Language Learning & Technology
ISSN 1094-3501 CC BY-NC-ND

2022, Volume 26, Issue 1
pp. 1–24

ARTICLE

Dialogue systems for language learning: A meta-analysis

Serge Bibauw, Universidad Central del Ecuador; KU Leuven; UCLouvain

Wim Van den Noortgate, KU Leuven; imec

Thomas François, UCLouvain

Piet Desmet, KU Leuven; imec

Abstract

The present study offers a meta-analysis of effectiveness studies on dialogue-based CALL, systems affording a learner practice in a foreign language (L2) by interacting with a conversational agent ("bot"). Through a systematic inclusion and exclusion process, we identified 17 relevant meta-analyzable studies. We made use of Morris and DeShon's (2002) formulas to compute comparable effect sizes across designs, including k *= 100 individual effect sizes, which were analyzed through a multilevel random-effects model. Results confirm that dialogue-based CALL practice had a significant medium effect size on L2 proficiency development (*d *= 0.58). We performed extensive moderator analyses to explore the relative effectiveness on several learning outcomes of different types and features of dialogue-based CALL (type of interaction, modality, constraints, feedback, agent embodiment, gamification). Our study confirms the effectiveness of form-focused and goal-oriented systems, system-guided interactions, corrective feedback provision, and gamification features. Effects for lower proficiency learners, and on vocabulary, morphosyntax, holistic proficiency, and accuracy are established. Finally, we discuss expected evolutions in dialogue-based CALL and the language learning opportunities it offers.*

Keywords: *Meta-analysis, Dialogue System, Chatbot, Dialogue-based CALL*

APA Citation: Bibauw, S., Van den Noortgate, W., François, F., & Desmet, P. (2022). Dialogue systems for language learning: A meta-analysis. *Language Learning & Technology*, *26*(1), 1–24. https://hdl.handle.net/10125/73488

Introduction

The central aim of this study is to evaluate the effectiveness of dialogue-based computer-assisted language learning (CALL) for second or foreign language (L2) learning. Dialogue-based CALL encompasses all applications allowing one to practice an L2 through written or spoken conversational interactions with an automated agent, be it a voice-only virtual assistant, a computer-controlled character, or a physical robot. Recently, with the increased prevalence of chatbots and digital personal assistants, a renewed attention has been brought to the use of similar dialogue systems for language learning purposes, and commercial applications are being developed (for instance, *Duolingo Bots* was released in 2016). Yet beyond the hype, the question remains: how effective are these systems for learning a foreign language? The purpose of the present research is to establish whether and to what extent the use of such dialogue-based CALL applications has an impact on the development of learners' L2 proficiency, as it is commonly assumed by the proponents of these systems, and which instructional and study design characteristics moderate the size of the effect. We attempt to address these questions through a meta-analysis of existing effectiveness studies about these applications.

Dialogue-based CALL

Many names have been given to systems implementing dialogic interactions with an automated agent for language learning purposes: *intelligent tutoring systems*, *conversational agents*, *dialogue systems*, *chatbots*, and so forth. We gather under the term *dialogue-based CALL* all efforts to make a learner of a foreign language have a dialogue (i.e., a sequence of conversational turns) with any sort of automated agent (chatbot, robot, embodied agent, speech interface, non-player character in a virtual world, etc.) as a language learning task, be it written or spoken. This definition sets dialogue-based CALL apart from other types of language learning technology. First, interactions occur as part of a meaningful conversational context, rather than isolated items as in many tutorial CALL activities. Second, the interlocutor is the system, rather than another human as in computer-mediated communication (CMC). And third, the dialogue *is* the L2 task, not a means of providing scaffolding (pedagogical agent) or instruction in the learner's native language (tutorial dialogue) (Bibauw et al., 2019).

A general assumption behind many of these systems is that the meaning-oriented practice of an L2 contributes to the development of the learner's proficiency and that, even though a native speaker would be the ideal conversation partner, an automated agent can provide such practice in contexts where expert speakers are scarce (Sydorenko et al., 2018). The idea finds a theoretical foundation in the interactionist approach of second language acquisition: through the dialogue, learners receive input, feedback, opportunities for output, negotiation of meaning, and noticing, which are all essential for L2 development (Ellis & Bogart, 2007). While not all dialogue-based CALL systems provide corrective feedback or complete negotiation of meaning, they all provide input, output, and various forms of interactional feedback (Basiron, 2008).

Empirical effectiveness studies on CMC—text-based chat in particular—have already demonstrated that similar interactions with humans have significant effects on language learning outcomes (Lin, 2015a). In certain conditions, they might even have a higher impact on L2 speaking proficiency than face-to-face interactions (Ziegler, 2016). We hypothesize that well-designed dialogue-based CALL systems could provide learning opportunities comparable to CMC. Besides, these systems offer a few advantages over their human counterparts: permanent availability, infinite patience when needing to repeat or to correct, and potential for systematic adaptivity to the learner. They also offer a low-anxiety environment for language practice, which could raise learners' willingness-to-communicate (Fryer & Carpenter, 2006).

Building upon a systematic review of the literature, we have proposed a conceptual framework for dialogue-based CALL (Bibauw et al., 2019). Dialogue systems are generally categorized into *task-oriented*—in which the user has a certain goal they want to achieve through the dialogue (booking a hotel, setting an appointment, etc.)—and *open-ended systems*—where the conversation has no explicit purpose and looks more like small talk. Beyond this general distinction, we proposed a typology distinguishing four types of dialogue-based CALL systems, presented in Table 1. Some of these systems have been empirically evaluated, but little is known about their comparative effectiveness for L2 development.

Table 1

Typology of Dialogue-based CALL Systems with Examples

	Narrative system	**Form-focused system**	**Goal-oriented system**	**Reactive system**
Constraints	User must choose from a list of pre-set utterances with different meanings.	Meaning is pre-set (e.g., gap-filling) or constrained (e.g., questions with given answers).	Meaning influenced by set context and tasks.	Open-ended, free dialogue (chatbots).
Interaction	System-guided (branching paths)	System-guided	Interactive, less predictable	User-directed
Example	CandleTalk (T.-L. Chiu et al., 2007)	CALL-SLT (Bouillon et al., 2011)	Wilske, 2015	CSIEC (Jia, 2009)
Dialogue excerpt	User is playing a loud student. Their roommate (S) is complaining. **S:** Excuse me; have you noticed how loud it is in here? **U:** *[choose from list of sentences and pronounce it]* – What? What sound? I didn't hear anything. – Pardon me; what did you say? – Oh, I'm sorry. I was concentrating on the game so I didn't notice. Did I bother you? (...)	At a restaurant. (...) [*Instruction in L1*] Ask- check-politely **U:** [*free oral input*] I would like the check please. [Feedback on pronunciation and grammar]	Someone (S) stops you and asks you for directions. [Map with route provided] (...) **U:** [*free written input]* Turn left, in front of the coffee-shop. [Corrective feedback if erroneous] **S:** Okay, left in front of the coffee-shop, and then?	User is free to ask or say anything. System reacts to each last message. **U:** [*free written input]* Hello, I am Peter. **S:** Hi Peter. How are you? (...) **U:** I feel very happy to be a student. **S:** I'm a college student and my major is math. What is your major?

Note. U = User. S = System. (Adapted from Bibauw et al., 2019).

A Meta-analysis of Experimental Research

In the last two decades, researchers have carried out experimental evaluations of the learning effects of dialogue-based CALL. Some of these effectiveness studies brought favorable results (e.g., Harless et al., 1999), but other promising studies did not find significant learning gains. This inconclusiveness could be imputable to insufficient statistical power, stemming from methodological decisions such as small sample sizes and short treatment duration (e.g., Hassani et al., 2016), but also to an absence of an effect. Looking at the simple juxtaposition of these studies, which in some cases presents imprecise or conflicting evidence, does not allow one to draw clear conclusions. The very small sample sizes among some of these studies, in one case as low as n = 6 per condition, make it particularly difficult to obtain significant findings. With a meta-analysis of these results, however, we could aggregate all experimental evidence to obtain a stronger summary effect size, which would offer a clear-cut view on the general effectiveness of dialogue-based CALL and on the factors that affect its efficacy.

A meta-analysis is a quantitative synthesis of studies, using statistical methods to aggregate and analyze all the compatible effects measured by these studies (Plonsky & Oswald, 2015). It allows one to establish a more accurate estimate of the effects of a certain intervention, going beyond the statistical significance of results in individual studies.

More importantly, considering the diversity of system features, treatment characteristics, and methodological choices in dialogue-based CALL studies, a meta-analysis allows us to perform moderator analyses (i.e., comparisons of effects between groups of studies) defined according to certain variables (e.g., task-oriented versus open-ended systems), comparisons that are not made in individual studies. Therefore, meta-analyses have the potential to inform practice on how to set up effective dialogue-based CALL systems, and inform research on promising tracks and understudied questions.

In comparison with meta-analyses in applied linguistics, we propose a few methodological advances. One is to use a common (raw) effect size metric for within-group and between-group effects, allowing easier comparison through experimental designs. Another is the use of multilevel modelling to include multiple effect sizes from single studies, with their respective covariates and characteristics (Van den Noortgate et al., 2013). Our methodological procedures are fully detailed in the following section and supplementary information online, including our full data set and R processing script.

Research Questions

The research questions that have guided this meta-analysis are:

RQ1. In general, how effective is dialogue-based CALL for L2 development?

RQ2. How do different implementations of dialogue-based CALL, distinguished by characteristics of instructional and system design, compare to each other in terms of effectiveness on various language learning outcomes?

Methodology

Data Collection and Selection

We followed a systematic and reproducible data collection procedure, summarized in Figure 1. The first step was a search in major scientific databases, with a search query associating keywords for dialogue systems and language learning (search syntax in the Supplementary Methods). It was completed by an auxiliary manual collection-strategy through ancestry search (references mentioned in the previously found publications) and forward citations (new publications citing the previously found ones). As of January 2018, this resulted, after pruning duplicates, in a total pool of 419 records.[1]

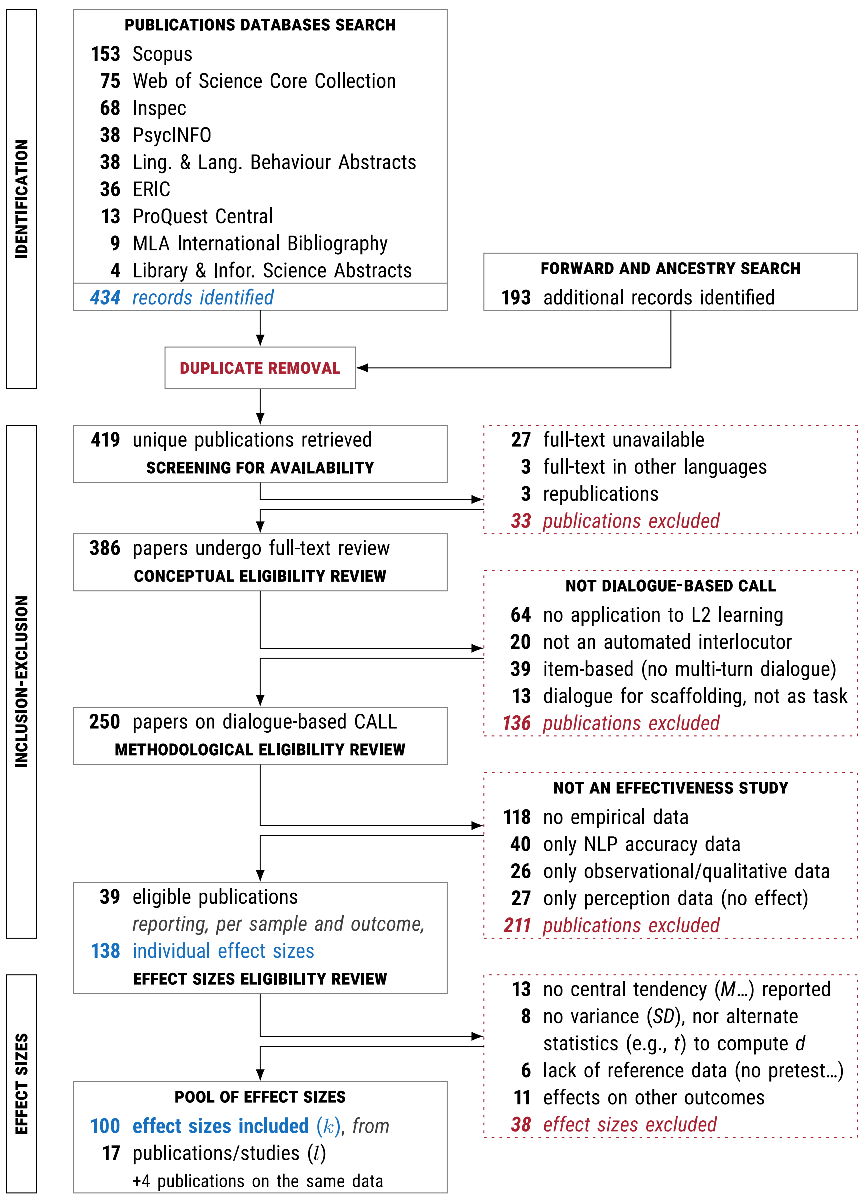
After screening publications for availability, the remaining 386 articles underwent a full-text review based on the definition of dialogue-based CALL given above, and 250 papers were kept. This excluded studies that, although using bots for second language learning, only explored scaffolding interaction, typically in L1 (e.g., Arispe, 2014), which we considered outside the scope of dialogue-based CALL. Finally, we retained only the publications presenting empirical effectiveness studies (i.e., quantitative studies reporting measurements of the effects of a dialogue-based application on a certain outcome variable). The final effectiveness corpus totaled 39 papers.

As many publications report various outcome variables or measurements, possibly on different samples of participants, each reported series of measurement was recorded as a separate effect size. Considering our intention to perform moderator analyses, we opted to maximize granularity by including the smallest possible aggregation levels for effect sizes. We identified k = 138 individual effect sizes mentioned in the publications.

Only one article explicitly reported effect sizes (Lee et al., 2011); for all the others, it was necessary to compute them based on disclosed summary statistics. For this reason, we could not include studies that did not report means, standard deviations (*SD*), or alternate summary or test statistics. We contacted the authors to obtain the missing data, but had limited success, despite warmly appreciated answers from most. We also had to exclude effects from a between-subjects study whose alternate condition did not match our control condition (no treatment) and lacked other reference data (no pretest; Wang & Johnson, 2008). Finally, because our meta-analysis focuses on the effects on L2 development, we excluded six publications measuring other outcome variables, such as motivation. In the end, we analyzed k = 100 effect sizes, corresponding to 17 publications, 17 dialogue-based CALL systems (some of them variations of a single system), and 11 research teams.

Figure 1

Flowchart of the Inclusion and Exclusion Process of Studies and Effects



Coding

Each of the articles and effect sizes were further analyzed and coded according to an extensive coding scheme including publication, system, treatment, population, and outcome categories of variables. The variables and their possible values or definitions are presented in Table 2, and the coding process is described in the Supplementary Methods. Our coding scheme was inspired by other meta-analyses and recommendations in second language acquisition research (Norris & Ortega, 2000; Plonsky & Oswald, 2015).

Table 2

Coding Scheme for Studies

Type	Variable	Possible values
Publication	Publication type	Journal article / Conference paper / Book chapter / Doctoral dissertation
Experiment	Experimental design	Independent groups (IG) / Repeated measures (RM) / Repeated measures in independent groups (IGRM)
	Group assignment	Random / Intact groups (only for IG/IGRM designs)
	Treatment sessions	(number of spaced sessions on the system)
	Treatment span	(number of weeks between first and last sessions)
	Time on task	(number of hours of usage of the system)
	Treatment density	Spaced (span > 1 week) / Packed (≤ 1 week)
System	Type of interaction	Task-oriented / Open-ended / System-guided
	Type of system	Form-focused system / Goal-oriented system / Reactive system / Narrative system
	Meaning constraints	None < Implicit < Explicit < Pre-set
	Corrective feedback	None < Implicit < Explicit
	Primary modality	Spoken / Written
Population	L1	Chinese / English / Farsi / Korean / Spanish / ... / Mixed
	Target language	Arabic / Chinese / English / French / German / ...
	L2 proficiency	A1 < A2 < B1 < B2
	Age group	6-11 < 12-17 < 18+
	Age mean	(if reported; otherwise extrapolated from given range)
	Context	School / University / Laboratory
Outcome	Outcome type	Production // Comprehension // Knowledge test
	Outcome variable	Proficiency / Accuracy / Complexity / Fluency // Listening / Reading // Grammar / Vocabulary
	Type of instrument	Meta-linguistic judgment / Selected response / Constrained response / Free response
	Outcome modality	Spoken / Written
	Outcome temporality	Short-term (immediate) / Long-term (delayed posttest)

The coding was performed independently by two coders, including the first author, on all studies and effects. The intercoder agreement was computed for all variables as Cohen's kappa, or Krippendorff's alpha for continuous variables and polytomous categorical variables. There was full agreement ($\kappa = 1$) for variables such as age and context. However, the agreement was initially approaching chance level for variables that required a lot of inferencing work, such as time on task and treatment span, because few publications disclose them in an explicit or standardized manner. In such cases, disagreements were subsequently resolved among the two coders by returning to the original study to reach an agreement and, occasionally, by iteratively refining the coding scheme.

Effect Sizes Calculation

At the core of a meta-analysis is an aggregation and comparison of individual effects, measured quantitatively. In second language acquisition and CALL research, considering the prevalence of experimental designs, many meta-analyses use Cohen's d or Hedges' g, which standardise a difference of means by dividing it by the pooled standard deviation (Plonsky & Oswald, 2015). However, these measures are meant for *independent-groups* (IG) design (i.e., in studies comparing posttest results from an experimental and a control group). They are not suitable for expressing the *within-group* effect in single-group pretest-posttest design (repeated measures, RM), which requires a formula of standardized mean change. Still other measures may be required for *independent-groups pretest-posttest* (IGRM) designs that combine features of IG and RM designs.

Morris and DeShon (2002) offer formulas for calculating effect sizes for these designs and for converting them to make them immediately comparable. Therefore, there is no reason to present two different summary effect sizes, one for between-group and another for within-group effects, as it is common meta-analytic practice in language learning and CALL (Plonsky & Oswald, 2014); the effect sizes can be transformed into a comparable metric, aggregated together, and thus offer a stronger estimate of the true effect.

In our pool of effect sizes, 92 studies follow an RM design and 8 follow an IGRM design; no IG design is represented. To compute a comparable effect size across study designs, we used the normalized *raw* metric (d_{IG}) proposed by Morris and DeShon (2002), which is aligned on the between-group effect that Cohen's d measures (see the Supplementary Methods for discussion of raw and change metrics). We used their formulas to compute d_{IG} for the RM and IGRM studies present in our data set and applied Hedges' correction factor J for small sample bias (Hedges & Olkin, 1985, chap. 5, eq. 7).[2] We use d hereafter as the general notation of this standardized mean difference. For the RM design, the mean change (M_{post}-M_{pre}) is normalized by the standard deviation of the pretest scores (SD_{pre}), which is more consistent across studies:

$$d = J(df_{\mathrm{RM}})\left(\frac{M_{\mathrm{post}} - M_{\mathrm{pre}}}{SD_{\mathrm{pre}}}\right) \tag{1}$$

For IGRM design, the standardized change in the control group (C) is subtracted from the change in the experimental group (E):

$$d = J(df_{\mathrm{IGRM}})\left(\frac{M_{\mathrm{post,E}} - M_{\mathrm{pre,E}}}{SD_{\mathrm{pre,E}}} - \frac{M_{\mathrm{post,C}} - M_{\mathrm{pre,C}}}{SD_{\mathrm{pre,C}}}\right) \tag{2}$$

Multiple Effect Sizes and Multilevel Modelling

The computing of an overall effect requires that the meta-analyst decides on a statistical modelling approach. A *fixed-effects model* assumes that all effect sizes are estimates of a constant true effect of "dialogue-based CALL on L2 development" and that the observed variation can only be accounted to *within-study* sampling variance. However, most recent meta-analyses do not make this assumption and use a *random-effects model*. This model assumes that, beyond sampling variance, studies have been observing different population effects, due to different study designs and characteristics, and takes this additional *between-studies* variation into account.

Traditional meta-analytic fixed-effects and random-effects techniques are meant to aggregate independent effect sizes estimates. However, in our pool of studies—as elsewhere—the analyzed publications rarely report only one effect size: they may report effects from distinct instances of a system, on samples from populations with distinct characteristics, or often through multiple tests and outcome measurements. These multiple effect sizes from the same publication cannot be considered independent, as they share certain sources of random variation, such as specificities of the population sampled from, a specific experimental procedure, or certain tendencies in rating non-objective tests. Various solutions have been used to avoid this dependency, usually through selecting or averaging dependent effect sizes, with the drawback of losing part of the information they convey (Plonsky, 2011).

To avoid the problem of dependence and the loss of information or power, we opted for a multilevel meta-analytic model, as described by Van den Noortgate et al. (2013). Whereas a fixed-effects model assumes effect sizes vary only on one level (within studies, due to sampling), and a traditional random-effects model assumes that effect sizes can vary on two levels (at the sampling level and at the study level), the multilevel approach adds a third, intermediate layer of potentially unexplained variation: within a single study, several population effect sizes may be estimated. The information that effect sizes from the same study share (e.g., they usually evaluate the same system with similar sampling, testing, and rating procedures) is still considered at the third, between-studies level. Table 3 summarizes the three layers of aggregation of the model, with their respective number of units.

Table 3

Levels of Multilevel Meta-Analytic Model

Level	Number of elements	Source of variance
1: Samples	$k_1 = 100$ *(N* = 803)	Random sampling variance
2: Effect sizes	$k_2 = 100$	Within-study variation (e.g., varying effect measurements)
3: Studies	$k_3 = 17$	Between-studies variation (e.g., varying systems, populations, designs)

Note. *k* = number of effect sizes at levels 1 (sampling variance), 2 (within-study effects), and 3 (number of individual studies/publications). *N* = total number of unique individuals tested in the various samples.

The major advantage of using a multilevel model is that it allows one to include as many fine-grained effect sizes as possible from the original studies. For instance, Wilske (2015) reports 20 distinct effect sizes, studying various versions of a system with multiple outcome variables and tests. By adding each effect size individually, we maintain the comparative information between a form-focused and an unconstrained input system, with or without corrective feedback, on written accuracy or speaking fluency, and so on. This information is particularly valuable for our moderator analyses, but it would have been lost if combined into a single per-study effect.

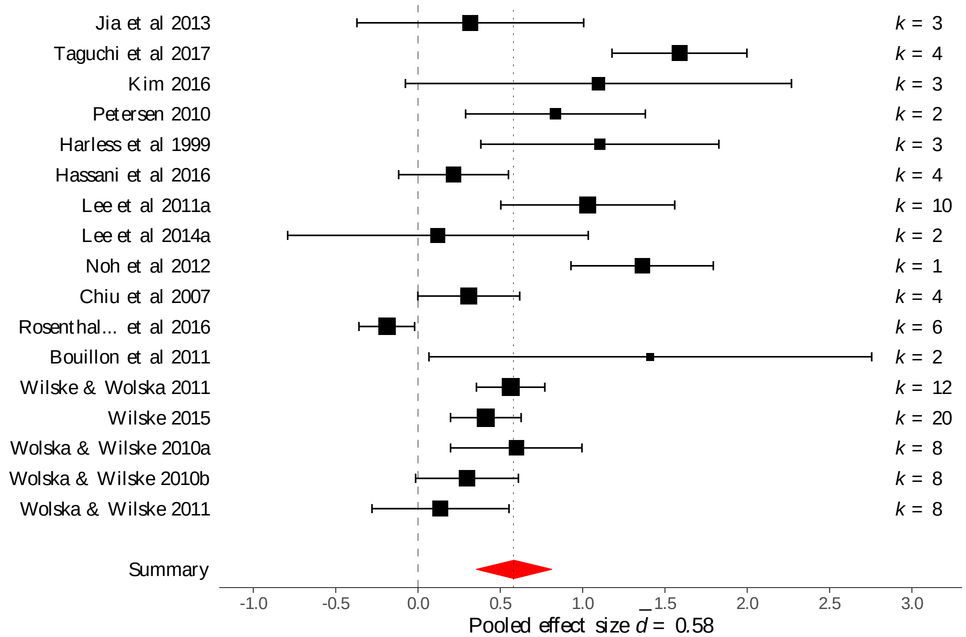
The multilevel models, with or without moderator variables, were fitted with the **metafor** package (Viechtbauer, 2010) in R, using the `rma.mv()` function for multilevel modelling and the restricted maximum-likelihood (REML) method.

Results

As detailed previously, after the inclusion and exclusion process, we retained 17 publications reporting 100 effect sizes on a total of 803 participants. Figure 2 presents a forest plot of the effects for each of the 17 studies. A complete list of all individual effects with corresponding variables can be found in the Supplementary Material.

Figure 2

Forest Plot of Study-Level Effect Sizes



Note. k = number of within-study effect sizes. The red diamond represents the 95% confidence interval of the summary effect (Fernández-Castilla et al., 2020).

Overall Effect

The summary effect established by the three-level random-effects model for all studies is $\bar{d} = 0.58$, with a 95% confidence interval of [0.35, 0.82]. It confirms that, globally, dialogue-based CALL has a highly significant *medium* effect on L2 development ($p < .001$).

Heterogeneity and Publication Bias

It is important to note that the observed outcomes vary substantially across studies. A Q-test for heterogeneity (Higgins & Green, 2008) confirms that there is substantial residual heterogeneity in the effect sizes at the second and third levels, Q (df = 99) = 311.1, $p < .001$, $I^2 = 68.02\%$. The variance is relatively higher between studies ($k_3 = 17$, $\sigma_3^2 = 0.18$), indicating potentially multiple true effects of dialogue-based CALL, than within studies ($k_2 = 100$, $\sigma_2^2 = 0.08$), with also a high sampling variance ($k_1 = 100$, $N = 803$, $Md\left(\sigma_1^2\right) = 0.17$), possibly imputable to less precise outcome measurements.

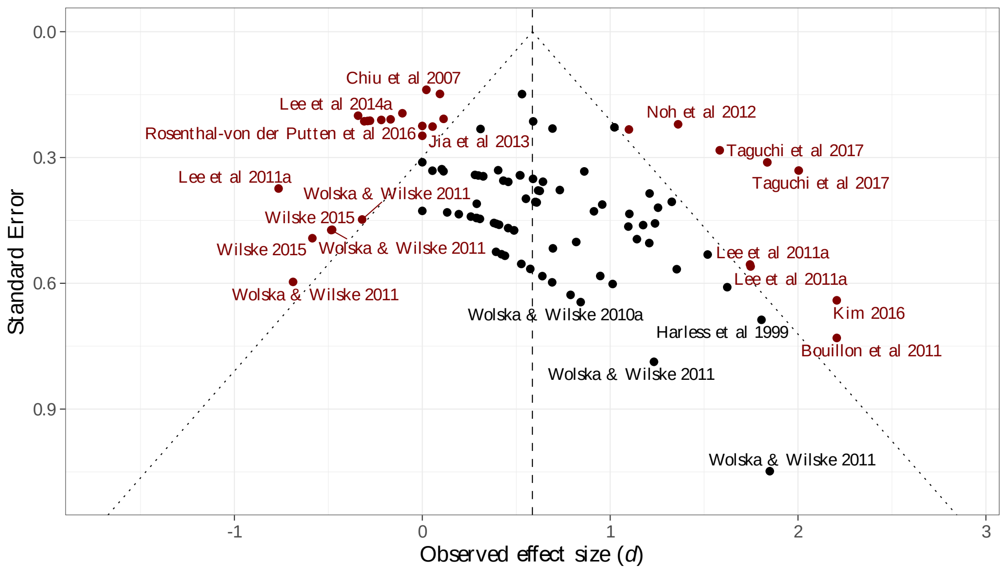
It thus seems clear that we are in the presence of different types of pedagogical interventions, with varying degrees of effectiveness on different outcomes and target groups. This supports our decision to use a random-effects model and especially incentivizes moderator analyses, to be able to disentangle the covariates of the observed effects and potential subgroups that can cause these varying effects.

Publication Bias

The funnel plot in Figure 3 reveals a potential publication bias, considering the absence of strong negative effects in the lower-left side of the triangle: it is reasonable to assume that highly negative effects in underpowered studies might not have been reported. However, the sample size is not a significant moderator of the effect (b = 0.00, 95% CI [-0.01, 0.01], p = .497) and including it does not improve the model fit, thus eliminating the possibility that more precise studies could bring less favorable results.

Figure 3

Funnel Plot of Effect Sizes against Study Precision



Moderator Analyses

As stated in our second research question, the ambition of this meta-analysis of dialogue-based CALL is also to get insights into the conditions under which the approach produces better outcomes. In particular, we will review the moderator effect of (a) publication and experimental design variables, (b) target population variables, (c) system characteristics, and (d) outcome measurement variables.

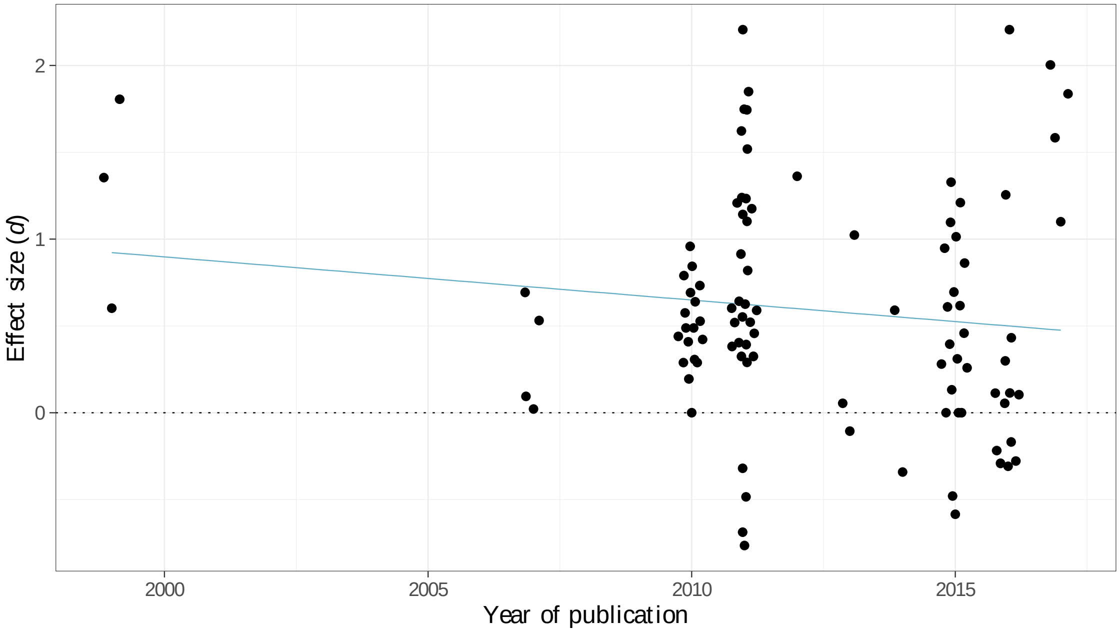
We control for the significance of the differences between moderators by reporting *Q*-tests, which are equivalent to ANOVA *F*-tests on categorical variables. For categorical variables, we report the estimated mean effect size (*d*)—which includes the intercept—for each possible value. For continuous variables, we report the regression weight (*b*) from the meta-regression model (i.e., how each additional unit influences the effect). Nevertheless, these multiple tests are not meant to confirm a pre-established hypothesis and should mostly be interpreted as exploratory.[3]

Publication and Experiment Moderators

The *type of publication* did not make a significant difference, even if the mean effect of journal articles in our sample tended to be higher than conference papers and doctoral dissertations. This tendency can be explained by field traditions: most conference papers are authored by specialists in natural language processing (NLP) rather than applied linguistics, with stronger technical evaluation procedures (e.g., recognition rate) and only peripheral effectiveness evaluations, whose instruments might not always bring the necessary power to reveal learning effects. There also did not appear to be any *chronological evolution* of observed effects across studies, as shown in Figure 4.

Figure 4

Effect Sizes against Year of Publication



Regarding the *experimental design*, we obtain very similar effect size estimates for within (RM) and within-and-between (IGRM) designs, as presented in Table 4. It seems that the slightly stronger bias to which the within-group design is susceptible does not heavily affect the results.

Conversely, *treatment length* deserves special attention. As any pedagogical intervention, the effect of dialogue-based CALL practice is a function of the time the participants spent using the system, and the way it was distributed. Looking at each treatment duration variable in isolation, none achieve significance, probably because of inconsistencies in reporting and accounting for these variables. However, in the analyzed studies, the number of sessions ($b = 0.02$) and the time on task ($b = 0.02$) did influence the outcome, while the total span of the experiment did not ($b = 0.00$). Counter-intuitively perhaps, studies using packed practice, operationalized as an intervention lasting for 1 week or less, seemed to present higher outcomes ($d = 0.97$) than those using spaced practice ($d = 0.53$).

Table 4

Moderator Analyses for Experiment Variables, including ANOVA-like Q-test of Moderators and Estimated Effect Size for Each Level

Variable	***df***	***Q***	***p***	**Values**	***k***	***d*/*b***	***SE***	**95% CI**
Type of publication	2	1.69	.431	Conference paper	31	0.36	0.22	[−0.07, 0.79]
				Dissertation	22	0.58	0.34	[−0.09, 1.24]
				Journal article***	47	0.70	0.15	[0.40, 1.00]
Experimental design	1	0.04	.836	IGRM*	8	0.65	0.30	[0.06, 1.24]
				RM***	92	0.58	0.13	[0.32, 0.84]
Group assignment	1	1.78	.182	Intact groups	3	0.32	0.34	[−0.36, 0.99]
				Random**	5	0.94	0.31	[0.32, 1.55]
Treatm. distribution	1	2.61	.106	Packed***	11	0.97	0.24	[0.49, 1.44]
				Spaced***	81	0.53	0.12	[0.31, 0.76]
Duration (weeks)	1	0.02	.896	+1 week (*b*)	92	0.00	0.03	[−0.06, 0.06]
Sessions	1	0.84	.361	+1 session (*b*)	100	0.02	0.02	[−0.02, 0.07]
Time on task	1	1.02	.314	+1 hour (*b*)	100	0.02	0.02	[−0.02, 0.05]

Note. *df* = degrees of freedom. *Q* = statistic from *Q*-test for moderator effect. *p* = significance of the *Q*-test. *k* = number of effect sizes corresponding to each value. *d* = mean effect size when including only effects matching this moderator value. *b* = regression weight (relative effect size increment for every increment of 1 unit in the moderator). *SE* = standard error of *d* or *b*. CI = 95% confidence interval of *d* or *b*.

*** significant effect at $p < .001$. ** significant effect at $p < .01$. * significant effect at $p < .05$.

Population Moderators

The *L2 proficiency level* of the learners seems to have some influence on the learning gains from dialogue-based CALL. While not reaching significance level, probably due in part to an unequal distribution of studies across levels (with very few conducted on beginners and advanced learners), the moderator, when considered as simply categorical, shows a downward trend from studies involving A1 learners ($d = 0.68$) to studies involving B2 learners ($d = -0.33$). This downward trend is also visible if we use proficiency level as a continuous variable with a linear effect ($b = -0.33$), in which case the moderator is closer to significance, $Q(1) = 3.24$, $p = .072$. This phenomenon can probably in part be explained by the increasing cost of learning gains along with the increase in proficiency.

By looking at each level in isolation, as presented in Table 5, it arises that the most noticeable effects seem to be observed on beginner (A1) and lower-intermediate (A2) learners, while the average effect on upper-intermediate (B1) fails to pass the significance threshold and the gain for advanced learners (B2) could very well be non-existent.

In addition, *age* does not seem to influence the results. While it could be due to the limited scope of the included studies (the majority conducted on adults), effect sizes for the three age groups are relatively similar and using the mean age of the sample leads to equally non-significant and low effects. Similarly, experiments conducted in school and higher education *contexts* present indistinguishable effects. The few “laboratory” studies conducted in isolated contexts, however, report weaker effects.

Table 5

Moderator Analyses for Population Variables

Variable	*df*	*Q*	*p*	Values	*k*	*d*/*b*	*SE*	95% CI
L2 proficiency	3	3.74	.443	A1*	15	0.68	0.33	[0.03, 1.32]
				A2**	93	0.70	0.25	[0.22, 1.18]
				B1	83	0.36	0.35	[−0.33, 1.05]
				B2	15	−0.33	0.41	[−1.12, 0.47]
Age group	2	0.44	.802	6–11*	13	0.77	0.30	[0.18, 1.36]
				12–17	5	0.54	0.37	[−0.19, 1.27]
				18+***	82	0.56	0.15	[0.27, 0.84]
Age (mean)	1	2.05	.152	+1 year (*b*)	97	−0.03	0.02	[−0.07, 0.01]
Context	2	0.69	.707	Laboratory	9	0.33	0.36	[−0.37, 1.03]
				School **	18	0.68	0.23	[0.23, 1.13]
				University ***	73	0.60	0.16	[0.29, 0.91]

Note. *** $p < .001$ ** $p < .01$ * $p < .05$.

System Moderators

In terms of *type of interaction*, the system-guided and task-oriented types produce significant effect sizes, with a potentially stronger effect for the former. The *type of dialogue-based CALL system* is not a significantly differential moderator, as shown in Table 6, but form-focused systems and goal-oriented systems present on their own results significantly different from a null effect. Even though the small number of narrative systems does not allow us to establish their effects, it is interesting to note that the low effect estimate ($d = 0.31$) is coherent with the fact that these systems offer limited opportunities for productive practice and would therefore have a lower effect on proficiency. The effect of reactive systems remains to be demonstrated, as it failed to reach significance. Similarly, the type of *meaning constraints* imposed on learner production could affect the effectiveness. The most constrained type, where the expected meaning is pre-set and only the form of the messages can be modified, presents the strongest effect size.

The absence or presence of *corrective feedback* in the system does not make a statistically significant difference in terms of effect, but the size of the observed effects of each type (with feedback: $d = 0.70$; without feedback: $d = 0.38$) fits the well-documented positive impact of corrective feedback on learning (Nassaji & Kartchava, 2017). The effects of implicit and explicit types of feedback are, on the other hand, very similar, with a slight potential advantage for explicit types.

Table 6

Moderator Analyses for System Variables

Variable	*df*	*Q*	*p*	Values	*k*	*d*	*SE*	95% CI
Type of interaction	2	2.39	.303	System-guided***	11	0.97	0.27	[0.43, 1.51]
				Open-ended	6	0.57	0.34	[−0.10, 1.24]
				Task-oriented***	83	0.50	0.14	[0.23, 0.76]
Type of system	3	1.49	.685	Narrative	4	0.31	0.49	[−0.65, 1.27]
				Form-focused**	15	0.87	0.27	[0.33, 1.40]
				Goal-oriented**	75	0.53	0.16	[0.21, 0.85]
				Reactive	6	0.57	0.37	[−0.16, 1.30]
Meaning constraints	3	6.93	.074	None	6	0.56	0.30	[−0.03, 1.15]
				Implicit***	75	0.52	0.13	[0.27, 0.78]
				Explicit*	15	0.44	0.22	[0.01, 0.86]
				Pre-set***	4	1.59	0.40	[0.80, 2.37]
Modality	1	0.00	1.00	Spoken***	35	0.59	0.17	[0.25, 0.93]
				Written***	65	0.59	0.17	[0.25, 0.93]
Corrective feedback	2	2.08	.354	No*	23	0.38	0.19	[0.01, 0.75]
				Implicit***	39	0.68	0.15	[0.38, 0.98]
				Explicit***	38	0.73	0.16	[0.42, 1.05]
Embodied agent	1	0.97	.325	No***	83	0.53	0.13	[0.28, 0.78]
				Yes***	17	0.73	0.19	[0.37, 1.10]
Gamification*	1	4.93	.026	No***	83	0.45	0.12	[0.22, 0.68]
				Yes***	17	0.99	0.21	[0.57, 1.41]

Note. *** $p < .001$ ** $p < .01$ * $p < .05$.

Outcome Moderators

As shown in Table 7, there is a significant difference between the effects on the *type of learning outcome*: dialogue-based CALL seems to have the highest impact on production outcomes and knowledge tests, while there was no significant effect on comprehension outcomes—but it may also be due to their under-representation ($k = 4$). It does, however, seem logical that active practice in dialogue-based CALL has a higher impact on productive skills. When considering a more specific classification of outcomes in terms of *dimension* of L2 proficiency being tested, the difference is still significant, with most notable effects on lexical development, holistic proficiency, and accuracy in production.

Also, the type of *testing instrument* significantly influences the results. It seems that tests asking for free constructed and constrained responses (more open-ended), as well as meta-linguistic judgement, are more sensitive to the effects than selected responses. This, again, is consistent with the mentioned focus on production.

The *modality* (oral versus written) of the system and the modality of the test have no significant influence on the effect size. While it is impressive how written and spoken systems have statistically identical effects in this data set, it is interesting that their interaction (i.e., the fact that the test targets the same modality as the one practiced in the system) had a significant influence on the effects: studies with matching modality had more than twice the effect size of the others. This fact provides insight on the question regarding transfer of ability across modalities; while some transfer of gains could be seen from written practice to speaking skills (*d* = 0.29, 95% CI [-0.21, 0.79]), and vice versa, from oral practice to writing (*d* = 0.19, [-0.31, 0.70]), it seems this transfer is quite limited in comparison with skill practice and acquisition in the same modality, either writing (*d* = 0.65, [0.27, 1.04]) or speaking (*d* = 0.84, [0.42, 1.26]).

In regards to the *temporality of effects*, we do not observe in this meta-analysis a clear difference between the effects on immediate posttests (*d* = 0.59, [0.36, 0.83]) and delayed posttests (*d* = 0.56, [0.24, 0.88]), which could indicate that the effects of dialogue-based CALL practice are generally well sustained in the long-term.

Table 7

Moderator Analyses for Outcome Variables

Variable	***df***	***Q***	***p***	**Values**	***k***	***d***	***SE***	**95% CI**
Outcome type**	2	13.43	.001	Knowledge test***	36	0.65	0.16	[0.34, 0.97]
				Comprehension	4	−0.49	0.33	[−1.14, 0.16]
				Production***	60	0.67	0.15	[0.37, 0.97]
Outcome dimension**	7	18.52	.010	Grammar*	21	0.50	0.20	[0.11, 0.90]
				Vocabulary**	15	0.84	0.27	[0.32, 1.36]
				Reading	1	0.63	0.71	[−0.77, 2.03]
				Listening	3	−0.58	0.35	[−1.28, 0.11]
				Complexity	2	0.82	0.47	[−0.11, 1.75]
				Accuracy**	28	0.60	0.18	[0.24, 0.96]
				Fluency	18	0.39	0.22	[−0.04, 0.81]
				Holistic proficiency**	12	0.73	0.25	[0.25, 1.22]
Test type*	3	10.23	.017	Free response***	38	0.66	0.19	[0.29, 1.02]
				Free response***	38	0.66	0.19	[0.29, 1.02]
				Constrained resp.***	32	0.85	0.19	[0.48, 1.22]
				Selected response	10	0.08	0.24	[−0.38, 0.54]
				Metaling. judgment***	20	0.74	0.21	[0.33, 1.15]
Test modality	1	0.03	.872	Spoken***	39	0.57	0.15	[0.28, 0.87]
				Written***	61	0.60	0.13	[0.34, 0.86]
Matching modality**	1	7.91	.005	No	28	0.27	0.17	[−0.06, 0.59]
				Yes***	72	0.71	0.13	[0.46, 0.96]
Temporality	1	0.06	.805	Short-term***	77	0.59	0.12	[0.36, 0.83]
				Long-term***	23	0.56	0.16	[0.24, 0.88]

Note. *** $p < .001$ ** $p < .01$ * $p < .05$.

Discussion and Conclusion

This meta-analysis is, to the best of our knowledge, the first to summarize the effectiveness of dialogue-based CALL systems—including dialogue systems, chatbots, and conversational agents—on L2 proficiency development. Methodologically it is also one of the first meta-analyses in applied linguistics to use a multilevel modelling approach to allow the inclusion of multiple effect sizes per study and the use of effect size conversion formulas to use a single metric across research designs. These methodological innovations allowed us to draw more insight into the relative effectiveness of dialogue systems for language learning, which we summarize and discuss hereafter.

How Effective is Dialogue-based CALL?

The results obtained from this multilevel meta-analysis indicate that dialogue-based CALL has a significant medium effect of $\bar{d}_{IG} = 0.58$ [0.35, 0.82] on L2 proficiency development when expressed in between-subjects metric. This overall effect is comparable to what some other meta-analyses have observed for CALL interventions (e.g., $d = 0.53$ for game-based learning in Chiu et al., 2012 or $d = 0.44$ for CMC in Lin, 2015a). It is, however, smaller than the averaged effect size ($d = 0.84$) calculated by Plonsky and Ziegler (2016) in their second-order synthesis of CALL.

When compared with other forms of interaction for language learning, dialogue-based CALL is roughly similar in its effectiveness. For instance, Mackey and Goo (2007) evaluated the overall effect of interaction at $d = 0.75$. It also stands within the range of observed effects that text-based chat has on L2 proficiency when measured in various meta-analyses ($d = 0.44$ in Lin, 2015b; $d = 1.13$ in Ziegler, 2016). However, it is quite low in comparison with the effects of interactional interventions on more focused grammatical and lexical acquisition, measured via knowledge tests rather than via L2 performance tests, as synthesized by Keck et al. (2006) at $d_{RM} = 1.17$.

In the current state of technology, dialogue systems can do their best to emulate interactions with human interlocutors and possibly systematize certain features such as corrective feedback, but there are still many shortcomings preventing them from being entirely up to the task. Such applications are thus made to compensate for a lack of real interactional opportunities, not to replace them, and can only hope to achieve an effectiveness that is close enough.

How do Different Implementations of Dialogue-based CALL Compare in Effectiveness?

The results of our moderator analyses should be interpreted at a very different degree of evidence in contrast with the previous conclusions regarding overall effectiveness, as most moderators do not achieve significance in Q-tests. The relative immaturity of the field, with few effectiveness studies and most being done on small samples, does not allow us to draw firm conclusions. Most of our observations here are strictly exploratory and should be regarded only as hinting at new hypotheses that remain to be tested.

In general, this meta-analysis provides supportive evidence for the claim that "the differences between human-computer interaction and human-only interaction do not bring about vastly different conditions for language learning" (Wilske, 2015, p. 244). In this sense, moderators known to affect the effectiveness of traditional forms of L2 interaction—such as corrective feedback (as previously demonstrated by Petersen, 2010; Wilske, 2015), treatment length, or sessions spacing—seem to behave similarly in dialogue-based CALL.

Which Systems Perform Best?

In terms of the general architecture of dialogue-based CALL systems, form-focused systems ($d = 0.87$, [0.33, 1.40]), as in Taguchi et al. (2017) and Harless et al. (1999), and goal-oriented systems ($d = 0.56$, [0.21, 0.85]), such as *POMY* (Noh et al., 2012), both achieve significant effects on their own, while effects from reactive ($d = 0.57$, [-0.16, 1.30]) and narrative systems ($d = 0.31$, [-0.65, 1.27]) are unclear due to the limited number of effectiveness studies for these two types. In any case, it is not yet confirmed whether dialogue-based CALL effectiveness would follow the distinction observed by Y.-H. Chiu et al. (2012) in their meta-analysis of games for language learning—that meaningful and engaging applications might have a much stronger effect than drill-and-practice ones.

Focusing on the interactional design of the dialogue management, system-guided interactions present potentially the strongest effect ($d = 0.97$, [0.43, 1.51]), in comparison to task-oriented interactions ($d = 0.50$, [0.23, 0.76]). It is in line with the effects produced by the type of meaning constraints on learner production, with fixed meaning producing very high effect sizes ($d = 1.59$, [0.80, 2.37]). This seems to favor system-guided interactions (i.e., highly constrained and fewer interactive dialogues) to the detriment of much more complex task-oriented interactions. A possible explanation is that, because the technological cost and the unpredictability of system-guided interactions are low, more attention can be dedicated to conversation design, complexity adaptation, and progressive introduction of target structures. In other words, trading off technological design for instructional design could be beneficial. If this difference was confirmed, it could discourage the development of complex dialogue management systems in favor of more constrained scripted dialogues. However, this might also be due to system-guided interactions, typically used in form-focused contexts, which assess learning on narrower and more achievable outcomes.

Regarding instructional features, corrective feedback seems to allow for higher learning gains, although not significantly in this meta-analysis ($b = 0.33$, [-0.14, 0.79], $p = .169$). There was no visible difference here between implicit (recasts, mostly) and explicit forms of feedback. These results are in line with previous evidence on the effects of corrective feedback in SLA (Li, 2010) and confirm the conclusions of Petersen (2010) and Wilske (2015) that corrective feedback in human-computer interactions could "be as effective at promoting L2 development as in an oral, dyadic context" (Petersen, 2010, p. 188). The lower relative effect of feedback here (in comparison with $d = 0.64$ in Li's 2010 meta-analysis) can probably be understood through the fact that in dialogue-based CALL, even in the absence of corrective feedback, there are always multiple forms of interactional and communicative feedback through the agent's responses, and thus the control condition is not the same as in SLA feedback studies. On the other hand, it is striking that the overall effect of dialogue-based CALL *with* corrective feedback ($d = 0.70$) is even closer to the mean effects of CALL or L2 interaction encountered in the above-mentioned meta-analyses (Mackey & Goo, 2007; Plonsky & Ziegler, 2016), as these interventions typically do include feedback.

Dialogue-based CALL applications that used some form of gamification had a significantly stronger impact on L2 development ($b = 0.54$, [0.06, 1.01], $p = .026$). These results advocate for the integration of game-based elements and for motivational considerations in the design of future dialogue systems.

On the other hand, the embodiment of the agent in the learning environment, as a virtual avatar or a physical robot, did not bring about significant changes in comparison with speech-only interfaces, even though the included studies that used agents with a visible representation had slightly higher effects ($b = 0.20$, [-0.20, 0.60], $p = .325$). The lack of significant difference is in line with the results of Rosenthal-von der Pütten et al. (2016), which did not find any effect from the type of embodiment, not even on perception of the system by the participants; contradictory to the review of Li (2015), which concluded that the physical presence of robots led to improved user perception and performance.

For Whom is it Most Effective?

In the past, some studies have reported tendencies towards higher effectiveness of dialogue-based CALL for low to moderate proficiency (Kaplan et al., 1998) or low-achieving learners (Huang et al., 2008), while others have hypothesized that because of the possible communication breaks and lack of adaptivity in open-ended systems, it might be more adequate for advanced learners (Fryer & Carpenter, 2006). This meta-analysis tends to support the idea that the learning gains may diminish for higher proficiency users, although the evidence for confirming this claim is still insufficient. Our results could not verify statistically significant effects for B1 learners, but more strikingly, there are no signs of positive learning gains for advanced learners (B2) at all. In contrast, the positive effects on beginner and lower-intermediate proficiency learners (A1 and A2) are established by the moderator analysis. We hypothesize that the meaningful practice of the target language facilitated by dialogue-based CALL is especially fruitful in the consolidation stages of the learning process, when some explicit linguistic knowledge foundations have been laid but production skills, in particular spoken exchanges with other speakers, may still be hindered by L2 anxiety and lack of practice.

In addition, age does not seem to have any significant impact on the effectiveness of these systems and there is no significant difference between school, university, and lab-based experiments. These results are in accord with observations of Jia (2009), which found no difference across age or educational context, and with what has been corroborated regarding CALL interventions in general (Grgurović et al., 2013).

For Which Learning Outcomes is it Most Effective?

What language learning outcomes are best impacted by dialogue-based CALL practice? Generally, the main research claim on intelligent tutors, as summarized by Golonka et al. (2014, p. 89), is that “learners demonstrate pretest-posttest gains in different areas, including speaking, reading comprehension, vocabulary, grammar, [and] fluency,” which holds here now with an updated and more quantitative evaluation of empirical evidence. More precisely, statistically significant effect sizes are established for vocabulary and morphosyntactic outcomes in knowledge tests, and for holistic proficiency and accuracy measures on production. Effects on fluency could be less important and remain to be demonstrated. Furthermore, effects on complexity as well as reading and listening comprehension have been insufficiently studied to present any clear pattern.

On the question of transferring this learning across modalities, this meta-analysis provides new insights about the quality of this transfer. First, it is noteworthy that primarily spoken and primarily written interface systems have virtually identical effect sizes, and that the effects on spoken tests and written tests are extremely close—statistically indistinguishable. But while modalities of practice and outcome do not seem to matter in isolation, their interaction, however, does make a statistically significant difference: effect sizes increase threefold when practice and test modalities are the same ($b = 0.44$, $p = .005$). While this finding does not invalidate previous evidence that written practice, particularly in computer-mediated communication, could promote the development of oral proficiency (e.g., Lin, 2015b), as effect size for non-matching modalities is not null, it does put this transfer into perspective as possibly partial and not equally effective as practicing in the same oral modality (Ziegler, 2016).

Limitations

This study is not without limitations. As most meta-analyses, despite our rigorous selection process, our data set suffers from biases. The most important limitation here is probably an issue of power: we could only include a small number of independent studies, which themselves have on average very small sample sizes. The total number of participants ($N = 803$) remains relatively low in comparison with other meta-analyses. Therefore, it should be emphasized that dialogue-based CALL strongly needs larger experimental studies to test most research questions.

We tried to avoid a publication bias by not restricting our inclusion process to peer-reviewed publications only. However, apart from the two included dissertations, we could not find unpublished effectiveness data, and it appears, according to the funnel plot presented in Figure 2, that some studies might have produced negative effects that the researchers decided not to publish.

This is linked to the fact that nearly all researchers who conducted the effectiveness evaluations were also the designers of each evaluated system or part of the same team. And even in the case of the one researcher who did evaluate an external system (Kim, 2016, evaluating *Indigo*), as this system was a general-purpose chatbot, the instructions built around it to transform the tool into a pedagogical task were designed by the same researcher. Hence, there is a high risk that any negative or inconclusive findings on the effectiveness of these systems may have been ignored or have simply not made it to publication (a very acute publication bias in fact). This is somewhat indicated in our meta-analysis through the absence of any clearly negative effects, as observed in Figure 2. Obviously, this self-evaluation bias is in great part explained by the relative novelty of the object and the extremely limited availability of previously developed systems, which usually remain at the level of internal prototypes and are rarely available to the public (Sydorenko et al., 2019).

Finally, the relatively high heterogeneity of the included studies could be regarded as problematic. We believe that these studies all share a common rationale and supporting theory—practicing an L2 through dialogue, including with an artificial conversation partner, leads to improvements in the learner's ability to use the language—and that their heterogeneity is also an opportunity to learn in detail how different variables impact the learning process. Yet, the differences between, for instance, form-focused and goal-oriented dialogue systems, are important, as is the variation in learning outcomes and testing procedures. In addition to the limited number of independent studies, and the even smaller number of research teams (11) represented in our meta-analysis, this fact could lead to strong biases in the moderator analyses.

Because of these shortcomings, our global effect size should be taken with caution and as mentioned above, our moderator analyses should only be regarded as exploratory and indicating potential hypotheses to test on new data. More generally, for the advancement of the field, more external effectiveness evaluations of systems conducted by independent researchers should be encouraged.

Maturity of the Field and Avenues for Research

The research domain of dialogue-based CALL is gradually entering a more mature phase, wherein systematic experiments are conducted to verify the main claims that have been at the foundations of developments in the field since its inception. It is still early, and the number of meta-analyzable studies remains limited. In particular, the lack of independent evaluations of these systems (i.e., experimental studies conducted by teams independent of their designers) certainly limits the strength of any claims of usefulness. This fact is intimately connected to the lack of access for the public to previously developed systems, most of which remained at a prototype level (Bibauw et al., 2019).

However, research and industry have recently shown encouraging signs of change on this matter, with major commercial players such as Duolingo, ETS, and Alelo releasing or planning to release public dialogue-based CALL applications. There is also incipient collaborations between industry and academia to compare the systems and establish common ground (Sydorenko et al., 2019). Such efforts could open the field both to a large audience of language learners and to many research opportunities.

We can also hope for future technological advances in natural language understanding and dialogue management making their way into dialogue-based CALL systems. To date, dialogue systems have not yet witnessed the breakthroughs that deep learning has brought to other NLP tasks, at least not with the same magnitude (Serban et al., 2018). While research on dialogue systems is actively pursuing fully data-driven end-to-end approaches, systems used in production tend to opt for rule-based and hybrid approaches, combining ad hoc and handcrafted subsystems to achieve satisfactory results (Harms et al., 2019). Currently, these approaches require very intensive manual work and offer limited scalability and adaptability, but hopefully probabilistic solutions will soon be adaptable for final-user applications.

From the available experimental studies to date, this meta-analysis has demonstrated that, overall, the effectiveness of dialogue-based CALL is comparable to other CALL or instructed SLA interventions, in particular when dialogue systems provide corrective feedback. Future research should thus focus more on which affordances and implementations of such systems provide better results, rather than comparing dialogue systems in general to other CALL or traditional instruction methods. As Chun (2016) reminds us, "a primary research question is not whether technology-based instruction is effective, but rather under what conditions and for whom" (p. 107).

Our moderator analyses have attempted to clear the path for future system design and evaluation by identifying trends and insights hidden in previous studies regarding the relative effectiveness of certain designs and features for defined populations and learning outcomes. While these findings are essentially exploratory, they present many questions that could be addressed in future investigations. Do relatively free task-oriented dialogue systems provide better learning opportunities than more constrained, possibly fully scripted, guided interactions? Is it possible, as our findings may suggest, that the major technological complexity and development efforts required for freer task-oriented systems do not necessarily lead to increases in learning outcomes? Would it instead be more beneficial to invest this development time in instructional content design? Is the incompleteness of transfer across modalities confirmed? Is there a significant effect on fluency, and is it indeed lower than on other dimensions of proficiency? Many more questions regarding the optimal technological and instructional design choices, the most useful features to implement, and the most benefited outcomes and types of learners are still in need of empirical responses. We hope that in the future SLA and CALL researchers, NLP and AI developers, and language learning content creators will be able to join their efforts to answer them.

Supplementary Materials

The supplementary materials for this study can be found online on the Open Science Framework and on IRIS. It includes the following information:

A. Supplementary Methods: additional information about data collection and selection, coding, computation of comparable effect size metrics across designs, estimation of undisclosed parameters, and adaptation of certain results.
B. Individual study results: effect size and main descriptive variables for all $k = 100$ effects.
C. List of identified publications.
D. Processing script in R.

Acknowledgements

We would like to thank Larissa Hoekstra for the double coding of the data. Many thanks to our colleagues, in particular to Anaïs Tack, for their comments on early versions of the manuscript. Thanks to the authors who answered our questions about their data: K. Arispe, J. McDonald, H. Morton, K. Lee, P.Vlugter, and S. Wilske. This research was made possible thanks to a SENESCYT (Ecuador) scholarship to the first author.

Notes

1. The list of considered publications is provided in the Supporting Information.

2. $J(df)$ is based on the degrees of freedom of the design, calculated from the sub-sample sizes (n) in each study as $df_{RM} = n_E - 1$ and $df_{IGRM} = n_E + n_C - 2$.

3. Given this exploratory purpose, we do not apply Bonferroni corrections for multiple comparisons.

References

*Publications included in the meta-analysis are preceded by an asterisk.

Arispe, K. (2014). What's in a bot? L2 lexical development mediated through ICALL. *Open Journal of Modern Linguistics*, *4*(1), 150–165. https://doi.org/10.4236/ojml.2014.41013

Basiron, H. B. (2008). Corrective feedback in dialogue-based computer assisted language learning. In J. Holland, A. Nicholas, & D. Brignoli (Eds.), *New Zealand Computer Science Research Student Conference* (pp. 192–195). NZCSRSC. http://eprints.utem.edu.my/42/

Bibauw, S., François, T., & Desmet, P. (2019). Discussing with a computer to practice a foreign language: Research synthesis and conceptual framework of dialogue-based CALL. *Computer Assisted Language Learning*, *32*(8), 827–877. https://doi.org/10.1080/09588221.2018.1535508

*Bouillon, P., Rayner, E., Tsourakis, N., & Qinglu, Z. (2011). A student-centered evaluation of a web-based spoken translation game. In *ISCA International Workshop on Speech and Language Technology in Education (SLaTE 2011)* (pp. 33-36). ISCA. https://www.isca-speech.org/archive_v0/slate_2011/papers/sl11_033.pdf

Chiu, T.-H., Liou, H.-C., & Yeh, Y. (2007). A study of web-based oral activities enhanced by automatic speech recognition for EFL college learning. *Computer Assisted Language Learning*, *20*(3), 209–233. https://doi.org/10.1080/09588220701489374

Chiu, Y.-H., Kao, C.-W., & Reynolds, B. L. (2012). The relative effectiveness of digital game-based learning types in English as a foreign language setting: A meta-analysis. *British Journal of Educational Technology*, *43*(4), E104–E107. https://doi.org/10.1111/j.1467-8535.2012.01295.x

Chun, D. M. (2016). The role of technology in SLA research. *Language Learning & Technology*, *20*(2), 98–115. https://doi.org/10125/44463

Ellis, N. C., & Bogart, P. S. H. (2007). Speech and language technology in education: The perspective from SLA research and practice. In *ISCA International Workshop on Speech and Language Technology in Education (SLaTE 2007)* (pp. 1–8). ISCA. https://www.isca-speech.org/archive_open/slate_2007/sle7_001.html

Fernández-Castilla, B., Declercq, L., Jamshidi, L., Beretvas, N., Onghena, P., & Van den Noortgate, W. (2020). Visual representations of meta-analysis of multiple outcomes: Augmentations to forest plots, funnel plots, and caterpillar plots. *Methodology*, *16*(4), 299–315. https://doi.org/10.5964/meth.4013

Fryer, L., & Carpenter, R. (2006). Bots as language learning tools. *Language Learning & Technology*, *10*(3), 8–14. https://doi.org/10125/44068

Golonka, E. M., Bowles, A. R., Frank, V. M., Richardson, D. L., & Freynik, S. (2014). Technologies for foreign language learning: A review of technology types and their effectiveness. *Computer Assisted Language Learning*, *27*(1), 70–105. https://doi.org/10.1080/09588221.2012.700315

Grgurović, M., Chapelle, C. A., & Shelley, M. C. (2013). A meta-analysis of effectiveness studies on computer technology-supported language learning. *ReCALL*, *25*(2), 165–198. https://doi.org/10.1017/S0958344013000013

*Harless, W. G., Zier, M. A., & Duncan, R. C. (1999). Virtual dialogues with native speakers: The evaluation of an interactive multimedia method. *CALICO Journal*, *16*(3), 313–337. https://journal.equinoxpub.com/CALICO/article/view/16544

Harms, J.-G., Kucherbaev, P., Bozzon, A., & Houben, G.-J. (2019). Approaches for dialog management in conversational agents. *IEEE Internet Computing*, *23*(2), 13–22. https://doi.org/10.1109/MIC.2018.2881519

*Hassani, K., Nahvi, A., & Ahmadi, A. (2016). Design and implementation of an intelligent virtual environment for improving speaking and listening skills. *Interactive Learning Environments*, *24*(1), 252–271. https://doi.org/10.1080/10494820.2013.846265

Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. Academic Press.

Higgins, J. P. T., & Green, S. (Eds.). (2008). *Cochrane handbook for systematic reviews of interventions*. Wiley-Blackwell. https://www.training.cochrane.org/handbook

Huang, Y.-T., Lin, Y.-L., Yang, J.-C., & Wu, Y.-C. (2008). An English dialogue companion system for supporting conversation practice. In *16th International Conference on Computers in Education* (pp. 43–48). APSCE. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.373.1434&rep=rep1&type=pdf

Jia, J. (2009). An AI framework to teach English as a Foreign Language: CSIEC. *AI Magazine*, *30*(2), 59–71. https://doi.org/10.1609/aimag.v30i2.2232

Kaplan, J. D., Sabol, M. A., Wisher, R. A., & Seidel, R. J. (1998). The Military Language Tutor (MILT) program: An advanced authoring system. *Computer Assisted Language Learning*, *11*(3), 265–87. https://doi.org/10.1076/call.11.3.265.5679

Keck, C., Iberri-Shea, G., Tracy-Ventura, N., & Wa-Mbaleka, S. (2006). Investigating the empirical link between task-based interaction and acquisition: A meta-analysis. In J. M. Norris & L. Ortega (Eds.), *Synthesizing research on language learning and teaching* (pp. 91–131). John Benjamins. https://doi.org/10.1075/lllt.13.08kec

*Kim, N.-Y. (2016). Effects of voice chat on EFL learners' speaking ability according to proficiency levels. *Multimedia-Assisted Language Learning*, *19*(4), 63–88. http://journal.kate.or.kr/wp-content/uploads/2017/04/07Na_Young_Kim.pdf

*Lee, K., Kweon, S.-O., Lee, S., Noh, H., & Lee, G. G. (2014). POSTECH immersive English study (POMY): Dialog-based language learning game. *IEICE Transactions on Information and Systems*, *E97.D*(7), 1830–1841. https://doi.org/10.1587/transinf.E97.D.1830

*Lee, S., Noh, H., Lee, J., Lee, K., Lee, G. G., Sagong, S., & Kim, M. (2011). On the effectiveness of robot-assisted language learning. *ReCALL*, *23*(1), 25–58. https://doi.org/10.1017/s0958344010000273

Li, J. (2015). The benefit of being physically present: A survey of experimental works comparing copresent robots, telepresent robots and virtual agents. *International Journal of Human-Computer Studies*, *77*, 23–37. https://doi.org/10.1016/j.ijhcs.2015.01.001

Li, S. (2010). The effectiveness of corrective feedback in SLA: A meta-analysis. *Language Learning*, *60*(2), 309–365. https://doi.org/10.1111/j.1467-9922.2010.00561.x

Lin, H. (2015a). A meta-synthesis of empirical research on the effectiveness of computer-mediated communication (CMC) in SLA. *Language Learning & Technology*, *19*(2), 85–117. https://doi.org/10125/44419

Lin, H. (2015b). Computer-mediated communication (CMC) in L2 oral proficiency development: A meta-analysis. *ReCALL*, *27*(3), 261–287. https://doi.org/10.1017/S095834401400041X

Mackey, A., & Goo, J. (2007). Interaction research in SLA: A meta-analysis and research synthesis. In A. Mackey (Ed.), *Conversational interaction in second language acquisition* (pp. 407–452). Oxford University Press.

Morris, S. B., & DeShon, R. P. (2002). Combining effect size estimates in meta-analysis with repeated measures and independent-groups designs. *Psychological Methods*, *7*(1), 105–125. https://doi.org/10.1037/1082-989x.7.1.105

Nassaji, H., & Kartchava, E. (Eds.). (2017). *Corrective feedback in second language teaching and learning: Research, theory, applications, implications*. Routledge. https://doi.org/10.4324/9781315621432

*Noh, H., Ryu, S., Lee, D., Lee, K., Lee, C., & Lee, G. G. (2012). An example-based approach to ranking multiple dialog states for flexible dialog management. *IEEE Journal of Selected Topics in Signal Processing*, *6*(8), 943–958. https://doi.org/10.1109/JSTSP.2012.2229692

Norris, J. M., & Ortega, L. (2000). Effectiveness of L2 instruction: A research synthesis and quantitative meta-analysis. *Language Learning*, *50*(3), 417–528. https://doi.org/10.1111/0023-8333.00136

*Petersen, K. A. (2010). *Implicit corrective feedback in computer-guided interaction: Does mode matter?* [Unpublished doctoral dissertation]. Georgetown University. https://doi.org/10822/553155

Plonsky, L. (2011). The effectiveness of second language strategy instruction: A meta-analysis. *Language Learning*, *61*(4), 993–1038. https://doi.org/10.1111/j.1467-9922.2011.00663.x

Plonsky, L., & Oswald, F. L. (2014). How big is "big"? Interpreting effect sizes in L2 research. *Language Learning*, *64*(4), 878–912. https://doi.org/10.1111/lang.12079

Plonsky, L., & Oswald, F. L. (2015). Meta-analyzing second language research. In L. Plonsky (Ed.), *Advancing quantitative methods in second language research* (pp. 106–128). Routledge. https://dx.doi.org/10.4324/9781315870908-8

Plonsky, L., & Ziegler, N. (2016). The CALL-SLA interface: Insights from a second-order synthesis. *Language Learning & Technology*, *20*(2), 17–37. https://doi.org/10125/44459

*Rosenthal-von der Pütten, A. M., Straßmann, C., & Krämer, N. C. (2016). Robots or agents: Neither helps you more or less during second language acquisition. In D. Traum, W. Swartout, P. Khooshabeh, S. Kopp, S. Scherer, & A. Leuski (Eds.), *Intelligent virtual agents* (pp. 256–268). Springer. https://doi.org/10.1007/978-3-319-47665-0_23

Serban, I. V., Lowe, R., Henderson, P., Charlin, L., & Pineau, J. (2018). A survey of available corpora for building data-driven dialogue systems. *Dialogue & Discourse*, *9*(1), 1–49. https://doi.org/10.5087/dad.2018.101

Sydorenko, T., Daurio, P., & Thorne, S. L. (2018). Refining pragmatically-appropriate oral communication via computer-simulated conversations. *Computer Assisted Language Learning*, *31*(1–2), 157–180. https://doi.org/10.1080/09588221.2017.1394326

Sydorenko, T., Smits, T. F. H., Evanini, K., & Ramanarayanan, V. (2019). Simulated speaking environments for language learning: Insights from three cases. *Computer Assisted Language Learning*, *32*(1–2), 17–48. https://doi.org/10.1080/09588221.2018.1466811

*Taguchi, N., Li, Q., & Tang, X. (2017). Learning Chinese formulaic expressions in a scenario-based interactive environment. *Foreign Language Annals*, *50*(4), 641–660. https://doi.org/10.1111/flan.12292

Van den Noortgate, W., López-López, J. A., Marín-Martínez, F., & Sánchez-Meca, J. (2013). Three-level meta-analysis of dependent effect sizes. *Behavior Research Methods*, *45*, 576–594. https://doi.org/10.3758/s13428-012-0261-6

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, *36*(3), 1–48. https://doi.org/10.18637/jss.v036.i03

Wang, N., & Johnson, W. L. (2008). The politeness effect in an intelligent foreign language tutoring system. In B. P. Woolf, E. Aïmeur, R. Nkambou, & S. Lajoie (Eds.), *Intelligent tutoring systems (ITS 2008)* (pp. 270–280). Springer. https://doi.org/10.1007/978-3-540-69132-7_31

*Wilske, S. (2015). *Form and meaning in dialog-based computer-assisted language learning* [Unpublished doctoral dissertation]. Universität des Saarlandes. https://doi.org/10.22028/D291-23654

*Wilske, S., & Wolska, M. (2011). Meaning versus form in computer-assisted task-based language learning: A case study on the German dative. *Journal for Language Technology and Computational Linguistics*, *26*(1), 23–37. https://jlcl.org/content/2-allissues/14-Heft1-2011/3.pdf

*Wolska, M., & Wilske, S. (2010a). Form-focused task-oriented dialogues for computer assisted language learning: A pilot study on German dative. In *ISCA International Workshop on Speech and Language Technology in Education (SLaTE 2010)*. ICSA. https://www.coli.uni-saarland.de/~sw/publications/slate10.pdf

*Wolska, M., & Wilske, S. (2010b). German subordinate clause word order in dialogue-based CALL. In *Proceedings of the 2010 International Multiconference on Computer Science and Information Technology (IMCSIT)* (pp. 553–559). IEEE. https://www.coli.uni-saarland.de/~sw/publications/cla10.pdf

*Wolska, M., & Wilske, S. (2011). Assessing the effect of type-written form-focused dialogues on spoken language fluency. In *ISCA International Workshop on Speech and Language Technology in Education (SLaTE 2011)* (pp. 57–60). ISCA. https://www.coli.uni-saarland.de/~sw/publications/Wolska_Wilske_2011_slate-11.pdf

Ziegler, N. (2016). Synchronous computer-mediated communication and interaction: A meta-analysis. *Studies in Second Language Acquisition, 38*(3), 553–586. https://doi.org/10.1017/S027226311500025X

About the Authors

Serge Bibauw is Professor of Language Teaching Methods in the English teacher education program at Universidad Central del Ecuador. He is also affiliated with the imec-research team ITEC at KU Leuven, where he is concluding his PhD, and the CENTAL and TeAMM research groups at UCLouvain, in Belgium. His research focuses on the use and effectiveness of dialogue systems for language learning.

E-mail: sbibauw@uce.edu.ec

Wim Van den Noortgate is Full Professor of Statistics at the Faculty of Psychology and Educational Sciences and at ITEC, an imec research group at KU Leuven focusing on domain-specific educational technology. His major research lines are learning analytics and meta-analysis.

E-mail: wim.vandennoortgate@kuleuven.be

Thomas François is Associate Professor of Applied Linguistics and Natural Language Processing at UC Louvain, Belgium. He is currently leading a team of about 15 researchers and is coordinating projects focusing on efficient communication in business contexts, automatic readability assessment, automatic text simplification, and computer-assisted language learning.

E-mail: thomas.francois@uclouvain.be

Piet Desmet is Full Professor of French and Applied Linguistics and Computer-Assisted Language Learning at KU Leuven. He coordinates the imec research team ITEC, focusing on domain-specific educational technology with a main interest in language learning and technology. He leads a range of research projects in this field devoted to topics such as the effectiveness of adaptive and personalized learning environments.

E-mail: piet.desmet@kuleuven.be