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Abstract. *We live in a time of transition from print reading (off-line) to screen reading (on-line), where the role of the book and other literature is being taken over by different types of electronic devices (computers, tablets, smart phones). In the lives of young people, there is less and less printed media, because it is being pushed out by electronic media. Most written media that is still used is thus bound to the classroom. However, in recent years schools have also become more like e-schools. It is almost impossible to find a school that does not use e-material in its educational process. Research indicates that there are differences in reading comprehension when reading off-line and on-line. In a study in which 78 students from the 8th grade of elementary school participated at the course Technology and science (n=77; 53.2% female), it was shown that in order to overcome this difference, individualised and adaptive Intelligent Tutoring Systems (ITS) can be used. The evaluation of the results also indicates that, for such a form of ITS, there is still plenty of space for optimisation, which is a permanent method of improvement and upgrade in such systems.*

Key words: *reading comprehension, Technology and science, ITS, elementary school.*

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ONLINE FUNCTIONAL LITERACY, INTELLIGENT TUTORING SYSTEMS AND SCIENCE EDUCATION

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Introduction

With the early introduction of e-material in the education process, the e-material in schools had many positive effects – especially motivational ones. Nowadays, however, a decline in positive effects and the rise of negative can be seen. Researchers are wondering whether electronic material is as effective as material on paper, what can be done to make e-material more effective, and what is the effect of different aspects of digital textuality on reading comprehension (Kerr & Symons, 2006; Mengen, Walgermo, & Brønnick, 2013; Wastlund, Reinikka, Norlander, & Archer, 2005). The basis of how to answer the above questions should be the fact that successful readers use different types of metacognitive (reading) strategies in order to achieve higher levels of understanding from different things they read/see. From this point of view, it is possible to ask the following question: which types of texts does the student have to deal with when the teacher/school confronts him with material? Roughly speaking, e-material could be divided into pdf material, where the teacher converts classical linear text (the textbook) into a pdf format and gives it (unchanged) to the student to read; hypertext – type text, which is used to describe what advanced e-textbooks have to offer; or lastly the teachers use e-material as content that is available on-line. Reading each type of e-material requires special reading strategies from the reader on one side and, on the other, certain interventions within the text from the teacher/author in order to achieve higher levels of readability and a higher level of understanding of what was read (acquired knowledge). In the following article, focus will be given to the most commonly used types of text, hypertext, which is used in e-textbooks (DeStefano & LeFevre, 2007; Dolenc, Pesek, & Aberšek, 2013; Mayer & Moreno, 2003). However, researchers (Mengen et al., 2013) are establishing that not every digital text is hypertext and that digital reading does not heighten the cognitive load to the same level as hypertext does. They are finding out that, in contrast to a large numbers of studies in connection to hypertext, the number of studies that directly compare the potential difference between sequential and continuous reading of linear, narrative and non-narrative text in print and on screen is very small (Dillon, 1992; Graesser, Millis, & Zwaan, 1997). Researchers (Mengen et al., 2013) have carried out research with a sample of 72 students between the age of 15 and 16, where the main aim of the study was the potential impact of reading on certain aspects of reading comprehension.



Their results indicated that reading linear, narrative and expository text on computer screens leads to poorer reading comprehension than reading the same text on paper. They also assumed that changing the current length of text with shorter text could have an impact on reading performance. Similar results were reached by researchers (Wastlund et al., 2005) who compared production (writing) and comprehension performance in two experiments. In both experiments (writing and reading comprehension), the performance with computers was inferior to the performance with paper. They also established that the participants who used the computer experienced higher levels of stress and tiredness. In one of the rare studies assessing children's reading performance, they researched whether children's reading rate, comprehension and recall were affected by computer presentation. Children who participated in the research were, on average, 10 years old. The researcher came to the conclusion that children read text on a computer more slowly than on paper and that they are also less efficient at comprehending what they have read.

Scientists are looking at several possible explanations for why subjects perform better under print reading conditions than under computer reading conditions (Bregant, et al., 2010). Researchers (Baccino, 2004; Eklundh, 1992) believe that it could be related to issues of navigation between documents. Scrolling through the document is known to hamper the process of reading because it imposes a spatial instability which could negatively affect the mental presentation of the text. Another explanation is also connected to immediate access to the complete text. Readers under computer conditions do not have the whole insight into the text but only one page of text at a given time. Organisation, structure and the course of the text could be hampered due to limited access to the text (Eklundh, 1992; Piolat, Roussey, & Thunin, 1997). Some researchers also suggest that one explanation might be related to differences in metacognitive levels (Ackerman & Goldsmith, 2011; Garner, 1987; Paris, Wasik, & Turner, 1991) while others (Baccino, 2004; Garland & Noyes, 2004; Noyes & Garland, 2003) suggest that another explanation might be related to visual ergonomics. Ackerman and Goldsmith (Ackerman & Goldsmith, 2011) have suggested that people perceive the medium of print as more suitable for concentrated learning and electronic media as more of a tool for fast and shallow reading of short texts such as e-mails, news and notes in their research.

The majority of mentioned researchers are of the opinion that students with higher cognitive abilities have the least problems with reading comprehension, whereas the majority of problems occur with students that are considered average or sub-average. To overcome such problems it is crucial to individualise e-material. Reaching suitable reading comprehension is just the first step in making e-learning materials. In evaluating and analysing the suitability of e-learning with e-material, suitable individualisation of content is needed, which must also be suited to the students' capabilities. Bloom concluded in his research that an average student who had tutorial instruction (one-on-one tutoring) was about two standard deviation ($d=2$) above the average of a student who had only conventional classroom teaching (Bloom, 1984). The difference is equivalent to an increase of the students' achievements from 50% to 98% (Fig. 1). This difference became the foundation of all subsequent research in the field of e-learning. All researchers started looking for a way to accomplish such a result (Dolenc & Aberšek, 2015).

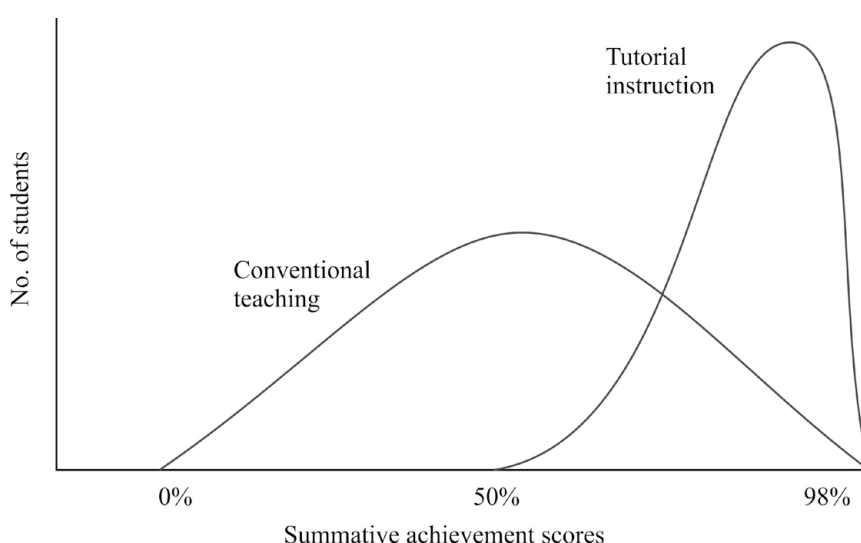


Figure 1: Achievement distributions for students under conventional teaching and tutorial instruction (B. S. Bloom, 1984).



Another study that has provided a referral point for all future researchers who deal with evaluating the effectiveness of e-learning and e-learning systems is Fletcher's research (Fletcher, 2003) where he summarised some research findings for technology based instruction. On the basis of meta-analyses of the research from the given field, he calculated the effect size based on the distribution theory of Glass's estimator of effect size (Hedges, 1981) instead of Cohen's. Cohen's d is defined as the difference between two means divided by the standard deviation for the data while Glass's estimator of effect size includes only the standard deviation of the second group. Fletcher has given the following conclusions for the evaluation of the effectiveness of e-learning: computer based instruction 0.39 sigma (233 studies), interactive multimedia instruction 0.50 sigma (47 studies), intelligent tutoring systems 0.84 sigma (11 studies), and recent intelligent tutoring systems 1.05 sigma (5 studies). The results of the latest ITSs are still around 1.05 sigma (Craig et al., 2013; Jaques et al., 2013; Wijekumar, Meyer, & Lei, 2013). The results of Fletcher's research and the future development of ITSs indicate gradual improvement in e-learning's effectiveness.

Many researchers have tested and evaluated the effectiveness of e-material, but has never come close to the 2 sigma marker that was set by Bloom. An important study in this field was done by VanLehn (VanLehn, 2011) who compared the effectiveness of learning with a human tutor, a computer tutor and a conventional tutor. To calculate the effect size he used Cohen's (Cohen, 1988) estimator of effect size (d). A common belief among researchers (Bloom, 1984; Corbett, 2001; Evens & Michael, 2006) is that human tutoring has an effect size of $d=2$ relative to conventional teaching in classrooms and ITS an average effect size of $d=1$. VanLehn's research did not confirm the mentioned belief. It turned out that the effect size of human tutoring is much lower, $d=0.79$, and that the effect size of his ITS was $d=0.76$ – almost as effective as human tutoring. VanLahn believes that Bloom's effect size of $d=2$ was so high because tutors were holding students to a higher standard of proficiency than the classroom teachers.

Research Focus

In this research the basic characteristics of the individualised and adaptive TECH8 ITS will be presented as well as research which could give an answer to the main research question: Is it possible to achieve a better effect size by using the intelligent and adaptive TECH8 system than conventional teaching or instruction from other similar ITSs. The idea was, through gathering data, to establish if it were possible that the same correlation between time and the achieved knowledge exists when learning with the help of hypertext as it does with conventional teaching, where more capable students, students who achieve better results, use less time for learning than less capable students.

Learning and Teaching

It can be claimed that teaching is something unique, unpredictable and tightly bound to a person as a member of society. If formal constants could be set for school lessons, it could be written as a formal mathematical model. By doing so, conditions for creating a *virtual teacher* would be made, or in a somewhat simplified form, intelligent e-learning material.

The behaviour of some humans is very elementary and needs no adaptation. Humans react automatically to internal and external stimulation. Other more sophisticated behaviours require remembering pleasant or unpleasant prior experiences and using a suitable reaction depending on that experience. Such behaviour represents the majority of social and cultural knowledge that humans have acquired. Further behaviour requires more sophisticated planning. It requires imagination and a very abstract way of thinking in order to develop a strategy that will ensure the least uncomfortable or the least painful reaction. These represent creativity and innovation; conscience, the abilities of the human mind, that are, in education, most commonly identified with Bloom's higher cognitive levels (Aberšek, Borstner, & Bregant, 2014).

The main misconception in *technology based learning* is that it is based on *structuralism* (Searle, 1983). This philosophy defends the thesis that the same organisation and the same laws apply for human thinking as they do for the world of machines, which, according to critics, means disregarding the differences between the psychological and pedagogical features of mental activity on one side, and the characteristics of technical systems on the other. If this effect is to be overcome in modelling higher cognitive processes and also include the special features of the educational field, where a student is not only an object of study, but also a subject of his own guidance and



oversight, structuralism as a foundation needs to be exchanged with modern *cognitive science* (Bermudez, 2010; Graesser et al., 1997; Markič, 2010; Winograd & Flores, 1986). The latter developed from cybernetics in the 1950s and has since experienced numerous pragmatic changes.

Cognitive scientists are also trying to transfer their findings into practice – especially in the fields of teaching and learning, cooperation, machine learning and decision making. Prior to showing how the learning process can be formalised, without disregarding the differences between the psychological and pedagogical features of mental functioning on one side, and the characteristics of technical systems on the other, *cognitive theory of learning* shall be examined, (Bermudez, 2010), which is currently one of the most important paradigms in modern learning.

Cognitive Science and Learning

All memories from one's personal history to his knowledge and experiences, determines his identity: it seems that people are what they remember about their past. Gathering knowledge is a complex and prudent process where people make decisions, summaries and assumptions. Knowledge that is acquired in such a way allows them to foresee situations and to choose how to correctly respond to them. This process is called *adaptation* or simply *learning*. Memories (experiences) are crucial for our individuality. In the human brain multiple memory systems can be found with different characteristics that can be roughly divided into *declarative* and *process memory* and which are supported by different *biological neural networks*. A number of theories exist on how new memories are formed. To mention only one, the neuroscientific theory, according to which new memories are formed by learning i.e. a process called *synaptic plasticity* (Morris & Filenz, 2003).

From recent explanations, it is evident that there are different types of learning which could be classified into four groups on the basis of what type of memory they use and whether they form new symbolic structures or only insert sub symbols into pre-existing ones, which can be seen in the table below (Anderson, 2007, p. 92).

Table 1. Learning and memory.

	Declarative memory	Process memory
Symbolic learning	Learning of facts	Acquiring skills
Sub symbolic learning	Reinforcing	Conditioning

1. *Learning of facts*: In declarative memory new memories are formed. This memory is in the narrowest sense of the word that which most people understand as memory. This is the only way of learning which results in new conscious memories. In the past it was also referred to as rote learning or to Bloom's elementary level – *knowledge* (Bloom, Engelhart, Furst, Hill, & Krathwohl, 1956)
2. *Reinforcing*: When forming new declarative memories it is possible to make them more accessible. This process is called reinforcing knowledge.
3. *Acquiring skills*: Different forms of learning bring about new procedures (new production rules). Acquiring skills lead to routine, when certain tasks are performed subconsciously, e.g. touch typing or driving a car.
4. *Conditioning*: With experience people learn that individual activities are more effective in certain circumstances. Conditioning is widely understood as the most used procedure of learning, a classical example would be Pavlov's conditioning in dog training (Pavlov, 1927).

In view of this, two ways of acquiring new knowledge in the taxonomy of learning need to be taken into account i.e. symbolic and sub symbolic learning. The goal of cognitive psychologists in searching for the answers on how one remembers and how one learns is therefore to find an internal mechanism of human thinking and acquiring knowledge (Horgan & Tienson, 1996; Searle, 1983). In other words a mental process needs to be found that is connected to the way integration and memory recall work (to put it simply, the way the human brain works). On the basis of the most recent results of modern cognitive and neuroscience research, the present TECH8 ITS was designed and evaluated in practice.



Intelligent Tutoring System (ITS): TECH8

TECH8 is a pilot individualised and adaptive e-material, designed on the basic principles of programmed lessons and cognitive science that adapts to students on the basis of their cognitive abilities. TECH8 includes the Gears subject matter, which is the last chapter of the Technology and Science course in the 8th grade of elementary school in Slovenia. The results of the National Assessment of Knowledge (RIC, 2013) show that this subject matter received the worst result in the whole curriculum of the subject of Technology and Science.

Basic Architecture of TECH8

TECH8 is structured modularly, which means that the contents are divided into small chunks called learning steps. Each learning step includes a text and possible interactive and multimedia elements, such as pictures, animations or films. Learning steps have a branched structure and are not fragmented but connected to the previous and the following learning steps. They are also adapted to the individual needs, levels of knowledge and cognitive abilities of the students. Each learning step includes regular assessments with feedback that guides students from the beginning to the end. A formative assessment at the end is a part of each learning step (Dolenc et al., 2013). A learning step assembled in such a way makes it possible to not exceed the user's cognitive load with the given information. A number of fundamentally connected learning steps form a building block. They are basic and essential elements. They consist of various learning steps and at the end they must have a summative assessment. With each building block, certain knowledge standards are achieved which are required by the curriculum of Technology and Science. They consist of a didactic "step by step" approach and the basic principles of Bloom's cognitive taxonomy.

TECH8 also includes a system for collecting and analysing metadata and variables (SCAMV) which takes care of the individualisation and adaptivity of the system. Through analysis and evaluating the metadata, SCAMV guides the students towards their most suitable learning path.

Research Methodology

The purpose of this empirical research is the evaluation and optimisation of TECH8, which is founded on adaptive and individualised e-learning with ITS. In this study, TECH8 was implemented in a real class environment. For the Gears subject matter, two 45 minute lessons are prescribed in the curriculum. The chosen schools took part with students from the 8th grade, where the students independently used TECH8 and the teachers were merely the observers of the individual self-learning process.

The data on students' success was gathered through a summative assessment of knowledge at the end of the subject matter. The summative assessment consisted of 17 tasks, where achieved standards of knowledge are assessed according to taxonomic levels: (Bloom et al., 1956)

- 4 tasks (taxonomic level I) assess knowledge,
- 5 tasks (taxonomic level II) assess understanding and use,
- 8 tasks (taxonomic level III) assess analysis of synthesis and evaluation.

Participants and Sample Selection

Participants (n=78; 53.2% female) were 8th grade students in three randomly chosen urban and suburban primary schools in Slovenia which had not yet studied the chosen subject matter. A pilot research was undertaken with two generations of students in the years 2013 and 2014. All subjects selected were 13 or 14 years old, according to the class records. The sample is middle-class Caucasian and hence homogeneous with respect to socioeconomic status and ethnicity.

On average, between 4135 and 4841 students from the 9th grade, coming from between 119 and 121 schools, participated in the National Assessment of Knowledge of the Technology and Science subject in the years 2008, 2010 and 2013, which represents approximately 25% of the entire population of 9th grade students.



Data Analysis

Quantitative data were collected via the SCAMV system for collecting metadata and variables, which was developed to evaluate students and to adapt and evaluate TECH8. Quantitative data were analysed according to the following phases, or by: encoding, defining and organizing data and interpreting the results.

Data from the NAK was collected, evaluated and statistically processed by the national curriculum committee for the Technology and Science course and published in a yearly report on the National Assessment of Knowledge.

Results of Research

The achieved results of the National Assessment of Knowledge (NAK) are traditionally the worst, especially in the subject matter Gears, as can be seen from Table 1, with the exception of 2013.

Table 1. Analysis of results of the NAK from the Technology and Science subject course from the Gears subject matter. Empirical results from the research with TECH8 are listed in Table 2.

Year	No. students	Mean of (content Gears) in %	Standard deviation in %	Number of tasks
2008	4841	33.3	17.4	6
2010	4762	27	17.73	4
2013	4135	69.66	16.03	3

In 2008 and 2010 the tasks for the Gears subject matter in the NAK were balanced upwards and contained a small percentage of tasks that assessed standards of knowledge according to taxonomical level I and a large percentage of tasks that assessed standards according to taxonomical level III. But in 2013 the tasks only assessed knowledge according to taxonomical level I, hence the seemingly improved result. The standard deviation was high in all years, which indicates that there are big differences in students' knowledge. Detailed analysis of the results of the NAK from the Gears subject matter in 2008, 2010 and 2013 is shown in Table 1.

Table 2. Analysis of TECH8 results from the Technology and Science subject course from the Gears subject matter.

Number of students	Mean of total score in %	Standard deviation in %	Skewness	Mean of time used for self-learning with TECH8 in seconds	Mean of time used for summative assessment in seconds
78	44.7	22.17	0.215	2896.78	547.38

The average result of the summative assessment was 44.7%. The standard deviation was high, at 22.17%, which points to large differences in students' knowledge. The average time for reading the content was 2896.78 seconds (approximately 49 minutes). The average time for solving the 17 tasks of the summative assessment was 547.38 seconds (approximately 9 minutes). Skewness value is positive which indicates that the mass of the distribution is concentrated on the left. The results of the effect size calculations show that TECH8 effect size is; according to:

- The results of the NAK in 2008 $\Delta=0.51$ calculated with Glass's estimator or $d=0.57$ calculated with Cohen's estimator.
- The results of the NAK in 2010 $\Delta=0.80$ calculated with Glass's estimator or $d=0.57$ calculated with Cohen's estimator.

The results of the NAK in 2013 cannot be compared to TECH8 results because the difference in the difficulty of the questions is too great. The estimated effect size of the NAK for 2009 and 2010 with TECH8 is medium for 2008 and large for 2010 but it does not reach or exceed the threshold of 1.05 sigma that was set for ITSs.

In preliminary research with TECH8, a minimum time of 1800 seconds was set (approximately 30 minutes) that was needed for students to read only the content in TECH8. This minimum time does not include the time for



regular, formative and summative assessment. With the help of metadata acquired by the SCAMV system, it was established that as much as 24.7% of students were below the threshold of the minimum time (Table 3)

Table 3. Analysis of TECH8 results from the Technology and Science subject course from the Gears subject matter according to the criteria of minimum time.

Number of students	Mean of total score in %	Standard deviation in %	Skewness	Mean of time used for self-learning with TECH8 in seconds	Mean of time used for summative assessment in seconds
58	55,70	20,78	-0.236	3395,8	664.5
19	24.9	10.9	1.366	1353.37	125.48

Students that were under the threshold of the minimum time achieved results of 24.9% and with a standard deviation of 10.9% on average. The average time for reading the content was 1353.37 seconds (approximately 23 minutes). The average time for solving the 17 tasks of the summative assessment was 125.48 seconds (approximately 2 minutes). Skewness value is positive which indicates that the mass of the distribution is concentrated extremely on the left.

Students that were above the threshold of the minimum time, who stuck to the rules and used TEHC8 as a tool for self-learning, achieved 55,70% on average in summative assessment. The standard deviation was 20,78%, which still points to big differences in students' knowledge. Skewness value is negative, which indicates that the mass of the distribution is concentrated on the right (Dolenc & Aberšek, 2015). The results of the effect size calculations show that TECH8 effect size is; according to:

- The results of the NAK in 2008 $\Delta=1.11$ calculated with Glass's estimator or $d=0.99$ calculated with Cohen's estimator.
- The results of the NAK in 2010 $\Delta=1.47$ calculated with Glass's estimator or $d=1.30$ calculated with Cohen's estimator.

The average time for content reading was 3395,8 seconds (approximately 56 minutes). The average time for solving the 17 tasks of the summative assessment was 664.5 seconds (approximately 12 minutes). Time has a statistically significant effect on the result reached by summative assessment (Table 1-15). The students from the experimental group, that spent more time for self-learning, achieved better results and as seen from R^2 the achievement can be in 29% explained with time.

Table 4. The result of bivariate regression analysis of the time spent for self-learning on the achieved results of the students

b	β	p	R	R^2
0.004	0.541	0.000	0.541	0.293

Discussion

As seen from the results, when taking into account minimal time, 24.7% of students were below the threshold of the minimum time. With the help of the gathered metadata it was possible to establish five most common behaviours in these students:

1. Instead of correct or incorrect answers they randomly pressed buttons on the keyboard,
2. Extremely short time spent on certain TECH8 contents,
3. Answering questions in regular, formative and summative assessment without reading the questions,
4. Latency for question (time measured from the time the question was shown to the time of the response) was on average between 1-3 seconds,
5. When deciding on a path for additional content in the case of a wrong answer they decided to skip that path.



These behaviours, in addition to the results, confirm the fact that the students were not able to learn by themselves. TECH8 was not used as a tool for self-learning and they merely clicked through the content with the sole purpose of finishing as quickly as possible.

With the students who persisted with the rules and used TECH8 as a tool for self-learning the estimated effect size of the NAK from 2008 and 2010 was large for both years and it reaches, and indeed in 2010 it even exceeds, the threshold of 1 sigma that was set for ITSs (Fletcher, 2003). By using the intelligent and adaptive TECH8 system, a better effect size was achieved than conventional teaching and equivalent or better than others with similar ITSs. VanLehn (VanLehn, 2011), with his step based ITS, achieved an effect size of $d=0.76$. Verdu, Regueras, Verdu and de Castro (Verdu, Regueras, Verdu, de Castro, & Perez, 2008) analysed the results of some adaptive ITSs and established that the effect size is most frequently between the values of $d=0.60$ and $d=1$. The conformity of the results also confirms the study done by researchers Ma, Adesope, Nesbit, and Liu (2014), who carried out a meta-analysis on 107 papers from different journals, proceedings and dissertation. For calculating the effect size they used Hedge's (g). They established, that the average effect size in comparing ITS to conventional teaching is $g=0.44$.

Correlation between time spent for self-learning and the number of achieved points in the summative assessment exists and is statistically significant ($R=0.541$, $p=0.000$). In conventional teaching, more capable students, students who achieve better results, use less time for learning than less capable students. In self-learning with ITS, it is just the opposite. The correlation indicates that students who, on average, achieve better results, use more time for reading the content and solving the tasks. Furthermore, if the time for self-learning on average changes for 1000 seconds, then the achieved results of the summative assessment of average changes for 4 points.

Conclusions

The results of this study indicate that better results are achieved with the intelligent and adaptive TECH8 ITS than with conventional teaching and in comparison with other ITSs the results are similar. They also indicate that a correlation between time spent for self-learning and the number of achieved points in summative assessment exists. The research confirmed that the choice of the design of TECH8 is sound, and the rest of the gathered data indicates many opportunities for system optimisation. The texts will have to be optimised, and at the same time less capable students need to be taught and trained to use different reading strategies in order to achieve higher levels of readability and higher level of understanding of the acquired knowledge. The majority of students, 75.3%, achieved better results with the intelligent and adaptive TECH8 ITS, but the fact that even a minority of students achieved results that were lower than the NAK results is alarming. When optimising TECH8, certain fail safes need to be installed to prevent the most frequent unwanted behaviours and encourage and motivate students towards self-learning. However, it can be claimed that self-learning with the help of TECH8 brings forth certain desirable results, but cannot replace the classroom teacher or the classroom experience. ITS should be used to replace homework and perhaps other activities.

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