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# Personalization of language learning through adaptive technology

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# Definitions and claims

The purpose and promise of adaptive technologies is to facilitate online instruction that is personalized to the needs of individual learners. This paper will focus on what adaptive technologies do, or attempt to do, rather than on what they are in technical terms (e.g. the different kinds of algorithms<sup>1</sup> that constitute the technologies), but the key words in the brief functional definition above (i.e. 'adaptive' and 'personalized') are highly contested.

Personalized learning is at the heart of educational programmes around the world and there appears to be general agreement that the personalization of learning is one of the great education challenges of the twenty-first century (Trilling & Fadel, 2009: 33). It is also now so closely associated with technology that the term is sometimes used interchangeably with 'adaptive learning' (Worlock, 2015: 3). However, 'personalized learning' (see the section on 'Hype and research' below) is what the philosopher Jamie Whyte (Whyte, 2005) has described as a 'hooray word': even though it is undefined, everyone must approve of it, since its opposite, 'depersonalized learning', often disparagingly referred to as 'one-size-fits-all', inevitably evokes negative reactions. The term 'personalized learning' carries little generally agreed meaning (Feldstein & Hill, 2016; UNESCO, 2012).

There appears to be general agreement that the personalization of learning is one of the great education challenges of the twenty-first century.

Different writers continue to mean different things when referring to 'personalization' and the associated terms 'individualization' and 'differentiation' (Means et al., 2014: 14–16). For reasons of clarity, however, the disambiguation of these terms by the U.S. Department of Education (2010) is useful. Based on this taxonomy, we can say that adaptive technologies can personalize instruction as outlined below:

TYPE OF PERSONALIZATION: 'INDIVIDUALIZATION'	
<b>Learning objectives</b>	The same for all students.
<b>Pace</b>	Tailored to individual needs: some learners may need more or less repetition of material and some learners may be able to skip some material. Automated study reminders (via an app or via email) may be issued to optimise individualised pace.
<b>Order</b>	The same for all students.
<b>Instructional methods</b>	The same for all students.
<b>Additional resources</b>	Not applicable.
<b>Feedback</b>	Usually just right or wrong.
<b>Hints</b>	Not applicable.
<b>Progress</b>	Typically displayed on some kind of dashboard <sup>2</sup> that can be seen by both teachers and students.

1 Algorithms are sets of rules (for example, 'if x, then y') that are used in computing.

2 The dashboard is a visual representation of basic information, such as the amount of time the user has worked on the program, the progress that has been made and so on. The information is often represented in bar charts.

TYPE OF PERSONALIZATION: 'DIFFERENTIATION'	
<b>Learning objectives</b>	The same for all students.
<b>Pace</b>	Tailored to individual needs.
<b>Order</b>	Tailored to individual needs.
<b>Instructional methods</b>	Tailored to individual needs. Some learners may benefit from more scaffolding: breaking a learning item down into smaller constituent parts may help them. <sup>3</sup>
<b>Additional resources</b>	Available, especially remedial resources.
<b>Feedback</b>	Tailored to individual needs.
<b>Hints</b>	Tailored to individual needs.
<b>Progress</b>	Typically displayed on some kind of dashboard.

Adaptive technologies capture a learner's interactions with the software, and algorithms determine the next step in the learning programme. At the most simple level of implementation, this would be whether or not the learner has correctly completed a task or how long they have taken to complete it. The more a learner interacts with an adaptive system, it is claimed, the better the recommendations that the system can make. When information about an individual learner is compared with information about a large number of learners, an adaptive system can make more confident recommendations, by looking at what has helped similar learners.

With some systems it is possible to capture a lot of other data (beyond simple measures of right and wrong) to feed into the algorithms which generate recommendations. This can include, for example, performance on particular task types, the length of the learner's online learning sessions and their use of learning support tools (such as online dictionaries). Drawing on this data, the system may recommend a particular task type (for language presentations, this could be video or text-based or a discovery approach), shorter or longer study sessions, or greater use of a particular tool.

TYPE OF PERSONALIZATION: 'PERSONALIZATION'	
<b>Learning objectives</b>	Tailored to individual needs.
<b>Pace</b>	Tailored to individual needs.
<b>Order</b>	Tailored to individual needs.
<b>Instructional methods</b>	Tailored to individual needs.
<b>Additional resources</b>	Extensive resources available.
<b>Feedback</b>	Tailored to individual needs.
<b>Hints</b>	Tailored to individual needs. Learners who are struggling may be given more direct help.
<b>Progress</b>	Typically displayed on some kind of dashboard.

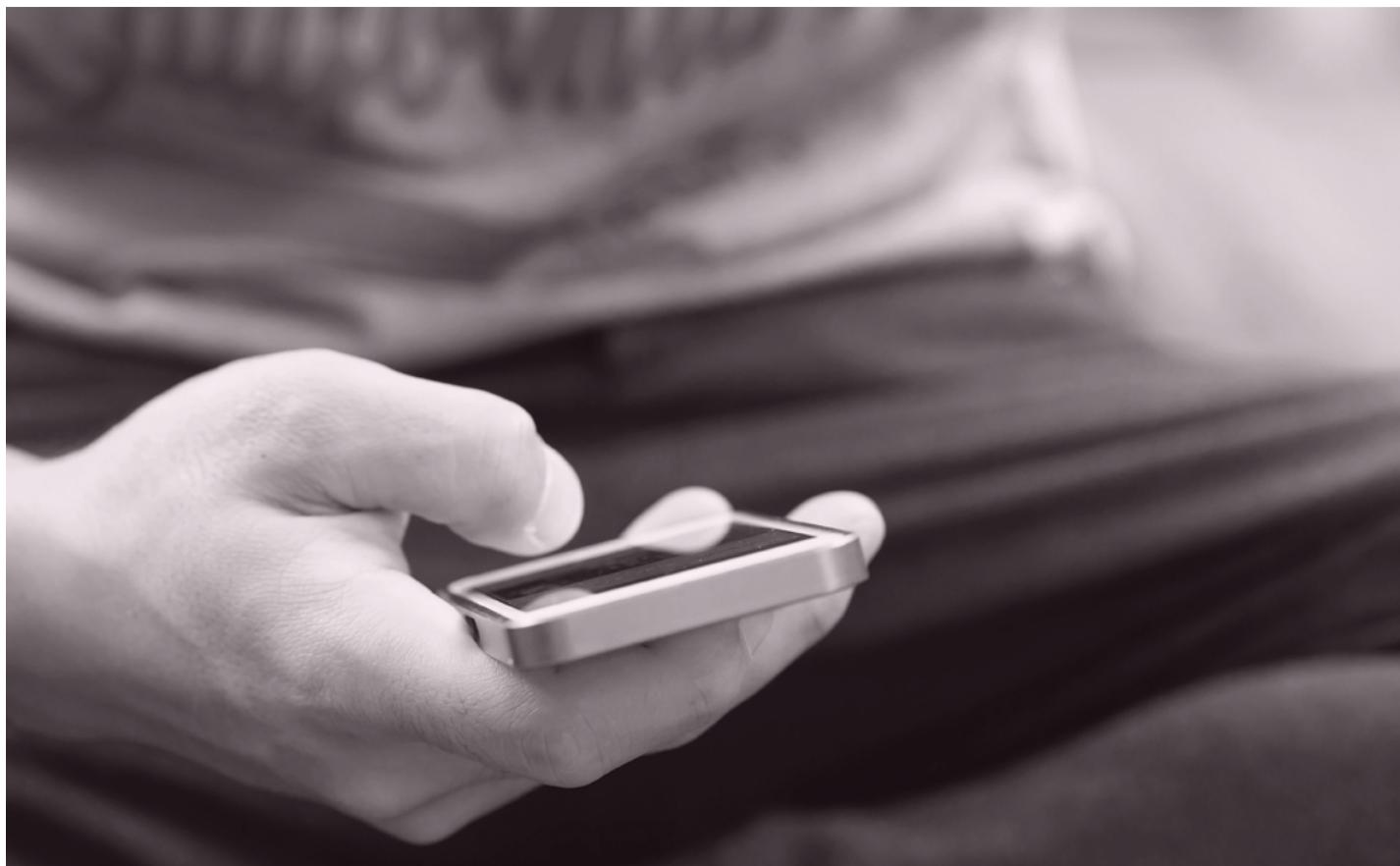
With the use of cookies<sup>4</sup>, other data about a learner's online behaviour (outside the learning software) may also be recorded. If, in addition, the learning programme is connected to institutional administrative software that holds personal information (e.g. demographic, attendance and disciplinary records), this may also be fed into the algorithms. Again, when data about one individual can be compared to larger learner populations, recommendations for next steps in a learning programme are likely to be more reliable. It is, however, worth bearing in mind that these recommendations can never be 100% reliable: there are too many differences between individual learners for this to be possible.

The simplest adaptive systems determine, in advance, how the data from an individual learner will lead to recommendations for personalized learning pathways. More complex systems can use artificial intelligence and machine learning<sup>5</sup> algorithms to analyse and find patterns in the huge amounts of data being captured.

3 It is often argued that a differentiated approach to instructional methods can cater to different 'learning styles', despite the fact that 'learning styles' are now widely recognised by researchers as a 'neuromyth' (Newton, 2015). Nevertheless, it is probable that a varied menu of task types will be highly beneficial to all users.

4 Cookies are small amounts of data about an internet user that are saved on your computer.

5 Machine learning is a kind of artificial intelligence that makes it possible for a computer to learn without being programmed to do so.



From this, the extent of the individual student's knowledge (along with other attributes) can be inferred, the likelihood of success can be quantified and automated recommendations can be made in real time (San Pedro & Baker, 2016: 241). The technology is very close to that used by companies like Google and Facebook to determine which advertisements they will present to individual users.

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**The more a learner interacts with an adaptive system, it is claimed, the better the recommendations that the system can make.**

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## **The promise of adaptive personalized learning**

It is not uncommon to hear advocates of adaptive learning talk about education systems being 'broken'. They claim that education typically operates on a nineteenth-century 'factory' model (i.e. a 'one-size-fits-all' model), which does not serve the needs of twenty-first century learners or society. Adaptive technologies are often presented as adaptive 'solutions'. Whether or not such a 'factory' model actually existed in the nineteenth century and whether or not it continues to predominate now is open to question (Watters, 2015), but few would argue with the claim that there is much that could be done to improve current practices (Enyedy, 2014: 5).

The possibility of personalizing instruction in the ways listed in the table above is certainly extremely attractive. In the process, it does not seem unreasonable to expect enhanced student motivation, increased teacher support and improved learning outcomes. What is more, in times of shrinking educational budgets, adaptive personalized learning appears to have the potential to increase educational opportunities without increasing costs. It seems to offer the promise of extending high quality, low cost instruction to greater numbers of people.

# Hype and research

The history of educational technology (dating back to even before radio and the first moving pictures) is a history of inflated claims and subsequent disappointments (Cuban, 1986). The promotion of adaptive technologies is closely linked to a more general promotion of all digital technologies in education. The interrelated organisations (intergovernmental, governmental, institutional and commercial) that are investing huge sums of money in digital education have been described by Stephen Ball (2012) and Joel Spring (2012), among others.

A cursory glance at the results generated in an online search using the search term 'adaptive learning' indicates an overwhelmingly enthusiastic response to adaptive technologies. A recent report by EdSurge (2016), commissioned by Pearson (a company that has invested very heavily in these technologies), observed that the world has 'fawned over the possibilities of adaptive learning technology' and spent hundreds of millions of dollars on its development, hoping that it would be the magic bullet that would solve the world's educational problems (EdSurge, 2016: 12).

Interest in adaptive learning peaked (according to Google Trends, which measures the frequency of online search terms) over ten years ago, in 2004. Since then, adaptive learning technologies have been widely deployed, most widely in the U.S., in both secondary and tertiary education for the teaching of academic subjects, especially mathematics. It was not, however, until much later (in 2013) that this technology began to attract serious attention in the world of English language teaching. It was in that year that Knewton, one of the largest vendors of adaptive technologies signed contracts with two large ELT (English Language Teaching) publishers, Macmillan and Cambridge University Press.

As is typical with new ideas in educational technology, enthusiasm has since waned. As of summer 2016, neither Macmillan nor Cambridge University Press have brought to market any significant products which incorporate adaptive technologies. Gartner, an IT research and advisory company, publishes regular 'Hype Cycles' which chart the popularity of new technologies. In their most recent publication (Gartner, 2015), they describe adaptive learning as having fallen into the 'trough of disillusionment', the time when a technology no longer generates as much interest as before, having failed to deliver on its earlier promises. What evidence is there that adaptive learning has failed to deliver?

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## Adaptive learning and personalization mean different things to different people.

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There are a number of problems with research into adaptive learning. First of all, as we have seen, adaptive learning and its reason for being, personalization, mean different things to different people. Secondly, adaptive technologies have not been deployed for long enough to permit reliable longitudinal research findings. Thirdly, as with all educational research, it is very difficult in practical terms to restrict the number of variables when investigating a sufficiently large number of students, thus making any conclusions very tentative, at best. Lastly, much of the research that has been carried out has been commissioned by adaptive vendors or by those with a close connection to them. There is, in fact, little if any agreement about what sort of evidence could be considered robust enough to allow meaningful conclusions to be drawn from it.



There is no shortage of reports that indicate that adaptive technologies have been beneficial in improving learning outcomes (especially in mathematics) and in improving student retention rates (see, for example, Johnson, 2016; IMS Global Learning Consortium, 2013). There is equally no shortage of teachers and educational administrators who believe that adaptive technologies have had a positive impact on their students (see, for example, Vander Ark, 2013). Nevertheless, the last few years have seen a marked swing in the opposite direction. Three reports are worth particular mention. The first of these, an academic study carried out by two researchers at Kennesaw State University (Murray & Pérez, 2015), found that adaptive technologies had negligible impact on learning outcomes (the context was a digital literacy course in higher education). The second, a report for the U.S. National Education Policy Center (Enyedy, 2014), concluded that such research as existed showed mixed results, ranging from limited to zero impact. Noting the first of the problems with research outlined above (that adaptive learning means different things to different people), the report observed that it is simply not possible, at present, to draw any firm conclusions about the efficacy of this technology.

The third, and perhaps the report of greatest interest, was commissioned by the Gates Foundation, whose multi-million dollar Adaptive Learning Market Acceleration Program (ALMAP) was set up to promote adaptive technologies. The report's brief was to investigate the extent of the efficacy of the projects supported by ALMAP. Its conclusion was as inconclusive as the report from the National Education Policy Center. It found that there is no firm evidence that adaptive learning systems are leading to better course grades or course completion (SRI Education, 2016).

Research into adaptive technologies in English language teaching contexts is extremely limited. This is unsurprising, given the relatively late take-up of adaptive learning in ELT. Some research findings will, however, be described in the next section, and the case study at the end of this white paper describes one primary research study carried out by Cambridge University Press.

# Adaptive technologies in ELT

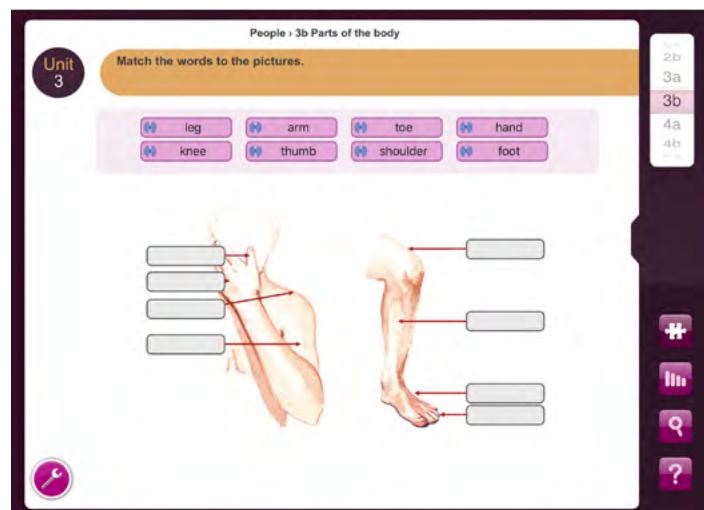
The use of adaptive technologies in English language teaching is growing relatively rapidly, but it is probably uncontroversial to say that we are in an exploratory phase as regards the potential of these technologies. The following three sub-sections will consider three very different contexts.

## Vocabulary apps

Most vocabulary apps are essentially memory trainers and can be used for the memorization of any kind of information. The software is driven by algorithms that determine the optimal interval between presentations of the items to be learned. If, for example, a student gets an answer correct, there will be a longer delay before it is re-presented than if the student gets the answer wrong. In other words, the software provides automated spaced repetition<sup>6</sup>. Typically, these trainers consist of packs of flashcards with a target item (for example, a word or a short phrase) on one side and a definition or translation on the other. Users flick through the sets of words and complete simple tasks (e.g. matching words to meanings, matching audio recordings to written forms, or typing words into gaps in sentences) or simply indicate how well they think they know the item. A user's performance on these tasks influences the order and the frequency with which individual items are presented to the learner for review. In this sense, they are personalized and adaptive learning tools, of an admittedly fairly simple nature.

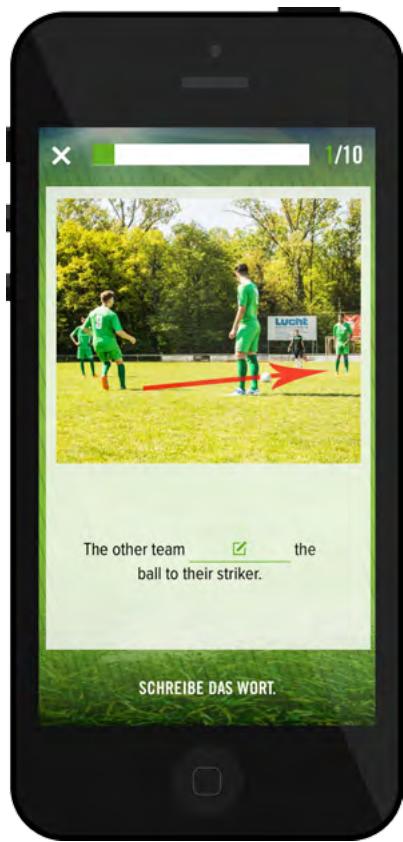


Flashcards in a vocabulary app



A matching exercise

<sup>6</sup> Early research into the psychology of memory showed that items are more effectively learned when there are progressively longer periods of time between the moments when a student studies a particular item. It is now well established that this kind of study is more effective than 'cramming' – very intensive study over a short period of time. Spaced repetition is a technique that draws on this insight.



#### A gap-fill exercise

In addition to the automatization of spaced repetition, vocabulary apps may offer other features. Examples of such features include the automated display of authentic examples of the target item in context. These may be decontextualized sentences that are pulled from a database or, in more sophisticated programs, examples of the target item that are found in longer, authentic texts (including video) on a topic of interest to the user. Gamification elements (e.g. leaderboards that allow a learner to compare their scores to other learners, badges for completing certain tasks, or the possibility of challenging other users to competitive tests) are another common feature. Automated hints and feedback (beyond simple right / wrong) can also be provided. With these, a learner can be informed, for example, that the incorrect answer they have provided is close to the required answer but that they have used the wrong spelling or part of speech.

Data captured from the user's interaction with such features can be used by the software to impact on both the spaced repetition and the use of these features. This is adaptive technology of a more sophisticated kind and offers a more personalized learning experience.

The value of spaced repetition in the memorization of vocabulary items is well researched and now widely accepted (e.g. Barcroft, 2015). Digital flashcards have some obvious advantages over traditional paper- or card-based systems: they are more flexible, they can include audio recordings, the spaced repetition is automated, and automatic reminders can be sent out. It is, therefore, reasonable to assume that they should lead to better learning outcomes. Research into digital flashcard systems is limited, but there are indications (e.g. Nakata, 2011) that they conform to expectations (i.e. they do lead to better learning outcomes). There is, as yet, no evidence that the use of the more sophisticated features of adaptive learning in vocabulary apps lead to learning gains.

The exaggerated claims of some digital flashcard systems (along the lines of 'Learn a language in three months!') need to be taken very lightly. Such systems have enormous potential for learners in facilitating the rapid acquisition of high-frequency or important items (e.g. the learning of the 570 word families in the Academic Word List for students of English for Academic Purposes). They cannot, however, do more than facilitate the initial learning of new vocabulary, particularly for receptive use. Fuller word knowledge for productive purposes can only come about through repeated exposure to the items in meaningful contexts (i.e. through extensive reading and listening) and the opportunity to use them in communicative situations (i.e. through speaking and writing). Nation (2013) has suggested that the deliberate learning of vocabulary through, for example, flashcard systems is only of value for high-frequency items and that this deliberate learning should not represent more than about 25% of the total amount of time devoted to vocabulary development.

#### Tests

In the most recent U.S. Educational Technology Plan (U.S. Department of Education, 2016), references to adaptive technologies are mostly found in the contexts of testing. In English language teaching, computer-adaptive tests for the purposes of both placement and proficiency testing are becoming increasingly widespread. During a test of this kind, algorithms determine both the order and degree of difficulty of test items based on the student's response to previous questions. Test questions can become progressively more or less challenging in a very fine-grained way. The advantages of well-designed adaptive testing include a greater precision of scoring and a reduction of the time (and therefore cost)

needed to complete a test. The major concern with such online tests is security, leading to significant developments in proctoring<sup>7</sup> services (involving webcams, for example) as the demand for online testing grows.

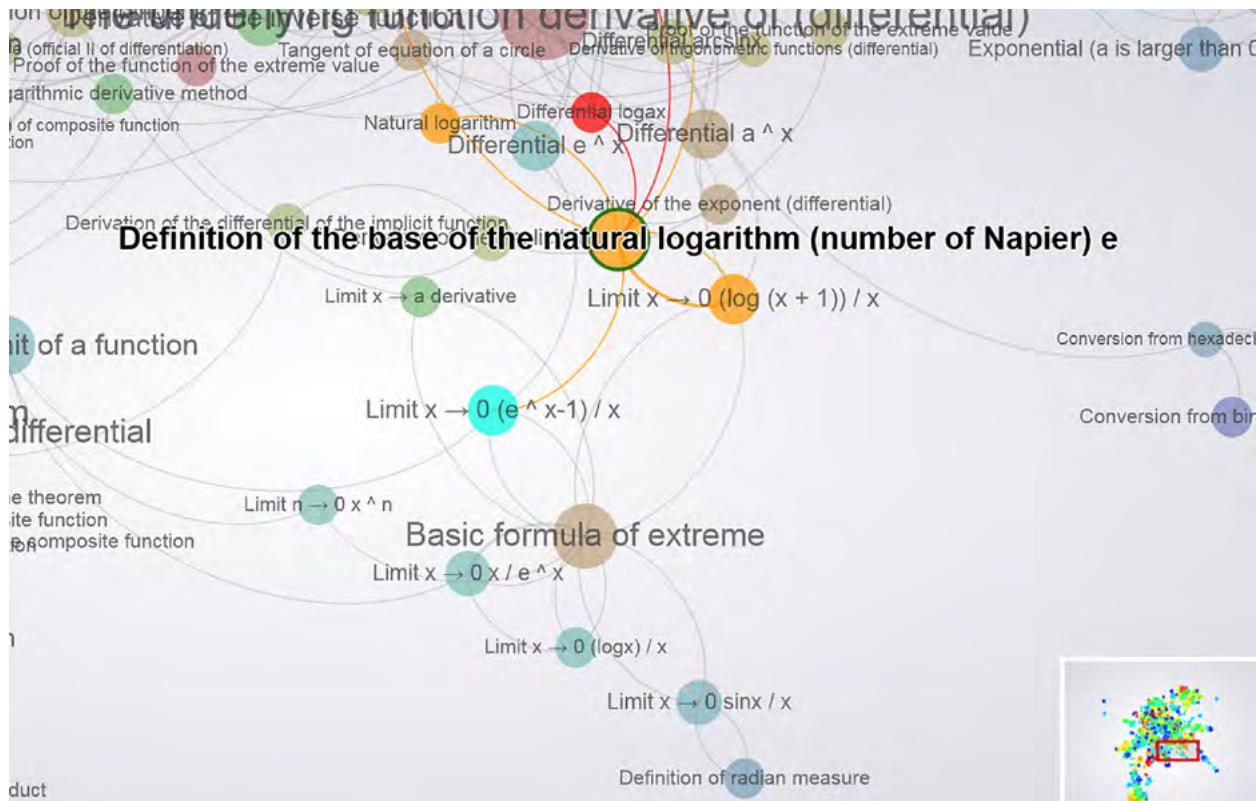
It is much easier to conduct research into the reliability of tests than it is into the efficacy of learning interventions, such as digital flashcards. In the fiercely competitive world of language testing, it is imperative for test vendors to carry out and publish this research before the global launch of their test products. Examples of such products and research include the Cambridge English BULATS Test (Cope, 2009) and the Standard English Test of EF (EF, 2014). It is very likely that computer-adaptive tests for English language will continue to grow in popularity.

## Platforms

The most ambitious attempts to leverage adaptive technologies for English language learning involve the use of Learning Management Systems (LMS) or Virtual Learning Environments (VLE). In these scenarios, an adaptive online course would reproduce and replace

what happens in a face-to-face classroom with a teacher using a coursebook. The teacher's role in such a course – if there is a teacher at all – is largely supervisory (although evaluation of spoken and written work may be needed). None of the major international publishers has yet launched such a product, although online courses with elements of adaptive learning do exist.

There are many challenges in developing a completely adaptive course, and it may be the case that some of these challenges cannot be satisfactorily resolved. In platform-delivered adaptive courses for mathematics, the subject matter is broken down into detailed granular items and a 'knowledge graph', which maps the relationships between the learning items, is constructed. It is assumed that learners will proceed in a linear manner through this graph, although different routes are possible.



Kanazawa Institute of Technology: <http://w3e.kanazawa-it.ac.jp/math/gexf-is-en/index.cgi>. Reproduced with kind permission of Kanazawa Institute of Technology.

## Example of a knowledge graph for mathematics

<sup>7</sup> Proctored exams are not taken in traditional examination halls or classrooms, but the student is overseen by a supervisor or proctor. Automated proctoring programs listen to sounds in the room and detect questionable behaviour by, for example, tracking the test-taker's eye-movements.

Such a step-by-step progressive route is much more problematic in language learning. Whilst this may be feasible at lower levels for work on language systems (especially vocabulary and, to a lesser extent, grammar), there is no generally accepted framework for dividing language skills into granular concepts that can be arranged linearly on a knowledge graph. If, as Larsen-Freeman and others (e.g. Larsen-Freeman & Cameron, 2008) have argued, language is a complex dynamic system, no linear representation of the kind needed for an adaptive approach to the language learning syllabus would be accurate or adequate.

Even if the adaptive element of a course were restricted to vocabulary and sentence-level grammar (as is the case with most of the products that are currently available), it would need a significantly larger amount of content than a coursebook or non-adaptive online course. This would entail huge content-development costs.

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**For teachers to be able to act on all this data, they will need some degree of technological competence and, to some extent, a rethinking of their roles as teachers.**

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Thornbury (2016) lists 12 challenges, derived from Second Language Acquisition research, that an adaptive language learning platform would need, but struggle, to meet. These include the need for students to have regular opportunities for personalized language production in interaction with other students, to receive formative and informative feedback on this, and to allow them to set their own goals. Given the more general current reappraisal of the potential of adaptive technologies, given the current uncertainties about the future of digital education (whether web-based or app-based, for example) and given the huge development costs that would be involved in meeting Thornbury's challenges, the kind of large-scale, platform-based, adaptive course that was being hyped by adaptive software vendors in 2013 now looks less and less likely.

More commonly, institutions are turning to blended approaches where adaptive materials are used with more limited goals. These materials can be used alongside normal classroom English work either as a supplement or as preparation. They can also be used for review purposes (i.e. an adaptive online workbook). In most of these cases, the more limited objectives are the mastery of particular grammatical structures or sets of vocabulary.

This less ambitious leveraging of adaptive technology is likely to prove more fruitful than attempts to develop fully adaptive online courses. Without any certainty that a fully adaptive course will lead to better learning outcomes, it is wise to move forward cautiously. Enyedy (2014: 15) notes that where positive impacts have been observed in the use of adaptive technologies, these typically derive more from the use of blended instruction than from the adaptive technologies themselves. In this light, making sure that the blended model is workable is probably more important than the adaptive elements that are part of it.

Recent experience (McCarthy, 2016) shows that teachers do not always find it easy to modify their established routines to the challenges of working in blended contexts. If, on top of the need to develop a new skill set for blended learning, they also need to develop their understanding of the way that adaptive systems operate, there will be considerable training needs (and costs).

Sophisticated adaptive systems can provide detailed data about learners' interactions with the software. They can give information about the particular items the students have 'mastered' or are having difficulty with, the sorts of mistakes they are making, and so on. They can make recommendations about remedial actions that the teacher could take with the class in face-to-face moments. For teachers to be able to act on all this data, they will need some degree of technological competence and, to some extent, a rethinking of their roles as teachers.

# Teacher training and development

Teachers working in blended contexts<sup>8</sup> will have rather different, more facilitative roles, and a different balance of roles, to those working exclusively with students who only study in traditional classroom-based lessons. Teachers working in blended contexts need to adjust their methods to the technologies they are using. As noted above, changes to traditional roles are likely to be even more pronounced when students are studying in programmes with adaptive elements. Since the success of an adaptive, blended programme is likely to be determined more by the teachers' interaction with it than by the choice of platform or software, adequate teacher training and development will be crucial.

The primary purpose of adaptive technologies is, as defined at the start of this paper, to facilitate a personalized approach to learning. The most effective way of encouraging teachers to explore the possibilities of personalized instruction is, probably, to allow them to experience personalized learning themselves in the course of their training and development. It would appear that this is rarely the case. A report by the U.S. Center for Public Education (Gulamhussein, 2013) indicates that, in the U.S., professional teacher development is most commonly of the one-size-fits-all kind, with little or no modelling of what is being taught. It is probable that in most contexts globally, the situation is little different, despite some exceptions (e.g. Moloney & O'Keeffe, 2016).

There is the potential for adaptive technologies to play a useful role in blended teacher development. Factual knowledge could be plotted on a knowledge graph and teacher competency frameworks, such as the Cambridge English Teaching Framework<sup>9</sup>, the British Council's Continuing Professional Development Framework<sup>10</sup> or the EAQUALS Framework for Language Teacher Training and Development<sup>11</sup>, could form the basis of such a graph. Particular pieces of teacher training content (e.g. webinars, tasks, readings) would need to be tagged to locations on the graph, allowing the software to make personalized recommendations for learning paths. Qualifications like the Cambridge Teaching Knowledge Test (TKT)<sup>12</sup> that focus more on teacher knowledge than teaching skills would readily lend themselves to such an approach.

It is also possible to use data from classroom practice, which could be fed into an adaptive personalized system. A tool like Visible Classroom<sup>13</sup> can automatically evaluate aspects of teacher talk, including speed, the proportion of teacher talking time to student talking time and the kinds of questions a teacher asks, and compare these with best-practice benchmarks identified by the research of John Hattie (Hattie, 2009).

<sup>8</sup> For a very readable overview of blended language learning, see King, A. (2016). *Blended language learning: Part of the Cambridge Papers in ELT series*. [pdf] Cambridge: Cambridge University Press. Available at [www.cambridge.org/betterlearning](http://www.cambridge.org/betterlearning).

<sup>9</sup> Information about the Cambridge English Teaching Framework can be found at <http://www.cambridgeenglish.org/teaching-english/cambridge-english-teaching-framework>

<sup>10</sup> Information about the British Council's Framework can be found at <https://www.teachingenglish.org.uk/article/british-council-cpd-framework>

<sup>11</sup> Information about the EAQUALS Framework can be found at <https://www.equals.org/our-expertise/teacher-development/the-equals-framework-for-teacher-training-and-development>

<sup>12</sup> See the TKT website for further information: <http://www.cambridgeenglish.org/teaching-english/teaching-qualifications/tkt>

<sup>13</sup> Information about Visible Classroom can be found at <http://visibleclassroom.com>

# Future directions

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The making of predictions about future technology and its uses is at best guesswork. Although the ideas behind adaptive technology have been around for a long time, it is only since the commercial development of Web 2.0<sup>14</sup>, cloud computing<sup>15</sup> and improved connectivity that the sciences of learning analytics<sup>16</sup> and educational data mining<sup>17</sup>, which underpin adaptive learning, have been able to take off. As we have seen, the use of adaptive technologies in English language learning is still in its infancy. While the initial hype and hope has already led to a degree of disappointment, adaptive technologies can be expected to evolve in their search for commercially viable roles. One such possibility, which combines adaptive and other technologies, is described at the end of this section.

One of the greatest limitations to date has been the fact that implementations in language learning have been based on the models for other academic subjects like mathematics where the adaptive technology is used to determine paths through pre-determined content. The focus has been on leveraging the technology to accelerate and improve the learner's knowledge of language systems (typically, vocabulary and grammar), rather than on developing the language learner's ability at listening, reading, speaking and writing (language use). In this sense, the apps and platforms that use adaptive technology closely resemble many of the printed books that they are gradually replacing.

It is generally agreed that an effective language learning programme needs to be both input and output-oriented. Learners must have the possibility to use the language in communicative contexts and receive appropriate feedback on this. Until now, it has not been possible to offer this with technology, except in very limited ways.

The software has only computed the formal similarity of a learner's utterance to an expected utterance: it has not been able to compute the learner's intended meaning, thus limiting the kind of feedback that can be provided.

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## The use of adaptive technologies in English language learning is still in its infancy.

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Recent advances in Natural Language Processing (NLP) and semantic computing are making it increasingly possible to decode the intended meanings in the language of language learners, even when this language contains errors<sup>18</sup>. At the same time, these technologies can be used to respond, meaningfully, to learner language in the same way that Chatbots (computer programs which simulate human conversation) are now being used with a variety of internet services, from online banking to social media. Rapid developments in automatic speech recognition mean that spoken, as well as written, learner language can be processed in this way.

Much research is still needed, but the possibilities for online language learning that is driven by learner output are becoming clearer. Communicative writing and speaking between learner and bot, or between two or more learners with bot interventions, coupled with appropriate support or feedback from the bot, now seem within reach. If these technologies are also linked to adaptive technologies, much more in the way of personalized support, feedback and suggestions for further language practice or study become possible.

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14 Web 2.0 refers to the way that webpages now (since the early twenty-first century) allow users to interact with them, produce their own content and interact with other users.

15 Cloud computing refers to the way that individual computer users can use networks of remote servers to process and store information, rather than using their own devices to do this.

16 Learning analytics is the collection and analysis of data about the ways that learners interact with a learning program. Its purpose is to improve their learning outcomes.

17 Data mining is the analysis of large amounts of data in order to discover meaningful patterns within it.

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18 For a general and very readable introduction to semantic computing, see Jeff Hawkins' best-selling *On Intelligence* (Hawkins, 2004). Heift and Schulze (2007) provide an overview, with extensive technical details, of Natural Language Processing in language learning.

# Case study

In 2015, Cambridge University Press set up a pilot and research project to investigate the efficacy of an adaptive platform-based course with a focus on grammar.

As such, it is of relevance to the section above on platforms, but not to other uses of adaptive technologies that have been discussed.

The overall message from the project was mixed. Institutions, teachers and students were enthusiastic about adaptive learning, although initially unsure what it was. The course was successful in promoting learning, but this learning was disappointing in the sense that there were significant variations in the gains for individual learning items and of individual learners. In this respect, the insights gained from this research were largely in line with other research reported in the previous sections of this white paper.

The insights (below) from the research project have been selected with the general (i.e. non-technical) reader in mind.

- Detailed attention needs to be given to all aspects of user experience design (UX). The ease of interaction with, and navigation around, the software impacts significantly on its efficacy.
- An adaptive approach to grammar requires a sophisticated and very granular knowledge graph, with a clear understanding of the multiple relationships between individual learning items. This, in turn, requires a very high level of expertise in pedagogical grammar.
- Both in an adaptive technology context and in general, the premise that the linear acquisition of granular, grammatical learning items will lead to mastery of these items may be flawed (c.f. the discussion about language as a complex, dynamic system). Fundamental questions remain about what constitutes an appropriate grammatical syllabus.

- High-quality content is needed, and this must be closely mapped to granular learning items. This requires expert content writers. At the same time, the appropriate amount of content, both for individual learning items and for the course as a whole, is difficult to determine.
- Students expect to receive supportive feedback on their errors. Simple (i.e. 'right / wrong') automated feedback is not sufficient.
- Any study programme which involves substantial periods of self-study needs to consider ways of motivating learners to maintain their efforts.
- Many teachers are unprepared for working with adaptive learning. They need guidance in using the software and they need, to some extent, to rethink their roles and expectations as teachers. They also need very clear, actionable feedback on the work that their students are doing.

This particular project did not set out to compare the learning gains of the group using the adaptive system to a control group using a more traditional approach. It is possible that a comparable research project investigating traditional approaches with the same grammatical content would find an equal number of reservations. Many, but not all, of the issues listed above could be addressed with further research, trialling and investment. However, as this white paper has suggested, it may be the case that the greatest potential for adaptive technologies in English language learning and teaching lies somewhere other than the mastery of grammatical structures.

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Philip Kerr is a teacher trainer and ELT materials writer. He is the author or co-author of titles in a number of coursebook series, including *Straightforward* and *Inside Out*. He is also the author of the award-winning *Translation and Own-Language Activities* and two e-books, *A Short Guide to Adaptive Learning in ELT* and *How to Write Vocabulary Presentations and Practice*. He is a member of a team working on the development of a variety of digital educational products that use adaptive technologies and Natural Language Processing.

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