were Very 204  
 good, Good, Neutral, Poor and Very poor. For example, 205  
 in the seen cases, performance was assessed as Very good 206  
 by 6% of the evaluators, as Good by an additional 52% 207  
 of evaluators, as Neutral by 28% of them, and as Poor by 208  
 the remaining 14%. The overall average score, obtained by 209  
 averaging the mean scores given to the 9 evaluated aspects, 210  
 was of 3.84 out of 5 for seen cases, and of 4.05 for unseen 211  
 cases. This is above the Likert-scale midpoint. The total 212  
 number of dialogues with Poor or Very poor scores ranges 213  
 from 16% (naturalness) to 0% (user-understanding) for seen 214  
 cases, and from 6% (naturalness) to 0% (speed) for unseen 215  
 cases. 216

Regarding the system correctness, we analysed 8,078 217  
 turn-reply pairs from 131 dialogues (Tables 4 and 5). We 218  
 removed 149 turn-reply pairs with out-of-task questions or 219  
 statements. The two researchers who double-checked the 220  
 subset of turn-reply pairs had a kappa agreement of 0.827. 221  
 In the full set of dialogue logs (seen and unseen cases), 222  
 when analysed per medical specialty, an average of 74.3% 223  
 (±9.5) system replies were correct (min = 53.6%, max = 224  
 93.8%), i.e. answers were coherent with regard to inputs and 225  
 provided accurate information from the record. An average 226  
 of 14.9% (±6.3) of system replies were incorrect; however, 227  
 unseen words only caused 2 errors. Incorrect replies affected 228  
 the system's faithfulness (26.5%), the dialogue flow (56.2%) 229

**Table 1** Evaluation rounds and medical specialities

	Development 2016 through May 2017	Test				
		July 2017	Oct 2017	Dec 2017	Jan 2018	Feb 2018
Evaluators	20	6	4	10	4	10
# cases	6	5	4	6 + 3 (dev)	8	6 + 7 (from Jan 2018)
Medical specialities (# cases)	AN(1), CD(1), GP(1), PN(1), P(1), U(1)	N(2), CD(1), RH(1), ON(1)	OG(1), PN(1), GH(1), RH(1)	AN(1), CD(3), D(1), GE(1), GH(1), NE(1), PN(1), UC(1)	GH(3), ID(1), N(1), OG(1), PN(2)	GH(3), E(1), ID(2), N(3), PN(2), OG(1), OT(1)
Medical specialities in development+test (Total # of cases) [# of dialogues]						
	AN: Anesthesiology (1) [11]	GP: General Practice (1) [6]	OT: Otolaryngology (1) [2]			
	CD: Cardiology (1 + 3) [9 + 8]	ID: Infectious Diseases (2) [5]	PN: Pneumology (1 + 4) [13 + 10]			
	D: Dermatology (1) [5]	NE: Nephrology (1) [2]	P: Psychiatry (1) [5]			
	E: Endocrinology (1) [3]	N: Neurology (4) [15]	RH: Rheumatology (2) [7]			
	GE: Geriatrics (1) [1]	OG: Obstetrics/Gynaecology (3) [4]	UC: Urgent Care (1) [1]			
	GH: Gastroenterology/Hepatology (5) [13]	ON: Oncology (1) [5]	U: Urology (1) [6]			

230 and the *exhaustiveness of the information* provided by the 235  
 231 virtual patient (17.3%) (Table 8, Appendix). The system 236  
 232 determined that the rest of the questions were beyond the 237  
 233 dialogue task and answered *I do not understand* (an average 238  
 234 of 7.8% ±5.3) or asked for more precision (an average of 239  
 2.9% ±2.7). This defers giving an incorrect reply and is  
 an additional average 10.7% of correct system behaviour,  
 despite having a negative impact on the *dialogue flow*.  
 When analysing the data per dialogue, results obtained were  
 very similar (Table 5).

**Table 2** Medical evaluators' profiles

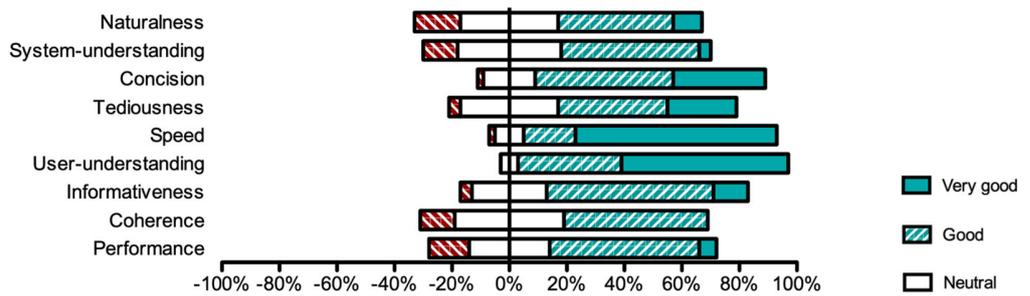
Profile	Evaluators		Description
	S	U	
Students	♂	0	Students were in their 3rd year of medical studies and had limited experience with real patients (1-3 terms of part-time hospital internship).
	♀	3	
	Unique:	7 (3, 7)	
Residents	♂	2	Residents had at least 6 years of medical studies and passed the National Classifying Exam; they had broader experience than students (one or more full-time terms as practising physicians).
	♀	4	
	Unique:	10 (6, 7)	
Practitioners /Instructors	♂	8	Practitioners were private doctors or practising doctors in hospital or general practise.
	♀	0	
	Unique:	11 (8, 5)	
Researchers /Other	♂	5	Researchers included non-practising doctors, such as PhD students and postdoctoral researchers. Other profiles include doctors working for a drug database publisher or those whose profile was undeclared (anonymous evaluators).
	♀	0	
	NA	4	
	Unique:	11 (9, 4)	
Total unique	♂	15 (57.7% of 26)	13 (56.5% of 23)
	♀	7 (26.9% of 26)	7 (30.4% of 23)
	NA	4 (15.4% of 26)	3 (13.1% of 23)
	Unique:	39 (26, 23)	

We report the number of evaluators for seen (S) and unseen (U) conditions. The total of unique participants of each profile is not always the sum of subjects in seen and unseen conditions, since some evaluators tested only seen or unseen cases, but others tested in both conditions. NA stands for 'not available' information

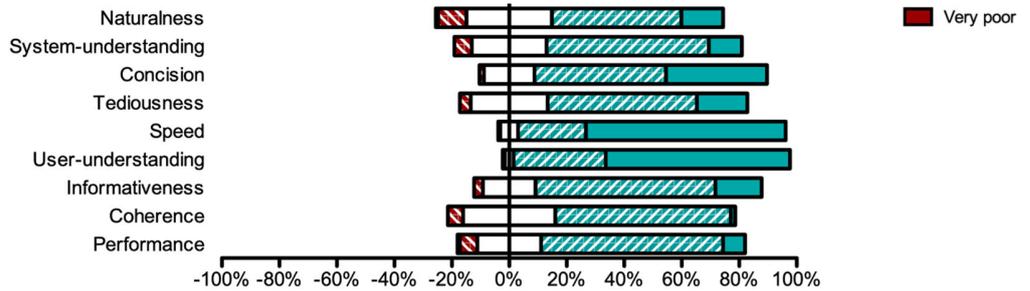
**Table 3** Description of aspects addressed in the qualitative evaluation; scores ranged from 5 (*Very good*) to 1 (*Very poor*)

Performance	An overall assessment of the system's global functioning.
Coherence	Adequateness of system answers in relation to user input.
Informativeness	Satisfaction with the information provided by the system.
User-understanding	Degree of comprehension of system replies by the user.
Speed	System quickness in replying to the user.
Tediousness	Verbosity of information answered by the system.
Answer concision	Quality of replies with regard to their length.
System-understanding	System degree of comprehension of user input.
Naturalness of replies	Realism of the utterances produced by the system.

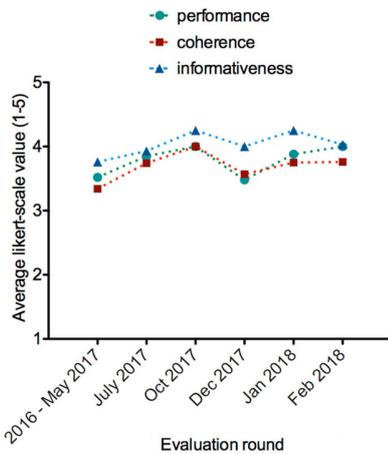
**a Seen cases**



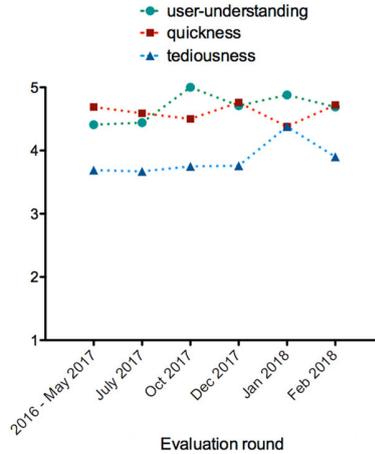
**b Unseen cases**



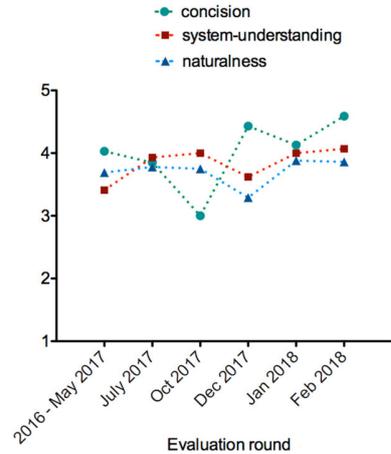
**c**



**d**



**e**



**Fig. 4** Results of the qualitative evaluation and comparison between *seen* cases (used in development) and *unseen* cases

**Table 4** Evaluation data for all collected dialogues ( $d = 131$ ): #T: count of turns; #W: count of words; stdev: standard deviation; #U/d: average turns per dialogue; #W/d: average words per dialogue

	Turn reply-pairs		Words	
	#T	#T/d (stdev)	#W	#W/d (stdev)
User's input	4,044	30.9 ( $\pm 11.7$ )	21,986	167.8 ( $\pm 78.3$ )
System's reply	4,034	30.8 ( $\pm 11.7$ )	21,921	167.3 ( $\pm 78.5$ )
Total	8,078	61.7 ( $\pm 11.7$ )	43,907	335.2 ( $\pm 78.4$ )

**240 Performance with unseen cases across specialities**

241 Panels A and B of Fig. 4 display, respectively, the proportion  
 242 of scores given to each aspect for the 6 seen and 29  
 243 unseen cases. Evaluators rated every aspect better in the  
 244 unseen cases. The differences in evaluation scores were  
 245 statistically significant for the following aspects: system  
 246 performance (a mean of 3.50 (95% CI[3.27-3.73]) for seen  
 247 cases versus 3.81 (95% CI[3.64-3.97]) for unseen cases, p-  
 248 value = 0.029, Mann-Whitney test), coherence in replies  
 249 (a mean of 3.38 (95% CI[3.18-3.58]) for seen cases versus  
 250 3.73 (95% CI[3.61-3.86]) for unseen cases, p = 0.004,  
 251 Mann-Whitney test), informativeness (a mean of 3.78 (95%  
 252 CI[3.58-3.98]) for seen cases versus 4.03 (95% CI[3.86-  
 253 4.20]) for unseen cases, p = 0.047, Mann-Whitney test) and  
 254 system-understanding (a mean of 3.44 (95% CI[3.22-3.66])  
 255 for seen cases versus 3.90 (95% CI[3.72-4.07]), p = 0.001,  
 256 t-test).

257 We also examined the variation of scores along  
 258 evaluation rounds; panels C-E in Fig. 4 show the average  
 259 scores for each aspect. When we compared the scores given  
 260 in the first evaluation round (using seen cases) with those  
 261 in the last round (using unseen cases), the following aspects  
 262 showed statistically significant differences: performance (a  
 263 mean of 3.48 (95% CI[3.21-3.74]) in the first round versus  
 264 4.00 (95% CI[3.86-4.14]) in the last round, p = 0.003,  
 265 Mann-Whitney test), coherence (a mean of 3.31 (95%  
 266 CI[3.09-3.53]) in the first round versus 3.76 (95% CI[3.56-  
 267 3.95]) in the last round, p = 0.005, t-test), informativeness  
 268 (a mean of 3.69 (95% CI[3.48-3.90]) in the first round  
 269 versus 4.03 (95% CI[3.87-4.19]) in the last round, p =  
 270 0.018, Mann-Whitney test), concision (a mean of 4.00 (95%  
 271 CI[3.76-4.24]) in the first round versus 4.59 (95% CI[4.40-  
 272 4.78]) in the last round, p = 0.001, Mann-Whitney test), and

system-understanding (a mean of 3.36 (95% CI[3.11-3.60]) 273  
 in the first round versus 4.07 (95% CI[3.89-4.24]) in the last 274  
 round, p<0.0001, t-test). 275

Figure 5 plots the evaluation scores of the unseen cases 276  
 grouped by speciality. From a qualitative point of view, we 277  
 could not find any speciality that would consistently obtain 278  
 scores below the others; outlier values correspond to cases 279  
 where few dialogues were conducted. 280

Concerning the diversity of the vocabulary, unseen cases 281  
 contained 1,488 types (unique word forms). 1,017 types 282  
 (68.4%) appeared in isolated records; that means that only 283  
 one third of the types (31.6%) occurred in more than one 284  
 case. The average proportion of unique types per record is 285  
 34.6% ( $\pm 7.4$ ). Those numbers show to which extent the 286  
 lexical content of each case differs across records in the 287  
 unseen cases. 288

We also analysed the quantity of out-of-vocabulary 289  
 words (OOVs) in unseen cases. Out of the total 1,488 types 290  
 in the unseen cases, only 33 words (2.5%) were missing in 291  
 system resources (avg = 1.2 OOVs per case,  $\pm 1.66$ ). That 292  
 is, our resources covered 97.5% of the vocabulary in the 293  
 29 new cases. Our analysis showed that most OOVs were 294  
 spelling mistakes made when inputting data to create a new 295  
 record. Our methods predicted the PoS category of these 296  
 OOVs with a precision of 69.8%, a recall of 76.9%, and an 297  
 F-measure of 73.2% (micro-average). Regarding the OOV 298  
 words for which the system predicted the correct category, 299  
 our methods to predict morphology data showed a precision 300  
 of 59.4%, a recall of 61.3%, and an F-measure of 60.3% 301  
 (micro-average). Table 7 (Appendix) shows further details 302  
 about our results per category. 303

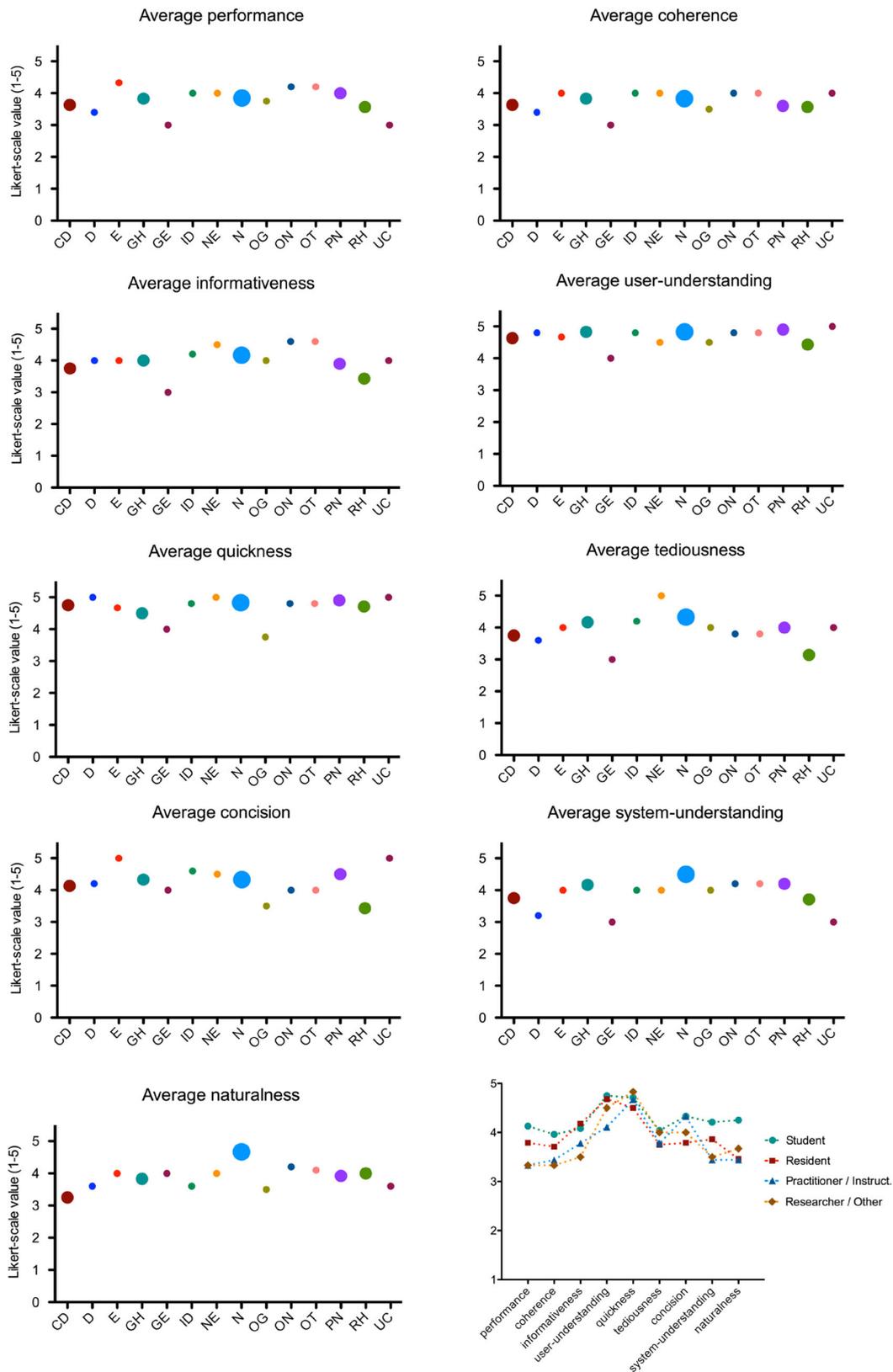
Lastly, Fig. 5 (bottom right) depicts differences in 304  
 assessment according to the evaluators' profiles. The 305  
 average scores of the majority or totality of evaluators 306  
 agreed on user-understanding, quickness, tediousness and 307  
 concision. Students and residents gave higher average 308  
 scores to system performance, coherence of replies, 309  
 informativeness, system- and user-understanding. Senior 310  
 doctors generally gave lower scores. 311

**Discussion** 312

The quality of the natural language dialogue in seen and 313  
 unseen cases received very positive, positive, or neutral 314

**Table 5** Evaluation of system correctness expressed as average percentage ( $\pm$ standard deviation) [minimum - maximum]

	Per medical specialty	Per dialogue
Correct	74.3 ( $\pm 9.5$ ) [53.6–93.8]	74.9 ( $\pm 12.6$ ) [40.0–100.0]
Incorrect	14.9 ( $\pm 6.3$ ) [0.0–31.6]	14.7 ( $\pm 9.4$ ) [0.0–38.9]
Not understood	7.8 ( $\pm 5.3$ ) [0.0–25.0]	7.5 ( $\pm 7.7$ ) [0.0–40.0]
Request for repair	2.9 ( $\pm 2.7$ ) [0.0–11.5]	2.9 ( $\pm 3.9$ ) [0.0–20.0]



**Fig. 5** Qualitative evaluation across medical specialties and evaluator profiles. The size of each point expresses the number of dialogues conducted: 1–5 (small size), 6–10 (medium size) and >10 (large size). The abbreviations of specialties are given in Table 1

315 judgements from between 93% and 100% of the evaluators,  
 316 allowing us to answer Q1 positively. System performance  
 317 and coherence of replies received Good and Very good  
 318 scores and overall satisfaction was high with an average of  
 319 3.84 (seen cases) and 4.06 (unseen cases) across all aspects.  
 320 We cannot compare the error rate with other works (e.g.  
 321 [34]) without bias, since we tested more patient cases.

322 Regarding Q2, in the test on unseen cases, every  
 323 aspect received a higher user evaluation score than on  
 324 seen cases. The improvement of some features proved  
 325 statistically significant. The system was robust enough to  
 326 cope with new cases without quality loss. The system's  
 327 vocabulary coverage of unseen cases was very high  
 328 (97.5%). Overall, we tested 35 different cases covering  
 329 18 medical specialities. To the best of our knowledge,  
 330 this is much larger than what was reported so far in the  
 331 literature.

332 The unseen cases covered varied medical specialities  
 333 among which we could not highlight consistently less well-  
 334 handled specialities from a qualitative point of view. To  
 335 analyse this aspect from a quantitative perspective, a larger  
 336 number of dialogues in each speciality would be needed.  
 337 The comparison of scores across evaluators' profiles  
 338 showed that medical students and residents evaluated the  
 339 system better. This is a good point since they are the first  
 340 targeted users of the system.

341 The correction rate of system replies varied across cases  
 342 largely due to each record content: e.g. the performance  
 343 was lower in a postpartum case, where some questions  
 344 referred to the patient's newborn, but the system could  
 345 not distinguish them from those related to the VP.  
 346 Our analysis of logs across cases unveiled that most  
 347 errors were due to the lack of variants of question  
 348 formulations, missing question types, or processing errors  
 349 (Table 6, Appendix). These weaknesses require fallback  
 350 strategies, which we explored using machine learning  
 351 [51].

352 At a technical level, we want to improve the performance  
 353 of the dialogue manager and the comparison and update  
 354 procedures. Given the lack of dialogue corpora for the  
 355 task, we did not apply machine/deep learning approaches.  
 356 Terminological components can mitigate the needs of the  
 357 domain—rich in variant terms and acronyms, but without  
 358 open training data available. This is the asset of our  
 359 system. Once enough dialogue logs are collected via  
 360 a rule- and terminology-based system, the data can be  
 361 trained to complement the dialogue policy manager, or to  
 362 generate word-embeddings for OOV terms. This is left for  
 363 future work. The naturalness of system replies needs also  
 364 refinement, especially the way it simplifies long sentences  
 365 or outputs negative symptoms and layman terms. We are  
 366 interested in evaluating the system in the overall framework  
 367 of a simulated consultation, where medical students should

diagnose the patient. This would allow us to know whether  
 the system helps students to obtain all key elements of the  
 history-taking step, and to ascertain whether students make  
 a correct diagnosis. Finally, we need to gather dialogue data  
 to evaluate the English and Spanish versions.

**Lessons learned**

Regarding development, several aspects demanded a heavy  
 investment in resource creation: terminology components  
 for concept mapping, update procedures to compare the  
 existing knowledge base and OOVs, and linguistically-  
 motivated modules to transform the data created by  
 medical trainers according to the patient's perspective.  
 Moreover, misspellings in trainers' input needed spelling  
 correction tools. To fix the OOV errors related to spelling  
 mistakes, the most reliable approach would be to include  
 a correction module on the back-office interface that  
 trainer doctors use to create the patient record. The  
 system vocabulary could be mapped to misspellings, flag  
 them, and the trainers could correct them before the  
 interaction. Nevertheless, the developed modules were  
 capable of adapting the system to new cases without  
 causing problematic interactions, according to the end-user  
 evaluation.

Regarding the system design and evaluation, we strongly  
 advise that medical professionals be involved from the  
 beginning. The closer to reality the patient data we received,  
 the better the system was tested and improved. The more  
 iterations were conducted for inspecting logs and fixing  
 errors, the better the system was rated. Our evaluation  
 revealed that experienced practitioners assessed the system  
 as less satisfactory, given their greater diagnosis experi-  
 ence and different perception of these tools. This high-  
 lights the careful choice of the end-user and its impact  
 on the framework design. This multi-case, adaptable VP  
 system seems to fit medical students and interns, since  
 they can bear infelicities in system replies and need to  
 engage in the interaction to gain experience. A tool with  
 canned answers would be rigid and necessitate more engi-  
 neering to adapt to new cases. If no dialogue data are  
 available for the task, collecting dialogue logs with poten-  
 tial end-users seems feasible before data-intensive methods  
 (machine or deep learning) can be applied. Finally, this sys-  
 tem is not yet suited for simulating VPs with chronic condi-  
 tions needing follow-up consultations. Evolving symptoms  
 would require a more advanced model of the VP's disease  
 timeline.

Overall, the tradeoff between adaptability and nat-  
 uralness has design implications related to immediate  
 vs long-term needs, or sophisticated case-specific vs  
 generic applications. Table 12 (Appendix) outlines our  
 observations.

**419 Conclusion**

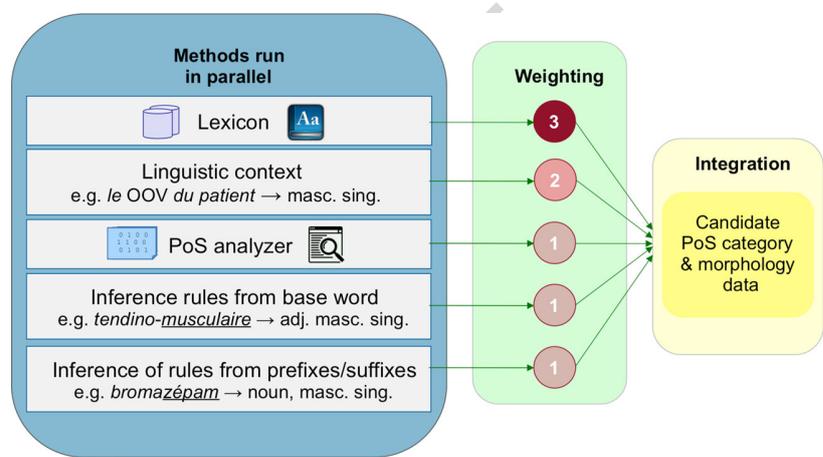
420 Medical doctors need to master medical history taking  
 421 and these abilities may be enhanced through practice  
 422 by using software simulations. To complement the direct  
 423 contact with patients, we proposed a dialogue system  
 424 for simulating the interview with multiple virtual patient  
 425 cases. Because this system features interaction through  
 426 natural language, it provides favourable conditions to  
 427 improve medical students' anamnesis skills. We reported  
 428 here the usability evaluation of the French system. We  
 429 assessed to which extent it is mature enough in a real use  
 430 context.

The agent was tested with 35 different cases from 431  
 18 different specialities. Medical evaluators considered 432  
 that this system provides quality dialogue through natural 433  
 language, that it does so across heterogeneous cases and 434  
 medical specialities, and that it processes new records 435  
 without quality loss compared to already known cases. 436  
 Our usability evaluation showed that this multi-case system 437  
 can support student training in history taking and provided 438  
 us with lessons we thought useful to share regarding its 439  
 strengths and limits. 440

**Appendix**

441

**Fig. 6** Interface to input data to create a new virtual patient record



**Table 6** Examples of correct, incorrect and deferred replies (I: 'input'; R: 'system reply'); we show the English translation of dialogue interactions using the French system

Correct	The information is accurate with regard to the patient record ( <i>correctness</i> )	I: Since when have you had these symptoms? R: I have been nauseous for 2 weeks
	No information is invented ( <i>faithfulness</i> )	I: Do your parents suffer from any disease? R: I can not answer this question (This information is not available in the patient record)
	No data are omitted ( <i>exhaustiveness</i> )	I: Do you smoke? R: I smoke one packet a day since I am 18 years old. I want to stop.
Deferred or	Context information	I: How did <u>it</u> start?

**Table 6** (continued)

	Request for repair	unprocessed	R: What do you refer to? Could you give more details?
		Declarative statement	R: I have a dry coughing since yesterday evening at 23 h I: That is very precise! R: Excuse me?
		Joint questions or dialogue acts	I: Yes, I see you have difficulty breathing but since when are you feeling like that? R: What do you refer to? Could you give more details?
		Processing error	I: Do you have coagulation problems? R: I do not understand what you are asking for
		Question type does not exist	I: Have you lifted something too heavy? R: Excuse me?
		Spelling	I: <u>Poid</u> ? (poids) '(your) weight?' R: Pardon ? 'Excuse me?'
		Term missing in vocabulary list	I: Do you <u>limp</u> ?
		Variation of query phrasing	R: I do not understand what you are asking for I: Avez-vous un <u>concubin</u> ? 'Do you have a partner?' R: Pardon ? 'Excuse me ?' (The system replies correctly to a synonym question: 'Avez-vous un couple?')
	Incorrect	Context information unprocessed	I: Do you have a history of diseases? R: Bronchitis I: Frequently? R: Yes, bronchitis
		Question type does not exist	I: How much sport do you do each week? R: Biking, and I go swimming occasionally
Processing error		I: Never had a surgery procedure? R: I have never had that type of surgery	
Spelling		I: Avez-vous des maux de <u>tete</u> ? (tête, 'head') 'Do you have headaches?' R: J'ai des coliques, j'ai extrêmement mal au ventre 'I have colics, I have a strong stomach ache'	
Term missing in vocabulary list		I: Do you often eat <u>fast food</u> ?	
Variation of query phrasing		R: I do not follow any special diet I: Rhythm of the pain? R: I felt a big pain in my right side (The system replies correctly to the question: 'How often do you have pain?')	

**Table 7** Results of prediction methods of part-of-speech (PoS) category and morphology data for out-of-vocabulary (OOV) words (in percentage); the number of instances per class is shown in brackets; results of morphology data were only computed on OOVs for which the PoS category was predicted correctly

PoS category	P	R	F1	Morphology data	P	R	F1
Adjective (9)	100.0	66.7	80.0	Conjugation data (3)	25.0	33.3	28.6
Adverb (1)	100.0	100.0	100.0	Feminine singular (6)	80.0	66.7	72.7
Noun (20)	75.0	90.0	81.8	Feminine plural (2)	0.0	0.0	0.0
Preposition (2)	100.0	100.0	100.0	Masculine singular (15)	77.8	93.3	84.8
Proper name (3)	0.0	0.0	0.0	Masculine plural (2)	0.0	0.0	0.0
Verb (4)	30.0	75.0	42.9	No inflection (3)	0.0	0.0	0.0
Micro-average	69.8	76.9	73.2	Micro-average	59.4	61.3	60.3

**Table 8** Analysis of incorrect replies with examples (*I*: ‘user input’; *R*: ‘system reply’); we show the English translation of dialogue interactions using the French system

Severe errors (26.5%)	Answers that give misleading information (including those in coherent replies). These errors have an impact on systems’ <i>faithfulness</i> . It would be preferable to request for repair or reply <i>I have not understood</i>
Example:	I: Have you lost consciousness? R: Yes [Error due to an incorrect match between ‘lose consciousness’ (input) and ‘sight loss’ (record)]
Moderate errors (56.2%)	Replies that are incoherent regarding the user question, but provide correct information from the patient record; or when the system should reply that no information is available in the record. Because of the incoherence, the user might not pay attention to the information and would reformulate the question or change the topic. These have an impact on the <i>dialogue flow</i> . Especially, when no data are available, the user should be informed to stop reformulating questions on the same topic. These errors could be more harmful if the user changes the topic without having found key information from the record.
Example:	I: And does your wife have any symptom? R: I am married [The system should reply that details are not available in the record]
Errors that impact the exhaustiveness of information	Answers that do not provide all the information in the patient record. The severity would depend on each dialogue context and on the design strategy of the agent; i.e., whether the system should always provide all the information (as in our system), or let the user be trained in asking for further details.
Example:	I: Where do you have pain? R: Yes [The virtual patient should reply: ‘I have thorax pain’]

**Table 9** Sample clinical record (top) and sample of the output for OOV words in a new VP record (bottom); *adj* stands for 'adjective'; *fp*, for 'feminine plural'; the format is YAML

Sample clinical record

```

aimOfConsultation:
  aim: the patient is consulting you about persistent backache.
informations:
  patientFirstName: Patricia
  patientLastName: Hurst
  patientAge: 65
  maritalStatus: single
  profession: accountant
  children: none
  weight: 72 kilograms
  height: 162 centimetres
lifestyle:
  food:
    items:
      - the patient often eats fish and chips; the patient hates vegetables
  physicalActivity:
    items:
      - the patient goes to country and western dance club twice a week
  addictions:
    items:
      - the patient drinks about two pints of dark beer every day.
  socialBehaviour:
    items:
      - the patient lives alone but often spends time with her family
medicalRecord:
  allergies:
    nonmedicationAllergy:
      - allergy: tree pollen
      observationsValue: the patient is allergic to many types of tree pollen
  medicalHistory:
    - disease: stomach ulcers
      durationValue: for 8 years
      treatment:
        - therapeuticClassValue: proton pump inhibitor (omeprazole)
  surgery:
    - operation: the patient had a broken leg and a dislocated knee
      age: at the age of three
      observationsValue: the patient has a slight limp
complaints:
  - symptom: pain in the lower back
    observationsValue: the pain is in the lower back and sometimes down the legs
    durationValue: for months
  - symptom: the patient has a pain that disrupts sleep
    frequencyValue: often
  
```

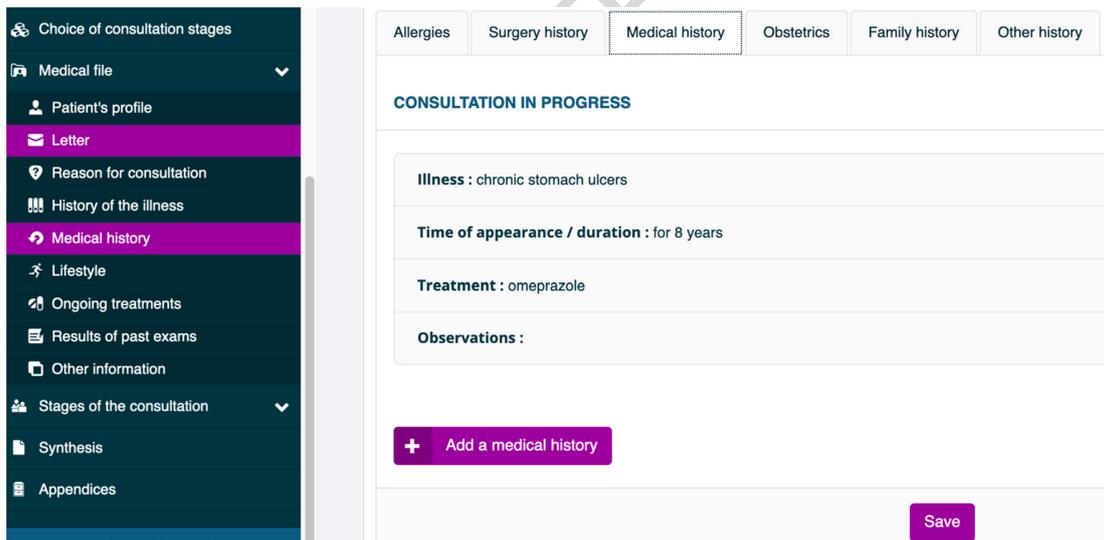
**Table 9** (continued)

Sample clinical record

observationsValue: the pain often makes it difficult to fall asleep  
currentTreatment:  
- therapeuticClassValue: proton pump inhibitor  
methodOfAdministrationValue: oral  
frequencyValue: three times a day  
observationsValue: the patient used to be on esomeprazole magnesium  
- therapeuticClassValue: pain-killer  
methodOfAdministrationValue: oral  
doseValue: 1 gram  
frequencyValue: 3 a day  
observationsValue: the patient's pain is not relieved

Linguistic data output for OOV words in a new VP record

symptoms:  
token: insomniantes  
lemma: insomniant  
data:  
cat: adj  
mor: fp  
string:  
douleurs parfois insomniantes ('pain often causing insomnia')



**Fig. 7** Procedures and weighting scheme to predict linguistic information for OOV items

**Table 10** Description of the seen cases used in the usability study

Description	Diagnosis	Spec.
A 41-year-old woman comes for a pre-anesthesia checkup before a gallbladder surgery.	NA	AN
A 41-year-old man comes for a medical certificate for a sport competition.	CD	
A 49-year-old man consults about a violent thoracic pain since last night.	Essential hypertension Pneumopathy	PN
A 35-year-old man complains of a considerable fatigue and weight loss.	Depressive episode	P
A 40-year-old woman complains of a sore throat.	Throat infection	GP
A 49-year-old man consults about urinary problems.	Prostatic hyperplasia	U

Abbreviations of medical specialities (Spec.) are given in Table 1; NA stands for *not available* (no diagnosis); not all consultations lead to a diagnosis (e.g., pre-anesthesia checkup), and some cases only contained the case description for the dialogue system, without further training feedback

**Table 11** Description of the unseen cases used in the usability study

Description	Diagnosis	Spec.
A 57-year-old man comes for a medical check-up after an episode of cardiac insufficiency.	Cardiac insufficiency	CD
A 64-year-old man consults because he had a myocardial infarction.	Extended anterior myocardial infarction	CD
A 65-year-old man consults for a thigh wound that developed progressively	Psoriasis	D
A 27-year-old woman complains of diarrhoea, hot flushes and palpitations for one year.	Thyroid disorders	E
A 70-year-old woman consults for knee pain.	Knee osteoarthritis	GE
A 29-year-old man consults for a disabling diarrhoea and increasing tiredness.	NA	GH
A 60-year-old man consults for epigastric pain.	Chronic gastroesophageal reflux	GH
A 56-year-old man complains of weight loss and abdominal pain.	NA	GH
A 31-year-old woman has been having abdominal pain within the last 24 h.	Mesenteric adenitis	GH
A 78-year-old man consults for bloody stools and loss of appetite.	NA	GH
A 24-year-old woman consults for pains in her lower abdomen and foul-smelling vaginal discharge.	Sexually transmitted disease	IT
A 24-year-old man consults for hair loss and a rash on his feet.	Syphilis	IT
A 24-year-old woman has been having gait problems and tingling recently.	Multiple sclerosis	N
A 32-year-old woman has been suffering from regular headaches over the last year.	Migraine	N
A 70-year-old man has suffered a sudden vision loss.	Cerebrovascular accident	N
A 28-year-old woman has suffered a progressive vision loss.	Possible multiple sclerosis	N
A 67-year-old man comes with alteration of the general state, left lumbar pain and vomiting.	Renal Insufficiency	NE
A 66-year-old woman complains of vaginal bleeding.	NA	OG
A 32-year-old woman gave birth two months ago and feels very tired.	Postpartum depression	OG
A 25-year-old woman complains of right leg pain and a fever.	Phlebitis	OG
A 59-year-old man comes to a follow-up consultation for a multiple myeloma.	Multiple myeloma	ON
A 71-year-old man complains of difficulty swallowing over the past months.	Possible oesophageal cancer	OT
A 66-year-old man complains of shortness of breath on any exertion.	NA	PN

**Table 11** (continued)

Description	Diagnosis	Spec.
A 21-year-old woman has suffered an episode of respiratory distress on effort.	NA	PN
A 55-year-old man consults for coughing, often with blood-tainted sputum.	NA	PN
A 37-year-old man complains of coughing with sputum and shortness of breath.	Bronchitis	PN
A 60-year-old man complains of a back pain that does not go away.	Persistent sciatica	RH
A 57-year-old man presents with a back pain started suddenly 5 days ago.	Acute lumbar sciatica	RH
A 55-year-old woman comes into urgent care with a fever and abdominal pain.	Cholecystitis	UC

Abbreviations of medical specialities (Spec.) are given in Table 1. *NA* stands for *not available* (no diagnosis)

**Table 12** Summary of lessons learned from the development and usability evaluation and implications on design and development

Design	<ul style="list-style-type: none"> <li>• Create a patient record model for the medical trainers to input the virtual patient's health state in a semistructured template</li> <li>• Devise a knowledge model for the task: range of question types, dialogue acts and entity types concerning history taking</li> <li>• Conceive the appropriate dialogue strategies:                             <ul style="list-style-type: none"> <li>– Careful fallback replies when user's question is not in the patient record or it is out-of-scope or out-of-domain</li> <li>– Accurate information regarding the patient record (<i>correctness</i>), without inventing information (<i>faithfulness</i>) nor omitting data (<i>exhaustiveness</i>)</li> <li>– And all the above, in a <i>dynamic dialogue flow</i>: maximising user engagement in interaction and minimising tiredness or boredom</li> </ul> </li> <li>• Outline the end-users' profile (students, interns or experienced practicing doctors)</li> <li>• Analyse the users' needs in order to balance the trade-off between generalisability (adaptable system) and specialisation (a tailored, engineered application for a specific case or a medical specialty)</li> </ul>
Development	<ul style="list-style-type: none"> <li>• Invest in creating termino-ontologic resources:                             <ul style="list-style-type: none"> <li>– Terminology modules for concept mapping and term variation</li> <li>– Components to compare the existing knowledge base, detect out-of-vocabulary words in new cases and update system resources</li> <li>– Linguistically-motivated modules to change the patient record from the input description to patient's perspective (3rd to 1st person)</li> <li>– Term simplification modules to map technical to laymen words</li> <li>– Spelling correction tools</li> </ul> </li> <li>• Minimise human intervention or engineering needs to adapt the system to unseen cases on-the-fly</li> <li>• Have medical professionals involved from the start of the project</li> <li>• If no training dialogue data are available, collect dialogue logs simulating the task with real end-users via a rule-based and terminology-based system, crowdsourcing, or a wizard-of-oz protocol</li> </ul>
Evaluation	<ul style="list-style-type: none"> <li>• Get close-to-reality patient cases to simulate a wide range of virtual patient profiles (e.g. medical transcripts or cases prepared by medical trainers and aimed at medical students)</li> <li>• Conduct tests by real end-users as soon as possible</li> <li>• Iteratively inspect patient logs to detect and fix dialogue errors before each evaluation round</li> <li>• Warn the users about the system limitations (what it can do and it cannot do)</li> </ul>

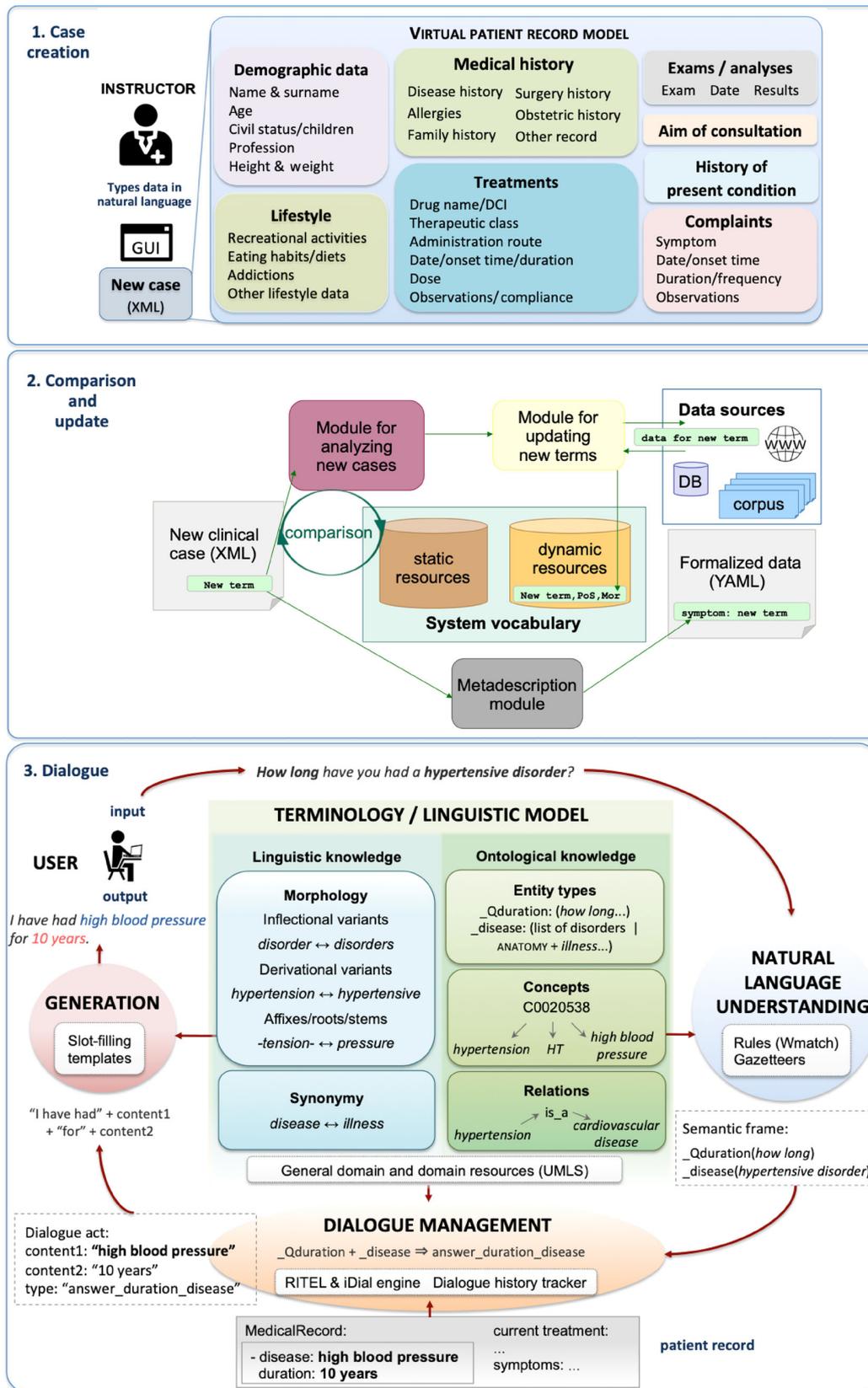


Fig. 8 Overall functioning of the dialogue system and update components; further technical details are provided in [27, 46, 47]

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448 **Author contributions** Sophie Rosset (SR), Leonardo Campillos-  
449 Llanos (LC) and Catherine Thomas (CT) developed the VP dialogue  
450 system, and Pierre Zweigenbaum (PZ) contributed to the medical  
451 terminology components and patient record model. Éric Bilinski (EB)  
452 implemented the web evaluation tool and the online demonstration  
453 of the dialogue system. Antoine Neuraz (AN) helped to engage the  
454 evaluation participants and made valuable remarks about the system  
455 and article. SR and PZ designed the evaluation protocol, and LC  
456 collected and analysed the evaluation data. LC and SR double-checked  
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463 interpretation of data and writing the manuscript.

464 **Data availability** The dialogue data collected during development and  
465 evaluation is available at: <https://pvdial.limsi.fr/data/PG-logs-eval.zip>  
466 A demonstration of the dialogue system can be tested at: <http://vps-9069f76a.vps.ovh.net>  
467

468 **Code availability** Not applicable.

## 469 Declarations

470 **Conflict of interest** The authors declare that they have no conflict of  
471 interest.

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