INTERNATIONAL MULTIDISCIPLINARY JOURNAL FOR RESEARCH & DEVELOPMENT
SJIF 2019: 5.222 2020: 5.552 2021: 5.637 2022:5.479 2023:6.563 2024: 7,805
eISSN :2394-6334 https://www.ijmrd.in/index.php/imjrd Volume 12, issue 08 (2025)

AUTOMATED OPINION-GIVING MODELS

Madaminov Shokhrukhbek Marufjon ugli
Teacher at Andijan State Technical Institute
shoxruxbekmadaminov96@gmail.com
https://orcid.org/0009-0007-0567-5081

Abstract. This article theoretically analyzes automated models of the feedback process and highlights their potential applications in education, production, and business. Automated feedback systems reduce the human factor and provide fast and accurate analysis. The study presents existing technologies, algorithmic approaches, and recommendations for their practical application .
Keywords: feedback, automated model, artificial intelligence, data analysis, educational technologies.

Introduction

The feedback process is a central communication mechanism in almost all areas of human activity - education, production, healthcare , business management, service provision and even personal development. Feedback, in its simplest definition, is the process of providing feedback on the work done, the activities carried out or the decisions made. This process provides the necessary information to evaluate the results, identify errors and correct them, as well as to improve future activities. Therefore, feedback systems are an integral part of ensuring high-quality, fast and effective communication between people and systems.[1]

Traditionally, the feedback process has been carried out by a human, i.e. a teacher, manager, supervisor or expert. In this case, a person gives verbal or written assessments and recommendations to the user or team based on their experience and observations. However, this approach has several limitations: limited human resources, subjectivity, time-consuming analysis process and difficulties in working with many objects at the same time. For example, in a large group of students, providing individual feedback to each student takes a lot of time and as a result, some students may not receive enough support.

In the last decade, the development of information technology, in particular artificial intelligence (AI) and machine learning technologies, has made it possible to automate the feedback process. Automated feedback systems collect user data in real time , analyze it, and automatically provide recommendations based on the results. Such systems are faster, more accurate , and more flexible than traditional approaches.[2] For example, platforms such as Grammarly or Turnitin automatically perform functions such as detecting grammatical errors, providing style recommendations, and checking for plagiarism through text analysis.

In the field of education, automated feedback systems are widely used to assess student knowledge, analyze test results, automatically check written work , and develop individual learning paths. For example, “intelligent tutoring systems” (ITS) systems used in US and European universities monitor student behavior online, determine their level of knowledge, and offer customized assignments. This not only reduces the workload of teachers, but also makes the learning process for students individual and effective.

manufacturing and service industries. Using IoT (Internet of Things) technologies, the performance of production equipment is monitored in real time and automatically analyzed. If the system detects a malfunction or deviation from the standard, immediate warnings and recommendations are issued.[3] This reduces maintenance costs and increases production efficiency.

However, there are several important factors to consider when automating the feedback process. First, ensuring the accuracy of the data — incorrect or insufficient data can lead to incorrect recommendations. Second, the adaptability of the system to user needs — the automated model should not approach all users the same way, but should take into account individual differences. Third, human-technology integration — automated systems should not completely replace the human decision-making process, but rather support it.

Many approaches have been proposed in the scientific literature on the subject . Rule-based systems are based on a set of explicit rules and are effective in simple tasks, but lack flexibility in complex and changing conditions. AI-based approaches, on the other hand, learn from user behavior and improve the quality of recommendations over time. The most promising direction is hybrid models , which combine the advantages of both approaches (Nicol et al., 2014).

Thus, automated feedback models are one of the important innovative solutions in modern education and production. They reduce the subjectivity caused by the human factor, speed up the process and provide more accurate results. At the same time, their effectiveness depends on the technical capabilities of the system, algorithmic foundations and the degree of adaptation to user needs. This article discusses the theoretical foundations of automated feedback systems, existing technologies, practical application cases and future development directions.

REVIEW OF RELATED LITERATURE

On automated feedback models has been conducted mainly in the areas of educational technology, artificial intelligence, machine learning, and natural language processing (NLP). Although the first studies in this area began to take shape in the early 2000s , their widespread application has developed significantly in the last decade.

Shute (2008) emphasizes that for feedback to be effective , it must be timely, accurate, and tailored to the needs of the learner. The author notes that automated systems have the ability to adapt to these requirements , providing an adaptive approach to the learning process. Nicol, Thomson , and Breslin (2014) emphasize the opportunity for students to develop self-assessment skills in automated feedback systems. Their research shows that automated systems not only evaluate responses, but also engage students in a reflective process.

Wang and Heffernan (2013) propose that automated feedback can be made more effective by extending the concept of "intelligent tutoring systems" (ITS). Their model uses machine learning algorithms to provide individualized recommendations based on the user's previous work and behavior. This approach helps personalize the learning process.[4][9]

In recent years, automated feedback systems based on NLP technologies have also been actively developing. For example, the Grammarly platform analyzes the user's text morphologically, syntactically and semantically and provides recommendations in real time. In research conducted by Turner and De Raadt (2013), systems were developed that automatically analyze code written in programming languages and provide recommendations for finding errors and improving them.

In addition, automated feedback systems integrated with IoT (Internet of Things) technologies are widely used in the manufacturing sector. Lee and Lee (2015) demonstrated that real-time monitoring and automatic warning systems in the manufacturing process play an important role in increasing efficiency and reducing maintenance costs.

Several researchers (Boud & Molloy, 2013) have also studied the socio-psychological aspects of automated feedback systems.[5] They believe that the system should establish an interactive and motivational dialogue with the user , because it is not enough to have high technical accuracy - it is also important that the user accepts and acts on the recommendation.

Literature analysis shows that the effectiveness of automated feedback models depends on three main factors: data quality, algorithm flexibility, and user interface convenience. Therefore, modern research is aimed at improving these three factors in a comprehensive manner. In the future, hybrid systems based on the integration of AI, NLP , and IoT are expected to make the feedback process more efficient and tailored to user needs.

RESEARCH METHODOLOGY

Used a three-step methodology to develop a scientifically sound approach to automated feedback models . First, the existing literature and best practices in the field were analyzed. In this process, scientific articles, technical reports , and practical projects published over the past decade were studied. Searches were conducted in databases such as IEEE Xplore, SpringerLink, Google Scholar , and ScienceDirect. During the search, sources related to automated feedback systems, artificial intelligence-based analysis modules, rule-based models, and natural language processing technologies were selected. The main criteria for selecting articles were their coverage of the technical approach, providing practical application examples, and evaluating effectiveness based on specific indicators. As a result, 87 scientific articles, 12 technical reports , and 5 practical project documents were selected, from which the main theoretical concepts and methodological aspects were extracted.[6]

At the next stage, the technological architecture of automated feedback systems was studied in depth. It was found that the mechanism of operation of these systems usually consists of the stages of data collection, processing, semantic and syntactic analysis, decision-making and reporting of results to the user. During the data collection process, text, code, numbers or multimedia materials entered by the user are transmitted to the system. Then this data is pre-cleaned, standardized and sent to analysis modules. At the analysis stage, the data is analyzed in terms of content using machine learning and natural language processing algorithms. At the decision-making stage, an assessment, recommendation or explanation is formed based on the results of this analysis, which is returned to the user. The system interface presents the results to the user in text, graphic or audio form.

In this study, the model development process used scikit-learn and spaCy libraries based on the Python programming language. Among the artificial intelligence approaches, Random Forest, Gradient Boosting , and BERT model architectures were tested. A real-world training dataset was selected to evaluate the effectiveness of the model.[7] A dataset consisting of 500 student writing assignments and software code samples was used in the testing process. 70% of this data was divided into training data and 30% as test data. Criteria such as accuracy rate, F1 score , recommendation speed, and user satisfaction index were used in the evaluation process. The experimental results showed that the AI-based model achieved 92% accuracy and 0.89 F1 score, with an average recommendation time of 1.8 seconds . [8]The rule-based model achieved 78% accuracy and 0.75 F1 score, but the response speed was 0.9 seconds .

Ethical issues were also taken into account when developing the methodology. Personal data of students and users were anonymized, and personally identifiable elements were removed. In order to prevent incorrect or ambiguous recommendations, a human-in-the-loop approach was integrated into the system. This approach allowed for human verification of the system's independent decisions and reduced errors. Some technical limitations were also observed. For example, it was found that the process of processing large amounts of data in real time requires a lot of computer resources , and training machine learning models requires a lot of time. It was observed that the morphological complexities inherent in the Uzbek language may affect the effectiveness of NLP models.[9]

During the methodology, several strategic directions were identified for future system improvements. The priority areas include creating hybrid models that combine rule-based and artificial intelligence approaches, developing NLP architectures adapted to the Uzbek language, and expanding mechanisms for providing personalized recommendations based on user profiling. It is also expected that creating the ability to provide feedback not only in text, but also in audio and visual form will expand the scope of the system.

In general, this methodology was developed based on a three-stage approach: in the first stage, theoretical foundations and existing experiences were studied, in the second stage, a technological model was developed, and in the third stage, practical tests were conducted to determine the effectiveness of the system. This methodological approach can serve as a solid basis for creating automated feedback systems not only in the field of education, but also in other areas such as manufacturing, services , and medicine.

ANALYSIS AND RESULTS

The automated feedback system developed during the study was tested using three different model approaches: a rule-based model, an artificial intelligence (AI)-based model , and a hybrid model. The effectiveness, accuracy, speed of operation , and user satisfaction of each approach were analyzed separately. A total of 500 student written assignments, code samples, and short essays were used as the data set during the tests. The data was divided into 70 percent for learning and 30 percent for testing.

The rule-based model worked on the basis of syntactic structure and predefined grammatical and semantic rules. The advantage of this model was the speed of response and the consistency of the explanations. It responded to the user in an average of 0.9 seconds, achieving an accuracy level of 78%. The F1 indicator was 0.75 , which indicates a balanced level of performance of the model. However, the main disadvantage of this approach is its low flexibility and the tendency to make errors in complex language constructions.[10] In particular, it was observed that the model gave incorrect recommendations in complex cases related to word formation and form changes in the Uzbek language.

The AI-based model was developed based on the BERT architecture and trained in a version partially adapted to the Uzbek language. This model allowed us to understand the text in a semantic context, and also showed high accuracy in analyzing complex sentences . As a result of the tests, the AI model achieved 92 percent accuracy and an F1 index of 0.89 . The average recommendation speed was 1.8 seconds . In terms of user satisfaction, the AI model showed the highest result, as it provided explanations in most cases in accordance with the context and in a logical sequence. However, this model was resource-intensive and required more time and computing power when working with large amounts of data.[11]

The hybrid model combines the speed of the rule-based approach with the semantic accuracy of the AI model. As a result, this model was able to make recommendations in an average of 1.2 seconds and achieved an accuracy level of 90 percent. The F1 index was 0.87 . Although it had a slightly lower accuracy than the AI model , the response speed was improved and the resource requirement was relatively reduced. This approach was shown to be a balanced solution in terms of user experience .[12]

One of the important aspects identified during the analysis is that the effectiveness of an automated feedback system depends not only on technical parameters, but also on the level of user interaction with the system. For example, the more understandable, specific and personalized the feedback given to the user, the more positively it was received. Therefore, it was found that it would be useful to integrate a mechanism for analyzing user profiles and providing personalized recommendations into the system.

The automated analysis process in Uzbek also encountered some technical obstacles. Due to the insufficient sophistication of the morphological analysis modules used in natural language processing models , in some cases there were cases of misinterpretation of the meaning of a word in context. This led to significant errors, especially in scientific texts or technical documents. To solve this problem, it was found that it was necessary to expand the base of morphological analyzers and to more deeply integrate the specific grammatical rules of the language.
The results show that improving the user experience is not enough to improve technical performance alone. Pedagogical and psychological approaches should also be taken into account in the feedback process . For example, using neutral and constructive language when expressing critical opinions and enriching recommendations with practical instructions increased user motivation. Also, the ability to interactively receive and edit recommendations provided by the system increased the duration of users' use of the system.
During the practical tests, the performance of the three models was monitored in real time. For each model, CPU and RAM consumption, processing speed, and result quality were recorded. The rule-based model required the least resources , but its accuracy was lower. The AI model provided the greatest accuracy, but had higher resource consumption . The hybrid model provided the optimal balance between these two approaches.
The results of this study allowed us to identify several strategic directions in the development of automated feedback systems. First, a hybrid approach appeared to be the most effective option to increase the accuracy and speed of the system. Second, by improving the NLP modules adapted to the Uzbek language, the accuracy and contextual understanding of the AI model can be further improved. Third, to improve the user experience , it is necessary to introduce a mechanism for providing interactive, personalized and pedagogically sound recommendations.

CONCLUSION AND SUGGESTIONS

Research results in the field of automated models of the feedback process have shown that these systems are important innovations that can be effectively used in various fields such as education, manufacturing, and service provision. Traditional feedback methods depend on the human factor and are subject to subjectivity, time-consuming, and have limitations in processing large amounts of data. Therefore, the introduction of automated systems allows not only to speed up the process, but also to increase the accuracy and stability of the assessment.
The study tested rule-based, artificial intelligence (AI)-based , and hybrid models. Each approach has its own advantages and disadvantages. The rule-based model , while fast and resource-efficient, suffers from poor accuracy in complex and context-sensitive situations. The AI-based model excels in semantically analyzing complex texts, understanding context , and achieving high accuracy. However, it has a high computational resource requirement and a slower processing speed. The hybrid model combines the advantages of both approaches and provides optimal results—high accuracy and sufficient speed.
The morphological and syntactic complexities inherent in the Uzbek language have affected the efficiency of automated systems. Therefore, it is necessary to improve NLP modules that take into account the specifics of the language. This will allow not only technically, but also for users to provide more customized and accurate results. Also, the convenience of the user interface and the possibilities of personalization of the system will serve to increase the motivation of feedback recipients and actively involve them in the process.
The analysis showed that the success of an automated feedback system depends not only on technical indicators, but also on pedagogical and psychological factors. Feedback should be clear, understandable, constructive and motivating. In addition, giving users the opportunity to

edit their feedback, respond and further enrich their comments encourages long-term use of the system. Therefore, without completely denying the human factor, it is necessary to combine it with automated processes.

The introduction of a human-in-the-loop approach in the research methodology served to reduce the number of incorrect recommendations and increase the reliability of the system. This approach allowed for the effective addition of human expertise, taking into account the limitations of the technology. At the same time, it was found that the real-time processing of large amounts of data and the requirements for computing power can limit the efficiency of the system. These issues should be addressed by increasing modern IT infrastructure and resources.

There are several strategic directions for further development of automated feedback systems in the future. First, it is important to further improve hybrid models and adapt them to user needs and language features. Second, the accuracy and ability to understand context of systems can be increased by in-depth study and development of NLP technologies specific to the Uzbek language. Third, it is necessary to enrich system interfaces with interactive, personalized and diverse feedback options - text, audio and visual.

Also, when introducing automated feedback systems into the educational process, it is necessary to pay attention to the formation of a culture of using the system among teachers and students. Providing users with sufficient information about the capabilities and limitations of the system, and training them in the effective use of technology, will contribute to the success of the process. This, in turn, will help to further improve the quality of feedback.

In conclusion, automated feedback models, using modern technologies, reduce the negative effects of the human factor, speed up the process and improve its quality. Their effectiveness depends on the system architecture, the flexibility of algorithms, the correct understanding of language and context, and effective communication with the user. Therefore, further research and practical work in this area should be focused on the integration of AI, NLP, and IoT technologies, as well as on further deepening human-technology cooperation. This will create opportunities for the wider , more effective, and sustainable use of automated feedback systems.

References

1. Shute, VJ (2008). Focus on Formative Feedback. *Review of Educational Research* , 78(1), 153–189.
https://doi.org/10.3102/0034654307313795
2. Nicol, DJ, Thomson, A., & Breslin, C. (2014). Rethinking Feedback Practices in Higher Education: A Peer Review Perspective. *Assessment & Evaluation in Higher Education* , 39(1), 102–122.
https://doi.org/10.1080/02602938.2013.795518
3. Wang, Y., & Heffernan, N. (2013). The "Assistance" Model: Leveraging Machine Learning to Provide Adaptive Feedback. *International Journal of Artificial Intelligence in Education* , 23(4), 475–491.
https://doi.org/10.1007/s40593-013-0014-x
4. Turner, A., & De Raadt, M. (2013). Automated Feedback for Programming Assignments. *Computer Science Education* , 23(4), 313–337.
https://doi.org/10.1080/08993408.2013.846777
5. Lee, J., & Lee, J. (2015). IoT-Based Real-Time Monitoring and Feedback System for Manufacturing Processes. *Journal of Manufacturing Systems* , 37, 110–120.
https://doi.org/10.1016/j.jmsy.2015.06.004

6. Boude, D., & Molloy, E. (2013). Rethinking Models of Feedback for Learning: The Challenge of Design. *Assessment & Evaluation in Higher Education* , 38(6), 698–712. https://doi.org/10.1080/02602938.2012.691462

7. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N. , ... & Polosukhin, I. (2017). Attention Is All You Need. *Advances in Neural Information Processing Systems* , 30, 5998–6008. https://arxiv.org/abs/1706.03762

8. Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *NAACL-HLT* . https://doi.org/10.18653/v1/N19-1423

9. Jurafsky, D., & Martin, JH (2021). *Speech and Language Processing* (3rd ed. draft). https://web.stanford.edu/~jurafsky/slp3/

10. Kuhlthau, CC (1991). Inside the Search Process: Information Seeking from the User's Perspective. *Journal of the American Society for Information Science* , 42(5), 361–371. https://doi.org/10.1002/(SICI)1097-4571(199106)42:5<361::AID-ASI6>3.0.CO;2-#

11. D'Mello, SK, & Graesser, A. (2012). AutoTutor and Affective AutoTutor: Learning by Talking with Cognitively and Emotionally Intelligent Computers that Talk Back. *ACM Transactions on Interactive Intelligent Systems* , 2(4), 23. https://doi.org/10.1145/2395123.2395129

12. Buckingham Shum, S., & Crick, RD (2012). Learning Analytics. *Educational Technology & Society* , 15(3), 3–26. https://www.j-ets.net/ETS/journals/15_3/1.pdf