A Prevalence Trend of Characteristics of Intelligent and Adaptive Hypermedia E-Learning Systems

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Abstract: - The main aim of this research is to determine a prevalence trend of characteristics of intelligent and adaptive hypermedia e-learning systems (IAHe-LS). IAHe-LS characteristics were determined by examining published scientific papers indexed in relevant databases. We analysed 1170 papers and identified 61 systems. The description of system architecture was used as the selection criterion, which yielded 21 characteristics used to describe the systems, namely: learning style, cognitive style, adaptivity inference mechanism, granularity of learning content, pedagogical model, domain knowledge model, learner activity tracking, knowledge testing, testing previously acquired knowledge, experimental use, form of presented content, adaptivity criteria, standardisation, system interface model, teacher model, description model, and interactive tools. A prevalence of characteristics was clustered by the didactic pyramid. The learner's characteristic of the highest prevalence is learning style and of the lowest is cognitive style. All analysed characteristics related to educational technology have increased prevalence from 2008 onwards. The teacher's characteristic of the highest prevalence is knowledge testing, whereas the one with the lowest is teacher model. The most difficult part was to investigate the prevalence of characteristics associated with the content as in the analysed articles that part is explained poorly. However, we noticed that from 2008 onwards both identified characteristics have increase in prevalence. A Poisson regression analysis was carried out in order to determine the connection between the occurrence of characteristics of IAHe-LS and the year they occured. Although the number of occurrences for some characteristics was too little in order to conduct an analysis, it has shown that the model obtained by Poisson regression is suitable for all other characteristics.

Key-Words – Adaptive hypermedia e-learning systems, Intelligent e-learning systems, Learner's characteristics, Teacher's characteristics, Content's characteristics, Educational technology characteristics, Prevalence

1 Introduction

The transfer of knowledge is one of basic social activities. The use of information and communication technologies (ICTs) intensifies significantly its dynamics regarding the way this activity is carried out and the changes in requirements that are set upon it. The use of computers and the Internet is evident in all fields of human activity including education. The first applications of ICT at schools date back to the early 1980s, and mainly referred to the use of applications simulating teachers' work in the classroom and were focused on mastering and practicing basic skills, while the way of teaching and the process of learning remained the same. With the development of ICT, especially communication technology and its increased use in the learning process, led to changes in teaching and learning. The process of learning by applying ICT represents a process based on the learner's interaction and participation in activities that are related to the course content. Achieving educational goals in a teaching context where ICT is being used means that educational contents and methods are mediated through particular technical media and technologies. Different authors very often use the terms medium and technology to signify the following: the carrier of information, the form of information, the ways of communication, and technologies for teaching [2], which together make up the so called educational technology. The presence of educational technology leads to the transformation of the didactic triangle into the didactic square [45]. The suggested interrelationships between the educational process elements are perceived as the didactic pyramid [16], which places the learner at its top, while its foundation represents a triangle involving the teacher, the content, and educational technology. The didactic pyramid illustrates co-dependency of all the elements of the educational process, especially emphasising the learner as its most important element placed at the top.

"E-learning represents an intersection of the two worlds – the world of the information science and communication technology and the world of education." [35] E-learning systems are those systems that allow learners (users) to access electronic resources for learning without any spatial and temporal restrictions [1]. Traditional hypermedia e-learning systems are systems that provide the same content to every learner. Conversely, adaptive hypermedia e-learning systems are those systems that offer adaptation of navigation and content presentation based on different criteria and user needs [4],[48]. In order for adaptivity to be as efficient as possible, adaptive hypermedia e-learning systems are combined with intelligent learning systems [38], [39], [40]. To achieve adaptivity of navigation and content presentation, these systems employ the advantages of intelligent learning systems, allowing appropriate behaviour in situations of uncertainty that arise during the process of e-learning.

Adaptivity goals are defined by either the learner or the teacher, depending on the context in which the system is being used. Learner characteristics, according to which the system adapts, are often used as adaptivity criteria.[55] The term adaptivity is often used synonymously with personalisation, even though that is not entirely correct. Personalised systems are just one type of adaptive systems. The main characteristic of personalised systems is their adaptation to the learner. Five different dimensions of personalisation are defined in [12]: Implicit – explicit, Hidden – perceivable, Deterministic – predictive, Uncontrolled – controlled, Stereotyped – individual personalisation. Stereotyped personalisation refers to a group of learners, while individual refers to a single learner.

This classification of personalisation dimensions is applicable to most user-centred systems that point out individual personalisation as a primary dimension [10], [22], [31], [56]. Adaptivity technologies (content and/or navigation) are most commonly linked to using content that is based on various media and has different granularity of learning content [43], [25], as well as to adaptive navigation support. Adaptivity techniques and methods are related to adaptivity criteria, but also to adaptation inference mechanisms, where the application of intelligent methods becomes prominent educational process, especially emphasising the learner as its most important element placed at the top [20], [53].

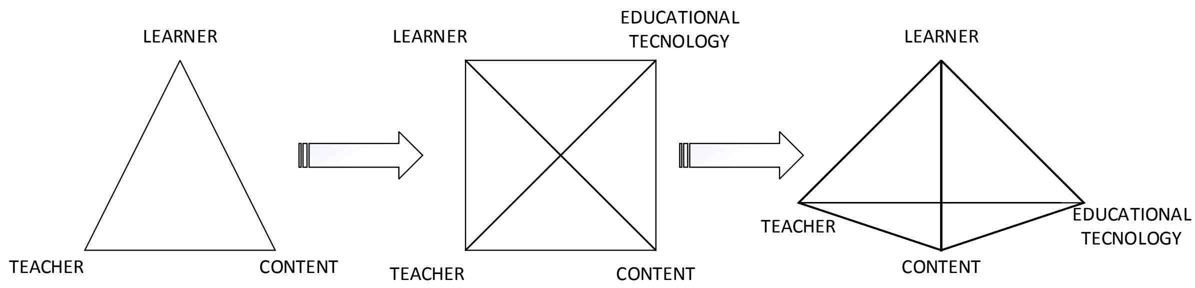

Figure 1: *Evolution of the didactic triangle toward the didactic pyramid [16]*

Research in the field is mostly focused on examining the frequency of appearance of adaptivity criteria or system characteristics from the point of view of either the learner, the teacher, or the content [3], [36]. The need for further research in the field of IAHe-LS, with an emphasis on individual personalisation, is imposed on us by the dynamics of changes within all the segments of a society, including the process of learning and education.

The aim of this paper is to determine a prevalence trend of the IAHe-LS characteristics. We analysed characteristics that were most frequently used in IAHe-LS descriptions in order to reach certain conclusions about the prevalence of this characteristics. This research is part of the development process of a new IAHe-LS system with a high level of individual personalisation.

The reminder of this paper outlines the methodology and results of the research that aimed to give an overview of a prevalence trend of the characteristics of IAHe-LS, ranging from the early 1990s to July 2014. Section two describes related work, section three research methodology, section four presents research results with discussion and section five concludes the paper and offers guidelines for future research.

2 Related Work

Searching through the studies that were conducted in the last several years, and which are related to characteristics of adaptive and intelligent hypermedia e-learning systems, resulted in several papers: „Adaptive Educational Hypermedia Systems in Technology Enhanced Learning: A Literature Review“ Mulwa et al. [36], „Adaptive and Intelligent Systems for Collaborative Learning Support: A Review of the Field“ Magnisalis, Demetriadis and Karakostas [33], „Adaptive Educational Hypermedia Accommodating Learning Styles: A Content Analysis of Publications from 2000 to 2011“, Akbulut and Cardak [3] and PhD thesis „Adaptive student's knowledge acquisition model in e-learning“ by Grubišić [18]. Research carried out so far has shown that different authors apply different approaches and research methods to this topic.

For the purpose of their research Magnisalis, Demetriadis, and Karakostas [33] searched through the following databases: IEEE Xplore Digital Library, Elsevier Digital Library through Scopus Search Engine, Science Direct, Wiley InterScience, Oxford University Press Digital Library http:///port6al.acm.org and Springer. The key words that were used in searching are: „intelligent“ OR „adapt“ OR „adaptation“ OR „adaptive“ AND („collaboration and collaborative“) AND („CSCL“ OR „learning“). In the process they limited the search to examine only summaries and titles, and not the entire papers. The searched papers were published in magazines and collected papers from conferences, in the English language and in the period from 1998 to 2010. The result of the search were 216 papers after which 105 papers were selected and analyzed, and were divided into three groups in the following way: group 1 included the articles which presented specific characteristics of AICLS systems (Adaptive and Intelligent Systems for Collaborative Learning Support), group 2 consisted of the articles which presented the architecture of AICLS systems, and group 3 encompassed articles which focused on the implementation of advanced technologies in the development of AICLS systems. Additional classification into subgroups was made according to the following characteristics: pedagogical objective, target of intervention, modeling, technology, design space. In the interpretation of results the authors explain basic characteristics used in the classification into groups and subgroups, and cite in which papers and systems they occur using the descriptive method of interpretation.

In her PhD thesis Grubišić [18] searched the Science Direct base with the help of the following words: adaptive e-learning systems, intelligent tutoring systems, courseware generation, adaptive courseware and the automatic generation of courseware. It is not stated whether the Science Direct base was searched as a combination of abovementioned key words or every term was searched separately. The time period from 1990 to 2009 was examined. The number of 142 articles was analyzed and 17 systems were identified. The systems were analyzed in a way that the number of quotations was determined quantitatively, and the systems themselves were analyzed according to the following characteristics: domain knowledge, student model, computer-generated teaching matter, adjustment criteria, assessment, testing previous knowledge. The author determines whether a system has or does not have stated characteristics, and presents the result of the analysis in the form of a table. These systems were analyzed in more detail so that they were divided into groups in a way student models were constructed and according to the following categories: the systems containing a Bayesian student model and the systems with a stereotypical student model. The descriptive method was used in the analysis and interpretation of the obtained results.

Akbulut and Cardak [3] conducted a study of the papers that were published recently and that are connected to adaptive educational hypermedia with an emphasis on the learning style. They analyzed the articles published in the following databases: JSTOR, Sage, ScienceDirect, EBSCOhost Web, SpringerLink, Proquest Dissertations and Thesese, Ulrich's Periodicals Directory, ISI Web of Knowledge, Wiley InterScience, Google Scholar and ERIC. The search was limited to peer-reviewed articles, full-text proceedings of international conferences, symposia and workshops and dissertations in English. In the search the key words were: adaptive/adaptable e-learning, adaptive/adaptable hypermedia, adaptivity, adaptation, adaptability, personalized e-learning and learning styles. The authors state that due to the fact that simple key words were used, they also applied the snowball method to search through the references of the appropriate articles. More than 300 articles published in the period from 2000 to 2011 were checked. The number of 70 papers was selected: 47

peer-reviewed journal articles, 17 proceeding papers and 6 dissertations. After the qualitative paper analysis, the following characteristics were singled out: publication type, main focus, purpose, study nature, variables used for adaptivity, learning style model, student modeling, tools for modeling, tools for dynamic modeling, research settings participants, type of empirical studies, data collection tools. The systems were not listed individually, learning style being the only characteristic where 30 systems were identified, and which was one of the main aims of that study. Also, the authors analyzed the number of quotes of the authors of selected papers, but not the country of origin of these authors. In the interpretation of results the descriptive method and the methods of descriptive statistics were used. Mulwa et al. [36] also gave the list of papers in which they searched for an answer to the research question connected to the contribution to technology-enhanced learning and adjustable systems in which the style of learning was installed. In their analysis they are focused on the qualitative analysis of papers, not listing the specific number of quantitative number of analyzed papers, but applying the descriptive method to present the results. In the process the term chart was made, which is connected to technology-enhanced learning, certain terms were explained and papers in which they appear were listed. On the basis of the results of research in the form of a diagram the generalized architecture of adjustable systems for e-learning was shown. The main goals of previous studies were oriented towards the identification of articles and/or systems in relation to some specific characteristic such as: students modeling in Grubišić [18] the learning style in Akbulut and Cardak [3] and Mulwa et al. [36] or Magnisalis et al. [33] where the articles and systems were identified in which the system architecture was described and that were classified according to chosen characteristics without additional analysis, in contrast to our research, which aims to determine a prevalence trend of the IAHe-LS characterizes in the period from 1990 to 2014. Previous research were conducted on the sample of 142 papers in [18], more than 300 papers in [3], that is 216 papers in [33], whereas the number of papers in our research exceeds these numbers greatly. The methodology used in our study is different from other studies in the number of analyzed articles from different databases, combination of key words that were used to search databases, and the observed period of publishing of the articles, identified systems and the number of identified characteristics, as well as methods of analysis and the interpretation of the research results.

3 Research Methodology

The research was conducted in two phases. The first phase took place during December 2012 and the second during July 2014. The research included the following scientific databases: Science Direct, Current Contents (CC), and Academic Search Complete (EBSCO).These scientific databases have been chosen because they include different scientific areas. As the research focuses on IAHe-LS, the following keywords were used to search the databases: adaptive educational hypermedia systems + intelligent. In the first search cycle during December 2012, 456 papers were found in the Science Direct database, 9 papers in the CC database, and 576 papers in the Academic Search Complete database. In the second search cycle during July 2014, the number of papers in the Science Direct database rose to 568, and in the CC database to 15, while the Academic Search Complete database could not be searched again due to access restrictions. The search was limited to include only papers in the English language, full papers in PDF format, and reviewed scientific journals. A significant number of papers were indexed in both Science Direct and Academic Search Complete databases. The papers were analysed by searching for a detailed description of system architecture and characteristics. This yielded 79 papers. In order to obtain data about certain systems, more than one paper had to be analysed. Additionally, the Croatian Scientific Bibliography database was also analysed using the following keywords: (cro. *prilagodljivi hipermedijski sustavi za učenje i inteligentni sustavi za učenje*) adaptive educational hypermedia systems and intelligent learning systems. The search yielded a total of 11 papers. The identification of characteristics of selected IAHe-LS was based on the description of a system given in each paper.

The obtained data were analysed by applying the methods of the qualitative data analysis: classification (typology), quantitative/quasi - statistics, Matrix/Logical Analysis (mostly the use of diagrams and charts), content analysis and Poisson regression analysis. Based on the relationship of the number of characteristics of IAHe-LS and years when they appear (type of data), a Poisson regression analysis was performed using free statistical software R (http://lib.stat.cmu.edu/R/CRAN/). Additionally, qualitative data analysis techniques were also applied, including documenting data during the process of data gathering and organisation into an .xls file. (see Fig.2)

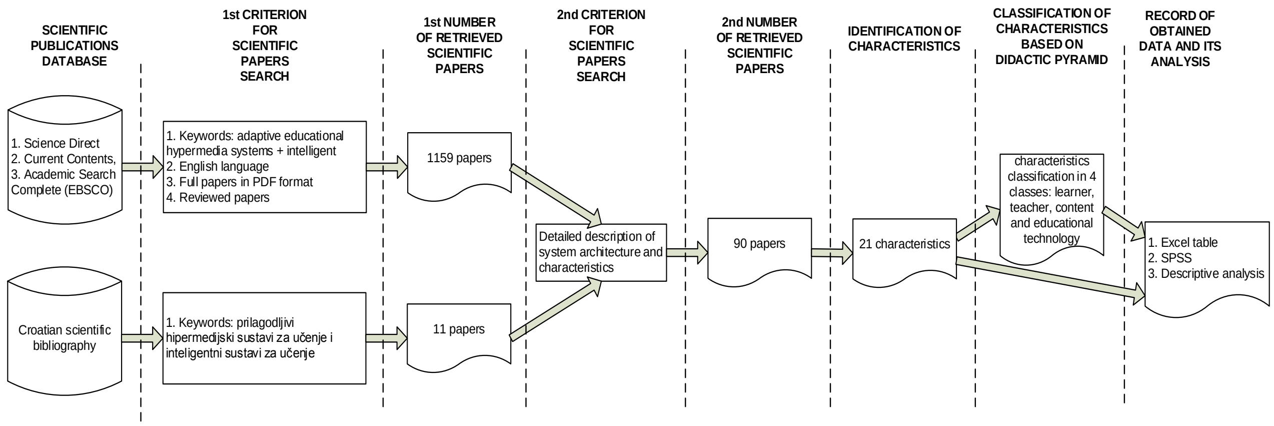

Figure 2: *Research methodology diagram*

4 Research Results and Discussion

A total of 90 papers were analysed, which yielded 61 systems overall. The number of papers published in a particular year reveals that most of the papers were published in 2011 and 2012, while the fewest were published in the 1990s. Certain systems were described in several papers with different publication years, but the analysis included only the most recent publications. (Appendix A)

By analysing the country of origin of the majority of papers' authors, a clear domination of authors from Germany, Greece, and Taiwan is noticeable. Only 6.5% (4 systems) were defined by their authors as being open-source, 1.6% (1 system) were defined as commercial, while the authors of the remaining 91.8% systems failed to define the terms of use of their systems.

The results regarding the description of experimental use are: tertiary education (76%), secondary education (3%), primary education (2%), and cannot be concluded (18%). It can be concluded that the systems were mostly tested and/or are still used in higher education, a significantly lesser percentage of systems were used in secondary and primary schools, while the description of all other systems did not reveal whether or where they were used.

The analysis yielded 21 characteristics, namely: learning style, cognitive style, adaptivity inference mechanism, granularity of learning content, learner habits during system use, learning goals, learner model, pedagogical model, domain knowledge model, learner activity tracking, knowledge testing, testing previously acquired knowledge, experimental use, form of presented content, adaptivity criteria, standardisation, system interface model, teacher model, description model, communication model, and interactive tools. The characteristics were identified based on the keywords of each paper and on authors' emphasis and description of particular characteristics. (see Table 1)

No	Characteristic	Description
1.	Learning style	An individual's preferred way of learning in order for it to be more efficient, e.g., visual, aural, etc. [39], [31], [17],[28], [44].
2.	Cognitive style	The way an individual organises learning content through cognitive activities such as thinking, information receiving, and memory [52], [43], [41], [32].
3.	Adaptivity inference mechanism	Covers all the ways of making inferences during system adaptation [5], [54].
4.	Granularity of learning content	The smallest unit of learning content [10].
5.	Learner habits during system use	Frequent learner activities during system use [58]
6.	Learning goals	What we want to accomplish by learning [51],[57].
7.	Learner model	Contains all the necessary data about the learner [40], [22], [32], [11], [42], [24].
8.	Pedagogic model	Covers all the teaching methods that are applied based on adaptivity criteria; simulates the work of a teacher and his/her role in the process of teaching and learning [32], [25], [30].
9.	Domain knowledge model	Comprises learning content and relationships between elementary content units [50].
10.	Learner activity tracking	Learner activities during system use [27].
11.	Knowledge testing	Includes the ways of knowledge testing by using the system [21], [29], [7].
12.	Testing previously acquired knowledge	Learning domain knowledge level prior to system usage [13].
13.	Experimental use	The system is tested in real conditions [54], [34].
14.	Form of presented content	The way learning content is presented (text, graphics, multimedia) [8], [15], [37], [47].
15.	Adaptivity criteria	Criteria used for adaptation in the system [46], [6].
16.	Standardisation	Standards used during system development or development of any of

		its parts [43], [14].
17.	System interface model	Data concerning the realisation of the presentation layer [39].
18.	Teacher model	Contains all the necessary data about the teacher [51].
19.	Description model (scenario)	A description of a series of steps through the learning content, consisting of a set of different learning resources intended for the same group of learners [26].
20.	Communication model	Connects the interface layer with the application layer [18], [49].
21.	Interactive tools	System tools that allow user interaction with the system [5].

Table 1: *Description of characteristics*

As the main aim of this research was to determine a prevalence trend of IAHe-LS characteristics. We started with the analysis of a number of characteristics that describe the observed system. Chart 1 shows the number of systems described by a particular number of characteristics. A large number of systems, 52 of them, are described using between 7 and 11 characteristics. The smallest number of characteristics used to describe a particular system is 3, while the largest is 14 (only 1 system).

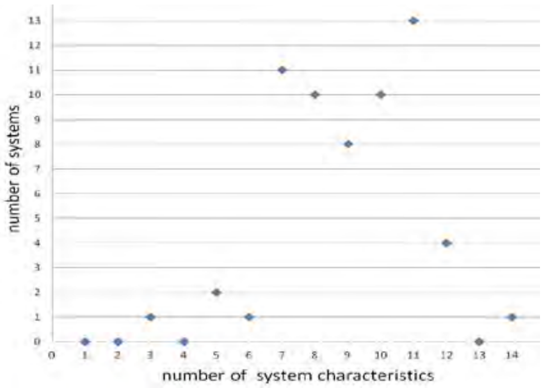

Chart 1: *The number of IAHe-LS systems described using a particular number of characteristics*

The data were obtained by analysing the prevalence of particular characteristics in the IAHe-LS systems. (see Chart 2)

The characteristics named granularity of content and form of content presentation describe the learning content, which is found in the description of all the IAHe-LS systems. The characteristic granularity of content appears in the following forms: concept (14), lesson (7), teaching unit (7), teaching topic (5), and learning object without a precisely defined level of granularity (14). Eight IAHe-LS systems do not have granularity of content defined. The same characteristic is not clearly defined in 14 IAHe-LS systems, while in 14 IAHe-LS systems the content is granulated to the form of concept, claimed by their designers to be an advantage due to its easier use in various contexts.

The characteristic form of content presentation is not separately explained in any of the papers, but based on the graphical presentations of IAHe-LS system interfaces, it can be concluded that the content is most often represented as a text and/or static graphics. However, multimedia content in the form of videos and animations also occurs.

The characteristics description model, cognitive style, communication model, and interactive tools appear the least often, while the characteristics learner model, domain knowledge model, adaptivity criteria, adaptivity inference mechanism, knowledge testing, pedagogical model, and experimental use are most commonly found.

Description model, communication model, and interactive tools are characteristics related to the description and application of employed technology, while cognitive style is a characteristic especially interesting from the point of view of individual personalisation of IAHe-LS. The latter characteristic appears in only 5 systems, which can be seen as a challenge when designing new IAHe-LS systems, taking into consideration that cognitive style is a personal characteristic of each learner and that the personalisation level of learning system increases when it is applied.

The characteristics teacher model, standardisation, and learning style can be found in one third of the systems. The systems analysed here are mostly focusing on the learners' interests and needs so it is understandable that the teacher model is significantly less represented, even though the parts relating to the teacher are often integrated into the pedagogical model. Standardisation is for the most part focused on standardisation of learning objects (SCORM - Sharable Content Object Reference Model, LOM - Learning Object Metadata), and somewhat less on the standardisation of the whole systems (IEEE 1484 LTSA). As a characteristic of the learner, learning style is most commonly defined according to the Felder-Silverman (F-S) learning style model, while the least number of systems uses the Visual Aural Read Kinaesthetic (VARK) model of learning styles. These findings are consistent with previous findings [3]. The F-S model comprises the following categories: active/reflexive, rational/intuitive, visual/verbal, and sequential/global. The categories of learning styles according to VARK are visual, aural, read/write, and kinaesthetic types.

More than half of the systems are described by the following characteristics: system interface model, learning goals, learner habits during system use, learner activity tracking, and testing previously acquired knowledge. The characteristic system interface model is specific to adaptive hypermedia e-learning systems because it represents one of their core functionalities. The prevalence of this characteristic is surprisingly low in the analysed papers. This characteristic is commonly realised by applying different patterns for arranging and presenting learning content. In some systems, learning goals are related to the learner model and in others to the teacher model, depending on who sets them. Two systems use Bloom's taxonomy [18], [11] to present learning goals. One of the reasons for such a rare use of learning goals based on Bloom's taxonomy [9] is that learning goals defined in such a way increase the complexity of the system, i.e., development of learning content used to reach these goals. The characteristics learner habits during system use and tracking of their activity are extremely important, as they increase the level of individual personalisation of the system in order to get to know the learner better during the process of learning and system usage.

Testing previously acquired knowledge is a characteristic that represents the initial step in measuring acquired knowledge, and relates to system usage efficiency. The characteristics found in almost every system are learner model and domain knowledge model, which is expected taking into consideration that these are the basic elements of the didactic pyramid, next to the teacher who is described by the pedagogical model and teacher model characteristics.

Almost 80% of the IAHe-LS systems have been experimentally used, have knowledge testing, and use the pedagogical model. Systems that have been experimentally used confirm higher efficiency of intelligent and adaptive e-learning systems compared to traditional hypermedia e-learning systems [52], [22], [56], [28]. Traditional hypermedia e-learning systems allow the learner to choose their own learning path during system use. "Furthermore, standard learning paths can rarely be optimal for all kind of learners."[19]

As a consequence of using such systems, certain parts of the content may be skipped or the learning process may be sequenced erroneously. This however does not happen in IAHe-LS.

One of the main goals of this paper is to pinpoint the prevalence of characteristics used to describe the systems. The prevalence of the following characteristics was analysed: cognitive style, learner habits during system use, learning goals, learner activity tracking, knowledge testing, testing previously acquired knowledge, standardization, system interface model, teacher model, communication model, and interactive tools. The characteristics are grouped based on the didactic pyramid learner - teacher - content - educational technology (see Table 2).

The prevalence analysis did not include the following characteristics: learner model, pedagogical model, domain knowledge model, experimental use, form of presented content, and description model. Learner model, domain knowledge model, adaptivity criterion and adaptivity inference mechanism appear in all the systems, so their prevalence was impossible to follow during the time. But the prevalence analysis included the forms of adaptivity criterion and adaptivity inference mechanism. The same goes for the

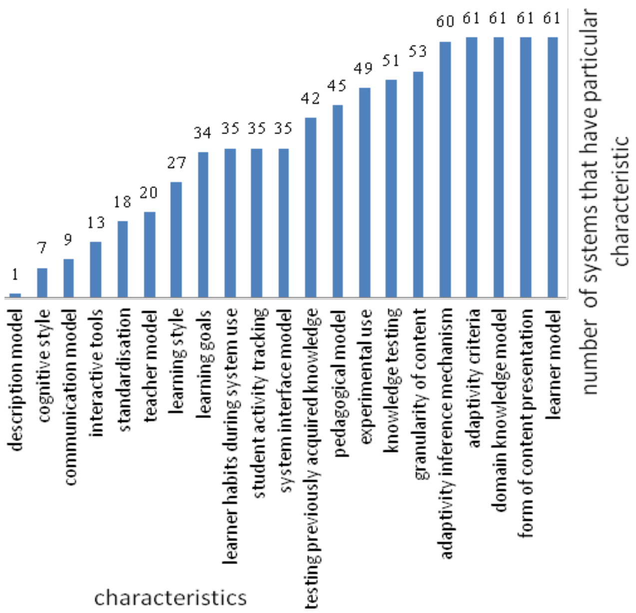

Chart 2: *Prevalence of characteristics in IAHe-LS systems*

characteristic pedagogical model (adaptation model), which occurs in the majority of systems (81.1%). Due to the fact that learning content is always present, the form of the presented content also appears in every examined system. The description model is featured in a single system so it was impossible to follow its prevalence.

Element of didactic pyramid	Characteristics
learner	learner model learning style, cognitive style, learner habits during system use, learner activity tracking
teacher	teacher model, previously acquired knowledge, knowledge testing, learning goals, pedagogical model

educational technology	interactive tools, standardization, communication model description model adaptivity inference mechanism adaptivity criteria experimental use
content	interface model form of presented content granularity of learning content domain knowledge model

Table 2: *Classification of characteristics according to the didactic pyramid*

4.1 The prevalence of learners' characteristics

Chart 3 illustrates the prevalence of the characteristics pertaining to the learner, namely: learning style, cognitive style, learner habits during system use, and learner activity tracking. It is noticeable that the prevalence of the learner activity tracking characteristic has increased with systems developed in 2008 and 2009 and the prevalence of habits during system has increased with systems developed in 2010 and 2011, which is related to the development of web technologies and the systems that enable it (see http://www.evolutionoftheweb.com/). It can be further observed that the cognitive style characteristic rarely appears in the systems so that it is difficult to even discuss the prevalence of it, when only two systems, dating back to 2011, exhibit this characteristic. The learning style characteristic has been present in almost every system since the late 1990s, and its presence in the systems increased during 2009, 2010, and 2011. In order to determine if the obtained model describes suitably the connection between the occurrence of a chracteristic and a time period of occurrence, that is if the occurrence of a single characteristic is not coincidental, an analysis was carried out by applying a Poisson regression method. The year 2014 was excluded from the analysis because there are no complete data for this time period. In table 3 there are results collected by applying a Poisson regression analysis for the following characteristics: activity tracking, habits during system use and learning style. A Poisson regression analysis was conducted for a characteristic *cognitive style,* however, due to little number of data and their dispersion, valid results have not been obtained (Appendix B).

Name of charac.	Residual deviance	P-value	Fitted model
Activity tracking	8,8236	0,8421	$y = e^{-163,81566+0,08209x}$
Habits during system use	8,6376	0,8535	$y = e^{-212,30727+0,10617x}$
Learning style	9,7192	0,7824	$y = e^{-201,03999+0,10044x}$

Table 3: *A Poisson r egresion analysis for t he following c haracteristics: ac tivity t racking, habi ts during system use and learning style.*

The null hypothesis is that the Poisson regression model provides an adequate fit for the data. We use the residual deviance to check the null hypothesis. The frequency of characteristics was used as criteria, while the year of occurrence served as predictor. The residual deviance for each characteristic was compared with a χ^2 distribution with 14 degrees of freedom. The P-value is large enough so that we do not have to reject the null hypothesis. The model appears to be adequate for each characteristic.

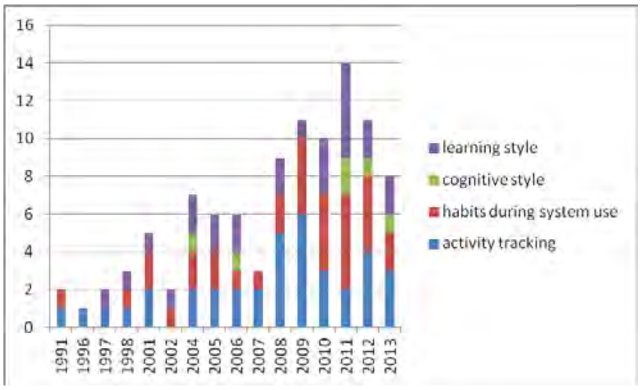

Chart 3: *The Prevalence of characteristics related to the learner*

4.2 The prevalence of teacher's characteristics

The prevalence of characteristics pertaining to the teacher, namely: teacher model, communication model, previously acquired knowledge, knowledge testing, and learning goals, are shown in Chart 4. The characteristics previously knowledge and knowledge testing appear more often starting from 2008, whereas the characteristic learning goals is present almost all the time, with its frequency increased during 2011 and 2012. One of the reasons for that might be the publication of the digital Bloom's taxonomy [9] where the classification of learning goals, based on the traditional Bloom's taxonomy, is adapted for the digital environment and the expected competences under those conditions. The teacher model characteristic has been appearing frequently since 2009, which exemplifies that the educational process is not determined solely by the parameters related to the learner, but also by those characteristics related to the teacher.

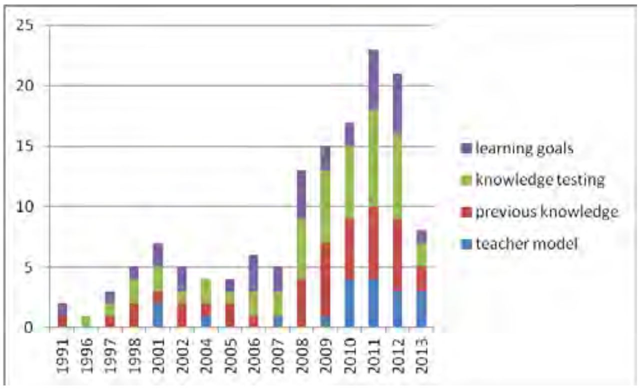

Chart 4: *The prevalence of characteristics related to the teacher*

We used the residual deviance (see Table 4) to check the null hypothesis which is that the Poisson regression model provides an adequate fit for data. A Poisson regression analysis was performed for all four characteristics.

Name of charac.	Residual deviance	P-value	Fitted model
Learning goals	12,550	0,5622	$y = e^{-166,9596+0,08358x}$
Know-ledge testing	11,682	0,6318	$y = e^{-242,7209+0,12152x}$
Previous know-ledge	16,096	0,3075	$y = e^{-218,0375+0,10914x}$
Teacher model	14,575	0,4078	$y = e^{-427,5258+0,21306x}$

Table 4: *The Poisson regression for characteristics related to the teacher*

The residual deviance for each characteristic, was compared with a χ^2 distribution with 14 degrees of freedom. The P-value is large enough that we do not have to reject the null hypothesis. The model appears to be adequate for each characteristic. (Appendix C)

4.3 The prevalence of educational technology's characteristics

The following characteristics are related to educational technology: interactive tools, standardisation, communication model, experimental use, description model, adaptivity criteria and adaptivity inference mechanism. Chart 5 illustrates the prevalence of characteristics: interactive tools, standardisation, experimental use and communication model. Experimental use and interactive tools appear most often in the period between 2008 and 2011. Conversely, standardisation has been occupying the interest of designers of IAHe-LS more often since 2007. Since 2008 and the arrival of HTML5 and CSS3, web technologies allow easier development of systems, as well as the design of educational content in IAHe-LS systems. As development is financially demanding, it is more profitable to reuse the already developed content units in various systems. In such cases, standardisation is of great help. The communication model occurs from 2009 onwards in each year in a single IAHe-LS.

As in the previous analysis of characteristics we performed a method of the Poisson regression for testing connectivity between variable frequency of characteristics related to the educational technology and the year of its appearance. The null hypothesis is that the Poisson regression model provides an adequate fit for the data.

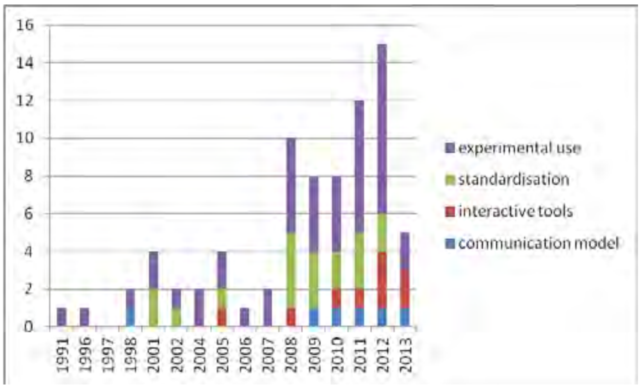

Chart 5: *The prevalence of characteristics related to educational technology*

The results are shown at Table 5 and graphic diagrams of a fitted model at Appendix D.

Name of charac.	Residual deviance	P-value	Fitted model
Experime-ntal use	11,914	0,6132	$y = e^{-247,0922+0,12366x}$
Interactive tools	6,16540	0,9621	$y = e^{-671,414+0,3340x}$

Table 5: *The Poisson regression for characteristics experimental use and interactive tools*

The prevalence of forms of characteristics adaptivity inference mechanisam and adaptivity criteria was analysed separately. Chart 6 shows the prevalence of forms of the adaptivity inference mechanism characteristic.

The prevalence of the adaptive rules form has increased during 2002 to 2005 and during 2008 to 2011. Form expert system has increase in appearance from 2008 onwards. The analysis does not cover the

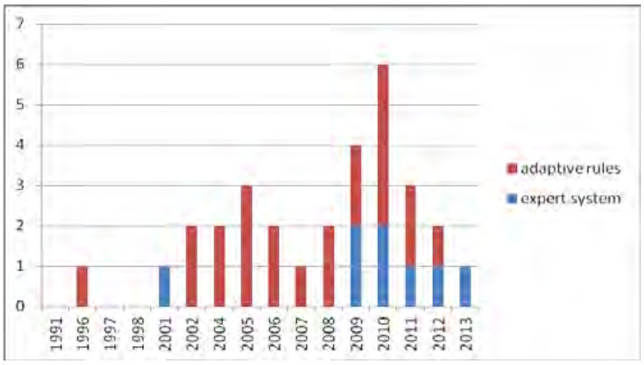

Chart 6: *The prevalence of forms of characteristic adaptivity inference mechanism*

forms that occur in one or two systems because it is not possible to follow their prevalence (apriori all algorithm, applicability, hierarchy model, cluster analysis predefined path based on adaptivity criteria, acyclic graph, dynamic path based on adaptivity criteria, recommendation system, neural networks, learning path agent, decision tree, Cohen neural network, fuzzy probability function, personalized learning path, Bayesian network, if-then rules, genetic algorithm, pedagogic rules and agent system). For an expert system characteristc we did not interpret the Poisson regression because of too little data. (Appendix E)

We calculated a fitted model for a characteristic *adaptive rules*. The P-value is 0,2799, which is large enough so that we do not have to reject the null hypothesis. The null hypothesis is that the Poisson regression model provides an adequate fit for the data.

Name of charac.	Residual deviance	P-value	Fitted model
Adaptive rules	16,567	0,2799	$y = e^{-146,9907 +0,07345x}$

Table 6: *The Poisson regression for an adaptive rules characteristic*

Chart 7 shows the prevalence of forms of adaptivity criteria characteristics that occur in three or more systems such as the criteria of adjustments (cognitive style, content selection by the learner, learning priorities, system user's activity log, learning goals, previously acquired knowledge, learning style, knowledge).

Most of analysed forms are quite dynamic, with the advent of cognitive style from 2004 onwards, and learning style from 2010 onwards. The form knowledge has increased from 2004 with few declines. Forms previously acquired knowledge, learning preferences, system user's activity log have increased from 2008 onwards. The form learning goals is present in most of systems with enhanced dynamics during 2001 to 2008. Content selection by learner appear in a few systems in years 2001, 2008,

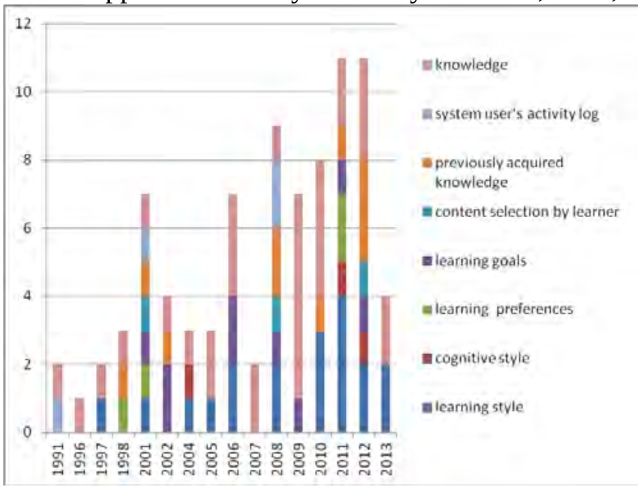

Chart 7: *The prevalence of forms of characteristic adaptivity criteria*

and 2012. At table 7 values for residual deviance, P-value and equation of the fitted model for forms knowledge and learning style of an adaptivity criteria characteristic are shown. A Poisson regression analysis was performed and it was concluded that the Poisson regression model provides an adequate fit for the data. For others forms of this characteristic we did not interpret the Poisson regression because of too little number of data or their big dispersion.(Appendix F)

Name of charac.	Residual deviance	P-value	Fitted model
Know-ledge	7,2376	0,9251	$y = e^{-143,9701+0,07213x}$
Learning style	12,857	0,5378	$y = e^{-279,9852+0,13962x}$

Table 7: *The Poisson regression for characteristic knowledge and learning style*

4.4 The Prevalence of content's characteristics

The characteristics related to the content are: interface model, granularity of learning content, form of presented content and domain knowledge model. The prevalence of characteristics domain knowledge model and form of presented content could not be analysed (reasons given in the introduction of chapter 4) The analysed characteristics are interface model and granularity of learning content. An increase in the prevalence of these characteristics is observed during the period between 2008 and 2012 (see Chart 8). A Poisson regression analysis was performed for these two characteristics. The null hypothesis is that the Poisson regression model provides an adequate fit

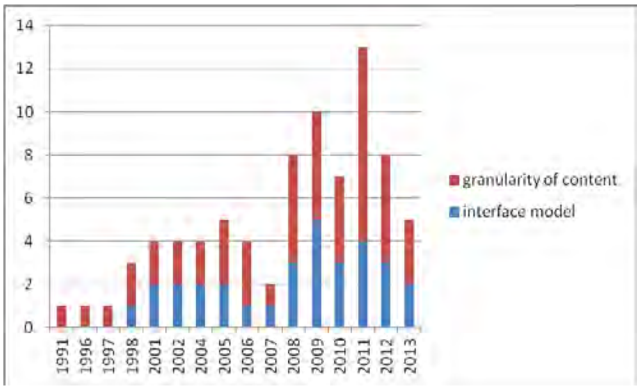

Chart 8: *The prevalence of the characteristic related to the content*

for the data. We used the residual deviance to check the null hypothesis. The residual deviance for each characteristic was compared with a χ^2 distribution with 14 degrees of freedom. The P-value is large enough so that we do not have to reject the null hypothesis. (see Table 8) The model appears to be adequate for each characteristic. (Appendix G)

Name of charac.	Residual deviance	P-value	Fitted model
Granularity of content	8,0162	0,884	$y = e^{-181,3863+0,09098x}$
Interface model	9,3324	0,8091	$y = e^{-219,7743+0,10988x}$

Table 8: *The Poisson regression for characteristic related to the content*

5 Conclusion and Future Research

The goal of this research was to give an overview of the prevalence of characteristics that describe IAHe-LS in the last 20 or so years, with the remark that we did not include 2014. By analysing 61 IAHe-LS systems, 21 characteristics were identified, namely: learning style, cognitive style, adaptivity inference mechanism, granularity of learning content, learner habits during system use, learning goals, learner model, pedagogical model, domain knowledge model, learner activity tracking, knowledge testing, testing previously acquired knowledge, experimental use, form of presented content, adaptivity criteria, standardization, system interface model, teacher model, description model, communication model, and interactive tools. The majority of IAHe-LS, 52 of them, were described by using between 7 and 11 characteristics. The smallest number of characteristics used to describe a particular system is 3, while the largest is 14 (only 1 system). This, however, does not mean that the number of characteristics of a particular IAHe-LS could not have been larger than identified, but that data concerning other characteristics were not available in the selected papers. Future research should reveal whether the number of characteristics improves the efficiency of IAHe-LS in knowledge transfer.

Granularity of content was not clearly defined in 40% of the IAHe-LS, which indicates that system descriptions did not pay sufficient attention to this characteristic even though content has been granulated to the level of concept in 25.4% of the systems. The characteristic form of presented content refers to the principal medium for carrying learning content. In the analyzed IAHe-LSs, this characteristic most often appeared as text and/or static graphics, and least often as multimedia content. Further research should be aimed at investigating the relationship between granularity of content, form of presentation and knowledge level in order to determine if the investments into more complex forms of content presentation are justified.

Cognitive style [23] is a characteristic that belongs among learner related characteristics not often found in descriptions of the systems. Observation of the prevalence of this characteristic has shown a slight increase during 2011. This characteristic should certainly be included into future IAHe-LS, as it will ensure a higher level of individual personalization of the IAHe-LS.

The learning style characteristic was found in a number of IAHe-LS. The prevalence of this characteristic is more intense in the period between 2008 and 2012. However, the VARK classification of learning styles is quite often used by teachers and should be the focus of future research.

In the last few years, the emphasis has been on defining learning outcomes in formal education, which represents learning goals that have been realized. The characteristic learning goals appeared in 34 IAHe-LS, but only 2 of them featured learning goals based on Bloom's taxonomy. The prevalence is increased in the period between 2011 and 2012, and is probably related to the emergence of the digital Bloom's taxonomy.

The characteristics adaptivity inference mechanism and adaptivity criteria were separately analyzed by identifying their forms and frequency of appearance. Most commonly employed adaptivity inference mechanism was adaptivity rules, followed by expert systems. Their prevalence enhanced from 2005 and 2008 onwards. However, the inference mechanism that uses neural networks method (Cohen's neural network) appeared in a single system. The application of algorithms from the field of neural networks represent space for new research and challenge in improving and increasing the individual personalization of IAHe-LS.

Regarding adaptivity criteria the most common criterion was knowledge, which was to be expected considering the purpose of the IAHe-LS. Some of those adaptivity criteria that were found less frequentl included: learner needs, emotions, motivation, mood, and personality. All these are, thus, learner characteristics, and by including them into a system, the level of individual personalization of the system would certainly rise. The years in which the enhanced prevalence incidence of most forms of characteristic adaptivity criteria are 2004, 2006, 2008 and 2012.

An analysis of the connection between the frequency of characteristics of IAHe-LS and years of their appearance using the Poisson regression method was performed. The Poisson regression model for all analised characteristics provides an adequate fit to the data.

Considering how widespread and available information and communication technology is, it has become possible to apply IAHe-LS in all types of education - formal, non-formal, and informal. Work on their development and on increasing the level of individual personalized learning should continue.

Acknowledgement

The research has been conducted under the project "Enhancing the efficiency of an e-learning system based on data mining", (reference number 13.13.1.2.02) supported by the University of Rijeka (Croatia).

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Appendix A

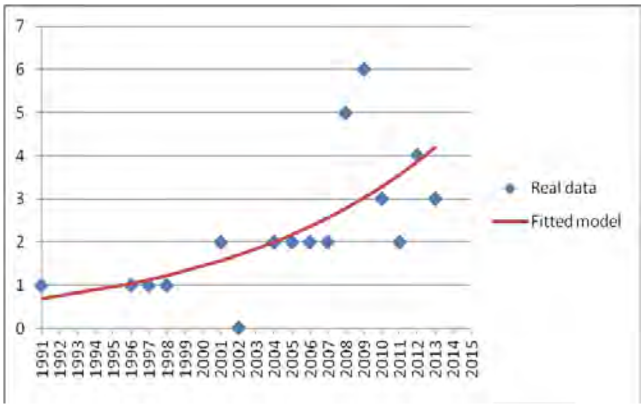
No.	System name/ Author's surname	Learning style	Cognitive style	Adaptivity inference mechanism	Learning goals	Learner habits during system use	Learner model	Pedagogical model	Domain knowledge model	Learner activity tracking	Knowledge testing	Experimental use	Adaptivity criteria	Previously acquired knowledge	Standardisation	System interface model	Teacher model	Description model	Interactive tools	Communication model	Year of publication	Country of origin
1	ACE			√	√		√		√		√	√	√	√		√	√				1998	Germany
2	Active math			√	√	√	√	√	√	√	√	√	√	√	√	√					2001	Germany
3	AC-ware tutor			√	√		√	√	√		√	√	√	√	√	√	√			√	2012	Croatia
4	ADAM			√		√	√	√	√		√	√	√	√	√	√	√				2010	Taiwan
5	Adaptive Multimedia Presentation System			√	√	√	√	√	√		√	√	√	√		√					2011	Great Britain
6	ADOPTA	√		√	√		√	√	√		√	√	√	√	√						2012	Bulgaria
7	Aguilar et al.	√		√	√	√	√	√	√		√	√	√	√		√	√				2011	Spain
8	AHyCo			√		√	√	√	√	√	√	√	√	√		√	√		√		2005	Croatia
9	Anh, Ha, Dam			√	√	√	√	√	√	√	√	√	√	√	√	√					2009	Vietnam
10	APeLS	√		√	√		√	√	√	√	√		√	√				√			2006	Ireland
11	ASM	√		√			√		√				√	√							2005	Greece
12	AST	√		√	√		√		√	√	√		√	√							1997	Germany
13	Bachari et al.		√	√	√		√	√	√		√	√	√								2011	Morocco
14	Beldagli, Adiguzel			√			√	√	√	√	√			√		√					2010	Turkey
15	Bittencourt et al. (E-Mathema)			√		√	√	√	√	√	√	√	√	√	√	√				√	2009	Brazil
16	Chen			√	√		√	√	√	√	√	√	√	√	√	√	√				2008	Taiwan
17	Conlan et al.	√		√	√		√	√	√			√	√	√	√	√					2002	Ireland
18	DEPTHS	√		√			√	√	√	√	√	√	√	√		√					2009	Serbia
19	ECSAI			√	√	√	√	√	√	√		√	√	√							1991	France
20	EDUCA	√		√			√	√	√		√	√	√	√	√	√			√		2011	Mexico
21	ELM-ART			√			√		√	√	√	√	√								1996	Germany
22	Esichaikul et al.			√			√	√	√		√	√	√	√							2011	Thailand
23	FLEXI-OLM	√		√		√	√	√	√	√	√	√	√			√					2004	United Kingdom
24	Flores et al.			√			√	√	√		√	√	√	√		√					2012	the USA
25	Gamalel-Din	√		√	√	√	√	√	√	√	√	√	√	√	√		√				2010	Egypt
26	Giugni et al.			√	√		√		√		√	√	√				√				2010	Spain
27	GPAM-WATA			√	√		√	√	√	√	√	√	√	√					√		2014	Taiwan
28	GTE	√		√		√	√	√	√	√			√	√							1998	Belgium
29	Huang et al.			√	√		√	√	√	√	√	√	√			√					2007	Taiwan
30	Huang and Shiu			√			√	√	√	√	√	√	√	√					√		2012	Taiwan
31	iClass		√	√	√		√	√	√				√				√				2006	Ireland
32	INSPIRE	√		√	√	√	√		√	√	√	√	√			√					2006	Greece
33	Juarez-Ramirez et al.	√		√		√	√	√	√	√	√		√	√		√	√		√		2013	Mexico
34	Karampipers, Sampson	√		√	√	√	√	√	√	√		√	√		√	√	√				2005	Greece

35	Kovačić			√	√		√	√	√	√	√	√	√	√						√	2009	Croatia
36	LeActiveMath			√	√		√	√	√	√	√	√	√	√	√	√			√		2008	Germany
37	Lecomps5	√		√	√		√		√		√	√	√	√		√	√				2011	Italy
38	Li et al.			√	√		√	√	√	√		√	√						√		2012	Taiwan
39	Lo, Chan, Yeh		√	√		√	√	√	√	√		√	√			√					2012	Taiwan
40	Mohamed et al.			√		√	√	√	√	√	√	√	√								2012	Algeria
41	NetCoach			√	√	√	√		√		√		√	√		√	√				2002	Germany
42	Ocepek et al.	√	√			√	√	√	√	√		√	√			√	√				2013	Slovenia
43	Pdinamet	√		√	√	√	√	√	√		√	√	√	√			√				2005	Spain
44	Pena-Ayala et al.	√	√	√	√	√	√	√	√	√	√	√	√		√	√			√	√	2014	Mexico
45	Peredo at al.			√	√	√	√	√	√	√	√		√	√	√						2011	Mexico
46	Phobun, Vicheanpanya	√		√		√	√	√	√		√		√	√		√					2010	Thailand
47	PROTEUS			√	√	√	√		√	√	√	√	√								2007	the Netherlands
48	PROTUS	√		√		√	√	√	√	√	√	√	√								2011	Serbia
49	Romero et al.			√		√	√	√	√	√	√	√	√	√	√	√					2009	the Netherlands
50	Sangineto et al.	√		√	√		√		√	√	√	√	√	√	√						2008	Italy
51	Somyurek			√		√	√	√	√	√	√	√	√	√		√			√	√	2014	Turkey
52	Sottilare, Proctor			√	√	√	√	√	√		√	√	√	√					√	√	2012	the USA
53	SPERO			√	√	√	√	√	√	√	√	√	√	√	√	√	√				2008	Greece
54	Triantafillou	√	√	√		√	√	√	√	√	√	√	√	√		√					2004	Greece
55	Tseng et al.	√		√		√	√	√	√	√	√	√	√								2008	Taiwan
56	UZWEBMAT	√		√	√	√	√	√	√	√	√	√	√			√	√			√	2013	Turkey
57	WELSA	√		√		√	√	√	√	√	√	√	√	√			√		√		2010	Romania
58	WINDS	√		√	√	√	√	√	√	√	√	√	√		√	√					2001	Germany
59	WISEngineering				√		√	√	√	√	√	√	√	√			√		√	√	2013	the USA
60	Yaghmaie et al.	√		√		√	√	√	√				√		√		√				2011	Iran
61	ZOSMAT			√		√	√	√	√	√	√		√	√		√					2009	Turkey

Appendix B

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8403  -0.2665  -0.1166   0.1420   1.5170

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -163.81566   63.88671  -2.564  0.01034 *
os_x           0.08209    0.03183   2.579  0.00991 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 16.4684  on 15  degrees of freedom
Residual deviance:  8.8236  on 14  degrees of freedom
AIC: 52.893
```

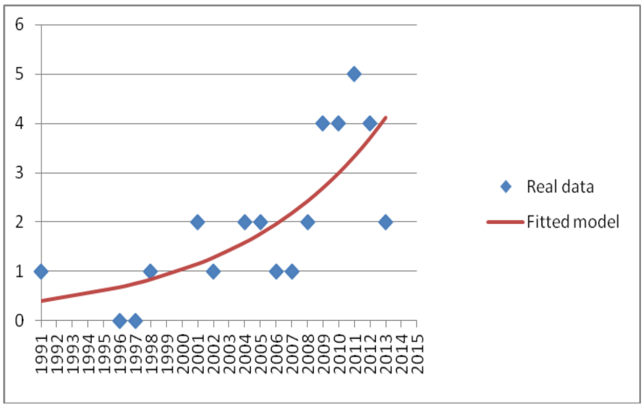
The Poisson regression calculate by R for characteristic activity tracking



The scatter diagram of real data and fitted model for characteristic activity tracking

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.2304  -0.7974   0.1550   0.5846   0.8414

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -212.30727   73.40267  -2.892  0.00382 **
os_x           0.10617    0.03656   2.904  0.00368 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 18.8670  on 15  degrees of freedom
Residual deviance:  8.6376  on 14  degrees of freedom
AIC: 48.984
```

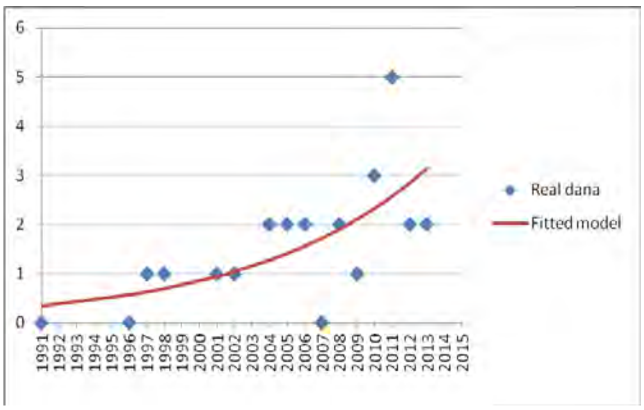
The Poisson regression calculate by R for characteristic habits during system use



The scatter diagram of real data and fitted model for characteristic habits during system use

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.85240  -0.72244   0.06815   0.42852   1.34412

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -201.03999   81.72300  -2.460   0.0139 *
os_x           0.10044    0.04071   2.467   0.0136 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 17.0072  on 15  degrees of freedom
Residual deviance:  9.7192  on 14  degrees of freedom
AIC: 45.874
```

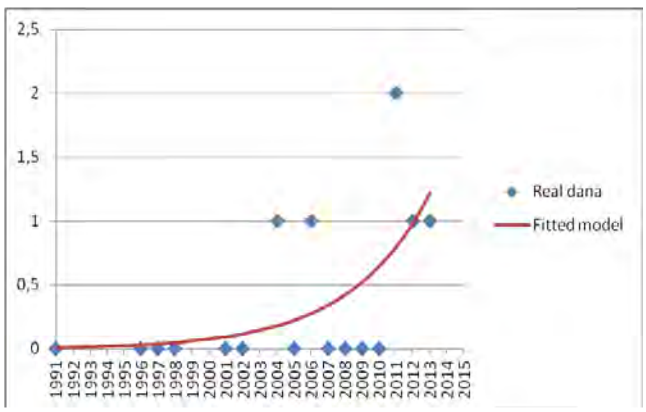
The Poisson regression calculate by R for characteristic learning style



The scatter diagram of real data and fitted model for characteristic learning style

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1391  -0.7116  -0.3051  -0.1124   1.3279

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -424.5443   228.7286  -1.856   0.0634 .
os_x           0.2110     0.1138   1.854   0.0638 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 14.5425  on 15  degrees of freedom
Residual deviance:  9.2311  on 14  degrees of freedom
AIC: 23.845
```

The Poisson regression calculate by R for characteristic cognitive style

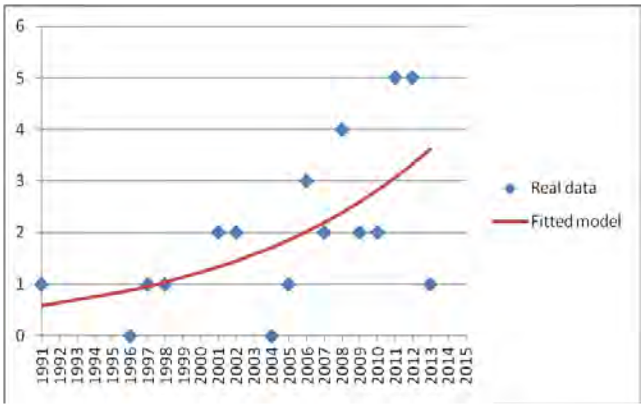


The scatter diagram of real data and fitted model for characteristic cognitive style

Appendix C

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.85364  -0.56792   0.00184   0.55901   1.00003

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -166.95968   68.97360  -2.421   0.0155 *
os_x           0.08358    0.03436   2.432   0.0150 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 19.372  on 15  degrees of freedom
Residual deviance: 12.550  on 14  degrees of freedom
AIC: 52.837
```

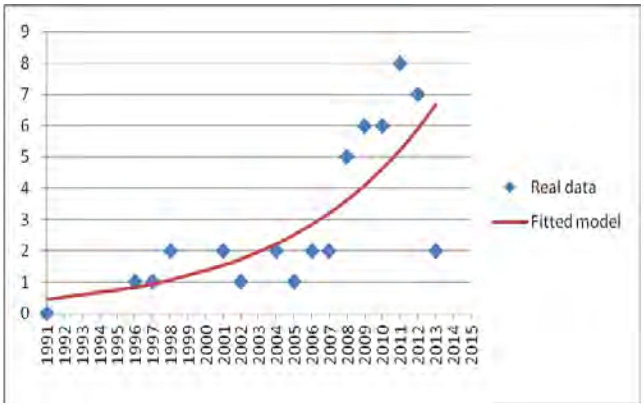
The Poisson regression calculate by R for characteristic learning goals



The scatter diagram of real data and fitted model for characteristic learning goals

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.14311  -0.65646   0.09775   0.60864   1.10369

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -242.72095   62.60226  -3.877 0.000106 ***
os_x           0.12152    0.03118   3.898  9.7e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 30.779  on 15  degrees of freedom
Residual deviance: 11.682  on 14  degrees of freedom
AIC: 57.905
```

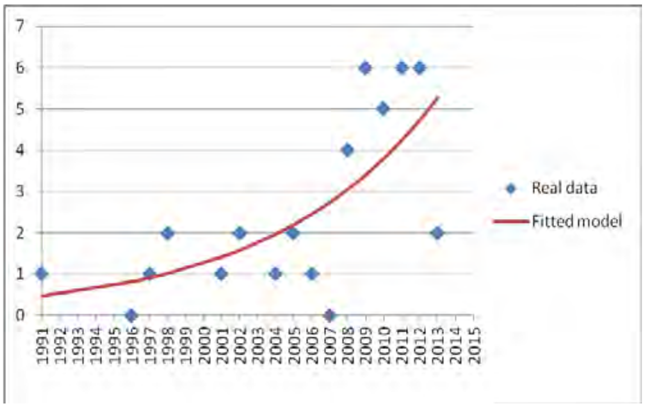
The Poisson regression calculate by R for characteristic knowledge testing



The scatter diagram of real data and fitted model for characteristic knowledge testing

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3368  -0.8350   0.2024   0.6101   1.2734

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -218.03757   66.20421  -3.293 0.000990 ***
os_x           0.10914    0.03297   3.310 0.000934 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 29.475  on 15  degrees of freedom
Residual deviance: 16.096  on 14  degrees of freedom
AIC: 58.27
```

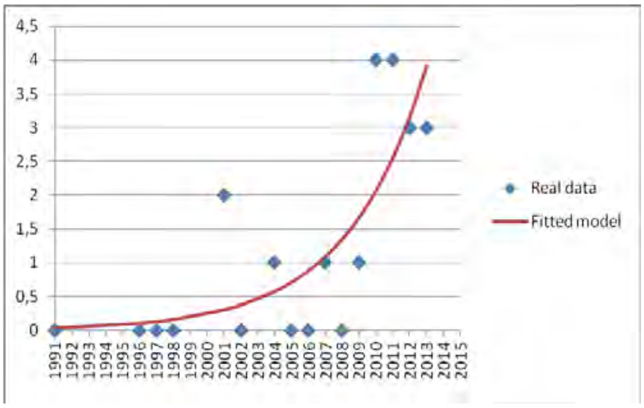
The Poisson regression calculate by R for characteristic previous knowledge



The scatter diagram of real data and fitted model for characteristic previous knowledge

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.63886  -0.63982  -0.46502   0.06532   2.04041

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -427.52581  129.26912  -3.307 0.000942 ***
os_x           0.21306    0.06433   3.312 0.000926 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 31.606  on 15  degrees of freedom
Residual deviance: 14.575  on 14  degrees of freedom
AIC: 39.704
```

The Poisson regression calculate by R for characteristic teacher model

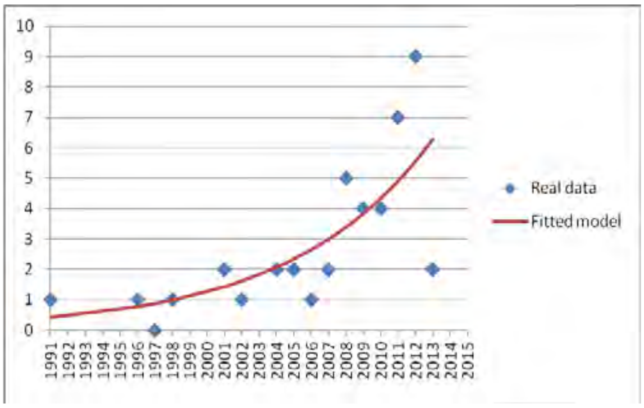


The scatter diagram of real data and fitted model for characteristic teacher model

Appendix D

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.97736  -0.53008  -0.00313   0.54331   1.36457

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -247.09229   65.78599  -3.756 0.000173 ***
os_x           0.12366    0.03276   3.774 0.000160 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 29.910  on 15  degrees of freedom
Residual deviance: 11.914  on 14  degrees of freedom
AIC: 56.855
```

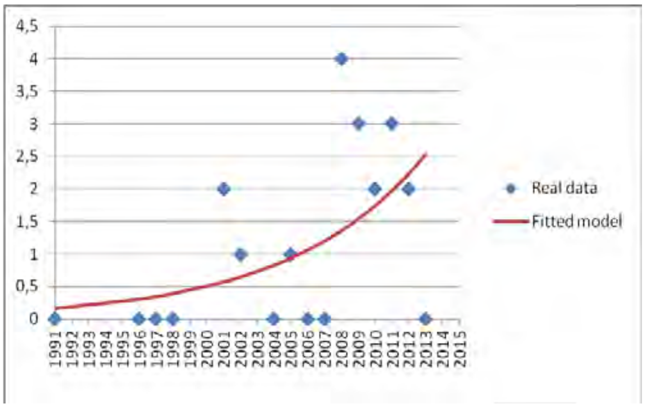
The Poisson regression calculate by R for characteristic experimental use



The scatter diagram of real data and fitted model for characteristic experimental use

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.2597  -0.9911  -0.3750   0.4658   1.8172

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -248.94533  102.99622  -2.417   0.0156 *
os_x           0.12413    0.05129   2.420   0.0155 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 28.351  on 15  degrees of freedom
Residual deviance: 20.944  on 14  degrees of freedom
AIC: 46.035
```

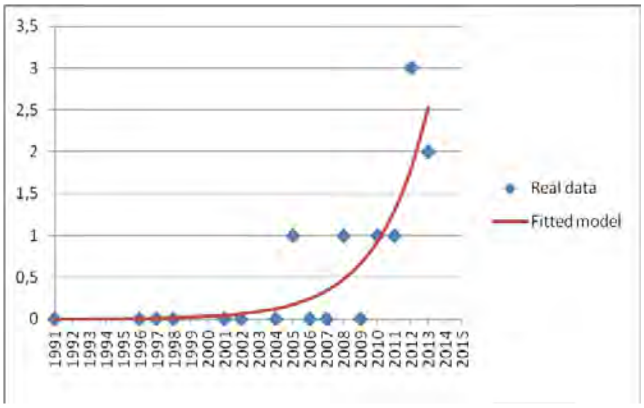
The Poisson regression calculate by R for characteristic standardisation



The scatter diagram of real data and fitted model for characteristic standardisation

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.17013  -0.41980  -0.24506  -0.03228   1.33787

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -671.4140   254.9232  -2.634  0.00844 **
os_x           0.3340     0.1268   2.634  0.00843 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 19.7208  on 15  degrees of freedom
Residual deviance:  6.1645  on 14  degrees of freedom
AIC: 23.77
```

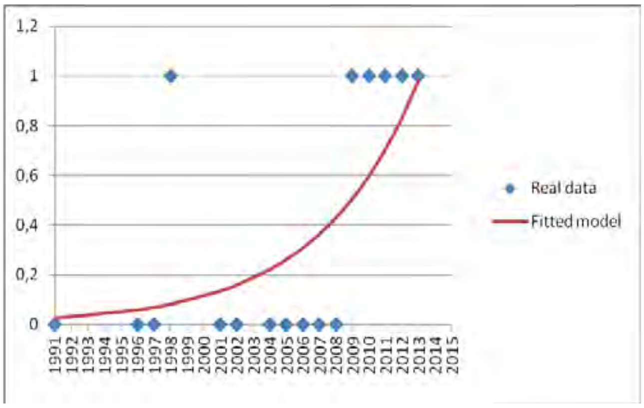
The Poisson regression calculate by R for characteristic interactive tools



The scatter diagram of real data and fitted model for characteristic interactive tools

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.9475  -0.6952  -0.3661   0.1743   1.7561

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -333.1720   201.0437  -1.657   0.0975 .
os_x           0.1655     0.1001   1.654   0.0981 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 11.7700  on 15  degrees of freedom
Residual deviance:  7.9568  on 14  degrees of freedom
AIC: 23.957
```

The Poisson regression calculate by R for characteristic communication model

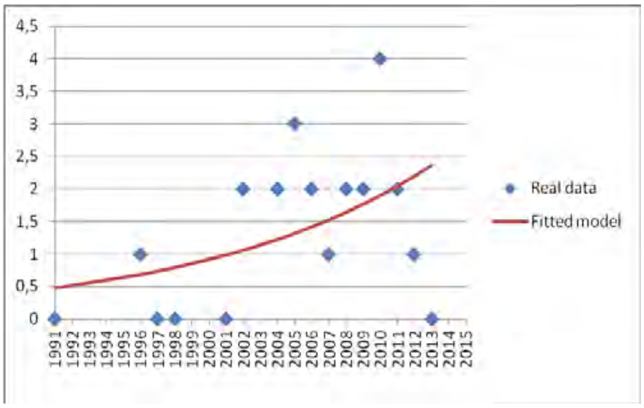


The scatter diagram of real data and fitted model for characteristic communication model

Appendix E

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.17125  -1.02756   0.07726   0.51281   1.33246

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -146.99077   80.98017  -1.815   0.0695 .
os_x           0.07345    0.04035   1.820   0.0687 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 20.306  on 15  degrees of freedom
Residual deviance: 16.567  on 14  degrees of freedom
AIC: 48.507
```

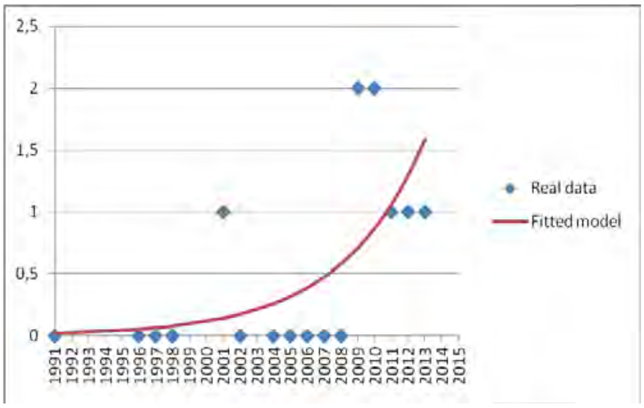
The Poisson regression calculate by R for
characteristic adaptive rules



The scatter diagram of real data and fitted model
for characteristic adaptive rules

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0724  -0.7356  -0.3727  -0.1579   1.4862

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -405.24007  192.92400  -2.101   0.0357 *
os_x           0.20154    0.09601   2.099   0.0358 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 16.6355  on 15  degrees of freedom
Residual deviance:  9.9661  on 14  degrees of freedom
AIC: 27.193
```

The Poisson regression calculate by R for
characteristic expert system

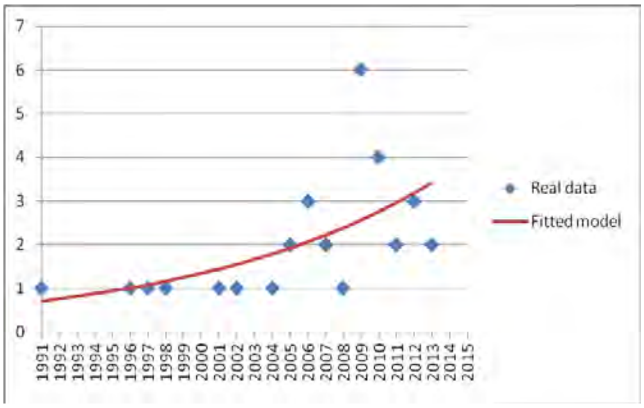


The scatter diagram of real data and fitted model
for characteristic expert system

Appendix F

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0077  -0.4939  -0.1170   0.1342   1.8364

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -143.97013   66.91471  -2.152   0.0314 *
os_x           0.07213    0.03334   2.163   0.0305 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 12.5038  on 15  degrees of freedom
Residual deviance:  7.2376  on 14  degrees of freedom
AIC: 50.599
```

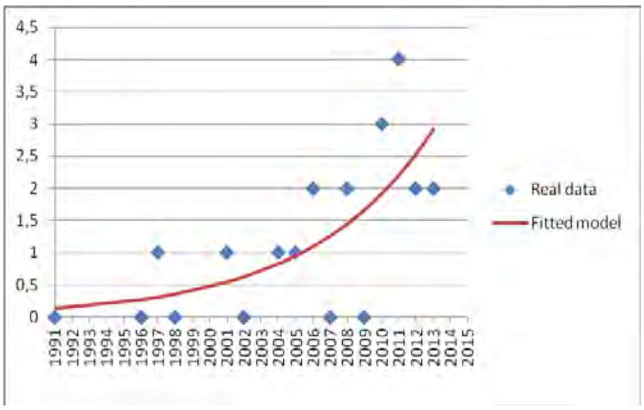
The Poisson regression calculate by R for
form knowledge of characteristic adaptivity criteria



The scatter diagram of real data and fitted model
for form knowledge of characteristic adaptivity criteria

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8223  -0.7629  -0.1457   0.5973   1.0912

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -279.98526  104.82366  -2.671  0.00756 **
os_x           0.13962    0.05219   2.675  0.00747 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 22.242  on 15  degrees of freedom
Residual deviance: 12.857  on 14  degrees of freedom
AIC: 41.569
```

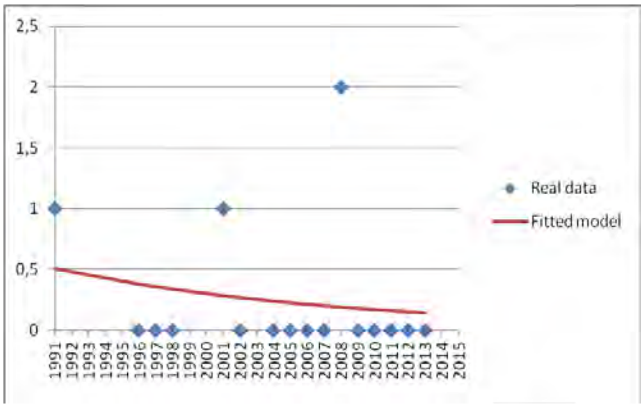
The Poisson regression calculate by R for form learning style of
characteristic adaptivity criteria



The scatter diagram of real data and fitted model for form learning
style of characteristic adaptivity criteria

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-0.8706  -0.7015  -0.6161  -0.5449   2.4087

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) 114.15631  152.44990   0.749    0.454
os_x         -0.05768    0.07615  -0.757    0.449

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 13.863  on 15  degrees of freedom
Residual deviance: 13.304  on 14  degrees of freedom
AIC: 23.918
```

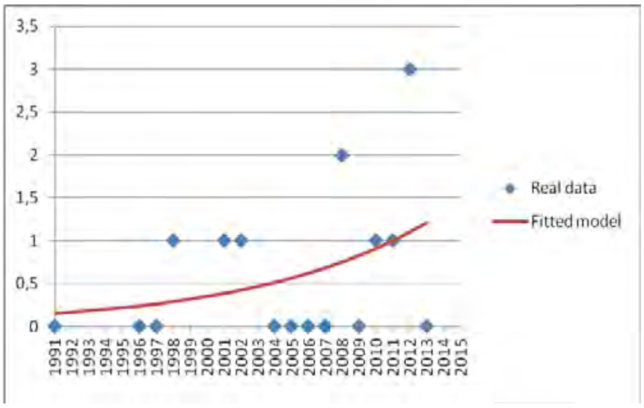
The Poisson regression calculate by R for form system user's activity log of characteristic adaptivity criteria



The scatter diagram of real data and fitted model for form system user's activity log of characteristic adaptivity criteria

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.5622  -1.0791  -0.6199   0.7644   1.4795

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -192.11096  127.46765  -1.507    0.132
os_x           0.09553    0.06350   1.505    0.132

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 18.764  on 15  degrees of freedom
Residual deviance: 16.084  on 14  degrees of freedom
AIC: 35.69
```

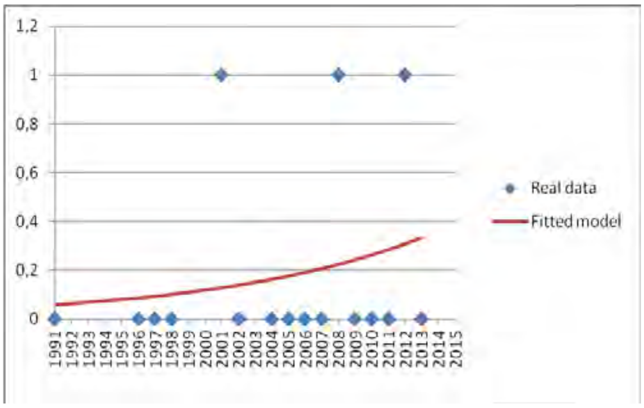
The Poisson regression calculate by R for form previously acquired knowledge of characteristic adaptivity criteria



The scatter diagram of real data and fitted model for form previously acquired knowledge of characteristic adaptivity criteria

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-0.8181  -0.6568  -0.5486  -0.3954   1.5385

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -162.28254  223.16155  -0.727    0.467
os_x           0.08007    0.11119   0.720    0.471

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 10.0439  on 15  degrees of freedom
Residual deviance:  9.4503  on 14  degrees of freedom
AIC: 19.45
```

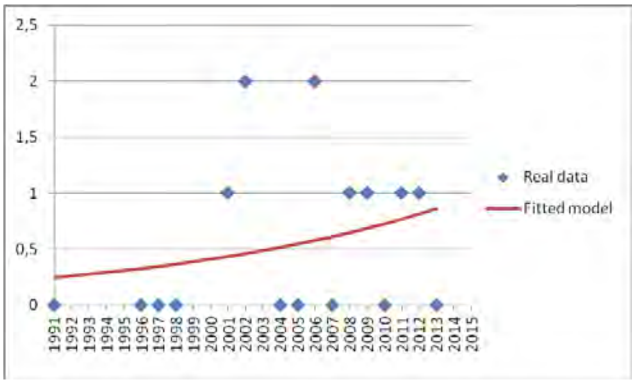
The Poisson regression calculate by R for form content selection by learner of characteristic adaptivity criteria



The scatter diagram of real data and fitted model for form content selection by learner of characteristic adaptivity criteria

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.3165  -1.0269  -0.7585   0.3614   1.6651

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -114.4894   121.3786  -0.943    0.346
os_x           0.0568     0.0605   0.939    0.348

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 15.902  on 15  degrees of freedom
Residual deviance: 14.940  on 14  degrees of freedom
AIC: 34.167
```

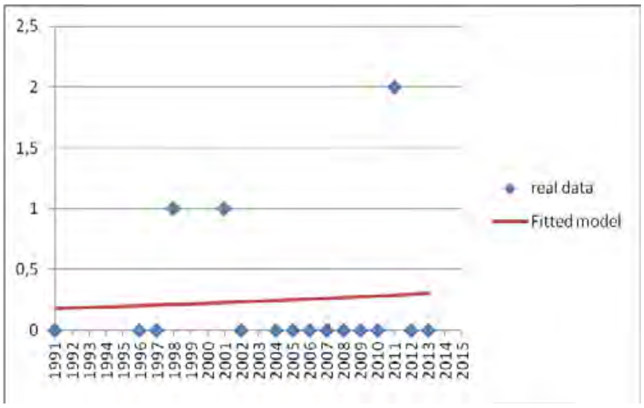
The Poisson regression calculate by R for form learning goals of characteristic adaptivity criteria



The scatter diagram of real data and fitted model for form learning goals of characteristic adaptivity criteria

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7793  -0.7366  -0.7045  -0.6276   2.0759

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -49.03943  169.01053  -0.290    0.772
os_x          0.02377    0.08428   0.282    0.778

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 13.863  on 15  degrees of freedom
Residual deviance: 13.781  on 14  degrees of freedom
AIC: 24.395
```

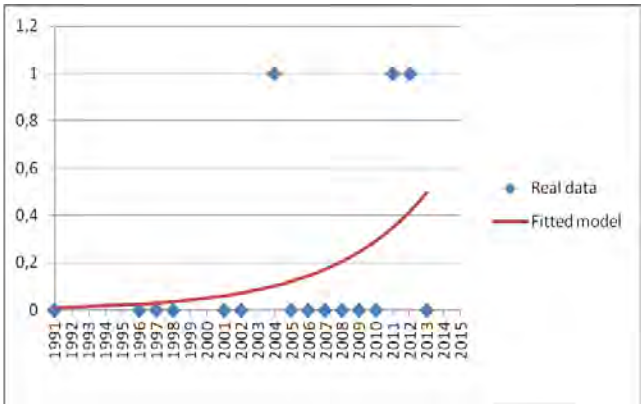
The Poisson regression calculate by R for form learning preferences of characteristic adaptivity criteria



The scatter diagram of real data and fitted model for form learning preferences of characteristic adaptivity criteria

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.0350  -0.6247  -0.3769  -0.2115   1.6230

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -354.5881   292.8805  -1.211    0.226
os_x           0.1758     0.1458   1.206    0.228

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 10.0439  on 15  degrees of freedom
Residual deviance:  7.9667  on 14  degrees of freedom
AIC: 17.967
```

The Poisson regression calculate by R for form learning preferences of characteristic adaptivity criteria

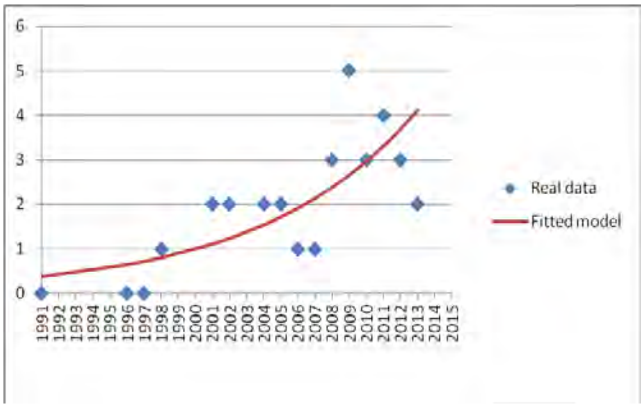


The scatter diagram of real data and fitted model for form learning preferences of characteristic adaptivity criteria

Appendix G

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1873  -0.8543   0.1301   0.3871   1.2947

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -219.77438   75.35990  -2.916  0.00354 **
os_x           0.10988    0.03753   2.927  0.00342 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 19.8160  on 15  degrees of freedom
Residual deviance:  9.3324  on 14  degrees of freedom
AIC: 48.123
```

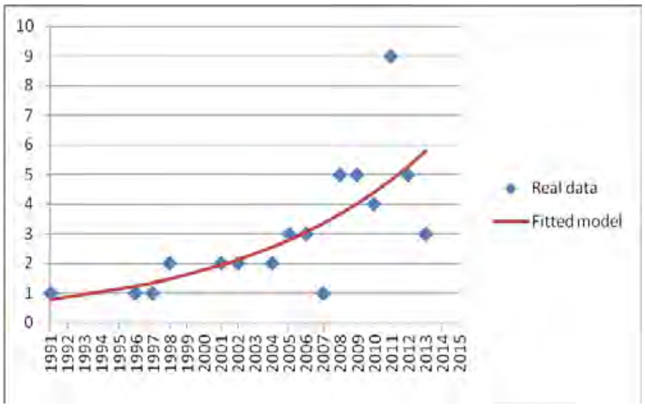
The Poisson regression calculate by R for characteristic interface model



The scatter diagram of real data and fitted model for characteristic interface model

```
Call:
glm(formula = os_y ~ os_x, family = poisson, data = podaci)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.52253  -0.24868  -0.07249   0.27203   1.67800

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -181.38633   56.86893  -3.190  0.00142 **
os_x           0.09098    0.02833   3.211  0.00132 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 20.1042  on 15  degrees of freedom
Residual deviance:  8.0162  on 14  degrees of freedom
AIC: 57.208
```

The Poisson regression calculate by R for characteristic granularity of content



The scatter diagram of real data and fitted model for characteristic granularity of content