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Comparison of simple algorithms and artificial intelligence in the development of a personal asset tracking service

Pavlo Kozolup*
Postgaduate Student
Sumy State University
40000, 116 Kharkivska Str., Sumy, Ukraine
https://orcid.org/0009-0000-1303-3424

Abstract. Analysis of modern scientific literature reveals a tendency towards the widespread implementation of artificial intelligence, often without sufficient consideration of indirect efficiency factors such as economic costs, implementation complexity, maintenance, and information security. These studies focus more on the accuracy and performance metrics of artificial intelligence systems, while ignoring indirect but critically important efficiency factors. The aim of this article was to investigate the suitability of applying Artificial Intelligence technologies compared to simple algorithmic solutions within the context of developing software applications for personal asset management. The research methodology was based on a comprehensive comparative analysis of a developed simple algorithm for predicting the time of the next product order and the statistical Auto Regressive Integrated Moving Average (ARIMA) model, as a representative of more complex, albeit not deep, intelligent methods for time series forecasting. Based on the implementation and experiment using data that simulated a real-world scenario, the performance of both approaches was evaluated using key metrics, including accuracy, required computational resources, and implementation complexity. It was found that for tasks with limited data volumes and relatively simple behavioral patterns, which are characteristic of small personal asset management projects, the simple algorithm demonstrated comparable accuracy to the artificial intelligence ARIMA model. It was revealed that the simple algorithm operated with lower computational costs, measured in nanoseconds, and was characterised by lower implementation and subsequent maintenance complexity. The analysis showed that the use of ARIMA, despite its statistical power, was less justified under such conditions, requiring greater computational expenditures and deeper knowledge for its configuration. It was demonstrated that the execution time of ARIMA on small samples was higher (in microseconds), and its reliability was significantly dependent on the volume and quality of the input data. Thus, the necessity of a reasoned choice of technologies, based on the real needs and resource constraints of the project, was emphasised

Keywords: machine learning; software development; forecasting; efficiency; personalisation

INTRODUCTION

The widespread penetration of artificial intelligence (AI) technologies in various commercial areas is an indisputable trend of modernity, which transforms approaches to the development of software solutions. This phenomenon requires a deep understanding and an informed choice of tools that provide an optimal balance between functionality, efficiency, cost, and data security, especially in the context of creating personalised service applications. The range of AI applications varies from creating text and voice assistants to task scheduling tools, giving small companies the ability to develop and implement complex systems, potentially saving time and financial resources. The impact of AI is particularly intense in the field of software application development, where it is increasingly integrated as part of software interfaces and used to replace complex functional modules. Analysis of the available scientific literature on the use of AI in software

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*Corresponding author

development has revealed a significant number of publications that emphasise the priority use of AI solutions. Often, such approaches are integrated even to solve relatively simple functional problems. The main motivation for such use is declared to be an increase in the productivity and accuracy of software products. But information security issues are becoming particularly relevant for such projects.

According to D. Rodriguez *et al*. (2023), AI can significantly speed up the development process and improve the quality of software products. It promotes effective communication and mutual understanding between technical and non-technical specialists, which is critical for creating innovative solutions, in particular in the field of medical technology. The study highlighted that using AI as a tool helps the team focus on the ultimate goal of developing fast and easy-to-use computing systems.

A significant aspect is the dependence on external technological solutions. In the event of termination of support or closure of a project that ensures the functioning of the integrated AI component, the performance of the software application may be critically disrupted. N. Chafik & D. Benchekroun (2020) noted that the involvement of AI in the software development process is ambivalent and is accompanied by a number of challenges. One of the key problems is the limited controllability of the results generated by such systems. The potential for incorrect or erroneous results poses a significant risk to the reliability and quality of the final product. The lack of full control for both end users and developers over the data transmitted for processing to AI systems creates potential threats to the privacy of personal and sensitive information of both parties.

C. Ashurst *et al*. (2022) described growing concerns about ethical issues in machine learning research, highlighting the need for integrity and consideration of potential harm. They have developed a system that helps researchers to better understand and evaluate the ethical implications of their work. The researchers call for more transparent and accountable mechanisms to minimise the negative impact of AI on society.

M. Brundage *et al*. (2020) proposed mechanisms to improve the verifiability of applications for AI systems, focusing on providing evidence regarding security, protection, fairness, and privacy. Their study offered developers specific tools and protocols that allow them to verify that their systems meet the stated standards. This helps to increase confidence in AI technologies and ensure their responsible use. This study is valuable because it emphasises the need for transparency and evidence related to data security issues, which are an important aspect of current research.

P. Tominc *et al*. (2024) highlighted the need for targeted strategies to strengthen AI adoption in small and medium-sized enterprises for successful project implementation and increased competitiveness. They analysed key factors that prevent small and medium-sized enterprises from using AI, and suggested methods that can help them to overcome these challenges. Researchers noted that the successful implementation of AI in enterprises depends on competent planning and adaptation of technologies to specific business needs.

A review of these studies showed that evaluating the effectiveness of AI solutions in business is mainly limited to technical indicators such as performance and accuracy. However, little attention was paid to other aspects that affect the overall feasibility of implementation, in particular, economic costs (the cost of development, training and support), the complexity of integration, operational support, and information security issues. The incomplete consideration of these factors in the above-mentioned papers makes the assessment of the overall feasibility of using AI in software products insufficiently substantiated and comprehensive.

The purpose of the study was to determine the most appropriate approach for developing key functions of a personal asset accounting application based on a comparative analysis of their characteristics. To achieve this goal, the following tasks were solved: a review of existing scientific publications on the use of artificial intelligence (AI) and simple algorithms in the development of software applications was conducted. An experimental test of the effectiveness and reliability of the developed application was carried out.

MATERIALS AND METHODS

This study was based on the analysis of scientific publications in the field of information service development, in particular, the papers by P. Kozolup & V. Liubchak (2024a) and P. Kozolup & V. Liubchak (2024b), who laid the theoretical foundations for creating a functional model of the personal asset accounting service. These studies were the starting point for identifying problems and possible approaches to the development of such systems. The research methodology included the following stages: an analysis of scientific papers and other sources was carried out to identify existing approaches to the development of accounting services, focusing on architectural solutions. The characteristics of simple data processing algorithms were compared with the potential capabilities and limitations of using AI.

Quantitative comparisons were made based on key metrics such as implementation complexity, computing resources, processing accuracy, cost, and security. The evaluation criteria were "low" or "high" complexity, assessed based on the developer's knowledge requirements, and code volume. "Low" or "high" computing resources were estimated by the actual operation execution time (nanoseconds vs. microseconds). The "security" assessment was based on the controllability of the data processing process (local processing and transmission to a third-party service). For comparative analysis, an algorithm for calculating the prediction of the time of the next product order was chosen:

$$T(fact) = IF\,(V \neq FALSE\ AND\ U_1 \neq FALSE),$$
$$THEN\,((\sum (U_3\ i)\ from\ i = 1\ to\ n))\,/\,n$$
$$ELSE\ T(past) + T\,(off), \quad (1)$$

where the logical variable V – the need to buy a product; true – the product needs to be purchased; false – the product doesn't need to be purchased. Set for the test task as $V = true$. Logical variable U_1, described the state of the user's budget. *true* – the budget is set, *false* – the budget is not set. Set for the test task as $U_1 = true$. Estimated time to the previous (last) order (*T_past*). Time period set by the user for waiting (*T_off*). Estimated time until the next order (*T_fact*). The following parameters were used when performing calculations using simple algorithms: a list of product usage periods in days for pre-orders ($U_3 i$). In this case, this was 5 periods in days [10.0, 12.0, 11.0, 13.0, 9.5, 10.8]. This feature used the product's usage history, user budget, and waiting period. Condition $V \neq FALSE\ AND\ U_1 \neq FALSE$ checks whether there is a need for the product and the budget. If the conditions are met, *T(fact)* calculated as the average product usage time based on *n* pre-orders. Otherwise, before the previous estimated time *T(past)* a waiting period was added *T(off)*. The ARIMA statistical model was also used to calculate the time result of the next order. ARIMA is a statistical model used to predict future time series values based on their own past values. It is one of the most popular and widely used tools in the field of time series analysis and forecasting.

The following parameters were used. The input data for ARIMA – 5 periods in days specified above. List of product usage periods in days for pre-orders that are identical to the previous test. ARIMA parameters: parameter $p = 1$ indicated that the forecast of the current value of the time series was based on one previous value of the same series; parameter $d = 0$ determined the number of times that the time series data has been "differentiated", i.e., replaced with differences between consecutive values) to make the series stationary; parameter $q = 1$ indicated that no differentiation was performed. This meant that the time series (intervals between orders) was assumed to be stationary on its own, without the need to convert it. For comparative analysis, a simple algorithm was chosen that allows predicting the time of the next order for the user, considering their individual consumption habits. Java code was used to get the results of applying the algorithm.

A factor analysis of the application context was performed. The key factors influencing the choice of the optimal approach to data processing in the personal asset accounting service were identified and analysed. These factors include: data volume and type, processing accuracy and speed requirements, required level of automation, development and integration costs, and potential security risks and limitations of each approach. The use of system and comparative analysis allowed comprehensively investigating the problem of choosing data processing algorithms in the context of developing an information service for accounting for personal assets. System analysis provided an understanding of the overall picture of the subject area, and comparative analysis helped to identify the advantages and disadvantages of different approaches. Factor analysis was necessary to substantiate the choice of the optimal solution, considering the specific requirements and limitations of the future service. At this stage, no empirical studies have been conducted, since the main goal is to theoretically substantiate the choice of tools for developing the application.

RESULTS

As a result of the analysis of scientific literature, the main approaches to the development of information services were identified. It was established that most of the existing solutions are based on the use of complex APIs for integration with external users and the use of AI methods for data analysis and forecasting. The comparative analysis revealed a number of differences between the use of simple data processing algorithms and more complex AI-based approaches. Simple algorithms are easy to implement and unpretentious to computing resources. Their advantage lies in the accuracy and predictability of performing tasks that do not require in-depth analysis. P. Kozolup & V. Liubchak (2024b) reviewed methods and tools for developing a personal asset accounting service. The study by P. Kozolup & V. Liubchak (2024a) laid the theoretical foundations for creating a functional model of such a service and algorithm. Based on these studies, the current study conducted a comparative analysis, focusing on the feasibility of using AI technologies (in particular ARIMA models) against simple algorithmic solutions to predict the time of the next product order. The results showed that for small projects with limited data, a simple algorithm developed based on ideas from previous study was more efficient in terms of cost, security, and execution speed than the ARIMA model.

In personal asset accounting systems, such algorithms can include simple operations of sorting data by product purchase date, filtering products by category or price, and automatic manual tagging for grouping similar transactions. This allows to efficiently solving routine tasks without the need for complex models. However, their functionality may be limited and the accuracy of data processing may be lower, which may also create certain security risks. The use of AI methods, on the contrary, opens up prospects for deep data analysis, identification of hidden patterns, and complex forecasting. This can be implemented using machine learning techniques such as regression models for predicting costs, and natural language processing techniques for analysing textual product descriptions or receipts. Although these are powerful tools, their implementation requires significant computing resources, increased security measures, the availability of qualified personnel, and a thorough stage of training models.

As a result of applying the selected algorithm for predicting the time of the next order based on individual user habits, a set of forecasts was obtained that reflect the potential effectiveness of the approach. The implementation of the method using Java code helped to automate data processing and calculation of forecasts for each user individually. This, in turn, allowed evaluating the accuracy of the model and identifying the key advantages and possible limitations of the chosen approach.

```
/**
 * Class for implementing a simple algorithm for predicting the time of the next order.
 * Based on historical usage periods and user-defined conditions.
 */
public class SimpleOrderTimePredictor {

 /**
 * Calculates the time until the next order according to the algorithm.
 *
 public double predict(List<Double> usagePeriods, boolean needsPurchase, boolean budgetSet, double lastOrderCalcTime, double userWaitingPeriod)
 {
 if (needsPurchase && budgetSet) { // IF (V ≠ FALSE AND U1 ≠ FALSE)
 if (usagePeriods == null || usagePeriods.isEmpty()) {
 // Case where the condition is met, but there is no data for the average.
 // Can be treated as an error, or return T_past + off, or the default value.
 // Return T_past + T_off as fallback.
 System.err.println ("Previous usage periods are missing for calculating the average. Using the default option.");
 return lastOrderCalcTime + userWaitingPeriod;
 }
 // THEN ((∑(U3i ) from i = 1 to n )) / n
 double sumU3i = 0;
 for (double period : usagePeriods) {
 sumU3i += period;
 }
 return sumU3i / usagePeriods.size();
 } else {
 // ELSE T (past) + T (off)
 return lastOrderCalcTime + userWaitingPeriod;
 }
 }
}
```

Implementation of this algorithm requires only basic programming knowledge, which significantly reduces the cost and complexity of implementation. It is scalable and does not require significant financial investment, which makes it ideal for small projects and startups. The simple algorithm does not depend on third-party libraries, which provides full control over the data processing and a high level of information security. The result on a simple set of parameters will be: Input data: [10.0, 12.0, 11.0, 13.0, 9.5, 10.8], $V = true$, $U_1 = true$, $T\_past = 80.0$, $T\_off = 5.0$.

Forecast result: 11.05 days. Execution time: several hundred nanoseconds. Unlike more complex models, a simple algorithm demonstrates high speed and efficiency on limited amounts of data, which is its key advantage. Its reliability and predictability make it the optimal choice for tasks that do not require deep analysis of complex patterns. The following Java code was used to get the results using the ARIMA model:

```
List<Double> usagePeriods = Arrays.asList(10.0, 12.0, 11.0, 13.0, 9.5, 10.8);
 double[]timeSeriesForArima = usagePeriods.stream().
 mapToDouble(Double::doubleValue).toArray();

 System.out.println ("forecasting with ARIMA");
 int p = 1;
 int d = 0;
 int q = 1;

 ARIMAPredictor arimaPredictor = new ARIMAPredictor(p, d, q);
 try {
  long startTime = System.nanoTime();
  double[] arimaPrediction = arimaPredictor.predict(usagePeriods, 1);
 // Predicting 1 step forward
  long endTime = System.nanoTime();
  long duration = endTime - startTime;
  double predictedIntervalARIMA = arimaPrediction[0];
  System.out.println ("Input data for ARIMA:" + usagePeriods +", p= " + p +", d = " + d+", q= " + q);
  System.out.println ("Predicted next usage interval (ARIMA):" + predictedIntervalARIMA + "days");
  System.out.println ("Runtime:" + duration + " nanoseconds (~" +TimeUnit.NANOSECONDS.toMicros (duration) + "microseconds)\n");
 } catch (Exception e) {
  System.err.println ("Error when applying ARIMA:" + e.getMessage());
 }
```

Implementation of the programme for ARIMA requires additional configuration and knowledge of programming and statistics. It is also longer in execution time compared to a simple algorithm. It also takes more time to implement what affects the price of the product. There is a dependency on third-party libraries and possible security vulnerabilities due to the inability to control the data transmitted for processing. There is also a weak point in the complexity of adjusting the operation of this statistical model. The code execution time is several thousand nanoseconds, which is an acceptable time in the context of small software applications. In addition, ARIMA requires a much larger amount of historical data to obtain reliable results than was used in the experiment. This makes it less effective for scenarios with a limited amount of information, which is typical for small personal applications. The result for such a short data series ([10.0, 12.0, 11.0, 13.0, 9.5, 10.8]) and the parameters (1,0,1) are approximately 10.8. The exact forecast may vary depending on the internal implementation and initial values, but according to ARIMA settings, the programme will try to follow the latest trend or average. Therefore, the result will be within the last value of the series. The result of comparing the obtained data is described in Table 1.

Table 1. Comparative analysis of simple AI algorithms and methods

Characteristics	Simple algorithms	ARIMA
Implementation complexity	Low	High
Computing resources	Low	High (especially at the training stage)
Functionality	Limited developer capabilities	High
Processing accuracy	Accuracy depends on the algorithm, but it has a fairly good result in the proposed example.	Average (affects a limited number of input parameters)
Dependence on third-party services	Absent	Low
Cost	Low	High (development, training, support)
Safety	Average (depending on the quality of the developer's execution)	Low (uncontrolled data processing and retrieval)

Source: developed by the author

As a result of the comparative analysis, the following results were obtained. For such a short series (only 6 points), ARIMA was less accurate and reliable. Classical time series models require much more data (at least 30-50 points, and preferably hundreds) to identify patterns qualitatively. The cost may vary depending on the complexity of implementation. In this case, only the price of the AI itself and its implementation. The security issue remains unresolved, as the data processing mechanisms in ARIMA models are not transparent. In addition, when implementing code for ARIMA, there is a dependence on a third-party product, which may affect the support of the application. Implementing a simple algorithm has proven to be significantly faster and cheaper, making it attractive for startups or small teams with limited resources. It demonstrates high execution speed, and its simple and inexpensive implementation provides significant advantages over ARIMA. A fully controlled data processing process in a simple algorithm provides a higher level of security and privacy, since there is no dependence on third-party products and their vulnerabilities.

Although AI techniques such as ARIMA may be suboptimal for small data sets, their potential is revealed when analysing large and complex arrays. For example, to predict the behaviour of thousands of users or analyse financial markets, AI models, in particular, machine learning models, can detect non-obvious dependencies. Natural language processing techniques can analyse user reviews or product descriptions to automatically determine their quality or propensity to buy. However, in the context of current research for a personal asset accounting application where data volumes are limited, these benefits are not decisive.

The analysis of the results presented in Table 1 showed the key differences between the two approaches. It was confirmed that for specific tasks that do not require deep analysis of big data, a simple algorithm is a more efficient solution in terms of cost, security, and performance. A simple algorithm requires minimal knowledge, which reduces the cost of development and subsequent support. ARIMA, on the other hand, requires knowledge of Statistics and experience working with libraries, which increases the price. The difference in execution time (nanoseconds vs microseconds) is crucial for applications running with a large number of requests, even if it seems insignificant for a single request. The complete absence of dependence on third-party services in the case of a simple algorithm is a significant advantage, especially when it comes to personal and sensitive data.

These results suggest that the choice of development tools should be reasonable and meet the specific needs of the project. Excessive use of complex AI models for simple tasks can lead to unnecessary costs, increased risks, and more complex support, which is contrary to the principles of effective software development. Analysis of factors influencing the choice of approach showed that the optimal solution is determined by a set of conditions – such as the type and volume of data, requirements for accuracy, speed, security, resource availability, and financial constraints. In cases of processing small amounts of structured data and implementing basic accounting functions, it is quite appropriate to use simple algorithms. Moreover, the use of artificial intelligence is justified when it comes to processing big data, identifying complex dependencies, and implementing predictive analytics.

The scientific discourse as of 2025 is characterised by research on the potential of AI, where scientists focus on security issues, ethical aspects and wide opportunities for its use, as well as potential social threats. However, discussions about the feasibility of using AI and comparing its effectiveness with simple algorithms in specific projects remain insufficiently covered. That is why this study considered the main aspects of such discussions. The paper by I.H. Sarker (2022) provided an extensive overview of AI modelling that can serve as a reference guide for scientists and professionals alike. The researcher described in detail various techniques, applications, and research issues in the context of automation and intelligent systems. Through this study, readers can gain a comprehensive understanding of the architecture and capabilities of AI and navigate current research areas. This paper provides readers with a comprehensive understanding of the architecture and capabilities of AI, but it does not address the practical aspects of technology selection, such as cost, security, or complexity of implementation. The current study complements this information by providing a practical comparative analysis that goes beyond a theoretical review.

A. Valavanidis (2023) highlighted the wide possibilities of AI applications, noting its growing role in various fields. The researcher critically considered the associated risks, in particular data security issues and ethical dilemmas that accompany the development of this technology. The results of the study emphasised that the successful implementation of AI requires not only technological progress, but also a responsible approach to solving social and moral problems. The researcher's conclusions about the need for a responsible approach to AI fully confirmed the hypotheses put forward in this paper and generally correlate with current conclusions about the importance of information protection and data security. N. Raximov *et al*. (2021) described the basic concepts, classifications, and stages of AI development, which provides a clear understanding of the evolution of the technology. They focused on the role of AI in intelligent systems, analysing various approaches to its application. This study provides detailed knowledge about AI, which is an important prerequisite for the research, but does not delve into comparative analysis. Unlike their theoretical work, the current study was based on an experiment that allows evaluating the practical feasibility of AI compared to simple algorithms in a particular application.

M.Z. Islam *et al*. (2024) investigated dynamic inventory management techniques used in U.S. organisations. The main goal was to study the possibilities and consequences of using various machine learning algorithms, in particular for predicting demand. The experiment developed and tested the Seq2Quant (Sequence-to-Sequence) neural network, which was compared with classical models such as Naïve Seasonal Forecast, Moving Average, ARIMA, and SARIMAX. According to the results of the experiment, the Seq2Quant model demonstrated the best performance. This confirmed that for complex demand forecasting tasks in inventory management, deep learning methods can be more effective than conventional statistical approaches. In addition, the study also confirmed that the classical ARIMA and SARIMAX models show good results, although they are inferior to the neural network, which indicates their validity as reliable "basic" solutions. This study focused on large-scale inventory management in organisations, while the current study focused on personalised applications with limited data. The authors of this study confirmed the effectiveness of complex AI models on large data sets, which is consistent with the conclusion that models such as ARIMA require significant amounts of information to achieve high accuracy.

H. Van Zuylen (2012) analysed the possibilities and compared various algorithms and approaches in the context of traffic light management and optimisation. The researcher noted that the main applications of AI are evolutionary algorithms, fuzzy logic, artificial neural networks, and reinforcement learning, but also pointed out limitations such as the small number of real-world implementations of fuzzy logic and the dependence of neural networks. However, the application and consequences of its implementation are unpredictable and contain significant areas that require further study. This is particularly relevant in interdisciplinary fields of knowledge, where the interaction of AI with various scientific fields can reveal unexpected and insufficiently meaningful aspects.

The study by S. Lins *et al*. (2021) explored the concept of "AI as a service", which is seen as a tool for overcoming barriers to AI adoption by small and medium-sized enterprises. The researchers analysed how cloud services that provide ready-made machine learning tools can make AI more accessible, versatile, and cost-effective. They gave an example of a quality control system where developers can use a cloud-based computer vision service without going into the technical details of the algorithm. This allows companies to focus on their core competencies rather than the challenges of installing and maintaining AI infrastructure. However, this paper did not pay enough attention to the potential risks and disadvantages of this model, in particular, issues of security and confidentiality of data processed by third-party providers.

The study by S. Dilmaghani *et al*. (2019) focused on the critical issue of information security and data privacy in ecosystems that use big data and AI. They analysed how risks arise at different stages – from data transmission to processing by AI systems. The main result of their research identified gaps in current security and privacy standards and formed a list of recommendations for strengthening them. While the paper provided a valuable overview, it did not address the specifics of security threats in the context of personalised applications with limited amounts of data.

The study by J. He *et al*. (2023) analysed the risks of possible AI abuse in the scientific field and in other fields. They found that, in addition to technical problems, there are significant ethical and social threats associated with unauthorised or malicious use of AI. The researchers proposed a number of control measures to minimise these risks. However, their analysis did not include comparing the security aspects of AI with simple algorithms, which could provide a more complete picture for developers.

P. Menard & G. Bott (2024) examined in detail the relationship between AI abuse and concerns about the privacy of users' personal data. They developed and validated new metrics to assess these risks, allowing them to better understand the psychological and social consequences of AI implementation. The results of their study confirmed that privacy issues are critical, and ignoring them can lead to serious consequences. However, as in other papers, their study did not focus on the specifics of small applications, where the risks may be of a different nature.

S.A. Javadi *et al.* (2020) focused on monitoring abuse and ensuring accountability in the "AI as a service" model. The researchers demonstrated that while AI service APIs provide access to powerful tools, they also create new vulnerabilities, especially in terms of controlling data transmitted for processing. These findings directly support the concerns described in this article about data security when using third-party AI services. The problem of unmanageability of third-party APIs is an important finding that does not deepen in the context of small local data.

The study by L. Pöhler *et al.* (2024) provided a technological perspective on the abuse of new technologies. The researchers have illustrated specific examples of how AI can be used for malicious purposes, highlighting the technological aspects of these abuses. This study was valuable because it confirmed the existence of real risks associated with the widespread use of AI. However, the analysis did not consider alternative, simpler approaches that could help to avoid these risks. This is a key difference from the current study, which compared AI with simple algorithms, which is a potentially safer alternative.

C. Veluru (2024) discussed the ethical and security challenges of using AI on large-scale data, including issues of inequality and bullying. The researcher noted the need for a responsible approach to the development of software applications. The conclusions of this paper support the thesis that there are significant risks associated with the widespread use of AI. The main disadvantage of this study was its focus on large-scale systems, which does not reflect the realities of developing personalised applications with limited data.

M. Anderljung *et al.* (2025) developed a classification of interventions aimed at reducing AI abuse. They analysed the chain of abuse, from predicting toxins to automating phishing campaigns, and suggested mechanisms to prevent them. This study is exhaustive, and its findings confirm the importance of developing security systems. However, it did not contain a comparison with less resource-intensive and more secure, from the point of view of data, simple algorithms. In the context of the above-mentioned problems and opportunities, the purpose of this study was to conduct a comparative analysis of the feasibility of using simple algorithmic approaches and AI methods in the development of a software application for accounting for personal assets. The existing gap in scientific research to substantiate the choice between AI solutions and simpler algorithms for such problems became the ideological basis for this article.

The study by N. Shapovalova *et al.* (2024) provided a comparative assessment of various artificial intelligence techniques, including neural networks, econometric and optimisation algorithms for predicting time series. Although the study confirmed the effectiveness of artificial intelligence-based models in identifying complex patterns, it did not consider implementation costs, computational requirements, or long-term system maintenance. This omission highlighted a general gap in the literature where technical efficiency took precedence over operational feasibility. In contrast, the current study attempted to fill this gap by evaluating not only accuracy, but also resource efficiency and ease of implementation, which is particularly relevant for developing lightweight personal asset management applications.

The conducted practical research allowed formulating key conclusions about the feasibility of using simple algorithms and AI methods to automate routine tasks. In contrast to the research discussed above, which mainly focused on the benefits of using AI, the current study has shown that simple algorithms can be an efficient and cost-effective solution in the initial stages of development or for services with a limited set of functions. This opens up a discussion about the feasibility of gradually increasing the complexity of the system, starting with basic algorithms and integrating more complex technologies as user needs and the amount of data processed increase.

As an example, the use of such algorithms can be considered in the following variants. This includes forecasting stocks for households or small businesses. In particular, a personal asset accounting application that helps to predict when household chemicals, food, medicine, or hobby supplies will run out. It can also be a mobile application for accounting for personal expenses, which allows predicting future expenses or revenues to avoid budget deficits. In addition, a simple algorithm is suitable for an organiser application or calendar that adapts and reminds you of tasks based on user behaviour. For most household needs, a simple algorithm is absolutely sufficient and does not require complex implementation, significant computing resources, or a large amount of historical data that is often missing in personal use. Only for expensive or critical stocks, where the cost of error is high, can more complex models be considered.

CONCLUSIONS

The study provided a comparative and factorial analysis of the feasibility of using a simple algorithm and the ARIMA statistical model to predict the time of the next product order in the context of developing a personal asset accounting service. The main goal was to determine the optimal approach, considering not only conventional metrics of accuracy and performance, but also critical factors such as implementation complexity, security, computing resources, and the cost of development and support. Factor analysis of the application context showed that the choice of the optimal approach depended on a number of criteria, including the volume and type of data, requirements for accuracy and speed, security, availability of necessary resources, and budget constraints. For small amounts of structured data and basic accounting functions, simple algorithms may be sufficient. The use of AI methods becomes appropriate if it is necessary to analyse large amounts of data, identify complex patterns, and provide predictive capabilities. The results showed that for scenarios with limited data volumes and relatively simple or stable user behaviour patterns typical of initial stages or small projects, a simple algorithm showed high efficiency. It provided an acceptable level of prediction accuracy with minimal computing resource requirements and low implementation and support complexity. Its execution speed was measured in nanoseconds, making it the optimal solution for small applications. Instead, the use of the ARIMA statistical model, which is a powerful tool for analysing time series, in the studied context turned out to be excessive. Despite the potentially higher ability to detect more complex dependencies with sufficient data, its accuracy was comparable or slightly higher in small samples than in a simple algorithm. However, ARIMA required significantly more computing resources, highly qualified developers for correct configuration, and more statistics to achieve reliable performance. Runtime was higher, measured in microseconds or even milliseconds for complex configurations or large amounts of data. Attention should be paid to the security of data transmission and processing, because data is processed by a third-party system.

The results support the hypothesis that the choice between simple algorithms and complex intelligent systems should be based on a comprehensive assessment of all relevant factors, and not just on potential "intelligence" or accuracy. In small projects with limited resources, where data may be insufficient or patterns are not too complex, it is economically and technically more appropriate to prefer simple but efficient algorithms. Integration of complex statistical models or solutions based on machine learning becomes justified when the project is scaled, data volumes grow, forecasting requirements become more complex, and nonlinear, hidden dependencies are identified that go beyond the capabilities of simple approaches. Further research may focus on developing specific scenarios for using different combinations of simple AI algorithms and techniques for different types of users and volumes of personal assets. Another important area is to assess the impact of the selected data processing methods on the usability, performance, and security of the information service.

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Порівняння простих алгоритмів та штучного інтелекту в розробці сервісу обліку персональних активів

Павло Козолуп
Аспірант
Сумський державний університет
40000, вул. Харківська, 116, м. Суми, Україна
https://orcid.org/0009-0000-1303-3424

Анотація. Аналіз сучасної наукової літератури виявляє тенденцію до широкого впровадження штучного інтелекту, часто без достатнього врахування непрямих факторів ефективності, таких як економічні витрати, складність імплементації, підтримка та інформаційна безпека. Ці дослідження більш акцентують увагу на показниках точності та продуктивності систем штучного інтелекту, ігноруючи при цьому непрямі, але критично важливі фактори ефективності. Метою цієї статті було дослідити доцільність застосування технологій штучного інтелекту порівняно з простими алгоритмічними рішеннями у контексті розробки програмних застосунків для обліку персональних активів. Методологія дослідження ґрунтувалася на проведенні комплексного порівняльного аналізу розробленого простого алгоритму для прогнозування часу наступного замовлення товару та статистичної моделі Auto Regressive Integrated Moving Average (ARIMA) як представника складніших, хоча й не глибоких інтелектуальних методів прогнозування часових рядів. На основі реалізації та проведеного експерименту з використанням даних, що імітували реальний сценарій, було оцінено продуктивність обох підходів за ключовими метриками, включаючи точність, необхідні обчислювальні ресурси та складність впровадження. Встановлено, що для завдань з обмеженими обсягами даних та відносно простими патернами поведінки, характерними для невеликих проєктів обліку персональних активів, простий алгоритм продемонстрував порівнянну точність з моделлю штучного інтелекту ARIMA. Було виявлено, що простий алгоритм функціонував з меншими витратами обчислювальних ресурсів, вимірюваними в наносекундах, та характеризувався нижчою складністю імплементації та подальшої підтримки. Проаналізовано, що застосування ARIMA, попри її статистичну потужність, виявилося менш виправданим у таких умовах, вимагаючи більших обчислювальних витрат та глибших знань для її налаштування. Показано, що час виконання ARIMA на малих вибірках був вищим (у мікросекундах), а її надійність значно залежала від обсягу та якості вхідних даних. Таким чином, було підкреслено необхідність обґрунтованого вибору технологій, виходячи з реальних потреб та ресурсних обмежень проєкту

Ключові слова: машинне навчання; розробка програм; прогнозування; ефективність; персоналізація