Open University of Cyprus

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Postgraduate (Master's) Programme of Study

Cognitive Systems (English)

Postgraduate (Master's) Dissertation

Application of User Modeling and Adaptation in E-learning Based on Learning Styles

Tatiana Shevtsova

Supervisor

Ilianna Kollia

December 2022

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The present Postgraduate (Master’s) Dissertation was submitted in partial fulfillment of the requirements for the postgraduate degree in Cognitive Systems
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Summary

The present Master's dissertation aims to research the capabilities of adapting a learning management system to the individual needs of students based on their psychological profile. The issue is viewed from the perspective of cognitive psychology, by considering personal characteristics of the users and the respective learning styles, and from the perspective of artificial intelligence, by focusing on the implementation of this concept in e-learning systems. A systematic approach to this task allows to study the relationship between the individual characteristics of students and the necessary changes in learning systems to achieve a good level of adaptability.

The Master's dissertation explores what techniques can be used to support adaptation of an e-learning system using an approach based on learning styles of its users. To achieve this goal, the following major tasks have been fulfilled in the work: 1) analysis of existing technologies for implementing user modeling and adaptation in general and in e-learning systems specifically; 2) review of personality scales that can be used as a psychological basis for defining learning styles of users; 3) analysis of methods of adaptation that can be applied at the level of planning the educational process to reflect personalization in the system based on individual characteristics.

The chapters of the Master's dissertation are dedicated respectively to three major areas: User Modeling and Adaptation, Learning Styles, and Application of AI. The User Modeling and Adaptation chapter includes a general review of user modeling, adaptation and personalization techniques with specific interest in the adaptation capabilities in e-learning platforms. The Learning Styles chapter considers psychological aspects of learning, in particular, learning styles associated with different personality types, based on a review of the literature and studies relevant to the research topic. The Application of AI chapter proposes how the suggested personality scale can be incorporated into an e-learning platform using the capabilities of Artificial Intelligence, in particular, fuzzy logic and deep learning techniques.

Περίληψη

Η παρούσα Μεταπτυχιακή διατριβή στοχεύει να ερευνήσει τις δυνατότητες προσαρμογής ενός συστήματος διαχείρισης μάθησης στις ατομικές ανάγκες των φοιτητών με βάση το ψυχολογικό τους προφίλ. Το θέμα εξετάζεται από τη σκοπιά της γνωστικής ψυχολογίας, λαμβάνοντας υπόψη τα προσωπικά χαρακτηριστικά των χρηστών και τα αντίστοιχα στυλ μάθησης και, από την πλευρά της τεχνητής νοημοσύνης, εστιάζοντας στην εφαρμογή αυτής σε συστήματα ηλεκτρονικής μάθησης. Μια συστηματική προσέγγιση σε αυτήν την κατεύθυνση αποτελεί η μελέτη της σχέσης μεταξύ των ατομικών χαρακτηριστικών των μαθητών και των απαραίτητων αλλαγών στα συστήματα μάθησης για να επιτευχθεί ένα καλό επίπεδο προσαρμοστικότητας.

Η Μεταπτυχιακή διατριβή ερευνά τις τεχνικές που μπορούν να χρησιμοποιηθούν για την υποστήριξη της προσαρμογής ενός συστήματος ηλεκτρονικής μάθησης, χρησιμοποιώντας μια προσέγγιση που βασίζεται στα στυλ μάθησης των χρηστών του. Για την επίτευξη αυτού του στόχου, οι ακόλουθες κύριες δραστηριότητες έχουν ολοκληρωθεί στην εργασία: 1) ανάλυση των υφιστάμενων τεχνολογιών για την εφαρμογή μοντελοποίησης και προσαρμογής χρηστών γενικά και ειδικά σε συστήματα ηλεκτρονικής μάθησης; 2) ανασκόπηση των κλιμάκων προσωπικότητας που μπορούν να χρησιμοποιηθούν ως ψυχολογική βάση για τον καθορισμό των στυλ μάθησης των χρηστών; 3) ανάλυση των μεθόδων προσαρμογής που μπορούν να εφαρμοστούν στο επίπεδο του σχεδιασμού της εκπαιδευτικής διαδικασίας ώστε αυτή να αντικατοπτρίζει την εξατομίκευση στο σύστημα με βάση τα ατομικά χαρακτηριστικά.

Τα κεφάλαια της Μεταπτυχιακής διατριβής ασχολούνται αντίστοιχα με τρεις βασικούς τομείς: Μοντελοποίηση και Προσαρμογή Χρηστών, Μαθησιακά Στυλ και Εφαρμογή Τεχνητής Νοημοσύνης. Το κεφάλαιο "Μοντελοποίηση και Προσαρμογή Χρηστών" περιλαμβάνει μια γενική ανασκόπηση των τεχνικών μοντελοποίησης, προσαρμογής και εξατομίκευσης χρηστών με συγκεκριμένο ενδιαφέρον για τις δυνατότητες προσαρμογής σε πλατφόρμες ηλεκτρονικής μάθησης. Το κεφάλαιο "Μαθησιακά Στυλ" εξετάζει ψυχολογικές πτυχές της μάθησης, ειδικότερα, στυλ μάθησης που σχετίζονται με διαφορετικούς τύπους προσωπικότητας, με βάση την

ανασκόπηση της βιβλιογραφίας και τις σχετικές με το ερευνητικό θέμα μελέτες. Το κεφάλαιο "Εφαρμογή της Τεχνητής Νοημοσύνης" προτείνει πώς η προτεινόμενη κλίμακα προσωπικότητας μπορεί να ενσωματωθεί σε μια πλατφόρμα ηλεκτρονικής μάθησης χρησιμοποιώντας τις δυνατότητες της Τεχνητής Νοημοσύνης, ειδικότερα, τη ασαφή λογική και τις τεχνικές βαθιάς μάθησης.

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Chapter 1
Introduction

Today, interaction with information systems has become a regular daily routine for most people. This includes online learning, professional activities, communication with friends, entertainment, and a variety of other tasks. The extensive use of information technologies opens up new opportunities for lifelong learning and makes education more accessible. This becomes possible with the help of various capabilities and techniques that e-learning platforms have to offer. Obviously, the advantage is that many people can learn in a more flexible way, going at their own pace and choosing courses based on their educational needs and interests.

However, there are certain challenges in this process as well. For instance, learners need to do a lot of work on their own to be successful in their studies. This being considered, it is especially important to personalize the learning experience in order to increase its effectiveness. At the same time, most existing e-learning systems are focused on a wide range of capabilities, but do not take into account individual characteristics of their users.

The combination of cognitive psychology and artificial intelligence opens up wide opportunities for improving human-computer interaction. In the field of learning, this approach can produce some of the most rewarding results. Well-educated professionals are capable of bringing innovations and benefits to all industries. In order to do that, there should be found a match between individual characteristics of users and software tools to create an adaptive e-learning system that will support the personalization of the educational process to improve the quality of its results.

Information services and products are becoming not only larger in number, but also more complex and diverse. Along with that, competition between their creators continues to increase and demands more attention to user satisfaction. The area of user modeling and adaptation provides basics for essential enhancement of user experience in information systems. Currently, most of the applications seem to use the 'one size fits all' approach that ignores individual characteristics of different users. Everyone deals with the same interface and content, despite having a distinct personality.

The fact that people have variations in their individual traits creates natural prerequisites for the information systems to be more specific depending on who uses them. With numerous options to choose from, users are inclined to prefer more personalized services that meet their specific needs. Given that, implementing user modeling and adaptation in web environments in order to satisfy the diverse needs of its users becomes increasingly important (Magnisalis et al. 2011: 5-20).

Adaptive interactive systems are used to enhance the usability and experience of users' interactions by providing personalized content and functionality based on their individual characteristics (Belk et al. 2014: pp. 15-26). Personalized content and functionality bring more value to a website or application by allowing users to navigate in a more comfortable manner, receive helpful suggestions and have an overall feeling of intuitively easy and friendly program interface. This, in its turn, makes such personalized environments stand out on the market and attract more users that want to have a better experience.

User study results show that personalizing content improves user interaction with the web environments. Individual adaptation adds value in task efficiency, effectiveness and user satisfaction when compared to using the basic content. When navigating in a personalized environment, users tend to be more efficient in finding information both in terms of task accuracy and completion time. It means that when the environment is customized based on a user's individual characteristics, it allows users to navigate in the system more successfully. Moreover, users seem to prefer a personalized version of the system over the standard one and are more satisfied when working in a customized environment (Belk et al. 2014: 15-26).

The process of user modeling involves collecting data about how people use web pages or apps, and then using this information to predict what users will like next time they visit a page or install an app on their devices. The capability for prediction can be beneficial in many areas, including personalized search, user interface design, ad targeting, social network recommendations, and many others.

While it's important to know the ways of incorporating personalization capabilities into the system, the process of user modeling and adaptation actually begins with the selection of cognitive factors of users that will be the basis for further adaptation. It is necessary to determine which information to collect in a system so that it can be adapted to the user's needs and preferences (Belk et al. 2014: 15-26). The chosen factors should match the area of application and the goals of the whole process. For example, if there's a need to adapt the interface of a website to allow for better navigation, it makes sense to consider the differences in visual perception among individuals.

Some systems are quite complex and can embrace a number of adaptation effects. This way, when it comes to learning management systems, there exist at least a few areas where personalization can be applied. It means that there are also a number of user factors that can be considered for adaptation, and selecting among those may not be an easy task. However, there is a user characteristic that seems most appropriate for this case; and that is the learning style of an individual. Thus, learning styles can be viewed as a psychological framework for further engineering of an adaptive e-learning system.

In general, psychology of learning is a very broad topic to explore, with numerous researches and different personality scales. Selecting the approach that is robust and most appropriate for adaptation is a fundamental challenge in this process. After all, this choice will influence all subsequent decisions regarding the construction of user models, techniques used for this, as well as adaptation mechanisms that will be implemented. Therefore, a separate chapter of the Master's dissertation will focus on review and selection of suitable personality scales.

Chapter 2
User Modeling and Adaptation

User modeling and adaptation are the techniques that are used to personalize content and functionality of web environments based on the unique cognitive characteristics of users. Simply put, user modeling is the process of predicting users' intentions, behaviors, and preferences using knowledge about them, whereas adaptation is the process of creating an environment that supports the needs and objectives of a user.

There is a range of techniques that are employed for user modeling, as well as for adaptation. Personalization systems adapt content and functionality according to the users' unique characteristics, in order to improve efficiency, effectiveness and user experience. To make a system personalized, it is necessary to determine the correspondence between user profiles and those aspects that need to be adapted. The next step is to implement adaptation mechanisms that will enable the alterations in system design based on personal characteristics of its users (Belk et al. 2014: 15-26).

The personalization process begins with user modeling that covers the human part in the course of human-computer interaction. User modeling defines what details about the user should be considered, how they should be collected and what user models (or profiles) should be created in the system. There are a bunch of human factors that can be used for this purpose, including human abilities, preferences, interests, prior knowledge, and goals of using the system.

Adaptation is, vice versa, on the side of computing in the course of human-computer interaction. It includes all the system's interfaces, mechanisms, and functions that can be changed to match the user's personal traits. In other words, these are the capabilities for adaptation representing the set of elements and the ways they can be adapted. Generally, all applications have at least two big areas for adaption, content and functionality. While content is usually the main reason for a person to actually use the system, functionality supports the acquisition of that information by providing easy navigation and visually appealing interface.

Thus, personalization can be described as a set of associations between user models and adaptation effects. It suggests how to connect user profiles with the adaptation techniques that should be used to make the system more individual. In other words, personalization serves as the guideline for understanding which adaptation mechanisms to use in a particular case and in which ways they should change the system's content or appearance to provide a better user experience.

User modeling and subsequent adaptation should be based on certain user characteristics. A good example of such characteristics that can guide personalization is variation in cognitive abilities and preferences. They reflect the ways people process and organize information based on their individual differences in brain mechanisms. These traits of users are particularly important for the learning process, and therefore, need to be considered when developing an adaptive and interactive e-learning system. A more personalized learning environment can provide a better user experience, which increases users' satisfaction and makes them more inclined to use a certain platform.

2.1 Technologies for Adaptation

Technologies that enable adaptation in information systems include a range of methods. They are divided into two broad groups: user modeling techniques and adaptation mechanisms. However, this division does not mean that they are being implemented separately. Most often, these methods are combined to achieve the best outcome. The goals, operating principles and examples of such technologies will be discussed below.

2.1.1 User Modeling Techniques

User modeling techniques can be described as a number of methods that are embedded into an adaptive interactive system and serve for extracting individual traits of users, analyzing them and building up user profiles based on these data. Factors for user modeling often include demographic data such as age and gender, interests, attitudes and cognitive characteristics. User profiles are created based on a set of selected personal traits, often being updated upon the user's interaction with the environment. Thus, the user modeling process involves a systematic collection of information about the users.

There are two main groups of methods for collecting this information: implicit and explicit (Belk et al. 2013: 2995-3012). Explicit methods of user data collection include the direct input of information via web forms, e.g., surveys, questionnaires, list of preferences or interests. This method is clear for the user because all questions are visible, and the user makes decisions regarding the response to such questions. This is straightforward and analogous to paper and pencil surveys. Implicit methods are more varied and aim to collect information about the users by tracking their behavior while working in the system. They include widely used user interaction analysis, and some more specific techniques like biometric sensors or facial expression tracking.

User interaction analysis mostly involves software capabilities to register how users interact with the system. For example, the program can track returns to previous pages or switches to certain information blocks. By collecting and analyzing these data, it is possible to make assumptions about individual traits and preferences based on their navigation. One of such techniques of user data collection is recording of browsing and search activity. This method provides tons of records related to users and allows to create a virtual user profile with the associated interests. The information then serves as a basis for recommending goods, services, and content to the users.

In the context of online interactions, collected user characteristics mostly include rather traditional traits such as age, gender, knowledge, and interests. However, researchers suggest that considering the cognitive factors as personalization parameters may lead to a more efficient adaptation process (Germanakos et al. 2008: 749-770). This suggestion is based on psychological research findings that indicate significant differences in cognitive abilities of individuals. Since interaction with computer systems employs processes of cognition in humans, it becomes reasonable that these interactions should be tailored to each individual's cognitive characteristics in order to improve their outcomes (Papanikolaou et al. 2003: 213-267). Cognitive styles of users can be detected explicitly by administering designated psychological tests online, but they can be also elicited with the help of implicit user data collection and user modeling (Belk et al. 2013: 2995-3012).

2.1.2 Adaptation Mechanisms

Adaptation mechanisms provide implementation of adaptation effects on the system's interface based on the user model. Adaptation mechanisms include a whole set of software tools and features that can change web environments in accordance with the needs of personalization. The greatest potential for adaptation is ensured by artificial intelligence methods. They allow for creation of systems that are more flexible and tailored to individual characteristics. AI technologies are used to model dynamic user profiles during the use of the system and apply changes accordingly, thus enabling an intelligent adaptation mechanism.

Various techniques can be employed to enable the adaptation mechanisms, including machine learning, classification and clustering. Machine learning, as an artificial intelligence method, can be helpful for automating data analysis and model building by identifying distinctive patterns in big amounts of data. Classification can be utilized when the existing data items should belong to predefined classes, while new ones should be associated with a prediction about their class and behavior. Clustering is suitable in cases when there are no predefined classes since this technique can assign users with similar characteristics to dynamic groups (Biancardi et al. 2021: 1-16).

There are various types of adaptation mechanisms that are based on certain methods. Basic adaptation mechanisms use the common information, like history of navigation or progress made by a user. Content-based and collaborative-based mechanisms both suggest content to the users based on either current page content or preferences of users with similar interests respectively. Mechanisms based on web mining utilize data mining techniques in order to identify patterns in the system's content, structure or usage. Rule-based mechanisms are straightforward in terms of design as they employ rules for the system to adapt content and functionality based on the user model characteristics (Langley, 2000: 357-368).

In addition to the listed types of adaptation mechanisms, artificial intelligence methods can also be used, for example, based on fuzzy logic. Fuzzy logic is a system designed to mimic human decision-making and deal with ambiguity. It can be used to model the inherent uncertainty in real information and to manage the behavior of machines. Fuzzy-based mechanisms are often combined with machine learning techniques for behavior modeling or used to implement the personalization engine, where user models are captured through machine learning techniques. Such mechanisms are used in various adaptive interactive systems for modeling user profiles and making inferences based on the imprecise information (Papatheocharous et al. 2013: 1-18).

Another specific example of the application of AI methods is the creation of semantic ontologies. The term ontology refers to a formal representation of the semantics of data, providing a uniform way for different parties to communicate and understand each other. Data in ontologies share a common vocabulary and grammar, as well as a semantic description that can be used by various applications. Thus, the ontology reflects the general understanding of the subject area in the form of an explicit specification (Taye 2010: 182-184).

The use of semantics and ontologies can support the adaptation process by providing a representation of Web content that is understandable to a computer. The semantically annotated content can be passed on to an adaptation mechanism which uses this information to understand the meanings of the content on each page and user's interactions with it. This way, semantic representation can be incorporated in the design of Web-based systems to enable adaptation of basic interface and specific sections according to user's characteristics and adaptation rules (Belk et al. 2012: 126-130).

2.2 Adaptation in E-learning

The learning process that is delivered through an e-learning platform has many different aspects. They range from traditional features like course material, tutor's involvement, schedule, etc. to the specific tools that support this type of learning including the user interface, types of content, automated tests and so on (Burgos et al. 2007: 161-170). When aiming to implement adaptation in e-learning, platform creators should evaluate the aspects and select the ones appropriate for their goals and contributing to the effective learning process. The system should also be adaptable, which means it should possess the ability to change in accordance with the current state of the external environment or input parameters. The task of adaptive learning systems is to optimize the educational process by providing the student with educational material in the most suitable way. As a result of this approach, the quality and efficiency of the educational process should be improved.

The user modeling community has long been interested in the adaptation of the learning systems to its users (Mitrovic 2012: 39-72). The number of studies featuring adaptive e-learning has been increasing recently, and this tendency is predicted to accelerate in the near future (Oxman & Wong 2014: 1-30). Adaptive learning environments are inspired by the ways that human tutors adapt to student learners in a real classroom. Thus, adaptive e-learning is a learning method that changes content taught to students based on their preferences or learning styles (Normadhi et al. 2019: 168-190).

Intelligent adaptations in e-learning usually require usage of user modeling techniques, which consider individual traits. Research findings suggest that, when it comes to learning, characteristics of the person are more indicative of user behavior than characteristics of the task itself. For instance, users' personalities and cognitive abilities can influence the effectiveness of study (Dennis et al. 2012: 297-302).

Personalization in an educational context requires a certain understanding of the learner and teaching tasks. The design of the model of the learner and the instructional model that is followed impacts the adaptation of the system. Adaptive e-learning environments assist learners by building profiles of each individual's preferences and styles. These user models are then used to help the learners' development and performance, thus enriching their learning experience (Qazdar et al. 2015: 1-8). Intelligent learning environments incorporating sophisticated learner models have been used more widely in recent years. Such systems often utilize user modeling techniques that can deal with uncertainty and vague information (Desmarais & Baker 2012: 9-38).

The learner's model should represent those distinctive characteristics of the learner which are meaningful to learning in a particular educational environment, such as prior knowledge of subjects, experience, learning preferences and cognitive style (Kay 2001: 111-127). Using the intelligent mechanisms, the system builds a learner model for each individual learner while they're interacting and updates the model in order to keep up with the learner's current state. In order to take advantage of information provided by the learner models, it's necessary to determine which instructional strategies are suitable for learners with particular traits and how these strategies could be supported by the system tools that are incorporated into e-learning platforms (Papanikolaou et al. 2003: 213-267).

Depending on the goals, various criteria can be used to evaluate the effectiveness of adaptation. Such criteria may include, for example, better educational outcomes, time economy or user satisfaction. In any case, all of them serve to support personalized learning adaptation, allowing the students to reach their learning objectives and stimulating their activity. Personalized instruction is believed to lead to higher learning performance (Burgos et al. 2007: 161-170). Therefore, adaptation in e-learning can be defined as a method to create a learning experience for the student, based on the configuration of a set of elements aiming to increase the performance of pre-defined criteria (Van Rosmalen et al. 2006: 72-83).

With certain aspects considered, there can be different approaches to adaptation in e-learning. Some of them involve the course tutor making manual adjustments (Van Rosmalen et al. 2006: 72-83) while others make use of programmatic tools to support automatic adaptation, for example, AI agents or nested conditions (Burgos et al. 2007:

161-170). Whatever approach is selected, the principles of its implementation are common: there are a number of inputs provided upon the learning process, which are taken into consideration, and thus assist in the decision of adjusting certain activities for the learners.

2.2.1 Levels of Adaptation in E-learning

In the adaptive and interactive system, adaptation can take place on several levels (Leka et al. 2016: 1-6, Paramythis & Loidl-Reisinger 2004: 181-194). With regards to e-learning, there can be identified at least three levels:

1. Adaptation at the level of planning the educational process. This level of adaptation provides the capabilities to create an individual curriculum and allow changes in the learning pace. Tutors should be able to provide students with a number of changeable options, thus giving them the opportunity to adjust the learning process in accordance with their needs and goals.
2. Adaptation at the level of the content of the educational material. At this level, it is required to perform significant work on the formation of educational content first. The more diversified the content is, the more options learners will have, thus selecting more preferred types of presentation of information.
3. Adaptation at the level of knowledge control. At this level of adaptation, knowledge control results are taken as learning parameters, the correction of which must be carried out through the entire learning process. Changes in these parameters are considered as the indicators for adaptation.

The present Master's dissertation suggests the application of an approach based on learning styles only within the second level of adaptation, that is, the level of the content of the educational material.

2.2.2 Types of Adaptation in E-learning

In general, there are three main types of adaptation that can be applied to an e-learning system (Burgos et al. 2007: 161-170):

1. Interface-based. This type mostly involves appearance of the system, including menu options, navigation, colors, sizes and positions of the elements (Ahmad et al. 2004: 925-934). It can provide personalized adaptation on the visual level of interaction with the e-learning environment, leading to better experience when using a more user friendly interface.
2. Learning flow-based. This type affects the sequence of the course content, implying that it's dynamically adapted to be the best fit for personal objectives of every user. The alterations can be made depending on the student's goals either at the start of learning or throughout the course based on their performance (Burgos et al. 2007: 161-170).
3. Content-based. This type of adaptation allows for changes in the resources and activities of the course, including alterations in their actual content. (Brusilovsky & Miller 2001: 167-206, De Bra et al. 2004: 387-410). It seems to require more complex mechanisms because of a wide variety of changes that can be applied. For example, even basic textual content can have several versions with different depth of topic disclosure based on a number of factors specific to a student (Burgos et al. 2007: 161-170).

The focus of the present Master's dissertation is on the latter type of adaptation, namely, content-based one. As the author believes, learning content and the activities that represent it play a huge role in the study outcomes.

2.3 Content-Based Adaptation

Content is the most important and at the same time the most diverse part of an e-learning course. Apparently, for this reason, there are also diverse approaches to applying adaptation and personalization to course content.

One of the significant content adaptation technologies is development of an Adaptive Educational Hypermedia system (Brusilovsky & Peylo 2003: 156-169). This technology aims to provide the capability to dynamically adapt the hypermedia form of the content to the changing needs and states of the learner. AEH systems take into account individual variations in goals, knowledge, learning style, cognitive abilities, requirements, and preferences. It operates by using knowledge represented in the user model to tailor the material and linkages being provided to the specific learner. This adaptation can benefit the student by offering individualized navigation aids and supplying individualized instructional information by changing the way the content is presented or organized (Grigoriadou & Papanikolaou 2006: 80-85).

The structural domain model of an AEH is represented as a network of domain concepts that are connected to one another to depict the subject domain's organizational structure. In order to construct the domain model of an AEH system, it is necessary to structure the knowledge space by identifying the domain ideas and their relationships. Additionally, content pages for the domain concepts must be created and linked to create a network of hypertext pages with educational content, meaning that the hyperspace must be organized and connected to the knowledge space (Grigoriadou & Papanikolaou 2006: 80-85). The important point to consider when designing AEH systems is to keep the balance between its capabilities for automatic and manual adaptation. The system should have the ability to modify its output based on the data about the end users and at the same time give the learners control over a variety of functionalities (Papanikolaou et al. 2003: 213-267).

The capabilities of AEH systems are supplemented and expanded with the help of authoring tools. Authoring tools are designed to lessen the mental workload associated with the various design phases of a learning environment. To do this, authoring tools explicitly depict the learning environment's design and direct course authors in managing its content. The final output of the authoring process becomes the internal representation of knowledge and information in a particular form that is understood and managed by the system (Brusilovsky 2003: 377-409). Content authors need to modularise the content into meaningful elements and design its hypermedia representation. Then, the author needs to determine the learning outcomes, considering conceptual connections among the chunks of the course content. It’s important to consider that the content will be accessed by different learners. Thus, the author should develop educational material for the domain concepts in multiple formats and present information from multiple perspectives, for example, knowledge level or learning approach (Grigoriadou & Papanikolaou 2006: 80-85).

Given this, authoring material for adaptive hypermedia educational systems is a difficult manual task, therefore the tools of the platform should assist by providing user modeling and adaptive functionality. A range of methods for developing such software solutions and content authoring tools for personalized learning have previously been proposed in the academic field (Dolog et al. 2007: 286-308).

Some researchers emphasize the need for adaptation in particular cases of e-learning, for example, in mobile learning. Although the benefits of mobile devices usage for learning are obvious, there are also certain technical limitations. For instance, the screen size of mobile devices is often insufficient in order to present pedagogical materials or complete lecture scripts. This creates a need for a tailored approach to restructuring content and organizing already developed course units (Madjarov & Boucelma 2010: 190-199). Proposals have been made to overcome the drawbacks of browsing regular course content on mobile devices. Thus, development of a learning content adaptation tool can provide different adaptation templates to help the author automatically reproduce high-quality learning content for specific devices. The adaptive web-based tool can satisfy various adaptation requirements by adjusting the template's parameters and changing the result if users are dissatisfied. At the same time, the tool allows users to preview the adapted content and decide whether the results are appropriate for mobile learning. This way, such a configuration tool represents a semiautomatic approach to learning content adaptation (Chang et al. 2008: 529-540).

A more comprehensive way to adapt educational content to the specific needs of mobile learning is to develop designated mobile authoring tools (Kuo & Huang 2009: 51-68). Such tools are capable of generating adaptive learning resources accompanied by assessment services. When developing mobile authoring tools, it's important to adhere to the same learning standards that are applicable to e-learning in general, for example, support of certain types of test tasks. Considering the specifics of mobile learning, attention should also be paid to visualization of the education material, so that course creators can control how the content will be presented on different mobile devices.

Chapter 3
Learning Styles

E-learning has the ability to be more individual and cater to specific educational needs. One of the most important conveniences is the ability to adjust various aspects such as class schedule, presentation of information, types of content offered, etc. Individual programs allow the students to choose the study options that better suit their personal characteristics, which helps to increase their productivity. Various parameters can be chosen as the basis for adaptation, depending on the goals of training, the technical capabilities of the system and the traits of the students. This Master's dissertation proposes to consider learning styles as a foundation for adaptation.

The theory behind learning styles is based on the idea that people have different predispositions and preferences in the process of acquiring knowledge. This theory found widespread support in the 1970s and continues to gain attention (Moayyeri 2015: 132-139). According to it, learners can be classified based on their predominant approach to learning. Research has provided evidence that people have certain preferences for how they learn new information (Cakiroglu 2014: 161-179). It is assumed that the introduction of an individual approach based on the learning styles can noticeably improve the educational process.

Effective learning is dependent on the comprehension of the material by each student. A student's unique abilities and personal character traits can influence their response to a lesson, as well as their ability to understand and retain information. Each student should be given the opportunity to learn in a way that is most comfortable for them; in other words, one size does not fit all. Learning styles refer to the different ways in which individuals prefer to receive, organize, and process information. When students learn in an environment that accommodates their learning style, they can more easily absorb new material and achieve better results (Cassidy 2004: 419-444).

In the traditional classroom, the one-way nature of most educational programs allows the instructor to dictate the methods used to teach in the classroom, which may not be compatible with students' learning styles. This can lead to a situation in which students spend more time trying to manipulate material than they do comprehending and applying it (De Vita 2001: 165-174). Observations show that students are more successful if the format of the classes is adapted to their learning style (Romanelli et al. 2009: 1-5).

As classes become larger and more diverse, the concept of learning styles becomes more relevant. Increased diversification of educational programs, combined with the use of more advanced technologies to deliver information, has led many educators to rethink traditional methods of instruction and the importance of considering individual differences of learners upon the design and delivery of course content (Lubawy 2003: 1-3). In the context of e-learning, where a student spends a lot of time online, interacting with the system on his own, and without personal support from the teacher, more attention should be paid to learning styles (Fahy & Ally 2005: 5-23).

Some studies have focused directly on the effectiveness of e-learning and student satisfaction with this process. Researchers have suggested that courses should be delivered in multiple formats to accommodate the learning styles of distance learners (Allen et al. 2002: 83-97). Others believe it necessary to conduct further research into the relationship among learning styles, the mode of delivery, and student success (Benbunan-Fich & Hiltz, 2003: 298-312).

Adaptation to individual learning styles is considered one of the important factors in determining success in higher education. They can serve as indicators of the personal preferences of the learners, influencing the effectiveness of the educational process and its outcomes. Learning style can also be described as the cumulative characteristic of the user that is associated with cognitive, behavioral, and psychosocial factors (Romanelli et al. 2009: 1-5). Therefore, when attempting to determine particular learning styles, they should not be considered in isolation from the learner’s personality. Learning style is associated with the ways that bring better performance upon learning, which, in turn, is strongly related to personality traits (Barrick et al. 2001: 9-30).

Historically, personalities were studied more thoroughly in correlation with job performance. A big number of such studies demonstrate quite diverse results. Their results state that only a few personality traits are associated with overall work performance, however, all other traits were shown to be predictors of at least some aspect of performance in at least some professional areas (Barrick et al. 2001: 9-30). That leads to a conclusion that personalities make a noticeable impact on performance. As long as it's true regarding work, this is likely to be true for the learning process as well.

The correlation between a student's learning style and the learning outcomes has been somewhat difficult to establish because there are many different learning style instruments available. Researchers have encountered difficulties in defining which instruments are most reliable and valid for measuring the learning styles (Romanelli et al. 2009: 1-5). Existing scales have their advantages and drawbacks, which should be considered when selecting them as the basis for adaptation.

3.1 Scales for Learning Styles

Research into learning styles has resulted in a multitude of methods used to categorize learners. There is no universal agreement regarding the commonly accepted methods, alternatively, many potential scales and classifications are seen as applicable to define learning styles. Most methods focus on sensory modalities, personality types or cognitive styles. These scales use a variety of learning style descriptors, and sometimes are viewed as measures of personality in essence (Romanelli et al. 2009: 1-5).

Some of the most widely used scales specifically designed to assess individual traits in learning are Kolb's Learning Styles Inventory (LSI) and Felder/Silverman Index of Learning Styles (ILS). Another scale, Riding's Cognitive Style Analysis (CSA), is more narrowly focused and evaluates cognitive styles, relying on the differences in information perception. There are also scales initially designed to evaluate personalities and psychological types, that are used to describe learning styles as well. Two personality scales, listed among the most popular, are Myers-Briggs Type Indicator (MBTI) and Big Five Personality Test. All of the aforementioned scales are further reviewed in more detail.

3.1.1 Myers-Briggs Type Indicator

The Myers-Briggs Personality Type Indicator is a self-report inventory that was created based on Carl Jung's theory of personality types (Jung 2016: 307-375). The questionnaire was modified to conform to Jung's model but with some changes in order to assign a person either one possibility or the other in all four categories based on their responses to a list of two-choice questions. According to this classification, most people tend to be one of two types: perceivers or judgers. These groups could be further split into people who prefer sensing or intuiting and thinking or feeling. All of the types are also divided into introverts and extroverts based on attitudes.

The MBTI test is one of the most popular personality inventories in the world. The personality test sorts people into one of 16 different personality types. The test includes 90 forced-choice questions, and each question offers two opposite options from which the respondent must choose (Romanelli et al. 2009: 1-5). People are then profiled according to four traits: introverted versus extroverted, sensing versus intuitive, thinking versus feeling and judging versus perceiving. Each type has a name and description of traits. For example, INTP (Introversion, Intuition, Thinking, Perceiving) type is linked as Thinker: quiet and introverted, known for having a rich inner world.

These dimensions can be used to describe various learning styles, each representing a unique aspect of a particular style. A person's individual learning style may be a combination of these dimensions (Jia et al. 2018: 83-91). Extraverted learners enjoy socializing and working in groups. Introverted learners usually derive energy and ideas from internal sources and prefer personal reflection and brainstorming. Sensing learners are realistic and practical, preferring to rely on information gained through experience. Intuitive learners tend to focus more abstract thinking, considering ideas, possibilities, and potential outcomes. Thinking learners use logical solutions to the problems and make rational decisions. Feeling learners are interested in personal relationships and manage information based on their emotions. Judging learners prefer order and structure, and tend to plan out activities and schedules. Perceiving learners are impulsive and immediately respond to new information and changing situations.

Although the MBTI has been widely used, there is not enough evidence to recommend its scientific use as a personality assessment. Some studies show test reliability, but still demonstrate variations in the results of the same participants (Capraro & Capraro 2002: 590-602). Other studies indicate that the reliability and validity of this inventory instrument are not supported by observations. Research results demonstrate that many people get different results when they retake the test even after short periods of time (Pittenger 1993: 467-488).

Another issue with this scale relates to limitations in the administration of the test and the interpretation of results. The test approach presumes that people are all one or the other. It arrives at the conclusion by giving people binary questions with only ‘yes/no’ options, with no room in between. While the scale has bimodal distribution, the evidence shows that most people fall on different points along a spectrum, between the two opposites. Several analyses have shown that about half of the people who take the test twice get different results each time (Pittenger 1993: 467-488).

3.1.2 Kolb’s Learning Styles Inventory

Kolb’s Learning Styles Inventory (Kolb & Kolb 2013: 39-47) describes four groups of learners, each with specific characteristics and preferences towards learning activities. These groups are defined as convergers, divergers, assimilators, and accommodators. The LSI focuses on how learners prefer to receive information, whether in a concrete or abstract format, and whether through action or reflection.

Convergers are those individuals that prefer to discover possibilities and relationships, concentrate better when studying alone and better understand through abstract thinking. Divergers include people that prefer real life experience and discussion, are imaginative, like brainstorming and group work, prefer observing.

Assimilators are the learners that solve problems with deductive reasoning and have the ability to create theoretical models. Finally, accommodators include individuals that solve problems by carrying out plans and experiments, challenges theories, are adaptable and work based on gut feeling rather than logic (Kolb & Kolb, 2005: 193-212).

Kolb's theory of learning styles is based on the types of personalities that were originally identified by K. Jung. Therefore, this scale, despite other category names, has much in common with the Myers-Briggs test. It focuses on how people choose to interact in the learning process and categorizes them into distinct groups. It is one of the main reasons for criticism of this scale. Each group is characterized as a pure and absolute type of learner, while in reality people can exhibit traits from different types by combining approaches.

Another reason for criticism is the claim by some researchers that this scale does not have enough convincing support based on empirical data (Smith 2001: 1-15). In particular, it has been little used and tested in various cultures and conditions, which could have a significant impact on the results of its application (Anderson 1988: 2-9).

3.1.3 Riding's Cognitive Style Analysis

Riding's Cognitive Style Analysis (Riding & Cheema 1991: 193-215) proposes a classification of users depending on the way they organize and process information. This scale operates with two major dimensions: Verbal/Imager and Wholist/Analyst. The Verbal/Imager dimension is related to how individuals process information, i.e. verbally or nonverbally. The Wholist/Analyst dimension deals with the organization of information, i.e. holistically or analytically.

Each dimension consists of three groups of users, two clearly defined groups according to their specifics, and one intermediate group (Sadler-Smith & Riding 1999: 355-371). This way, the Verbal/Imager dimension includes Verbal, Intermediate and Imager groups. Users who belong to the Verbal class can process textual and/or auditory content more efficiently than images, while users who belong to the Imager class do the opposite. Intermediate users do not differ significantly from either end point in terms of information processing. Likewise, the Wholist/Analyst dimension includes Wholist, Intermediate and Analyst groups. Those who belong to the Wholist class view a situation and organize information as a whole. Users from the Analyst class view a situation as a collection of parts and focus on one or two aspects at a time. The Intermediate class does not differ significantly from either end point.

The detection of cognitive characteristics of users within these two dimensions is conducted using a psychometric test (Sadler-Smith & Riding 1999: 355-371). The test is designed to show the position of a person on each of the dimensions by means of a ratio. In particular, users first complete a series of questions that measure their response time on two types of stimuli and the ratio between the response times for each type is calculated. This way, cognitive characteristics of individuals are elicited in terms of Wholist/Analyst and Verbal/Imager scale. This scale can be used to define the functionality of an application that would better suit a certain person. For example, for Wholists, the navigation of the app should consist of sections or steps, so that they have a whole picture first and then move to a particular category. At the same time for Analysts, it is better to have free navigation and see more details at first sight.

Though the scale is straightforward, there are some conceptual issues with the possibility of its application to define learning styles. While there are obviously individual differences in specific cognitive abilities, this does not necessarily mean that people who are better at verbal or visual tasks avoid other forms of thinking. Another issue is associated with the reliability of the test inventory that is used. It is problematic to assess cognitive style based on only one or two tasks, as well as using an exclusively verbal or non-verbal form of presentation for each dimension. This assessment is more dependent on situational factors. The findings of some studies reveal that this way of testing cognitive styles does not seem reliable (Peterson et al. 2004: 881-891).

3.1.4 Felder/Silverman Index of Learning Styles

Felder/Silverman Index of Learning Styles (Felder & Silverman 1988: 674-681) categorizes all learners within four major areas: preferable type and mode of information perception (sensory or intuitive; visual or verbal), ways of organizing and processing information (active or reflective), and the form of progress in knowledge acquisition (sequential or global). The respective dimensions are Sensing/Intuiting, Visual/Verbal, Active/Reflective, and Sequential/Global.

Each of them includes two groups of people according to their individual features in regards to learning. The Sensing/Intuiting dimension includes sensing learners that are concrete, practical, oriented towards facts and procedures, or intuitive learners that are conceptual, innovative, oriented towards theories and meanings. The Visual/Verbal dimension includes visual learners that prefer visual representations of the study material, or verbal learners that prefer written and verbal explanations. The Active/Reflective dimension encloses active learners that learn by experimenting and working with others, or reflective learners that learn by thinking things through and working alone. Finally, the Sequential/Global dimension involves sequential learners that work linearly, orderly and learn in small incremental steps, or global learners that have a holistic approach in learning and learn in large leaps (Litzinger et al. 2007: 309-319).

The test for the scale is based on a 44-item questionnaire with a choice between 2 responses to each sentence. Each dimension is scored in a range between +11 to -11 with steps of 2, where higher absolute values show stronger preference for either end of a dimension. After completion, it gives the result as a learning style that tends to be preferred by a student (Hawk & Shah 2007: 1-19).

Studies that analyzed the response data of this scale showed support for the proposed distribution of preferences for each dimension. Along with that, research outcomes also report reliability and validity of the ILS test inventory (Felder & Spurlin 2005: 103-112). However, this scale has some arguable issues despite being supported by experiments in general. The questions arise in regard to dependencies between some learning styles, as those may partially overlap. There are research findings that demonstrate tendencies for correlation between the dimensions of learning styles (Graf et al. 2007: 79-93). Some authors even claim that there can be latent dimensions that are not considered in this scale and require further investigation (Viola et al. 2007: 7-18).

3.1.5 Big Five Personality Test

The Big Five personality scale (Goldberg 1990: 1216-1229) includes five major dimensions that are used to evaluate individual qualities of people. These dimensions are: extraversion, agreeableness, emotional stability, conscientiousness, and openness to experience. Each of these traits covers a related set of characteristics.

Extraversion describes sociability and active engagement with the outside world. It encompasses such characteristics as dominance, ambition, positive emotionality and excitement-seeking. Agreeableness is defined by cooperation, trustfulness, compliance and affability. It essentially describes a tendency to be empathic and support others. Emotional stability is associated with the lack of anxiety, hostility, depression and personal insecurity. The opposite is referred to as Neuroticism and describes higher levels of anxiety. Conscientiousness describes commitment to organization, determination, planfulness and striving for long-term achievements. Openness to experience is associated with creative and adventurous behavior. It is described by intellectance, unconventionality and broad-mindedness. (Power & Pluess 2015: 1-4)

The scale uses five broad factors, and is not associated with any particular test. A variety of measures have been developed to measure the individual traits, each asking users to agree or disagree with a given statement on a scale. Results indicate the individual position of a user's personality on a spectrum for each trait. The results are usually interpreted in terms of having high, average, or low levels of the five personality factors. Each dimension is independent from the others; that is, a person can be high in one dimension and low in another (John et al. 2008: 118-128).

The Big Five model of personality has been widely used in academic psychology to describe the individual characteristics of people. The five core personality traits of this scale are often combined with specific behaviors or activities that differ among people, according to actual data collected (Power & Pluess 2015: 1-4). Many studies on the use of this scale show its reliability and convenience in assessing individuals. During the research, it was found that the Big Five model demonstrates stability across the lifespan and replicability of the structure across different assessment approaches including those in different cultures and different languages (Barrick et al. 2001: 9-30). The described personality traits were found to be important predictors of outcomes in education and work performance (Ozer & Benet-Martinez 2006: 201-221).

Furthermore, many studies also provide support for the theory that the Big Five personality traits have biological foundations. Each of the traits is found to be associated with certain processes in the human brain. Extraversion is covaried to the volume of medial orbitofrontal cortex and dopamine activity related to the response to potential rewards (DeYoung et al. 2010: 820-828). Agreeableness is associated with the activity of the superior temporal gyrus that is responsible for the recognition of emotions and intentions of others (Li et al. 2017: 1-8). Emotional stability is related to several brain regions, as in case of Neuroticism these regions are processing negative emotions and affects (Takano et al. 2007, 588-592). Conscientiousness is covaried with volume in the lateral prefrontal cortex and its activity involved in control of impulses and behavior (Asahi et al. 2004: 245-251). Finally, Openness to experience is associated with the degree of connection between certain brain regions (Beaty et al. 2016: 773-779).

3.2 Selection of the Scale

When analyzing various personality scales, it becomes obvious that many of them have certain limitations in the way they evaluate individuals. Corresponding psychological tests are designed to classify people into distinct, sometimes even the opposite groups. The results are quite segregated, for example, a person is either seen as an extravert or introvert. However, when researchers look closely at the scales and responses, it turns out that many people are actually somewhere in between, that is, a person can be a bit more extraverted than introverted, not an absolute extravert. This kind of approach doesn’t fully take into account the individual characteristics of learners. Therefore, selecting a strict scale of such type may lead to a situation when individual adaptation of course content will not give good outcomes, and, going further, adaptation will not be considered an effective way to support personalization in e-learning at all.

As a result of comparing some of the widely used scales, the optimal choice turns out to be the Big Five personality scale. The Big Five scale appears to be very reliable as a psychological model. Research findings show that the Big Five factors are replicable across different types of subjects, raters and data sources, in any form of the study. It was found that it makes no difference whether a trait was measured with trait adjectives, short phrases or questionnaire items. These results suggest that the five traits have the same conceptual status as other personality constructs. All five factors showed substantial and about equal heritability (John & Srivastava 1999: 102-138). It can be concluded that the scale describes the personal characteristics of students in a way that doesn't depend on situational tests and the format of presenting information. The results are not influenced by outside factors like current mood or test location setting.

The Big Five is not essentially a type model, as it measures traits not categorizing them into types. It does not put people into categories, and as such is a much more valid and evidence-based means of understanding personality than the other scales. The Big Five model asserts that people vary in their levels of five key personality factors and can describe them in terms of traits on a spectrum. The traits in this model have fuzzy definitions that allow for more flexibility when assessing individual differences (John et al. 2008: 118-128). Thus, this scale is well suited for classifying users according to their individual characteristics and building up more precise learner profiles.

This model is obviously supported in various studies, though there are some ambiguities as well. They derive from the fact that the categories of traits are very broad and rather vague. One of the resulting problems is the personal perception of the scale by different researchers. Since there is no single conventional standard for describing the five major traits, there may be variations among studies. Scientists not only perceive factors differently, but often call them differently as well. For example, Openness to Experience in various tests is designated either as simply openness, as intellect, and even as imagination; agreeableness is sometimes labeled social adaptability or friendly compliance; conscientiousness has appeared under the names like dependability and work. Researchers who include different variables in their factor solutions may come to different conclusions in their works (John & Srivastava 1999: 102-138).

The wide bandwidth of coverage of categories in the Big Five model can be seen as both an advantage and a disadvantage. On one hand, they allow to describe the fundamental differences between people and cover a sufficient share of the features that affect various areas of life, in particular, learning. On the other hand, they have low fidelity and imprecise definitions, which makes them not specific enough to be perceived unanimously. Like many natural categories, these five factors are fuzzy.
This drawback is usually compensated to some extent by defining prototypical traits that occur consistently across studies (John & Srivastava 1999: 102-138).

Another issue that is common for all personality tests is the changes in the traits over time. Research shows that there are changes in people's personality across the life course (Roberts 2006: 1-25). There are even tendencies for alterations in specific traits. For instance, as people get older they usually score higher on Agreeableness, Emotional Stability and Conscientiousness (Lucas & Donnellan 2011: 847-861). However, this issue should not make a significant impact if approached in a proper way. In the case of using the Big Five scale for adaptation in the e-learning system, it will be necessary to offer users to retake the test at certain intervals. This will make it possible to update the user model in the process according to the changes in personality.

Taking into account the features of this scale, the Big Five can become the psychological basis for adaptation in an e-learning system if implemented with the appropriate technologies. This scale is also quite practical for use because there is a clear process of administration of the Big Five tests and analyzing the responses in detail. Therefore, it can be used within an e-learning system for assessing the individual qualities of learners, creating user models and implementing adaptation based on them.

This personality scale has already been used previously in studies related to the adaptation of information systems. For example, in the field of tourism recommender systems, the Big Five personality dimensions were used to find a correlation between tourist traits and preferences for certain types of activities (Alves et al. 2020: 4-13). The online questionnaire was used to collect the data about personalities, tourist preferences, and socio-demographic parameters. Then the gathered data was analyzed to see the relations between user personalities and choices of attractions. As a result, it was found that there is a correlation between personal characteristics and tourist preferences. The set of associations between individual traits and choice of tourist experience is a great example of a psychological framework that can be implemented into an adaptive and interactive information system.

The choice of exactly this personality scale is not exclusive, however. Other scales can be taken as a basis for personalization as long as they are reliable and meet the requirements for adaptation of the e-learning platform. The important point is to find a good match between the psychological grounds and the implementation capabilities which will provide the most benefit to the end users of the system.

3.3 Big Five Test Administration

As previously mentioned, there is no single test that is used within this personality scale. All developed tests should comply with the main aspects of Big Five, measuring the five major factors by the degrees of user's agreement with a statement and analyzing the results with a range for each dimension.

One of the appropriate examples of the Big Five test questionnaire is based on the markers reported in the article by Goldberg (Goldberg 1992: 26-42) and implemented as presented in the International Personality Item Pool. Test participants are provided with 50 personal statements and should mark the level of their agreement with each item on the scale 1-5, where 1=disagree, 2=slightly disagree, 3=neutral, 4=slightly agree and 5=agree. The statements are presented in table 1.

#	Statement	#	Statement
1.	I am the life of the party.	26.	I have little to say.
2.	I feel little concern for others.	27.	I have a soft heart.
3.	I am always prepared.	28.	I often forget to put things back in their proper place.
4.	I get stressed out easily.	29.	I get upset easily.
5.	I have a rich vocabulary.	30.	I do not have a good imagination.
6.	I don't talk a lot.	31.	I talk to a lot of different people at parties.
7.	I am interested in people.	32.	I am not really interested in others.
8.	I leave my belongings around.	33.	I like order.
9.	I am relaxed most of the time.	34.	I change my mood a lot.
10.	I have difficulty understanding abstract ideas.	35.	I am quick to understand things.
11.	I feel comfortable around people.	36.	I don't like to draw attention to myself.
12.	I insult people.	37.	I take time out for others.
13.	I pay attention to details.	38.	I shirk my duties.
14.	I worry about things.	39.	I have frequent mood swings.
15.	I have a vivid imagination.	40.	I use difficult words.
16.	I keep in the background.	41.	I don't mind being the center of attention.
17.	I sympathize with others' feelings.	42.	I feel others' emotions.
18.	I make a mess of things.	43.	I follow a schedule.
19.	I seldom feel blue.	44.	I get irritated easily.
20.	I am not interested in abstract ideas.	45.	I spend time reflecting on things.
21.	I start conversations.	46.	I am quiet around strangers.
22.	I am not interested in other people's problems.	47.	I make people feel at ease.
23.	I get chores done right away.	48.	I am exacting in my work.
24.	I am easily disturbed.	49.	I often feel blue.
25.	I have excellent ideas.	50.	I am full of ideas.

Table 1. Statements for assessment on the Big Five scale.

Once the responses are collected, the values should be calculated for each dimension according to the formulas below. Numbers in parentheses refer to the statements. Each personality trait should have a score from 0 to 40. Higher scores indicate stronger exposure of the particular characteristic.

(1) Extraversion =
20 + (1)__ - (6)__ + (11)__ - (16)__ + (21)__ - (26)__ + (31)__ - (36)__ + (41)__ - (46)__

(2) Agreeableness =
14 - (2)__ + (7)__ - (12)__ + (17)__ - (22)__ + (27)__ - (32)__ + (37)__ + (42)__ + (47)__

(3) Conscientiousness =
14 + (3)__ - (8)__ + (13)__ - (18)__ + (23)__ - (28)__ + (33)__ - (38)__ + (43)__ + (48)__

(4) Emotional Stability =
38 - (4)__ + (9)__ - (14)__ + (19)__ - (24)__ - (29)__ - (34)__ - (39)__ - (44)__ - (49)__

(5) Openness to Experience =
8 + (5)__ - (10)__ + (15)__ - (20)__ + (25)__ - (30)__ + (35)__ + (40)__ + (45)__ + (50)__

An example of the results after taking a test can be interpreted and documented like this: low Extraversion 10/40, medium Emotional Stability 19/40, and high Openness to Experience 32/40, Agreeableness 32/40 and Conscientiousness 38/40.

The results for each dimension then get their interpretations in terms of the individual traits of people with certain scores on the spectrum:

1. Extraversion: individuals with high scores are more social, tend to seek ideas and fulfillment from communication with others; low scorers prefer to seek inspiration inside of themselves and work on the assignments alone.
2. Agreeableness: high scorers are typically friendly, polite and get on well with others while people with low scores are more critical towards others and don’t tend to adjust their behavior.
3. Conscientiousness: people who score high are diligent, tend to keep things in order and follow the rules; low scores are more impulsive and disorganized.

4. *Emotional Stability:* high scorers are more emotionally stable, feel less stress while people with low scores are reactive to stress factors, experience mood swings, and more often feel anxious or depressed.
5. Openness to Experience: individuals with high scores are more curious and creative, enjoy seeking new tasks and experiences; low scorers are more conventional, stick to routines and predictable tasks.

Chapter 4
Application of AI

Today, products and services in many subject areas involve Artificial Intelligence (AI) methods and tools. Many of the original ideas for creating artificial intelligence have been embodied in technologies that have entered our everyday life. Some of the application areas of AI are medical diagnostics, e-learning, time scheduling, robotics, control systems, natural language processing, and many others. The growing needs in all these areas and the potential business benefits have intensified AI research.

Artificial intelligence emerged in the 50s of the last century as an independent branch of computer science. The first advances in the automation of intelligent processes led to the formation of the leading paradigm of AI, which can be called the computer paradigm. This paradigm is based on the assumption that the brain from the information point of view is a large and complex biocomputer, and therefore intellectual processes must be implemented on the principles of working with information in a computer, i.e., based on symbolic representations of information and their processing using algorithmic and logical procedures (Negnevitsky 2005: 4-16).

The high and increasing speeds of machine computation, exceeding the speed of signals in the brain by numerous times, have made it possible to use complex sequential algorithms not typical for the human brain. Numerous achievements of AI in recent decades, implemented in intelligent technologies and systems, are based on logical algorithms and machine learning methods. While logical algorithms are based on a formal logical approach and utilize certain rules for functioning, machine learning resembles computational capabilities of the human brain and is capable of extracting meaning from big amounts of data. Therefore, many AI methods are also often referred to as computational intelligence methods (Negnevitsky 2005: 4-16).

The results of our latest McKinsey Global Survey on AI in 2021 (Chui et al. 2021: 1-11) indicate that the benefits of using AI in business continue to be significant. As it becomes more common, the tools and best practices of AI implementation also become more sophisticated. Findings from the 2021 survey show that 56 percent of all respondents report their companies have embedded at least one AI capability in their business processes. Business functions where AI adoption is most popular include a range of areas such as pattern recognition, computer systems with a speech interface, orientation in difficult situations, medical expert systems, creation of decision support systems, organization management, banking, and insurance business. Finally, respondents say their companies' investments in AI-related initiatives will continue to increase over the next three years.

Some of the most widely used AI methods are artificial neural networks, genetic algorithms and fuzzy systems. Artificial neural networks are inspired by biological neural systems and consist of a collection of nodes called artificial neurons, united in a number of layers. When the network is operating, the values of the input variables are fed into the input elements, then the neurons of the hidden and output layers are sequentially processed. Each of them calculates its activation value by taking the weighted sum of the outputs of the elements of the previous layer and subtracting the threshold value from it. Then the activation value is transformed using the activation function, and the result is the output of the neuron. After the entire network has worked, the output values of the elements of the output layer are taken as the output of the entire network (Negnevitsky 2005: 168-186).

Artificial neural networks are useful for solving problems where the relationship between inputs and outputs is not known and can't be determined using linear algorithms. The most important feature of artificial neural networks is that they can independently learn from previous experience, getting better at their task each time. The benefits of artificial neural networks are used in many different fields, including medicine, geology, information technology, security. Among the tasks that artificial neural networks solve are object identification, face and emotion recognition, diagnosis of a patient, spam filtering, license plate recognition, and speech input of text into a computer (Negnevitsky 2005: 168-186).

The genetic algorithms approach is modeled on biological evolution and uses the principles of natural selection, mutation, and adaptation to solve problems that cannot be solved by mathematical formulas alone. In essence, a genetic algorithm searches for solutions by creating a population of possible solutions and then choosing the best members of that population in each generation. Thus, at each step in the process, only the best solutions are considered, with the hope that they will provide even better ones at the next step (Negnevitsky 2005: 222-234).

Genetic algorithms are useful in finding optimal strategies for problems involving large amounts of data. Genetic algorithms can help solve a variety of scientific and engineering problems, including intelligent data processing, optimization of functions and requests, layout and scheduling, and others. These algorithms also help with solving economically significant business problems. Financial companies make extensive use of genetic algorithms to predict the development of financial markets (Negnevitsky 2005: 222-234).

Fuzzy logic systems are based on the concept that mimics the nature of human reasoning. People rarely think in mathematical terms and variable values, as their reasoning is almost always vague and unclear. This way of reasoning lies in the basis of natural languages, which contain many adjectives to describe different states or conditions. Fuzzy logic resembles human decision-making methodology. It, just like a person, can deal with vague information. A fuzzy system determines inferences based on fuzzy sets that allow for partial membership and fuzzy rules that apply to them (Negnevitsky 2005: 86-96).

The advantage of fuzzy systems is that they are flexible and can accept even imprecise information. Because these systems involve human-like reasoning and decision making, they are useful in making decisions in complex situations in various types of applications. If truth and falsehood are replaced by the degree of truth in an intelligent system, then perhaps this system of rules will more accurately reflect reality. Fuzzy logic is used in various applications, including smart home appliances, automatic gear shifting in transmissions, injection systems, noise suppression systems and air conditioners. Fuzzy logic is also used by software engineers to program and monitor process control applications (Negnevitsky 2005: 86-96).

4.1 User Modeling with Fuzzy Logic

Fuzzy logic approach can help to overcome the limitations of traditional classification of users into discrete categories. Based on the similarity to the human way of reasoning, fuzzy logic can simplify the implementation of vague parameters in informational systems. This method allows to achieve higher accuracy, and, accordingly, a more individual approach. With this technology, each user's profile can be formed as a set of specific personality traits. This seems to be a good opportunity to develop an adaptive e-learning platform that is tailored to individual characteristics of the learners as closely as possible.

The fuzzy logic approach has already been used in research that has incorporated cognitive factors into adaptive interactive systems. In this case, user modeling was based on the particular cognitive factors of users that were determined by a series of psychometric measures. The adaptation mechanism utilized artificial neural networks and fuzzy logic to exploit the concept of partial truth in the process of interaction. The outcomes of this approach were evaluated by a user study that has demonstrated an increase in efficiency and effectiveness when users completed tasks in the individually adapted version of the same environment (Papatheocharous et al. 2013: 1-18).

Another study combined fuzzy logic theory with a multi-agent system to model cognitive behavior that introduces uncertainty during decision-making of pedestrians. To model the psychological characteristics of pedestrians, the Big Five personality model is introduced. The proposed approach can generate different preferences that represent the intrinsic control factors for decision making. The relationships between personality traits and decision preferences are determined by a fuzzy inference system. The results of experiments indicate that the proposed model can generate more reasonable and heterogeneous behavior in the simulation and that individual personality has a noticeable effect on pedestrian dynamical behavior (Xue et al. 2017: 1-19).

The fuzzy logic approach was also applied to intelligent agents that provide support to users in various systems. In another study, a fuzzy agent with dynamic personality is modeled based on the Big Five personality model. It is implemented with adding an emotion component to support an agent's decision making based on personality factors and related parameters. Personality factors are calculated using the Big Five scale, while some fuzzy rules are used to determine the anger intensity of an agent when it is in a certain situation. The outputs of these rules can be used to make decisions in agent-based simulations. The package provides a framework for developing lifelike agents that exhibit personality and emotion (PourMohammadBagher et al. 2009: 535-553).

In order to implement user modeling based on fuzzy logic, it is necessary to create the process of forming a student model in the e-learning system. User modeling should occur when a new user is added to the system. This is a very significant part, since the learner model is essentially the main component of the system through which adaptation will be implemented. The learner model contains a set of user characteristics that serve as parameters used in the process of adapting the educational material. Besides the personal parameters, the model should also include the rules and methods for processing this set, such as fuzzy rules, for instance.

When a student profile is initially created, then before the start of learning, it is necessary to collect the data and fill in the user model. The e-learning system should therefore include a psychological testing unit that is designed to determine the personal characteristics of the student. This unit should automatically perform test tasks in accordance with the chosen personality scale. Personality inventories should be administered before the beginning of the study, so that course design and structure may be adapted accordingly (Cakiroglu 2014: 161-179).

As in the case of this Master's dissertation, the information about a student's personality within the Big Five scale can be collected using psychometrics tests in the form of personality questionnaires. An online questionnaire should be offered to the learners at the time of registration in the e-learning system. When the student's answers to the survey are received, it will be possible to determine the individual score for each of the scale's dimensions. Based on the results of the student's results on personality tests, the user profile will be formed with the appropriate parameters. After specifying the individual cognitive characteristics, fuzzy logic can be employed to adapt the course content to the distinctive traits of a certain person.

4.1.1 Fuzzy Inference Process

Fuzzy logic as a mathematical system uses degrees of truthiness to represent the concept of vagueness. It is a very useful method when it is necessary to deal with inaccurate information and make decisions based on it. The input space in fuzzy logic, also called the universe of discourse, is described by a linguistic variable that is divided into a number of linguistic values. Linguistic variables represent words or sentences in natural language. Each linguistic value has a corresponding fuzzy set defined by a membership function. While the classic set contains elements that satisfy the exact membership properties, the fuzzy set contains elements that satisfy the imprecise membership properties. So, the members of a fuzzy set can partially belong to a truthiness value (Ross 2010: 6-20).

Membership functions map real numbers into membership values that usually lie in the range from 0 to 1. This way, they define the degree of membership in a particular characteristic. This degree can be visualized in a graphical way, where the X axis represents the universe of discourse and the Y axis represents the degree of membership in the range [0, 1]. There are a few types of membership functions such as triangular, trapezoidal, sigmoidal, gaussian, and others. Triangular membership functions fuzzifies the input using three parameters a, b and c, where a and c define the base and b defines the height of the triangle on the graph. Trapezoidal membership function is defined by four parameters: a, b, c and d. Span b to c represents the highest degree of membership that an element can take. And if x is between (a, b) or (c, d), then it will have membership value between 0 and 1 (Ross 2010: 90-110).

Fuzzy logic can be applied for the Big Five personality scale in a way that the scale dimensions are represented as linguistic variables, and the degrees of expression of this trait in the user are linguistic values. Application of fuzzy logic makes it possible to say that a person, for example, is extraverted to some extent and introverted to some extent. For example, if a person is 75% extraverted it means that this person meets by 75% the criterion of "extraversion."

Fuzzy logic approach can produce a reasonable decision even with imprecise data using fuzzy rules. They are written as follows: IF (antecedence) THEN (consequence), where (antecedence) and (consequence) are formed by linguistic variables and their values. During the processing of rules, various operations can be performed on linguistic variables. Fuzzy operators include: union/disjunction (OR), intersection/conjunction (AND) and complement/negation (NOT). Union operator selects the element with the maximum membership value among the common elements in both the fuzzy sets. Intersection operator selects the element with minimum membership value among common elements in both the fuzzy sets. In case of complement, membership value of every element in the fuzzy set is complemented with respect to 1, i.e. it is subtracted from 1 (Ross 2010: 34-40).

Fuzzy inference system (FIS) tries to formalize the reasoning process of human language by performing a non-linear mapping of an input to an output using fuzzy logic. The process can be basically described as including three major steps: 1) fuzzifying the input data, which is typically crisp; 2) conducting fuzzy inference on the fuzzified data; and 3) defuzzifying the inference results to produce the final outcome (Negnevitsky 2005: 106-124).

FIS consists of several components that enable the possibility for fuzzy inference (Ross 2010: 140-158):

1. Fuzzy knowledge database. It stores basic information about the linguistic variables, linguistic values and membership functions that define the fuzzy sets.
2. Fuzzy rule base and Inference engine. It represents the mechanism that does the fuzzy logic reasoning, as well as the list of fuzzy IF–THEN rules for this process.
3. Fuzzifier. It converts a crisp input or linguistic variable into a degree of membership by using appropriate membership functions for the input.

4. Defuzzifier. It converts the fuzzy output to crisp values using the appropriate membership functions for the output values.

Defuzzification, as the process of converting a fuzzy output into a crisp value, can involve different methods for the procedure. Some examples are Centroid of area (COA), Bisector of area (BOA), and Mean of maximum (MOM). Centroid of area is considered the most popular defuzzification method. It is calculated as the center of the area under the aggregated fuzzy set (Ross 2010: 90-110).

There are different types of fuzzy inference systems, depending on the features of the inference process and the methods used. One of the common FIS types is Mamdani. Mamdani FIS Procedure consists of four steps (Negnevitsky 2005: 106-124):

1. Fuzzification. To fuzzify the input, the antecedents of each rule are evaluated in order to determine the degree of that input in each linguistic set. The output is a degree of membership in the qualifying linguistic set in the range from 0 to 1.
2. Rule evaluation. Fuzzy logic operators are applied to each rule to obtain the degree of support for that rule, also called the firing strength. If there are multiple parts to an antecedent, each part is resolved, and then the results are added together to produce a single truth value. This value is then used in the implication process which outputs a fuzzy set corresponding to the membership function of the consequent of the rule.
4. Aggregation. Aggregation is the process of combining the fuzzy sets that result from each rule, which can be done by applying a specific aggregation method. The output of the aggregation process is one fuzzy set for each output variable.
5. Defuzzification. For the defuzzification process, the input is a fuzzy set's aggregate output and the output is a single crisp number. The result can later be used for the decision making process in any application.

4.1.2 FIS Simulation

To implement user modeling and adaptation using fuzzy logic, a fuzzy inference system should be incorporated into an e-learning system. Such FIS should conduct inference by taking Big Five personality factors as input parameters and providing preference for a certain learning activity as an output. In the process of making a decision, the system should use the defined fuzzy sets, the list of fuzzy rules, and chosen method for defuzzification. The schematic structure of the FIS for application of fuzzy logic inference methods based on Big Five factors is shown in fig. 1

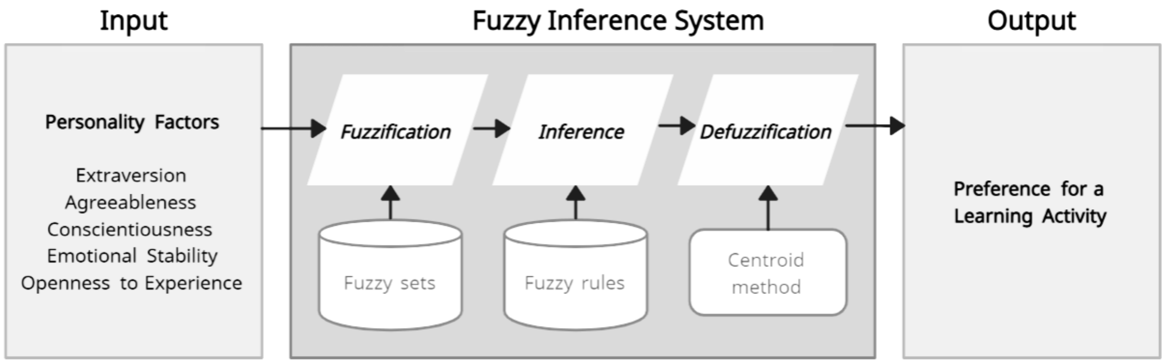

Figure 1. Structure of the proposed fuzzy inference system.

Simulation of this fuzzy inference system was made in Matlab, the programming and computing tool for data analysis, algorithm development, and model creation. System behavior was modeled using the Fuzzy Logic designer application. In order to demonstrate the underlying mechanism of adaptation based on the Big Five personality traits, there was created a Mamdani fuzzy inference system with 5 inputs and 1 output, as shown in fig. 2.

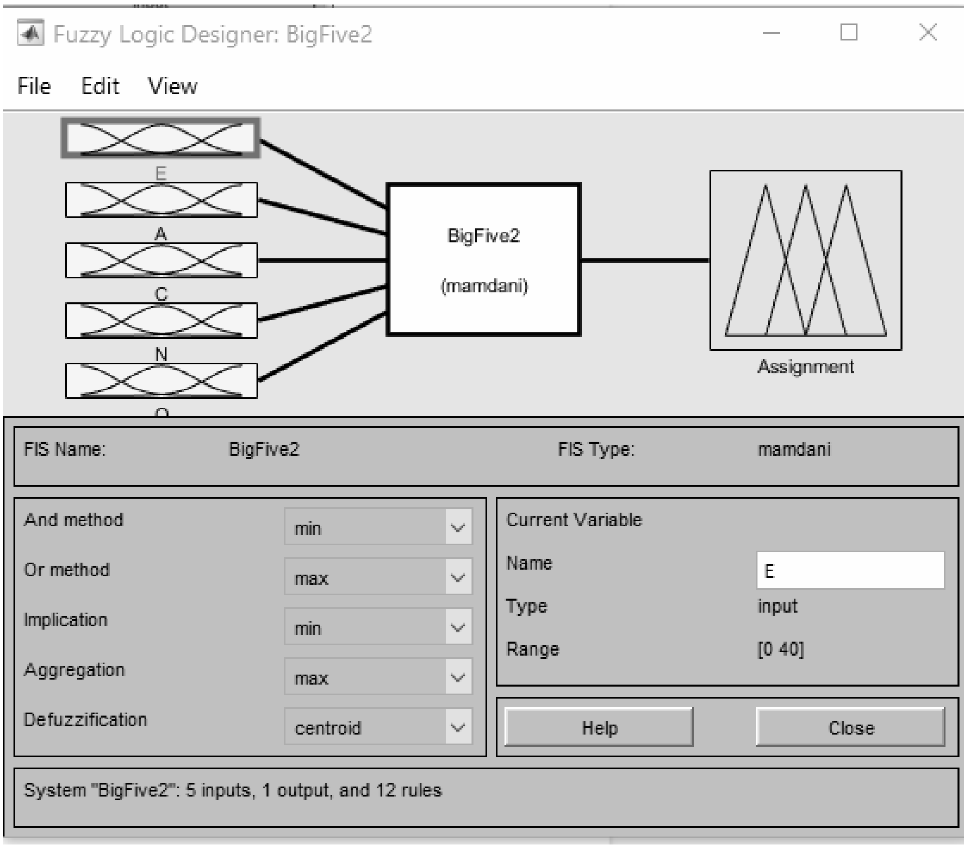

Figure 2. FIS structure in Matlab simulation.

Input linguistic variables are all five personality traits. Each of them is associated with 3 fuzzy sets: Low, Medium, and High. These fuzzy sets are associated with the level of expression of a certain trait in a person. At the same time, each linguistic value has a corresponding scale in crisp values from 0 to 40. The membership functions of trapezoidal type describe the degree of belonging of the person's score to each fuzzy set. They are essentially the same for all five factors and defined as below:

(6) $$\mu_{Low}(x) = \begin{cases} 1 & \text{if } 0 \leqslant x \leqslant 10 \\ (15-x)/5 & \text{if } 10 < x < 15 \end{cases}$$

(7) $$\mu_{Medium}(x) = \begin{cases} (x-10)/5 & \text{if } 10 < x < 15 \\ 1 & \text{if } 15 \leqslant x \leqslant 25 \\ (30-x)/5 & \text{if } 25 < x < 30 \end{cases}$$

(8) $$\mu_{High}(x) = \begin{cases} (x-25)/5 & \text{if } 25 < x < 30 \\ 1 & \text{if } 30 \leqslant x \leqslant 40 \end{cases}$$

The plot of these membership functions as configured in the Matlab application is shown in fig. 3.

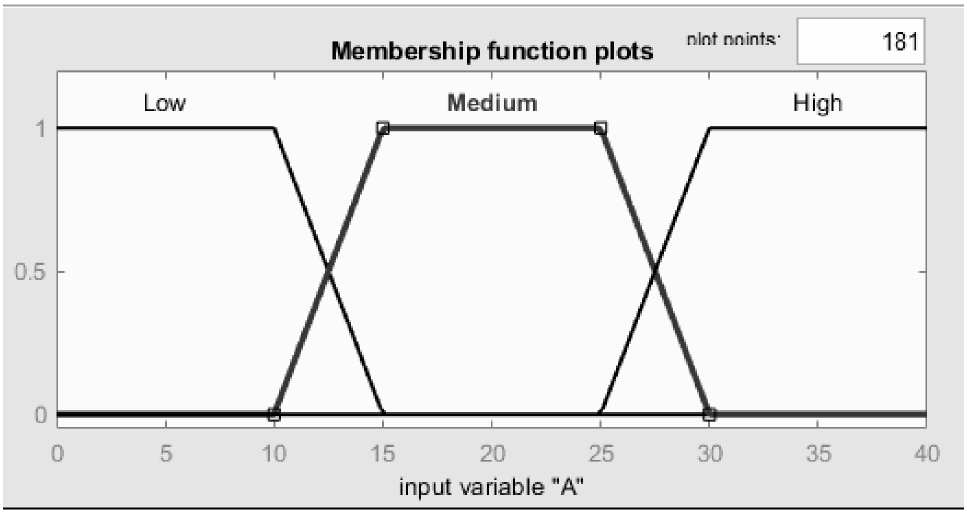

Figure 3. Membership function plots for input.

Output linguistic variable is a name of the learning task that is recommended to a user based on their individual traits. It is supposed that there are several options for tasks after the lesson in a course. The e-learning system can recommend to the student the choice of task based on the individual characteristics as measured on the Big Five scale.

There are three options available: group case task, structuring task, and essay task. Group case task describes a real-world situation where the solution should be found by small groups of students, 2-3 people. Structuring task involves the organization of the learned concepts, the establishment of the correct sequences and correlations from the provided pool of aspects. Essay task requires learners to write an essay about a particular topic with regards to the lesson.

Unlike the input of the personality scores, the output does not rely on any particular scale of crisp values. Instead, the values are used to make the distinction between the learning tasks. Each task is represented by a fuzzy set defined with a trapezoidal membership function as shown in fig. 4.

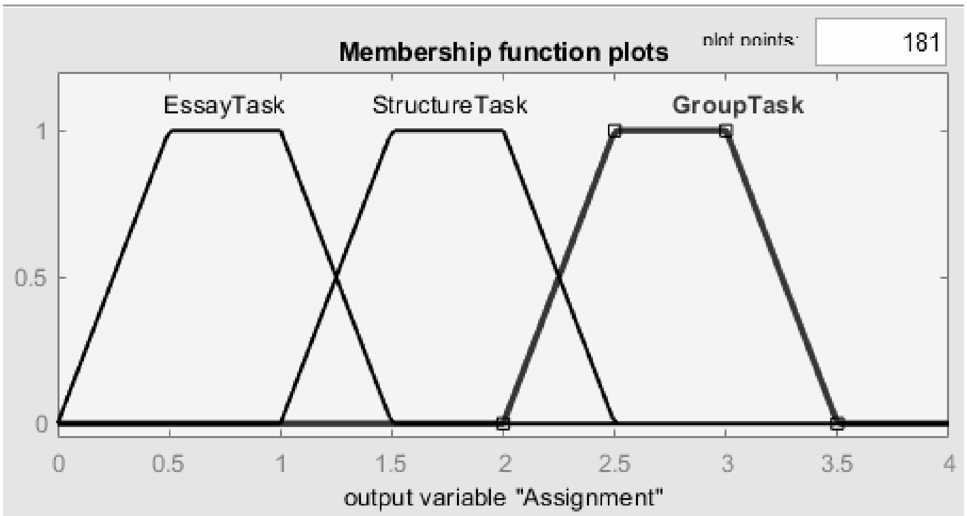

Figure 4. Membership function plots for output.

Table 2 contains personal characteristics that match different tasks. Assumptions are made based on the description of the traits and solely for the purpose of simulation of the approach in general. There are also fuzzy rules for each case that are used by the inference engine to map the input to the output to obtain the decision.

Assignment	**Assumptions**	**Rules**
Group Case Task	Learners who are likely to succeed in this task and enjoy it, should be high on Extraversion (E), high or medium on Agreeableness (A), and high or medium on Openness to Experience (O) (rules 1-4). This task may also be a good match for some learners, who are medium on Extraversion, only in case they are high on Agreeableness and Openness to Experience (rule 5). Other factors are not considered in this case.	1. IF (E is High) and (A is High) and (O is High) THEN (Assignment is GroupTask) 2. IF (E is High) and (A is Medium) and (O is High) THEN (Assignment is GroupTask) 3. IF (E is High) and (A is High) and (O is Medium) THEN (Assignment is GroupTask) 4. IF (E is High) and (A is Medium) and (O is Medium) THEN (Assignment is GroupTask) 5. IF (E is Medium) and (A is High) and (O is High) THEN (Assignment is GroupTask)

Assignment	Assumptions	Rules
Structuring Task	Learners who are likely to succeed in this task and enjoy it, should be high or medium on Conscientiousness (C) and high or medium on Emotional Stability (N) (rules 6-9). This task may also be a good match for some learners, who are low on Emotional Stability, only in case they are high on Conscientiousness (rule 10). Other factors are not considered in this case.	6. IF (C is High) and (N is High) THEN (Assignment is StructuringTask) 7. IF (C is High) and (N is Medium) THEN (Assignment is StructuringTask) 8. IF (C is Medium) and (N is High) THEN (Assignment is StructuringTask) 9. IF (C is Medium) and (N is Medium) THEN (Assignment is StructuringTask) 10. IF (C is High) and (N is Low) THEN (Assignment is StructuringTask)
Essay Task	Learners who are likely to succeed in this task and enjoy it should be Medium or Low on Conscientiousness (rules 11-12). Other factors are not considered in this case.	11. IF (C is Medium) THEN (Assignment is EssayTask) 12. IF (C is Low) THEN (Assignment is EssayTask)

Table 2. Task types with assumptions and corresponding fuzzy rules.

In order to provide a recommendation of a task suitable for a particular student, the scores for each factor of the Big Five scale should be passed to the system as input. Then, the FIS fuzzifies them and conducts the inference based on the list of fuzzy rules. When the conclusions are aggregated, the output is defuzzified by applying the Centroid of Area method. Matlab allows to view how fuzzy rules are fired in the process of fuzzy inference as shown in fig. 5.

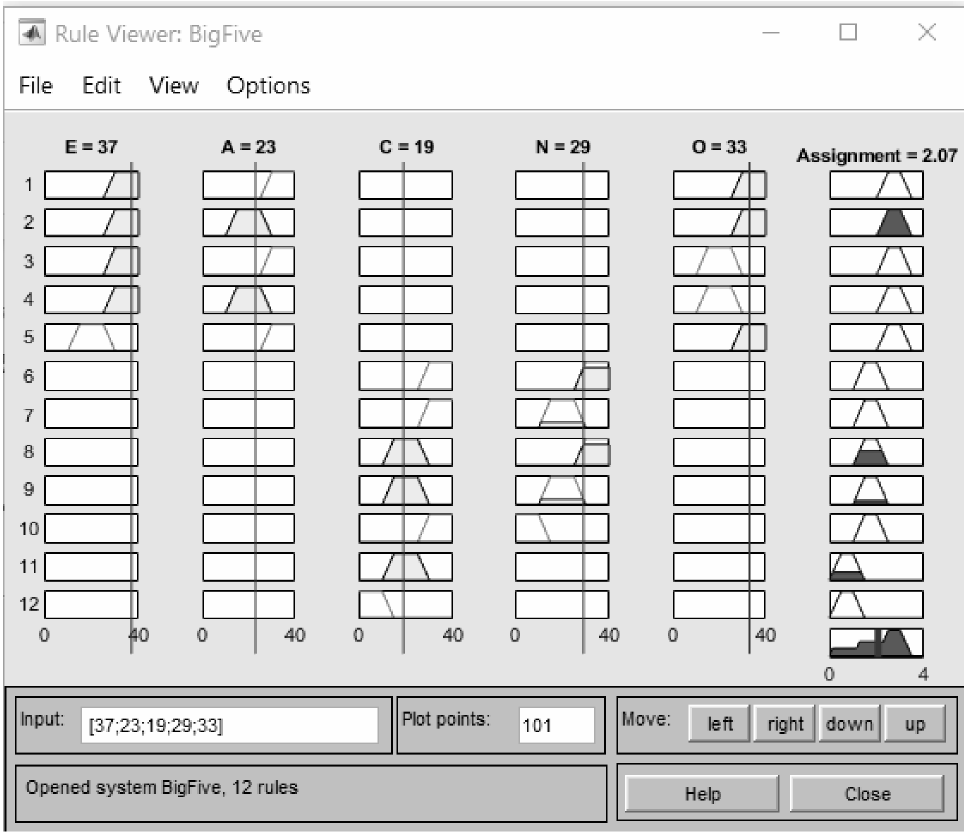

Figure 5. Simulation of rules' firing strength.

The source code for the simulation and the example of running it is shown in fig. 6. It involves the manual input of trait scores on the Big Five scale, which is done to test the method. It is assumed that the personality test will be built into the e-learning system, and data on its passage will be transmitted automatically. Also, since the FIS gives the output as crisp values, they need to be matched to the tasks, which is done by adding a few conditions before displaying the result.

```
Adaptation.m

E = input("Enter Extraversion score\n");
A = input("Enter Agreeableness score\n");
C = input("Enter Conscientiousness score\n");
N = input("Enter Emotional Stability score\n");
O = input("Enter Openness to Experience score\n");

fis = readfis("BigFive.fis");
ans = evalfis(fis, [E A C N O]);
if ans<=1 disp("Your recommended task is Essay Task")
elseif ans>1 && ans<=2 disp("Your recommended task is Structuring Task")
elseif ans>2 disp("Your recommended task is Group Case Task")
end
```

```
Command Window
>> Adaptation
Enter Extraversion score
22
Enter Agreeableness score
15
Enter Conscientiousness score
37
Enter Emotional Stability score
28
Enter Openness to Experience score
16
Your recommended task is Structuring Task
fx >>
```

Figure 6. Simulation of the FIS operation in Matlab.

This way, the simulation created in Matlab conceptually shows how it is possible to implement the adaptation of the e-learning process to the personal traits of each user. It employs the power of fuzzy logic to draw conclusions using the imprecise definitions of individual characteristics and the fuzzy rules. If a similar approach will underlie the adaptation mechanism in the e-learning system, then each learner will study in a more personalized environment. The student's initial profile will contain information about the psychological characteristics and the list of related fuzzy rules. These data will be taken into account in the process of creating an individual curriculum and suggesting the types of learning content that will be most suitable for a particular learner.

The development of a user model for each learner can be considered as the basis for the development of a high-quality adaptive system. However, building a user model based on the Big Five scale at the beginning does not mean that these parameters should be used as a constant. The student's model can be later enriched with other information about the user, more specific to the further interaction with the e-learning environment. Such information may include the purpose of learning, the knowledge of the student within the framework of the course being studied, the current state of the learning progress, etc. Combination of fuzzy logic and deep learning techniques can be used to analyze different parameters and create more accurate user models.

4.2 Big Five Model in Deep Learning

Deep learning is a form of machine learning that involves extracting, or modeling, data features using complex multi-layer filters. The underlying mechanism of deep learning is deep neural networks that can contain multiple layers of neurons. An artificial neural network is considered to be deep if it consists of a large number of layers or has non-standard layers. A deep neural network for a practical task can have more than ten hidden layers. Its topology can be quite complex. It is assumed that the more layers are included in the network, the more distinct characteristics it can recognize. This structure is more similar to the human brain than other AI mechanisms which may be the reason for its promising results in more complex tasks (Manning 2015: 701-707).

Deep learning is an important part of modern artificial intelligence, but it must be trained properly. The problem with training deep neural networks is that they are not universal and must be trained to solve very specific problems. A common solution to this issue is the creation of a loss function, which acts as an internal motivator for the AI system. The goal of the model is to optimize the loss function by creating outputs that lead to more positive feedback. Research findings suggest that feedback may be one of the key factors in improving the deep learning model's performance. The outcomes of its functioning are more focused on satisfying humans rather than meeting some formal set of rules or predetermined expectations (Jaques et al. 2018: 1-9).

Since deep learning is a very general way of modeling, it is capable of solving complex problems. This approach is significantly different from both traditional programming and other machine learning methods. Deep learning not only can give results where other methods will not work, but also allows to build a more accurate model or reduce the time to create it. Its successful use cases can be found in application to image analysis and classification, computer vision, analysis and translation of natural language texts, sentiment analysis, and others (Manning 2015: 701-707).

Deep learning methods are often used in studies where the Big Five scale is involved as a psychological annotation for differences among people. Datasets annotated according to this personality scale make it possible to identify various relationships between personality traits and other characteristics of individuals, including their behavior, appearance, emotions, etc.

One study investigated the associations of facial picture cues with self-reported Big Five personality traits. It tested the hypothesis that a real-life photograph contains cues about personality that can be extracted using machine learning. Volunteer participants were asked to provide their face photographs, which were then used as input for a personality diagnostics network. The neural network was implemented as a multilayer perceptron and trained on a dataset containing questionnaire scores from respondents and associated photo images. Then it was used to predict the Big Five personality traits as its output. The findings support the possibility of identifying personality traits using machine-learning algorithms trained on large labeled datasets. In addition, the study provides evidence that all the Big Five traits are associated with facial cues that can be extracted using capabilities of complex neural networks (Kachur et al. 2020: 1-12).

A neuro-physiological study was conducted to measure individuals' affective responses in relation to their personality and mood and the social context, as well as the duration of videos. The data of all participants of the research was collected into A dataset for Multimodal research of affect, personality traits and mood on Individuals and GrOupS (AMIGOS). The dataset includes personality profiles based on the Big Five scale, mood profiles, external annotations, and neurophysiological recordings of participants' brain activity when viewing videos. This file contains both self-assessment of emotional levels felt during the videos as well as external-assessment of valence and arousal levels. Researchers found significant correlations between internal and external affect annotations of valence and arousal, indicating that external annotation is a good predictor of the affective state of participants. The study also found that social context has an important effect on the valence and arousal expressed by participants (Miranda-Correa et al. 2018: 1-14).

In another study, the research addressed the hypothesis that Big Five personality traits can be identified based on electroencephalogram (EEG) features during emotional processing. This study used data from the AMIGOS dataset involving parameters of affect and personality traits. The EEG signal recordings reflected differences in brain networks and graph theoretical parameters, which then were dichotomized with the k-means algorithm. The feature set size was also reduced to a fixed number of features for each trait. Then each instance was classified with the help of support vector machines. The main findings revealed high detection accuracy for all of the Big-Five personality traits, demonstrating that an EEG recorded during emotional stimulation can predict Big Five personality features (Klados et al. 2020: 1-15).

One of the studies focused on devising a methodology based on neural networks to build a combined image-and-text based personality trait model. The model was trained with captioned images that correlated to specific personality traits. The approach was based on the Big Five personality scale and the MindPics dataset, which consists of images shared on Instagram with keywords most correlated to a particular personality trait. The experimental results suggest that images could be used for personality estimation because classification methods applied on some personality traits showed specific visual patterns. The correlation found between posted images and the personality estimated from their accompanying texts was found to be significant (Rodriguez et al. 2019: 6-12).

Another study that analyzed variation in image content with user personality across two platforms used data from Flickr and Twitter to identify differences. Research has focused on the correlations between users' personality traits measured with the Big Five model and their social media data. The dataset that was used, Psycho-Flickr, contains data about people who have accounts on both social networks and answered the Big Five test. The researchers used a variety of features extracted from images to analyze how personality traits can be predicted based on analysis of images posted to social media platforms. They found that combining different data sources improved the accuracy of their predictions (Samani et al. 2018: 1-19).

The study of emergent leadership analysis in newly formed groups has proposed a framework of inference based on a combination of features. Participants of the study were asked to perform a winter survival task in small groups, while the process was recorded on video. These recordings initially formed the Emergent LEAder corpus (ELEA), which was also enriched with annotations. The annotations added to this corpus consisted of self-reported personality traits according to the Big Five test, concepts related to leadership, and performance in the survival task. The recordings were used to automatically infer emergent leadership by extracting and analyzing nonverbal cues in behavior, prosodic features, visual activity, and motion. The research utilized a number of methods for analysis, including rule-based approach, classification, and machine learning. The findings showed that two factors of the Big Five model, extraversion and openness to experience, could predict emergent leadership in newly formed groups of people (Sanchez-Cortes et al. 2012: 816-832).

The outcomes of the aforementioned studies show that it is possible to determine the Big Five personality traits by applying deep learning methods. Such technologies create an opportunity to replace psychometric tests, which are prone to some degree of subjectivity or situational factors, when people manually evaluate themselves. Deep learning allows for collecting and analyzing the information about the learner automatically, for example by identifying the user's facial characteristics or speech patterns. Analysis of these data can give insights about learners' emotions, mood, and level of enthusiasm, at the time of performing a certain learning activity. Using the existing large annotated datasets like AMIGOS or ELEA, the Big Five personality traits can be identified at the time of user interaction with the e-learning platform.

This approach provides the ability to maintain dynamic user profiles in the system. Individual characteristics may change over time, for example, Emotional Stability may increase or decrease depending on the life circumstances of a particular person. The new data about specific user traits can be used to update and extend the user model using methods of knowledge extraction from deep neural networks. It is possible to adapt the knowledge base about the user's personal characteristics that affect the learning process using the combination of neural network classifiers and fuzzy logic methods. This approach may also involve the creation of a reasoning mechanism to support the generation of new knowledge in the base (Kollia et al. 2010: 159-172).

Some studies involve an adaptive network-based fuzzy inference system (ANFIS) approach to determine personality type patterns, based on the Big Five personality scale. In order to deal with the imprecise interpretations of the personality traits, it is proposed to use a fuzzy inference system type model with a set of rules to identify better patterns for these engineers. The model was constructed by hypothesizing a parametric model structure, collecting input/output data in a form that can be used by ANFIS for training, and then using ANFIS to train the FIS model to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion (Martinez et al. 2013: 1373-1380).

This technology can be also applied to analyze patterns between personality scores and outcomes on different types of learning tasks. There are yet no sufficient results of experiments that would establish the types of tasks that are most suitable for students with different individual characteristics. Moreover, the learning activities become more creative and diverse, and therefore, it may not be possible to update the theoretical recommendations for different assignments in a timely manner. Deep learning provides a unique opportunity to do this on the run. The initial matches can be established with some assumptions made on a basis of Big Five personality factors description. Then, deep neural network algorithms can be used to extract more precise correlations between activity types and individual traits.

It can be achieved by combining the methods of fuzzy logic and neural networks to form a fuzzy neural network. In this case, the system carries out inferences based on the apparatus of fuzzy logic, however, the parameters of the membership functions are adjusted using the learning algorithms of the neural network (Babuska & Verbruggen 2003: 73-85) . The e-learning system of this kind will utilize explicit methods of collecting user data, such as online questionnaires, visual and audio patterns, as well as implicit analysis of the navigation behavior of users upon interaction to further adapt and fine-tune the process of learning.

4.3 Aspects of Content Adaptation

Every functional part of an e-learning system undergoes three different stages in its life cycle. These stages include design-time, publishing-time and run-time (Burgos et al. 2007: 161-170). When introducing adaptation into a learning platform, it is important to decide which technologies will be used at the time of system architecture planning. Some methods or prerequisites for them can only be implemented at the stage of design, therefore there will be no possibility to add or change them at the time of publishing or running of the system. For example, basic course structure may be designed in a certain way, without a capability to alter it, or the set of learning activities may be limited to a predefined list of options. That is why it is important to decide at the outset which parts of the system should be adaptive and to what extent they can change, as well as what rules should be applied for their variability.

It makes sense to use the most flexible approach when designing an e-learning platform. This way the system administrator can customize the course structure, select the required types of learning units, manage content elements, and define individual learning paths for learners. This means that tutors will be able to adapt things on the run, as long as this was foreseen and implemented at the design stage (Burgos et al. 2007: 161-170). If such capabilities are introduced into the e-learning system at the design stage, this will ensure the potential possibility of its personalization not only manually, but also using various artificial intelligence methods. In this case, the adaptive e-learning system by the time it starts to operate should already be adapted to the conditions necessary to improve the learning process. It should be predisposed to operate with the information objects common for learning platforms, such as course lessons and types of learning activities. The further behavior of the system should be based on the rules for adaptation that will be generated automatically based on the initial scheme.

Development of an e-learning platform from scratch is often expensive, time consuming and requires specialized skills. In order to provide capabilities for online education, many companies use already existing Learning Content Management Systems (LCMS). Learning Content Management System is a software complex used to present, store, assemble and deliver personalized learning content to the user. Such platforms allow to quickly organize, deploy and manage online course content. Learning content units in LCMS can be presented using a SCORM (Sharable Content Object Reference Model) standard, created specifically for such purposes. This standard contains a number of requirements for the organization of content and uses XML (Extensible Markup Language) as a unified form of representing information. SCORM packages consist of small sections of the education material that can be seen as independent learning units (Cespedes-Borras et al. 2009: 92-97). This approach ensures their compatibility and the possibility to reuse them in another module, course, and even another e-learning system. Saving data in XML format opens up possibilities for converting content from one form to another, for example, creating audio recordings based on written texts.

Modern educational platforms offer a big variety of learning activities and content forms. With many alternatives, the task of implementing content adaptation is essentially the need to find a set of learning units that meets the student's personality in the best possible way. This implies that there should be different types of activities available, so that there can be more suitable options. Therefore, when creating a course, it is necessary to fulfill the requirements for various types of content, by adding them manually or using conversion where it is possible to do so. Adding the course to the learning platform in this case requires more effort from its tutors. As a result, each course will have a set of lessons that consist of different types of activities. Some of these activities can be mandatory for all students, and some may be selected individually. Intermediate assessment of learning outcomes should be in place to understand what volume and types of activities are sufficient for the thorough study of the educational material.

It is also necessary to develop an algorithm consisting of the association rules matching the user traits and types of learning activities. This can be implemented as an additional module for adaptation, built into an e-learning platform. The adaptation module will be responsible for, basically, personalization of educational material for different learners. This can be implemented with the help of AI methods, including rule-based mechanisms, fuzzy logic and deep learning techniques. The educational material offered to a particular student should be adapted based on the parameters of the user model formed on the basis of the results of personality testing.

The pool of all course learning units can be described as a knowledge base, a specific type of a database designed to operate with knowledge. Full-fledged knowledge bases contain not only factual information, but also the rules for searching, displaying and processing information (Martinez et al. 2003: 1373-1380). In relation to an adaptive educational system, factual information is understood directly as the material of the training course, and metadata refers to the parameters of this material used to adapt to the individual student and to form educational elements. This way, each learning unit should be characterized by a number of parameters that indicate its suitability for users with particular traits.

Thus, the adaptation module should be responsible for the interaction of the adaptive e-learning system with the knowledge base in the learning process using the parameters of the student's model. It should perform the adaptation function in accordance with the rules for selecting educational material, taking into account the individual values of the parameters in the profiles of the learners.

The adaptation module should also be compatible with the algorithms that are implemented underneath the knowledge base. The semantics is often powered by technology and languages that can capture a wide variety of relationship types using ontologies. Ontologies can be represented using Extensible Markup Language (XML), Resource Description Framework (RDF), or Web Ontology Language (OWL) (Dolog & Nejdl 2007: 697-719). The educational knowledge base can be created using OWL, the language designed to represent rich and complex knowledge about a certain subject area, its elements and relations between them. Semantic networks can be also used to represent the metadata in the knowledge base. The use of OWL will allow to exploit this representation by the programmatic tools of an e-learning platform.

The described approach will allow the learning process to be adjusted to the individual characteristics of the student by compiling an adapted curriculum, thus improving the effectiveness of the study process and the level of user satisfaction during interaction with the e-learning system.

Chapter 5
Conclusion

Modern educational standards require a personal approach to the learning process. It is necessary to take into account the individual characteristics and preferences of the student in the preparation of the curriculum, the formation of educational elements and the evaluation of learning outcomes. This approach will optimize the learning process as much as possible, filling it with educational material that is ideally suited to the needs and characteristics of each student. The expected result of this approach is to improve the quality of the results of the educational process.

In this case, adaptability becomes an important requirement for the e-learning system. Technical capabilities for adaptation create an opportunity to support individual curricula. The main feature of such systems is the ability to adapt the educational material to the individual characteristics of the student. When comparing an adaptive e-learning environment to a conventional approach, the experiments show that adaptive content has a positive influence on students' learning achievements (El-Sabagh 2021: 1-24). Adaptation of the system to the individual traits of the learners improves the overall quality of the educational process, including the learning outcomes and student engagement (Murray & Perez 2015: 111-125).

Online learning has proven to be a viable option for diverse populations of students, including learners with disabilities or other obstacles to attending in-person classes. As online learning environments continue to grow in popularity, barriers are removed and accessibility increases (Chaney 2010: 20-35). Online learning can help remove barriers to equitable education, such as physical distance and financial resources. To ensure that all participants have an equitable educational experience, it is important to focus on the needs of the students and to design courses that are accessible for all learners (Oswal & Meloncon 2014: 271-300).

Since e-learning platforms are used by people with a wide range of backgrounds, skills and abilities, a learner-centered design is particularly important. This type of design will make it possible to meet the needs of diverse learners (Quintana et al. 2000: 256-263). Research findings indicate that attention to learner diversity can increase student motivation and, in turn, improve learning outcomes (Larkin-Hein & Budny 2001: 276-281).

Currently, most popular e-learning systems on the market of educational services have limited capacities for the automatic correction of the curriculum in the learning process and don't fully convey the adaptive approach. Most of them operate with the predefined rules, that change content availability depending on the fulfillment of prerequisites, course progress or test results. However, these processes are unified for all students, thus individual differences are not taken into account. This approach seems outdated. Given today's opportunities in the field of applying artificial intelligence methods and enhancing e-learning platforms, it is possible to implement these methods in order to suit the individual needs of the learners.

The relevance of this Master's dissertation is associated with the need to consider psychological aspects when developing models and algorithms for an adaptive e-learning system in the field of information technology that will meet modern educational standards and at the same time support the personalization of the educational process to improve the quality of its results.

This topic has been researched within the framework of the Master's dissertation by carrying out theoretical studies of the relevant fields and concepts. First, existing technologies for implementing user modeling and adaptation were analyzed in order to understand the ways of their application in e-learning systems. Then, a few most popular personality scales were reviewed to determine which of them can be used as a psychological basis for user modeling, selecting the Big Five scale for further study. And, finally, there was proposed an approach to the adaptation in e-learning systems that can be applied at the level of planning the educational process to reflect personalization based on individual characteristics, with the application of artificial intelligence methods, particularly, the concept of fuzzy logic and deep learning.

Additional value of the present Master's dissertation in the scientific field is that it can be used as a starting point in further research on learning styles. Research correlating learning styles and outcomes has been somewhat limited. Multiple measurement instruments exist for learning style tests, making comparisons difficult. These factors have impeded the application of learning style theory to actual classroom settings. However, efforts to define and utilize learning style theory are growing and promising (Romanelli et al. 2009: 1-5). Utilizing AI methods for the analysis of correlations may lead to more valuable findings and achievements in this research area.

Potentially, it may be possible to conduct a series of experiments with a group of people and match their learning styles with the types of educational activities that they are most successful at. Such findings, in turn, may become the psychological framework for the development of a highly adaptive e-learning platform that can make a noticeable impact on the process of learning. A better understanding of learning styles may become increasingly important as technological advances continue to expand e-learning opportunities. Adaptation capabilities will allow to adjust the learning environment to individual characteristics of users, while AI methods such as fuzzy logic, deep learning and others can help to create sophisticated user models.

There is also a possibility of creating more complex e-learning systems by bringing together different computational intelligence methods. In order to do that, it may be required to create a more advanced intelligent system that can utilize the benefits of different approaches, such as, for instance, rule-based adaptation mechanisms, knowledge databases containing semantic ontologies of the subject area, fuzzy neural networks, and deep learning methods. The capabilities of deep neural networks could make it possible to find patterns or peculiarities in the actions, behavior and emotions of users, in order to make certain conclusions about their preferences regarding different types of learning activities and course content. This can help to greatly expand the capabilities of e-learning systems to take into account the individual characteristics of users and provide personalized adaptation.

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