**FACTA UNIVERSITATIS**
Series: **Automatic Control and Robotics** Vol. 22, Nº 2, 2023, pp. 57 - 73
https://doi.org/10.22190/FUACR230719005J

**Regular Paper**

# CHATBOT APPLICATION AS SUPPORT TOOL FOR THE LEARNING PROCESS OF BASIC CONCEPTS OF TELECOMMUNICATIONS AND WIRELESS NETWORKS

*UDC (621.397.444)*

**Mihailo Jovanović[1], Kristijan Kuk[2], Vladica Stojanović[2], Edis Mekić[3]**

[1]Ministry of Information and Telecommunications, Republic of Serbia
[2]Department of Informatics & Computer Sciences,
University of Criminal Investigation and Police Studies, Republic of Serbia
[3]State University of Novi Pazar, Novi Pazar, Republic of Serbia

**Abstract**. *There are several applications for Chatbots in education, as well as their contributions to mentoring in the learning process. Bots can assist teachers with staying up to date on new standards and evaluation methodologies. Bots can assist students in understanding tough subjects in a way that makes it appear as if they are being taught by another person. Chatbots serve as virtual assistants in the educational setting, improving efficiency or answering frequently asked questions. In this case, we work on the premise of investigating the potential of Chatbots as analytical tools for analyzing preferred types of learning material in a mobile learning environment, which leads to the acquisition of a proper level of knowledge on the topics of telecommunication and wireless networks.*

**Key words**: *Chatbots, sequential patterns, mobile learning, telecommunications, wireless networks*

## 1. Introduction

Programming as a skill is at the centre of attention all around the world. This skill is advertised as accessible and perspective, easy for understanding. Schools adapt learning methodology to adapt to new skills needed for the labour market. People are encouraged

---

Received July 19, 2023 / Accepted August 28, 2023
**Corresponding author:** Kristijan Kuk
University of Criminal Investigation and Police Studies, Department of Informatics & Computer Sciences, Cara Dušana Street 196, 11080 Belgrade, Republic of Serbia
E-mail: kukkristijan@gmail.com

to learn programing and coding skills themselves or through online resources [1-2]. Besides programming, many additional engineering skills are not in the spotlight, but knowledge and understanding of concepts of those skills can create a needed boost of skills which will enable increased employability of future engineers. One of the fast-paced industries with a paramount impact on Information Technology is the field of telecommunications. New technologies like next-generation Ethernet, the Internet of Things and new generations of mobile communication systems like 5G, push forward development and raise new questions and challenges in this engineering discipline [3].

Already stated implies that studying telecommunications principles can be a resume booster and provide good job opportunities for those with up-to-date technical skills. Additionally, universities can offer comprehensive programs that cover various aspects of modern telecommunication systems together with the background necessary to understand such systems and implement and use their advantage in the development of different IT-based systems.

Therefore, it is essential to modify the teaching methods of telecommunications and software engineering education by utilizing suitable methodologies and offering access to dedicated mentors or teachers, especially for students lacking sufficient mathematical or engineering knowledge. By comprehending the significance of telecommunications and software engineering skills within the broader STEM science context, we can install confidence in students regarding their development abilities and enable them to autonomously execute diverse telecommunication scenarios in their projects.

Various tactics can be used to attain the previously stated goals. Constructivism is frequently cited as an established method. Emphasizing a constructive approach encourages students to actively participate in learning by putting knowledge into practice. [4] The constructive approach allows students to be engaged in learning by doing and implementing engineering concepts [5-7].

All of these ideas are based on traditional teaching methods. The increased acceptance of mobile technologies, as well as their extensive accessibility, has moved attention to the effective application of these approaches in learning [8]. While studies offered and demonstrated a rise in mobile learning usage in education, all of these research addressed the topic of employing technology as a supporting tool to augment traditional teaching experiences [9]. The use of mobile technologies as a tool for increasing the pedagogical impact of these devices on student learning or as a tool for assisting teachers in improving their teaching skills has received little attention [10].

On the other hand, the rapid growth of new kinds of cyber structures, such as social networks and media platforms, has moved a younger generation to embrace this style of Internet usage. They no longer use single utility apps or websites, but rather use social networks to post problems and seek solutions. And the use of mobile communication tools has undeniably improved interaction between students and between students and teachers [11].

Viber, for example, can provide a communication link between a teacher and pupils, as well as the sharing of solutions and teamwork. Chatbots, which are being developed with a stated educational goal and act as instructors to students, are another important tool. They are used to guide students through the learning process or to establish a setting for certain activities and practices.

In the realm of digital education, two distinct yet complementary technologies developed for sole purpose of educational purpose stand out: chatbots and traditional Learning Management Systems (LMS). Chatbots, advanced conversational AI programs, engage users in dynamic text or voice-based interactions, responding to queries, offering assistance, and automating tasks in real time. In contrast, traditional LMS platforms provide structured environments for educational content, catering to formal learning needs by managing courses, assessments, and learner data through predefined interfaces. While chatbots excel in immediate, personalized interactions, LMS systems focus on content delivery and progress tracking, each offering unique pathways to enhance the digital learning experience.

In this study, we will investigate the use of Chatbots as a mobile learning tool in education. In Python programming language, we will create a Chatbot application to teach basic telecommunication ideas. We will use the Chatbot after it has been implemented to determine which form of the delivered lessons was most popular with the student population. This will serve as baseline research for future development of comparable mobile learning solutions.

## 2. Research Methodology

The considerable development and widespread adoption of mobile devices sparked interest in the educational benefits of this technology. Mobile learning refers to the use of mobile devices in a learning setting. A full definition of this term is: "*learning across multiple contexts, through social and content interactions, using personal electronic devices*" [12]. This definition sheds light on the educational benefits of using mobile devices for study. The major issue is that mobile learning is ad hoc, taking place across contexts, time, subjects, people, and technologies [13-15]. This created a lot of different fields of the educational benefit of mobile devices, methodological approaches for their usage, attires of the students and teachers, and success of learning. Since mobile phones are the most frequently used mobile devices [16], development of the learning platforms compatible with this format of the mobile devices is one of the issues tackled in research [17]. Other specific possibilities, such as the ability to use instant messaging and establish quick and reliable communication between teachers and students, have also been demonstrated to be a vital aspect of improving the educational environment.

During the implementation of this study, we will develop Chatbot that will be utilized as a specialized instrument for learning reinforcement. Because a communication tool will be developed as an inherent part of the learning platform, this Chatbot will allow interconnection between learning and communication tools. The primary benefit for learners will be the ability to obtain a direct access and control over the material and learning stored in the LMS via the Chatbot, without having to deal with cumbersome interfaces or sign-in. This will lay the groundwork for a more tailored and successful learning. Chatbots can be utilized effectively as part of L&D if the learning content and resources are specifically created for this purpose. Chatbots are categorized into the following categories based on the tasks they perform:

- *Administrative and management tasks to foster personal productivity. The main tasks are personal assistance to students, schedule and email management, submission deadline and assessment reminders.*
- *Taking care of FAQs*. The main task is providing a response to student FAQs regarding administration or learning concepts and contents.
- *Student mentoring.* The main task is to allow student mentoring during the learning process.
- *Motivation*. The main task is to provide the increase of students' retention. This is especially relevant in online learning environments.

- *Practice of specific skills and abilities*: The main tasks are to enable dialogues practiced in language learning, simulating conversations in contexts.
- *Simulations*: The main tasks are to simulate specific professional situations and can provide support for reflection and taking alternative routes toward solutions.
- *Reflection and meta-cognitive strategies*: The main task is to help the students regulate their own meta-cognitive processes (reflection on their own learning process).


**Fig. 1** The process of lesson study in [16, p. 113]

Chatbot application will be developed in order to follow the lesson study cycle given in Fig.1. Unlike the four steps diagrams presented in [17] since Chatbot will be used for learning of construct and install complex telecommunications networks and skills for telecommunications engineers. The goal setting will be acquiring the necessary strong analytical and problem-solving skills. Since we want to implement learning issues in the form of e-learning, first we need to establish content size. This size must fulfill the rules of decomposability and be usable as a part of a larger content. We will use aggregation levels learning object (LO) the IEEE Learning Object Metadata [18] used the term "*aggregation level*". According to ILSG's (Cisco Internet Learning Solutions Group (ILSG)), we can use a Reusable Learning Object (RLO) (see Fig. 2). The concept of reusable information is defined by [19] derivation of more global object thinking. Every part of the lesson in the Chatbot is defined in terms of concept, fact, process, principle, or procedure.

Every lesson in order to be applicable in the Chatbot will be decomposed into multiple constituent elements, including instructional design practices, pedagogic audits, scaffolding techniques, and problem-based learning techniques.

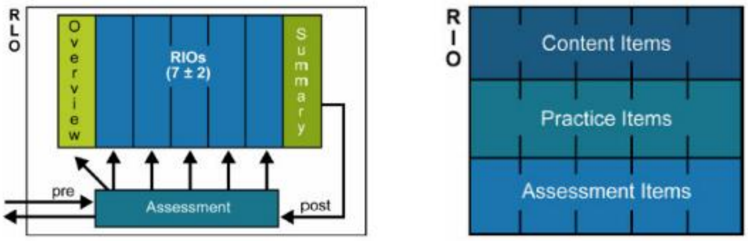


**Fig. 2** CISCO's Reusable learning object structure [20]

According to RLO Strategy, the Chatbot lesson will be organized as chapters for each teaching unit and every unit has one of the following functions:

1) Content with Practice items, at the beginning of each teaching unit. The topics will be presented with a short text. The information presented visually is processed extremely quickly by the brain, and in every unit, we use an image to illustrate the content of the lesson.
2) The second type of item will be assessments items which will help students solve some problems related to the topic. For additional students' motivation, these items include the quizzes and students' progress is encouraged by scoring points. Since our proposed framework needs a possibility of reflections on the learned content, our Chatbot application will involve a communication aspect, either. The communication will be implemented by a messenger system.
3) Finally, since we need tools, the reflections phase of this learning framework application must record data from interaction. This data must be accessible for analysis of learned material, missing information, recording of queries. In this way, the Chatbot will help students to take control of their learning.

For tracking of the student preferences, we will use concept sequences. They will be organized by using the Generalized Sequential Pattern (GSP). GSP is an algorithm of implementation sequential pattern mining, and it is capable to generate all possible candidate sequences, so that missing any actual sequences can be avoided [21]. The output of this algorithm is all maximal sequences in frequent-sequence sets. A sequential rule is an implication of the form, X→Y, where Y is a sequence and X is a proper subsequence of Y, i.e., the length of Y is greater than that of X. This implication means that if a sequence X exists, we can find a sequence Y containing it. In this study, X represents a sequence formed by concepts lesser used by students, and Y is a frequent concept sequence. If the sequential rule X→Y has a high confidence (the proportion of all materials that contain X also contain Y), which indicates the sequence Y has the relationship of implication with the concept sequence X; therefore, the sequence Y is a preferred learning path for the learner [19]. After that, a stochastic and dynamic analysis of the choice of different learning objects (LOs) by the students was performed, for which the well-known Markov chains (MCs) were used as the basic stochastic model. To that end, using the maximum likelihood (ML) method, the so-called transition probabilities from one LO to another are calculated. Thereafter, the marginal, stationary probabilities of choosing individual LOs by students were obtained.

## 3. Implementation of Lesson Study Cycle Through Chatbot - Telebot

Chatbot was created to aid in the teaching of fundamental telecommunication principles in the two courses telecommunications and digital telecommunications.

The principles, technologies, and standards of wireless communication systems and applications in information systems are covered in the courses. They give pupils a thorough understanding of diverse wireless technologies, their applications, and the standards that govern their use. Students will learn theoretical knowledge as well as the practical skills needed to build, implement, and manage wireless networks and integrate them in information systems.

In order to implement these Chatbot will cover the following topics:

- Students will learn about wireless communication systems. They will be introduced to the essential concepts and problems of wireless technologies. Highlighting significant milestones and advances in the sector.
- Wireless Signal Propagation. The concepts of wireless signal transmission are the focus of this topic. The radio frequency spectrum and its allotment for various wireless services will be investigated by students. They will become acquainted with various propagation models and their applications in wireless communication. Antennas and their importance in signal propagation will also be discussed.
- Wireless Communication Channels. Students will learn about the features of wireless communication channels in this topic. They will study about several channel types such as Additive White Gaussian Noise (AWGN), Rayleigh, and Rician. Channel models and their mathematical representations will be addressed, as well as fading mitigation measures.
- Wireless Access Technologies. This chapter focuses on multiple access techniques used in wireless systems. Students will explore Frequency Division Multiple Access (FDMA), Time Division Multiple Access (TDMA), Code Division Multiple Access (CDMA), and Orthogonal Frequency Division Multiple Access (OFDMA). They will also study cellular systems, starting from 2G to the latest 5G networks, understanding the evolution of mobile communication.
- Wireless Networking Architectures Students will learn about different wireless networking architectures in this topic. The focus will be on Wireless Local Area Networks (Wi-Fi), Wireless Personal Area Networks (Bluetooth, Zigbee), and Wireless Metropolitan Area Networks (WiMAX). The characteristics, applications, and standards associated with each architecture will be covered.
- Wireless Network Protocols. This chapter will introduce students to wireless network protocols and standards, such as IEEE 802.11 (Wi-Fi), IEEE 802.15 (Bluetooth, Zigbee), and IEEE 802.16 (WiMAX). They will gain a deep understanding of these protocols' operation, including the MAC layer protocols and mechanisms for quality of service (QoS) management in wireless networks.
- Wireless Network Security. Security is a crucial aspect of wireless networks, and in this chapter, students will explore wireless network vulnerabilities and threats. They will learn about encryption and authentication mechanisms used to secure wireless communications. Various security protocols designed for wireless networks will be discussed, along with best practices for ensuring network security.
- Wireless Sensor Networks. This chapter will cover the basics of wireless sensor networks (WSNs). Students will understand the unique characteristics, applications, and challenges associated with WSNs. They will explore protocols and algorithms used in WSNs for efficient data gathering, routing, and energy management.
- Wireless Internet of Things (IoT) Students will delve into the intersection of wireless communication and the Internet of Things (IoT) in this chapter. They will learn about IoT protocols and architectures such as MQTT, CoAP, and LoRaWAN. They will also explore wireless IoT applications and case studies, understanding the role of wireless technologies in enabling IoT connectivity.

- 5G and Beyond. Students will explore the evolution of mobile networks to 5G in this chapter. They will learn about the architecture, features, and key technologies of 5G networks, such as massive MIMO, network slicing, and edge computing. They will also discuss the challenges associated with 5G deployment and emerging trends beyond 5G.
- Wireless Network Planning and Optimization. This chapter focuses on wireless network planning and optimization. Students will learn about considerations for planning wireless networks, including coverage and capacity requirements. They will explore techniques to optimize wireless networks, mitigate radio frequency interference, and improve overall network performance.
- Wireless Network Management. In this chapter, students will gain an understanding of wireless network management. They will learn about performance monitoring and optimization techniques for wireless networks. They will also explore fault management and troubleshooting strategies, along with the tools and systems used for network management.

The second phase of the implementation of mentioned learning framework will be covered in preparation of lessons to be in the format of granular learning. We will granulate lessons onto the lower levels. In order to follow rules of granulation, the lessons must be presented in textual or video form which will give a theoretical background, and this lesson will be further subdivided. All of this is a part of the content items. The practice items are given in the form of a test incorporated into lessons. The tests are in the form of quiz questions. The questions are based on the presented lesson. The expected answers are in the form of short answers, or in the form of several offered answers. After solving of these answers, a student receives feedback, a number of correct answers, and the Chatbot delivers a proper solution to students.

The research and discussion part is covered in the communication part of Chatbot application. A student can send a message to the Chatbot if he has some special interest for some problem not stated in the Chatbot application. If this inquiry is about some new issue, this issue is notified and analysis and scoring of this inquire is delivered to a teacher in order to steer further teaching towards students' needs. The reflection phase is covered in the form of the final test. This test covers all questions from the overall course curriculum. The questions are given in a random order, also, this test in case of failure, has links to teaching material.

The used technologies are presented in the development phase of TELEBot, and also the communication way among certain segments of the applicative solution. Thus, when a user starts conversation with TELEBot via the Viber platform, using Viber APIs, a message is sent further on to Heroku platform, where Flask applicative server has been initiated, and the one processes messages, i.e. returns a message and records the users' questions into the base. After initiating it via Viber messenger, the conversation starts with the ChatBot application TELEBot. The first message a user receives is a greeting message and a button "*Continue*". As soon as a student clicks on the button, the Chatbot replies with a text message Choose some of the starting menu options and the starting menu contains the chosen areas of the telecommunication, being on offer to a student for learning. A student can choose a chapter and then, a smaller unit. After choosing the chapter, the Bot sends an introductory message for the chosen area and a new menu. Each of the menu options represents a smaller unit within the chapter it is chosen from. Thus, by choosing of an area, a student is guided through a lesson further on (learning). In a new menu, a student can choose one of the following options: Shorter lessons, Tests for checking knowledge from the area, and Return back/

starting menu. For example, by choosing an area of Wireless access technologies a student receives the lesson as an introductory one (in a form of a text message). By further choosing, one can receive processed stated parts (by clicking an option Sign lines, and one will get a text message and a new menu (Fig. 3).


**Fig. 3** Screenshot of TELEBot application

Depending on a lesson complexity, the one can receive additional options in the form of:

- Text message
- An image with a code part
- A link to a video lesson (short segments)
- A new menu (if a searched area is with more content)

A test where a user can check how well the one learned the lesson material. The Chatbot gives students certain topics by sending multimedia, like images, video recordings, links, and similar. Like any other classroom, the Chatbot gives them all the needed learning material, including tests. This makes following students' work easier and helps students understand how they learned certain lesson areas.

## 4. Monitoring Process on Students' Interaction with the Chatbot

Regarding the monitoring process, TELEBot collects feedback information from students. Each click to some of the menu options and intaking of other student messages is followed and recorded into Google Sheets, where by analyzing it, it is possible to conclude what are the areas of the most interest of students and if there are parts of their interest, but they were not processed and covered by lessons and similar.

### 4.1. Pattern recognition

The first step in analyzing dataset received from the Chatbot was to define lesson forms in line with GSP prerequisites. All lesson prepared in the Chatbot were prepared as a sequence of different multimedia materials (Fig. 4). We divided the level of students learning into distinctive learning objects: text, image, video and quiz. Group of 36 students could assess their knowledge after completing theoretical material supported by images, and then forward towards a quiz, during one semester of course learning. After initial test in the Chatbot, we set limit on 50% of success as minimum threshold for accepting results as positive and reviving. After quiz results students can reinforce knowledge by repeating lessons (they can choose which lessons format they prefer: a textual data, image-based presentation or a video material).

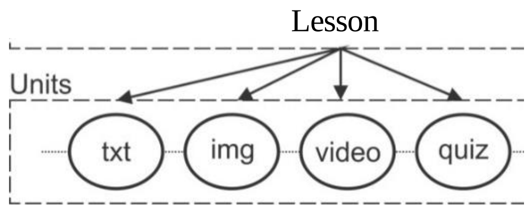


**Fig. 4** Design lesson objects (learning materials) in Chatbot

In order to implement this analysis, the Chatbot had implemented the report function. The report option gives feedback and summary of students' activities. These reports contain the number of clicks on the menu, the number of users, the number of multimedia material presentation, the results of assessments and tests, and also, the date information and information of the previous material chosen by a user. The GSP algorithm is applied on the received dataset to generate sequences and frequent sequences. Finally, the algorithm returns the maximal sequences. Table 1 shows the five most common sequences as well as sequences:

$$<\{txt\}\{txt\}\{txt\}\{img\}\{video\}>$$

and

$$<\{txt\}\{txt\}\{txt\}\{video\}\{txt\}>$$

which are maximal sequences for 0.4 values as minimum support thresholds.

**Table 1** The most frequent sequences of the LO system.

| 1-sequences | 2-sequences | 3-sequences | 4-sequences | 5-sequences |
|---|---|---|---|---|
| <{txt}> | <{img}{img}> | <{img}{img}{video}> | <{txt}{img}{img}{video}> | <{txt}{txt}{txt}{img}{video}> |
| <{img}> | <{im}{txt}> | <{img}{txt}{txt}> | <{txt}{img}{txt}{txt}> | <{txt}{txt}{txt}{txt}{video}> |
| <{video}> | <{img}{video}> | <{img}{txt}{video}> | <{txt}{img}{txt}{video}> | |
| | <{txt}{img}> | <{img}{video}{txt}> | <{txt}{img}{video}{txt}> | |
| | <{txt}{quiz}> | <{txt}{img}{img}> | <{txt}{txt}{img}{txt}> | |
| | <{txt}{txt}> | <{txt}{img}{txt}> | <{txt}{txt}{img}{video}> | |
| | <{txt}{video}> | <{txt}{img}{video}> | <{txt}{txt}{txt}{img}> | |
| | <{video}{quiz}> | <{txt}{txt}{img}> | <{txt}{txt}{txt}{txt}> | |
| | <{video}{txt}> | <{txt}{txt}{txt}> | <{txt}{txt}{txt}{video}> | |
| | | <{txt}{txt}{video}> | <{txt}{txt}{video}{txt}> | |
| | | <{txt}{video}{txt}> | | |

According to the 5 frequent concept sequences in Table 1, we can present those concepts not understood by the learner L0, where the results of sequences {img_L0}{video_L0} and {img_L0}. And these will notify as learner's un-comprehended concept sequences. The learner's un-comprehended concept sequences are then used to find their sequential rules which will emerge after these sequences. These rules are:

{img}{video} → Y and {img} → Z.

Those sequences Y and Z implies {img} and {img}{video}, respectively. Two paths can be found based in the maximum appearance:

- learning path 1: <{txt}{txt}{txt}{img}{video}> (12)
- learning path 2: <{txt}{txt}{txt}{video}{txt}> (12)

From this, it is obvious that students preferred to assess video material in cooperation with text-based material over other types of proposed material, in the cases before they could achieve level of learning. These results give straightforward references on how to develop and structure future learning material for the efficient usage in a mobile learning environment (Fig. 5).

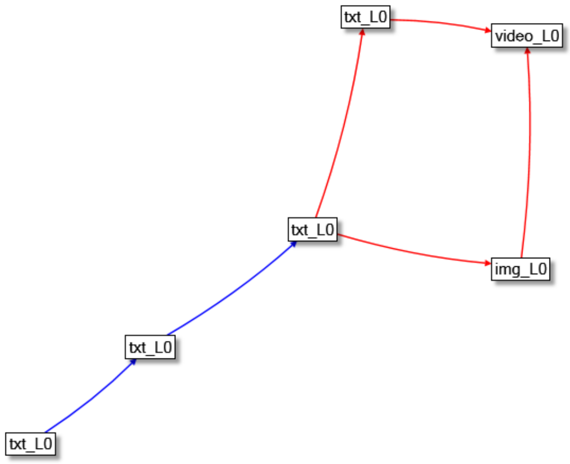


**Fig. 5** LO system with learning paths to state transition diagram

### 4.2. Markov chain analysis

In the next step, we use Markov chain (MC) models applied to analyze and predict the evolution of learning forms. MC models are based on the Markov property, i.e. the assumption that the current state of the system depends exclusively on the latest, i.e. current state, while earlier states of the process are not important. Note that this is one of the common assumptions of LO systems, as students choose the next learning object based solely on their current LO choice. In addition, MC models are easy to implement and provide the possibility of interpretation, evaluation and prediction of system dynamics in the future. For these reasons, they represent important stochastic models that are widely used in modern research.

According to the MC theory, suppose that the choice of a particular learning object (txt, img, video, quiz) represents the state of the LO system at some "*time*" point $t = 0, 1, 2, \ldots$, which we denote further with $x_1$, $x_2$, $x_3$, $x_4$, respectively. The Markov property assumes that the choice of certain LO in the next step $(t + 1)$ depends only on the currently selected LO in the step $t$, that is, in the state of the system "*in the present*". In terms of conditional probability, this property can be written as follows:

$$p_{ij} = P\{X_{t+1} = x_j | X_t = x_i,\ X_{t-1} = x_{i_1}, \ldots, X_0 = x_{i_r}\} = P\{X_{t+1} = x_j | X_t = x_i\}, \quad (1)$$

where $x_i, x_{i_1}, \ldots, x_{i_r}$ are the states of the LO system, $(X_t)$ is a series of random variables (RVs) that we call a Markov chain, while $p_{ij}$ represent the (unit) transition probabilities from state $x_i$ at time $t$ to state $x_j$ at time $t$+1.

In practice, it is usually assumed that transition probabilities have the property of homogeneity, that is, that they do not depend on the time index $t$. Then, all transition probabilities from each state to some (same or different) state of the LO system can be represented by the transition matrix:

$$\mathbb{P} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1r} \\ p_{21} & p_{22} & & p_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ p_{r1} & p_{r2} & \cdots & p_{rr} \end{pmatrix}.$$

Note that, for each $i = 1, \ldots, r$, the probability that the system will pass from state $x_i$ to any state in the next step is equal to one. In that way, the following normalizing conditions hold:

$$\sum_{j=1}^{r} p_{ik} = \sum_{j=1}^{r} P\{X_{t+1} = x_j | X_t = x_i\} = 1. \tag{2}$$

Also, in our case is $r = 4$, whereby the transition probabilities, that is, the elements of the matrix $\mathbb{P}$ can be estimated based on the obtained sample, i.e., using the choice of LO of all $25$ surveyed students. For this purpose, the maximum likelihood (ML) method is usually used, as can be seen in some recent publications related to application of MC models [22, 23]. In our study, the basic concept of the ML method is based on the observation of the random sample $\boldsymbol{X} = \{X_1, X_2, \ldots, X_n\}$ which represent state transitions during LO selection by the student. The main goal is to find a set of (unknown) probabilities:

$$\theta = \{p_{ij} | i = 1, \ldots, r; j = 1, \ldots, r\}$$

that make the given transitions set the most probable. Thus, the joint probability of all state transitions $X_1, X_2, \ldots, X_N$ is the product of corresponding probabilities from the set $\theta$. More precisely, let $n_{ij}$ be the number of observations with initial state $x_i$ and final state $x_j$ within the sample $\boldsymbol{X}$. The joint probability of the training data then can be written as a function of the probabilities from the set $\theta$, which is well known as the likelihood function:

$$L(\theta) = \prod_{i=1}^{n} \prod_{j=1}^{n} p_{ij}^{n_{ij}}.$$

Estimates of the probabilities $p_{ij}$ are obtained by the maximizing the function $L(\theta)$, or more simply, its logarithmic form. Thereby, notice that, according to the normalization equalities (2), the $n$ Lagrange multipliers $\lambda_i, i = 1, \ldots, r$ can be added, and their respective constraints can be used for the optimization procedure. In that way, the logarithmic likelihood function $\ell(\theta)$ is obtained, as follows:

$$\ell(\theta) = \ln L(\theta) - \sum_{i=1}^{r} \lambda_i \left( \sum_{j=1}^{r} p_{ij} - 1 \right) = \sum_{i=1}^{r} \left( \lambda_i + \sum_{j=1}^{r} \left( n_{ij}\, ln\, p_{ij} - \lambda_i p_{ij} \right) \right).$$

The maximum of the function $\ell(\theta)$ is then determined by calculating its partial derivatives with respect to $p_{ij}, i = 1, \ldots, r, j = 1, \ldots, r$, and $\lambda_i, i = 1, \ldots, r$, as well as by equating them to zero. Setting the partial derivatives with respect to the probabilities $p_{ij}$ to zero leads to the following equalities:

$$\frac{\partial \ell(\theta)}{\partial p_{ij}} = \frac{n_{ij}}{p_{ij}} - \lambda_i = 0 \quad \Leftrightarrow \quad p_{ij} = \frac{n_{ij}}{\lambda_i}. \tag{3}$$

After that, by equating to zero the partial derivatives with respect to $\lambda_i, i = 1, \dots, n$, and using Equation (3), the following conditions are obtained:

$$\frac{\partial \ell(\theta)}{\partial \lambda_i} = 1 - \sum_{j=1}^{r} p_{ij} = 0 \quad \Leftrightarrow \quad \sum_{j=1}^{r} \frac{n_{ij}}{\lambda_i} = 1 \quad \Leftrightarrow \quad \lambda_i = \sum_{j=1}^{r} n_{ij}. \tag{4}$$

Finally, according to Equations (3) and (4), the maximum likelihood (ML) estimates of the probabilities $p_{ij}$ are obtained, as follows:

$$p_{ij} = \frac{n_{ij}}{\sum_{j=1}^{r} n_{ij}}.$$

The estimated values of the probabilities of the transition matrix $\mathbb{P}$, obtained using the ML procedure mentioned above, are shown in the upper part of Table 2. As can be seen, the highest values of transition probabilities refer to the choice of TXT, while the probabilities of choosing IMG follow. On the contrary, video methods have by far the lowest transition probabilities.

**Table 2** Transition matrix, initial and stationary vectors of the MC system with LO.

| States | TXT | IMG | VIDEO | QUIZ | Σ |
|---|---|---|---|---|---|
| TXT | 0.664 | 0.172 | 0.051 | 0.113 | 1 |
| IMG | 0.518 | 0.343 | 0.073 | 0.066 | 1 |
| VIDEO | 0.529 | 0.118 | 0.029 | 0.324 | 1 |
| QUIZ | 0.552 | 0.095 | 0.029 | 0.324 | 1 |
| Initial state ($S_0$) | 0.250 | 0.250 | 0.250 | 0.250 | 1 |
| Initial state ($S_0$') | 0.680 | 0.160 | 0.000 | 0.160 | 1 |
| Stationary state | 0.613 | 0.191 | 0.051 | 0.145 | 1 |

Additional information about the state of the MC system at a certain moment can also be expressed by corresponding probabilities:

$$s_i(t) = P\{X_t = x_i\}, \qquad t = 0, 1, 2, \dots$$

Particularly, the probability of the state $x_i$ at the initial time moment $t = 0$ is denoted by:

$$s_i = s_i(0) = P\{X_0 = x_i\}.$$

Also, let us denote, for any $t \geq 0$, the so-called state vector:

$$\boldsymbol{s}(t) = (s_1(t) \quad s_2(t) \quad \cdots \quad s_r(t)),$$

whose coordinates satisfy $\sum_{k=1}^{r} s_k(t) = 1$. Then, for $t = 0$ is obtained the initial state vector:

$$\mathbf{s}(0) = (s_1 \quad s_2 \quad \cdots \quad s_r)$$

which describes the probabilities with which the MC system is in the initial state, when $t = 0$. As an illustration, in below part of Table 2 are shown two different initial state vectors. Firstly was taken the vector

$$\mathbf{s}(0) = (1/4 \quad 1/4 \quad 1/4 \quad 1/4)$$

that presupposes uniform (equal) selection of any of the four LO methods. Alternatively, it was taken as the initial vector

$$\mathbf{s}'(0) = (0.68 \quad 0.16 \quad 0 \quad 0.16),$$

obtained according to the estimated probabilities of choosing the initial LO method within a sample of 25 surveyed students.

Based on the state probabilities $s_i$ and previously described transition probabilities $p_{ij}$, the probabilities $s_i(t)$ can be determined for any $i = 1, \dots, r$ and $t \geq 1$. If we denote the events $A_i = \{X_n = x_i\}$, $B_k = \{X_{n-1} = x_k\}$, then, based on the well-known low of complete probability, it follows:

$$s_i(t) = P(A_i) = \sum_{k=1}^{r} P(A_i|B_k) \cdot P(B_k) = \sum_{k=1}^{r} s_k(t-1)\, p_{ki}. \tag{5}$$

Thus, the state probabilities of states of the system at some time $t \geq 0$ can be expressed as the product of the state probabilities at the previous time point $t-1$ and the corresponding transition matrix probabilities. Equation (5) can also be written in the matrix form:

$$\mathbf{s}(t) = \mathbf{s}(t-1) \cdot \mathbb{P}, \tag{6}$$

where $s(t)$ is the state vector of the MC system at the time $t$. According to Equation (6) the following recursive procedure is obtained:

$$\mathbf{s}(t) = \mathbf{s}(0) \cdot \mathbb{P}^t, \qquad t \geq 1.$$

On the other hand, in the limit case, when $t \to +\infty$, Equation (6) gives the so-called stationary equation:

$$\boldsymbol{s}^* = \boldsymbol{s}^* \cdot \mathbb{P} \;\Leftrightarrow\; \boldsymbol{s}^* \cdot (I - \mathbb{P}) = 0, \tag{7}$$

where *I* is the unit matrix of order $r$ and $\sum_{i=1}^{r} s_i^* = 1$. The vector

$$\boldsymbol{s}^* = (s_1^* \quad s_2^* \quad \cdots \quad s_r^*),$$

obtained by solving Equation (7), is called *the stationary, or steady-state vector*. It gives the stationary state of the MC system to which it will pass, after a sufficiently large time interval. In the steady state, each LO method will be chosen with a uniquely determined, stationary probability, which does not depend on its state at the beginning of the observed period, that is, on the choice of the initial LO method. As an illustration, Figure 6 presents the convergence of the MC learning system, using a recursive procedure given in Equation (6). It can be easily seen that the same stationary vector

$$\mathbf{s}^* = (0.613 \quad 0.191 \quad 0.051 \quad 0.145)$$

is obtained when both of two aforementioned initial state vectors are choosing. It is easy to prove that this vector also represents the solution of stationary Equation (7).

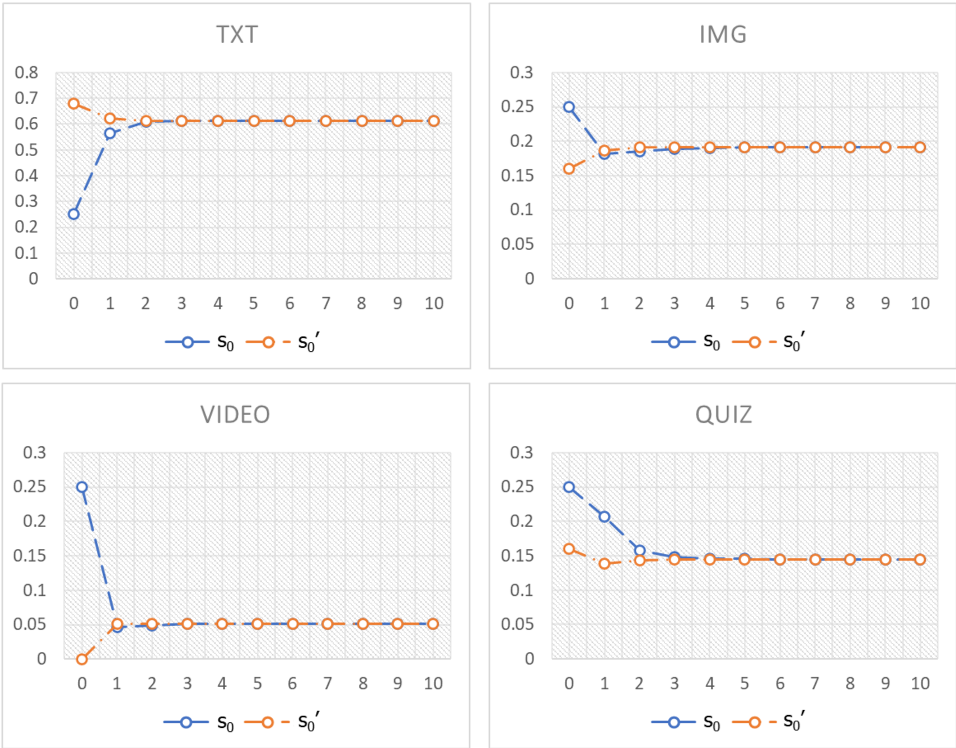


**Fig. 6** Convergence of the state vectors to the steady-state vector

## 5. CONCLUSION

Finally, incorporating chatbots into mobile learning settings has considerable benefits for increasing the relevance and accessibility of education. Chatbots provide a centralized platform that fosters a full learning experience by integrating multiple lessons and learning resources. Furthermore, these chatbots promote the student collaboration by encouraging dialogue and knowledge sharing. Data collecting on students' learning habits allows teachers to uncover patterns and trends, which aids in individualized training and course design. Furthermore, this data is used to create effective learning strategies and relevant learning materials, resulting in a personalised and optimal educational experience. Insights gained from analyzing chatbot-collected data can be used to influence instructional decision-making and improve the preparation of teaching materials, resulting in higher engagement and learning results. In general, chatbots have the potential to revolutionize education by creating dynamic and interactive learning environments that cater to individual students' needs. Chatbots proven to be a helpful additional tool in our case for fostering effective knowledge and information databases on complex mathematical issues such as telecommunications.

Further research will be incorporating Natural Language Processing (NLP) capabilities into chatbot systems which offers a diverse spectrum of transformative opportunities. By leveraging NLP, chatbots can intuitively comprehend user intentions, sustain meaningful conversations with contextual awareness, and accurately analyze sentiment for more empathetic responses. This integration empowers chatbots to efficiently retrieve information, generate content, and even provide personalized educational experiences. Moreover, the fusion of NLP and chatbots enables multilingual communication, assists in data analysis for insights extraction, and extends to voice-driven interfaces, thus revolutionizing user engagement, customer support, education, and various domains through heightened conversational competence.

**Acknowledgement**: *This paper was realized as a part of the projects III 47016, funded by the Ministry of Education, Science and Technological Development of the Republic of Serbia.*

## REFERENCES

[1] Cain, A., & Babar, M. A. (2016, May). Reflections on applying constructive alignment with formative feedback for teaching introductory programming and software architecture. In Proceedings of the 38th International Conference on Software Engineering Companion (pp. 336-345).

[2] Pecanin, E., Spalevic, P., Mekic, E., Jovic, S., & Milovanovic, I. (2019). E-learning engineers based on constructive and multidisciplinary approach. Computer Applications in Engineering Education, 27(6), 1544-1554.

[3] Vitturi, S., Zunino, C., & Sauter, T. (2019). Industrial communication systems and their future challenges: Next-generation Ethernet, IIoT, and 5G. Proceedings of the IEEE, 107(6), 944-961.

[4] Al-Emran, M., Elsherif, H. M., & Shaalan, K. (2016). Investigating attitudes towards the use of mobile learning in higher education. Computers in Human behavior, 56, 93-102.

[5] Mekic, E., Djokic, I., Zejnelagic, S., & Matovic, A. (2016). Constructive approach in teaching of voip in line with good laboratory and manufacturing practice. Computer Applications in Engineering Education, 24(2), 277-287.

[6] Pecanin, E., Spalevic, P., Mekic, E., Jovic, S., & Milovanovic, I. (2019). E-learning engineers based on constructive and multidisciplinary approach. Computer applications in engineering education, 27(6), 1544-1554.

[7] Pecanin, E., Mekic, E., Spalević, P., & Mohamed Himar Swhli, K. M. (2017). Trifocal constructive approach in developing coders, simulated, and hardware implemented, for the introduction of coding theory. Computer Applications in Engineering Education, 25(6), 867-880.

[8] Schrum, L. (2015).Technology as a tool to support instruction.Retrieved April 2, 2017 from http://www.educationworld.com/a_tech/tech/tech004.shtml.

[9] Crompton, H., & Burke, D. (2018). The use of mobile learning in higher education: A systematic review. Computers & Education, 123, 53-64.

[10] Khachan, A. M., & Özmen, A. (2019). IMSSAP: After-school interactive mobile learning student support application. Computer Applications in Engineering Education, 27(3), 543-552.

[11] Laurillard, D. (2007). Pedagogical forms for mobile learning: Framing research questions. In N. Pachler (Ed.). Mobile learning: Towards a research agenda (pp. 153–175). London: W1.E Centre.

[12] Traxler, J. (2010). Will student devices deliver innovation, inclusions, and transformation? Journal of the Research Center for Educational Technologies, 6(1), 3–15.

[13] Kaliisa, R., & Picard, M. (2017). A systematic review on mobile learning in higher education: The African perspective. The Turkish Online Journal of Educational Technology. 16(1), 1–13

[14] Brinton, C., Rill, R., Ha, S., Chiang, M., Smith, R., & Ju, W. (2015). Individualization for education at scale: MIIC design and preliminary evaluation. IEEE Transactions on Learning Technologies, 8(1), 136–148.

[15] O, S. (2016). Mobile instant messaging support for teaching and learning in higher education. The Internet and Higher Education, 31, 32-42.

[16] Sakhapov, R. L., & Absalyamova, S. G. (2015, February). The use of telecommunication technologies in education networks. In Proceedings of 2015 12th International Conference on Remote Engineering and Virtual Instrumentation (REV) (pp. 14-17). IEEE.

[17] Friesen, N. (2005). Interoperability and learning objects: An overview of e-learning standardization. Interdisciplinary Journal of E-Learning and Learning Objects, 1(1), 23-31.

[18] Labib, A. E., Penadés, M. C., Canós, J. H., & Gómez, A. (2015, April). Enforcing reuse and customization in the development of learning objects: a product line approach. In Proceedings of the 30th Annual ACM Symposium on Applied Computing (pp. 261-263).
[19] Cisco Systems. (1999, June). Cisco Systems Reusable Information Object Strategy: Definition, cre-ation overview, and guidelines. San Jose, CA: Cisco Systems, Inc. Retrieved from: http://www.cisco.com/warp/public/779/ibs/solutions/learning/whitepapers/el_cisco_rio.pdf
[20] Srikant, R., & Agrawal, R. (1996, March). Mining sequential patterns: Generalizations and performance improvements. In International Conference on Extending Database Technology (pp. 1-17). Springer, Berlin, Heidelberg.
[21] Han, J., Cheng, H., Xin, D., & Yan, X. (2007). Frequent pattern mining: current status and future directions. Data mining and knowledge discovery, 15(1), 55-86.
[22] Spanninger T., Büchel B., & Corman F. (2023). Train Delay Predictions Using Markov Chains Based on Process Time Deviations and Elastic State Boundaries. Mathematics, 11(4), Article No. 839.
[23] Paek J., Pollanen M., & Abdella K. A (2023) Stochastic Weather Model for Drought Derivatives in Arid Regions: A Case Study in Qatar. Mathematics. 11(7), Article No. 1628.