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CONTENT

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Designing the Application of a Distributed Control System and Creating a Portable Mechanism with Pc-Based Numerical Control (Cnc)

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Abstract: The trends in rapid production (RP) have largely impacted the development of technology in additional processes. Nevertheless, material incompatibility and accuracy issues with the additional processes have restricted the possibility of fabricating end-user products. The additional processes, including the more radical Computer Digital Control (CDC) machining, can in some cases be applied to RM. Using a 3-axis CDC milling machine equipped with an indexing device allows for increasing the accessibility of the cutting tools and avoiding numerous process restrictions. At the same time, more research should be conducted to advance the use of CDC in RM, which is the purpose of this thesis. This research aims to refine the process of deep machining and finishing operations and the application of cutting tools in CDC machining in order to make CDC machining applicable for RM. It is expected that the implementation of the proposed techniques will accelerate production and increase the quality of the parts produced.

Keywords: Distributed Control System (DCS), PC-Based CNC, G-code, Toolpath Optimization, Computer-Aided Manufacturing (CAM)

1.Introduction

Another way to increase the effectiveness of deep processing operations may include a change in the direction of cutting. Simulation analyses are conducted to change the values of orientations and calculate approximate cut-off times. Directions with a minimum processing time are chosen for performing deep processing operations. Further developments are aimed at changing geometrical tool characteristics and using straight and ball-nose cutters during the finishing process. An effective surface classification technique was developed to integrate milling tools and find out the cutting areas. The development of Computer-Aided Production (CAM) is implemented to conduct fast processing operations. It allows for the management of the CNC process with the help of special programming codes. Simulation study results are confirmed by the results of the processing experiment. First of all, this technology minimizes the time of rough work cutting in four independent directions and makes the process less sensitive to tool failures. Secondly, the use of milling tools increases the quality of the surfaces of machined parts. Finally, process planning programs provide effective simulation analysis and processing operations management. The application of computer numerical control (CNC) routers is very popular today because of the high-quality results that can be obtained [1]. This popularity is further supported by the widespread adoption of standardized data formats that facilitate diverse manufacturing applications [2].

The CNC machines are flexible enough that they use different tools, which allows them to undertake various operations like cutting, carving, and drilling of different types of material, including metal, wood, plastic, and steel. G-code instructions are used to control the movement of the CNC machine [3]. The correct interpretation of file structures, such as the RS274X standard, is critical for avoiding errors in CNC routing [4].

These instructions help to define where the machine is going to move and at what speed it will do so [5]. These codes are typically sent through the serial interface, such as a USB interface, from an external computer program [6]. This project deals with developing a computer program to run a CNC laser machine and generate G-code for the design of the pattern as per the plan. The primary application is the manufacturing of PCBs [7], [8], [9], [9]. Reliable CAD-to-CAM communication relies on modern format standards to ensure data accuracy and seamless integration [11].

The received results have been processed statistically.

Scientific novelty of the master's thesis.

• Use of PCB boards

• Installation of Stepper Motors

• Integration of open source software on hardware

Using a 3-axis CNC milling machine to ensure the availability of tools and justify many other technological priorities. But still, there is a need for improvement in the use of CNC in PC, and the task here is to improve deep machining and finishing operations, and the integration of cutting tools in CNC machining to adapt it to PC applications. The purpose of this research is to adapt CNC machining to rapid manufacturing [12], and it is assumed that implementation of the suggested approaches will help to accelerate the production process, improve the quality of parts, and make the process adaptable to PC. One of the ways to enhance deep machining operations is to apply various directions of cuts. The simulation analysis is conducted to manipulate the orientation values and obtain estimates of the cutoff times. For performing deep machining processes, directions with minimal processing times are chosen.

There are ongoing advancements to enable the combination of tools of varying geometry, and in the machining process, straight and spherical tools are applied. A technique for the classification of surfaces has been designed in order to facilitate the integration and definition of cut regions. The advancement of computer-aided manufacturing (CAM) technology is adopted to ensure rapid processing [13]. It enables you to control the planning process of the CNC process using individual programming codes. The results of the simulation study have been validated through the results of the processing experiment. Firstly, it ensures that there is a minimum roughing time in four separate directions while avoiding any sensitivity to tool breakage. Secondly, the combination of milling tools ensures better surface quality of the machined workpiece.

2. Running performance of the CNC-JS software

Tool guidance performance was assessed based on the performance of the application, meaning how efficient application processed the image into a G-code file, the run-time of the G-code file generated, and the cut-to-engrave process performed. The computer used in this experiment is a computer with an Intel i5-7200 dual-core (can run 4 threads at the same time) having a clock speed of 2.5 GHz and 8 GB of RAM; the following two images are used: 1. Image with a compact distribution of pixels to be deleted and 7 different resampling factors (Figure 1).

Image Properties				
Resample Factor	Pixels		Pixels %	
	Width	Height	To Remove	To Keep
0.125	125	103	39.25	60.75
0.25	250	205	38.08	61.92
0.5	500	410	37.34	62.66
1	1000	820	37.45	62.55
2	2000	1640	37.42	62.58
4	4000	3280	37.4	62.6
8	8000	6560	37.4	62.6

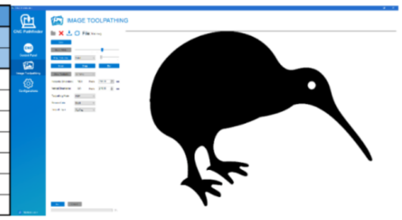

Figure 1. Compact distribution of pixels to be deleted.

An image with a more scattered distribution of pixels to be deleted and 7 different resampling factors (Figure 2).

Image Properties				
Resample Factor	Pixels		Pixels %	
	Width	Height	To Remove	To Keep
0.125	160	100	30.27	69.73
0.25	320	200	25.38	74.62
0.5	640	399	19.7	80.3
1	1280	798	21.27	78.73
2	2560	1596	21.3	78.7
4	5120	3192	21.28	78.72
8	10240	6384	21.27	78.73

Figure 2. Scattered distribution of pixels to be deleted.

As discussed earlier, the tool routing procedure can be broken down into five steps: image resampling, pixel segmentation, segment routing, segment linking, and guide generation. As image resampling uses the default interpolation methods, and both algorithms, zigzag and spiral, use the same resampled image, the execution time of image resampling is not considered. The following results were obtained for both Figures 1 and 2.

Table 1. G-code file generation time for Figure 1 with a compact distribution of pixels to be deleted

Tool Pathing Algorithm	Image Resample Factor	File Generation Time [in seconds]								
		Segmentation		Pathing		Connection		File		Total
		Time	%	Time	%	Time	%	Time	%	
ZigZag	0.125	0.0019	19.19	0.0026	26.26	0.0023	23.23	0.0031	31.31	0.0099
	0.25	0.0026	9.12	0.0009	3.16	0.008	28.07	0.017	59.65	0.0285
	0.5	0.0096	19.47	0.0021	4.26	0.0303	61.46	0.0073	14.81	0.0493
	1	0.0308	18.15	0.0044	2.59	0.1149	67.71	0.0196	11.55	0.1697
	2	0.1022	16.46	0.0142	2.29	0.4628	74.52	0.0418	6.73	0.621
	4	0.3984	16.48	0.0441	1.82	1.8611	76.98	0.1139	4.71	2.4175
	8	1.7011	17.18	0.1458	1.47	7.6036	76.78	0.4527	4.57	9.9032
Spiral	0.125	0.0005	1.82	0.0025	9.12	0.0009	3.28	0.0235	85.77	0.0274
	0.25	0.0163	16.65	0.0089	9.09	0.0024	2.45	0.0703	71.81	0.0979
	0.5	0.0463	14.92	0.0251	8.09	0.0109	3.51	0.228	73.48	0.3103
	1	0.1873	15.83	0.098	8.28	0.0458	3.87	0.8519	72.01	1.183
	2	0.7462	22.10	0.3821	11.32	0.0321	0.95	2.2157	65.63	3.3761
	4	3.0137	30.76	1.4901	15.21	0.0979	1.00	5.1969	53.04	9.7986
	8	12.1279	34.94	5.9168	17.04	0.2852	0.82	16.3849	47.20	34.7148

Table 2. Number of generated segments and Tool lines for Figure 1 with a compact distribution of pixels to be deleted.

Tool Pathing	Image	Number of Segments		Number of Lines				
Algorithm	Resample	Fill Segments		Tool On		Tool Off		Total
	Factor	Pre pathing	Post Pathing	Lines	%	lines	%	
ZigZag	0.125	103	167	167	49.85	168	50.15	335
	0.25	205	328	328	49.92	329	50.08	657
	0.5	410	659	659	49.96	660	50.04	1319
	1	820	1316	1316	49.98	1317	50.02	2633
	2	1640	2631	2631	49.99	2632	50.01	5263
	4	3280	5262	5262	50.00	5263	50.00	10525
	8	6560	10525	10525	50.00	10526	50.00	21051
Spiral	0.125	1	90	3008	97.06	91	2.94	3099
	0.25	1	178	11597	98.48	179	1.52	11776
	0.5	1	367	44061	99.17	368	0.83	44429
	1	1	732	177624	99.59	733	0.41	178357
	2	1	595	456097	99.87	596	0.13	456693
	4	1	967	1048047	99.91	968	0.09	1049015
	8	1	1670	3076772	99.95	1671	0.05	3078443

Table 3. G-code file generation time for Figure 2 with a scattered distribution of pixels to be deleted.

Tool Pathing	Image	File Generation Time [in seconds]								
Algorithm	Resample	Segmentation		Pathing		Connection		File		Total
	Factor	Time	%	Time	%	Time	%	Time	%	
ZigZag	0.125	0.0014	2.75	0.0008	1.57	0.043	84.48	0.0057	11.20	0.0509
	0.25	0.0055	1.44	0.0091	2.39	0.34	89.22	0.0265	6.95	0.3811
	0.5	0.0099	0.31	0.002	0.06	3.1009	97.39	0.0713	2.24	3.1841
	1	0.0319	0.30	0.0043	0.04	10.4474	98.56	0.1169	1.10	10.6005
	2	0.1261	0.28	0.076	0.17	44.1842	99.00	0.2444	0.55	44.6307
	4	0.409	0.22	0.0424	0.02	187.7034	99.48	0.5343	0.28	188.6891
	8	1.7478	0.21	0.1362	0.02	829.7499	99.61	1.357	0.16	832.9909
Spiral	0.125	0.0189	31.19	0.0095	15.68	0.0158	26.07	0.0164	27.06	0.0606
	0.25	0.0188	9.36	0.0107	5.33	0.1208	60.16	0.0505	25.15	0.2008
	0.5	0.0672	3.78	0.0156	0.88	1.3626	76.59	0.3336	18.75	1.779
	1	0.1994	4.71	0.077	1.82	3.4462	81.48	0.5068	11.98	4.2294
	2	0.7979	16.86	0.2441	5.16	2.4792	52.40	1.2102	25.58	4.7314
	4	3.1667	13.85	0.9318	4.07	15.6033	68.22	3.1692	13.86	22.871
	8	11.359	20.13	3.2112	5.69	33.7541	59.81	8.1123	14.37	56.4366

As can be seen in Tables 1 and 2, the Zigzag algorithm creates more segments and therefore spends more time connecting them. Note that the zigzag segments are controlled by only one plane, and the spiral groups move with pixels from the same "step" and thus control a larger area in the image of their middle segments. However, it also creates more space and not only spends more time on the road, but also calculates and converts physical positions in generating G-codes. Setting up more G-codes can lead to longer cutting and engraving operations. It may also be noted that the number of segments moving forward in a zigzag is equal to the height (in pixels) of the image, which is its largest size, and is equal to the number of segments moving in a spiral, a very compressed distribution of pixels to extract from a limited distance.

Table 4. Number of generated segments and tool lines for Figure 2 with a scattered distribution of pixels to be deleted.

Tool Pathing	Image	Number of Segments		Number of Lines				
Algorithm	Resample	Fill Segments		Tool On		Tool Off		Total
	Factor	Pre pathing	Post Pathing	Lines	%	lines	%	
ZigZag	0.125	100	611	611	49.96	612	50.04	1223
	0.25	200	2025	2025	49.99	2026	50.01	4051
	0.5	399	6457	6457	50.00	6458	50.00	12915
	1	798	12554	12554	50.00	12555	50.00	25109
	2	1596	25246	25246	50.00	25247	50.00	50493
	4	3192	51480	51480	50.00	51480	50.00	102960
	8	6384	106307	106307	50.00	106308	50.00	212615
Spiral	0.125	49	341	2204	86.57	342	13.43	2546
	0.25	207	1146	7260	86.36	1147	13.64	8407
	0.5	889	3881	22535	85.30	3882	14.70	26417
	1	627	6342	83092	92.91	6343	7.09	89435
	2	628	5303	196524	97.37	5304	2.63	201828
	4	638	10910	515410	97.93	10911	2.07	526321
	8	669	17962	1462043	98.79	17963	1.21	1480006

Unlike previous tables, the Zigzag algorithm generates many more segments due to the scatter of pixels that should be removed, as the groups of pixels to be removed are larger on the same line and thus generate many more segments per column of the image. Of course, an obvious flaw is the linkage of segments. It will adversely affect the performance of the software for large images due to the quadratic dependency of the number of iterations of the sorting procedure on the number of segments, as defined by Eq. One approach could be to carry out a less resource-intensive search by finding several groups of segments, which are at the same distance from the origin (lower-left corner). But it will require additional time for the cutting and engraving process. The difference in the total number of lines between the two algorithms is smaller than that of the previous image set, but the spiral still generates more instructions. When considering the efficiency of both algorithms, the following values (CNC motion) were found by choosing a resolution of one pixel per millimeter:

The biggest difference between these algorithms is obviously the distance traveled by the CNC without actually engraving. If we consider that the CNC tool will move at constant speed regardless of acceleration and deceleration of direction changes, having in mind the properties of the CNC machine, which have a maximum feed rate of 1300 millimeters per minute, we can estimate that worst-case (8x) resampling factor would require approximately 31.49 hours to complete for zigzag algorithm and 34.39 hours for spiral, which is 9% slower. In this example, the zigzag algorithm proved faster at producing a G-code file, requiring just 9 seconds against 35 seconds for the other algorithm.

Table 5. Number of tool lines generated for Figure 1 with a compact distribution of pixels to be removed and the distance traveled by the CNC tool.

Tool Pathing	Image	Number of Lines					Distance [in mm]				
Algorithm	Resample	Tool On		Tool Off		Total	Tool On		Tool Off		Total
	Factor	Lines	%	lines	%		Distance	%	Distance	%	
ZigZag	0.125	167	49.85	168	50.15	335	39088	91.54	3611	8.46	42699
	0.25	328	49.92	329	50.08	657	76756	95.05	3994	4.95	80750
	0.5	659	49.96	660	50.04	1319	151766	97.53	3841	2.47	155607
	1	1316	49.98	1317	50.02	2633	305771	98.87	3501	1.13	309272
	2	2631	49.99	2632	50.01	5263	612337	99.30	4311	0.70	616648
	4	5262	50.00	5263	50.00	10525	1225334	99.61	4848	0.39	1230182
	8	10525	50.00	10526	50.00	21051	2452174	99.85	3773	0.15	2455947
Spiral	0.125	3008	97.06	91	2.94	3099	39704	74.17	13829	25.83	53533
	0.25	11597	98.48	179	1.52	11776	77356	73.80	27458	26.20	104814
	0.5	44061	99.17	368	0.83	44429	152350	73.79	54124	26.21	206474
	1	177624	99.59	733	0.41	178357	306355	74.93	102493	25.07	408848
	2	456097	99.87	596	0.13	456693	613355	92.96	46428	7.04	659783
	4	1048047	99.91	968	0.09	1049015	1226408	89.30	146934	10.70	1373342
	8	3076772	99.95	1671	0.05	3078443	2453281	91.47	228802	8.53	2682083

Table 6. Number of tool lines generated for Figure 2 with a scattered distribution of pixels to be deleted and the distance traveled by the CNC tool.

Tool Pathing	Image	Number of Lines					Distance [in mm]				
Algorithm	Resample	Tool On		Tool Off		Total	Tool On		Tool Off		Total
	Factor	Lines	%	lines	%		Distance	%	Distance	%	
ZigZag	0.125	611	49.96	612	50.04	1223	33856	72.57	12796	27.43	46652
	0.25	2025	49.99	2026	50.01	4051	56876	71.65	22499	28.35	79375
	0.5	6457	50.00	6458	50.00	12915	87704	69.84	37870	30.16	125574
	1	12554	50.00	12555	50.00	25109	204732	83.35	40897	16.65	245629
	2	25246	50.00	25247	50.00	50493	422419	90.49	44405	9.51	466824
	4	51480	50.00	51480	50.00	102960	856603	94.91	45900	5.09	902503
	8	106307	50.00	106308	50.00	212615	1724609	97.17	50236	2.83	1774845
Spiral	0.125	2204	86.57	342	13.43	2546	36016	62.08	21999	37.92	58015
	0.25	7260	86.36	1147	13.64	8407	60392	61.13	38407	38.87	98799
	0.5	22535	85.30	3882	14.70	26417	92856	58.85	64937	41.15	157793
	1	83092	92.91	6343	7.09	89435	210944	65.49	111167	34.51	322111
	2	196524	97.37	5304	2.63	201828	432391	80.45	105088	19.55	537479
	4	515410	97.93	10911	2.07	526321	866745	76.32	268973	23.68	1135718
	8	1462043	98.79	17963	1.21	1480006	1735652	78.22	483380	21.78	2219032

Table 6 shows that, again, the difference in distance is still significant when the tool is not cutting or engraving. Assuming the same bit rate as before, the estimated completion time for the worst case (8x resampling factor) would be about 22.75 hours for the zigzag and 28.45 hours for the spiral, a 25% increase in time. This means that despite the toolpath taking 14 minutes, the zigzag algorithm generated a G-Code file about 6 hours faster than the spiral, which took only one minute to toolpath. This shows that the fastest algorithm is not always the most efficient. However, there is still much room for improvement.

Toolpath Quality. The quality of the engraving depends very much on the type of material being engraved. Plywood was used to compare the print quality of both algorithms and the SVG outline, and the following result was obtained:

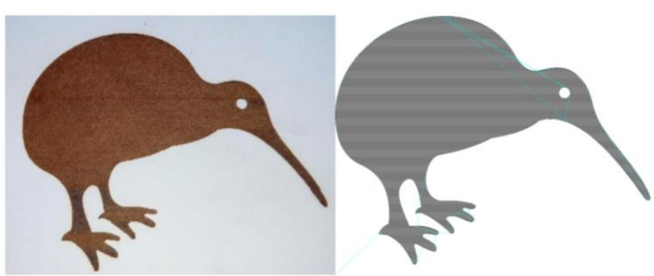

Figure 3. Image with a compact distribution of pixels printed using the zigzag algorithm. A. Print result (left); B. Simulation (right).

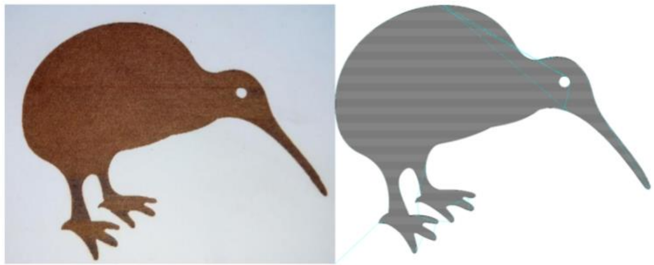

Figure 4. Image with a compact distribution of pixels printed using the spiral algorithm. A. Print result (left); B. Simulation (right).

The obtained results reveal that the engraving process using the zigzag algorithm is much smoother, as the number of turns or corners made by the CNC in the spiral algorithm leads to a greater duration of the laser being on in the same place [14]. The simulations have revealed a great difference between the distance covered when the laser is off, illustrated by the blue lines, thus resulting in a longer time for etching or cutting of the figure, as stated above. The physical size of the image was about 90 x 75 mm, and the duration of printing of both results was 14 minutes 28 seconds for zigzag and 19 minutes 14 seconds for spiral algorithms, respectively, using the feed rate of 1000 mm.

The main purpose of this project was to design a computer application that would be able to handle the CNC machine and tool path for all the most widely used types of image files. The CNC machine was controlled using the instructions given in G code, which explained how the CNC tool would move and what type of movement it should have [3]. A graphical user interface was created for the software using Windows Forms, which makes the user independent of the instructions and makes processes like calibration, printing, and orientation of the instruments easier. Such interface designs are essential for providing effective visual solutions that simplify the management of complex CNC workflows [15]. There is also a G-code simulator that analyzes the given file for the proper G-code instructions and displays the result so that the user can get an idea about the file and orient the CNC machine or the material before printing it. Coming to the image tool path, this project is related to the orientation of the raster images using the two most widely used methods, zigzag and spiral.. For the tests performed, the zig-zag method is the most efficient in terms of both time and quality of the cutting or engraving operation, although in some cases it takes longer to create the file. The selection and optimization of such path algorithms are critical for enhancing the efficiency of pocket milling processes [16]. While both try to minimize the distance traveled with the laser off, the spiral method also tries to create longer paths with the laser on, which results in fewer path segments with start and end points further apart.

The sorting algorithm that is employed to join the segments attempts to optimize only the proximity to the next path and not the entire length of the connection, making the latter unnecessarily elongated, sometimes even spirally. In order to address this issue, the sorting algorithm should analyze quite a few possible paths that may increase the time necessary to generate the toolpath file significantly. Utilization of the GPU for processing the toolpath would not only help to solve this problem but also speed up the process in general. Speaking about the SVG images, the conversion of Bezier and ellipses into simple lines and arcs was performed successfully, although there were some difficulties aligning the fill path with the outline. The latter were more noticeable for images with transformations like rotation or skew because the rendered version of the image did not correspond exactly to the outline path.

3. Result and Discussion

Although the project turned out to be significantly more complicated than I thought, it helped me learn about the topic of image processing and CNC machine control.

The results obtained demonstrate that the zigzag algorithm produces more uniform engravings since the number of turns made by the CNC in the spiral method results in longer exposure of the laser to the same place. In addition, the simulations reveal that there is a considerable difference in the distance traveled when the laser is not on, demonstrated by blue lines, thus making it more time-consuming to etch or cut a figure

The physical parameters of the image used were 90 by 75 millimeters, while it took 14 minutes 28 seconds and 19 minutes 14 seconds to print these two algorithms, respectively, at a feed rate of 1000 mm.

Practical significance of the research work: The results obtained are of great practical significance. So, the combination of CNC machines and software on the hardware, and its implementation on CNC-js JavaScript and distribution of algorithms may be significant.

Approval of work. The use of computer numerical control (CNC) routers has become extremely popular due to the high-quality results that can be achieved. CNC machines are versatile and can use different types of tools, allowing them to perform a wide variety of tasks such as cutting, engraving, and drilling different materials such as wood, plastic, or hard metals such as steel.

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Modeling a Software Solution for Analyzing Customer Complaints in the Banking Sector

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Abstract: The quick advancement in the creation of digital banking systems results in the emergence of more text data, such as complaints, reviews, and service requests, from consumers. The need for systems able to deal with a large amount of data in a sophisticated manner is vital in this situation. Studies show that NLP, together with machine learning, allows financial organizations to gather important information through analyzing texts produced during client-server interactions and thus make better decisions. Automated analysis of complaints made by bank consumers will lead to the identification of service problems and patterns of client discontent. It has been revealed by recent studies that sophisticated classification algorithms and neural network technologies are able to correctly classify complaints made by customers according to predefined categories of services offered by banks, thus minimizing efforts spent on manual analysis and response time. In addition, sentiment analysis techniques make it possible to determine the attitude of customers towards various services provided by banking institutions, which is helpful for effective planning purposes. Topic modeling techniques may also assist in uncovering hidden topics within a set of complaints.

Keywords: Customer complaints, Natural Language Processing (NLP), Machine Learning, Automated Complaint Analysis, Digital Banking

1.Introduction

The banking industry is experiencing accelerated digitalization due to advances in technology, internet penetration, and the development of online financial services. Modern banks gather large volumes of data about their customers via mobile applications, emails, chat conversations, and reviews on feedback forms. Most of the received data comes in the form of unstructured text (complaints, surveys, reviews) that cannot be easily processed manually but contains useful information for enhancing services and making business decisions [1]. Due to the efforts made by financial regulators to improve customer experience and keep banks competitive, there is an increased need for automatically analyzing textual data.

There are currently efficient natural language processing and machine learning solutions that allow for the automatic classification of texts, identification of sentiment polarity in customer feedback in the sentiments expressed by clients, discovery of urgent cases, and detection of common issues [2]. Automatic solutions for dealing with customer complaints can greatly decrease the workload and time required for analyzing textual messages and make decision-making more accurate and efficient [3]. Additionally, intelligent classifiers can be used by banks to properly direct customer inquiries to relevant departments and optimize the workflow [4].

Recent studies have shown that modern deep learning architectures, particularly those based on neural networks, surpass conventional rule-based and statistical methods when applied to financial text analysis [5]. Modern technologies enable algorithms to learn certain language peculiarities and context-based semantics in customer complaints and are well-suited for analyzing large amounts of information, where manual analysis would be impossible [6]. Moreover, sentiment analysis tools enable financial companies to analyze customer perceptions of services and their reaction to services, which helps them to improve customer service and maintain their brand image [7].

However, despite all these technological advancements, most banks operate using semi-automated and decentralized customer complaint management systems that do not allow them to make use of the data they receive. There is a great number of solutions available on the market, but very few provide an integrated and intelligent decision support system, which makes the process ineffective and time-consuming [8]. Thus, there is a growing demand for a solution that integrates data pre-processing and linguistic analysis.

The goal of the current study is to develop a conceptual model for software that can be used for automated analysis of customer complaints submitted by bank customers. This solution will incorporate modern techniques of NLP together with machine learning and the principles of system architecture to design an intelligent system capable of analyzing customer interactions. The purpose of the current research is to enhance intelligent banking support systems by developing a structure that can be easily expanded.

2. Proposed Conceptual Model

Modern banks are involved in communication with an enormous number of customers who provide feedback and complain about different problems in the form of text messages through mobile applications, emails, online forms, and even social networks. Processing and analyzing such volumes of textual data is rather complicated for financial institutions because the data is unstructured. However, effective and timely analysis of customer feedback is important for customer satisfaction. Manual processing of complaints can take too much time and is associated with errors that may lead to dissatisfaction and negative consequences [8].

While there is a variety of automated tools for banks, no single solution has been created that would allow for pre-processing the data, comprehending the text, and categorizing it correctly. Semi-automated solutions cannot identify the category of complaints accurately, their priority level, and overall sentiment because of the complexity of such data processing [3]. This problem increases due to the size of datasets and their complexity in terms of semantics because of the nature of textual data [5].

In conclusion, the principal objective is the development of a smart and robust system that automatically analyses, classifies complaints, determines the emotion of a customer, and gives valuable information for managers. It would be wise if such a system were designed with the aim of minimizing workloads, accelerating operations, improving the accuracy of complaint analysis, and supporting data-driven management decisions in the banking industry [2].

In this regard, the proposed research problem is solved by presenting a theoretical model of software that performs automatic analysis of inquiries from bank customers. The developed model uses state-of-the-art NLP techniques, classification algorithms based on machine learning, and visualization elements to develop a smart approach to managing complaints and making decisions [2], [8], [13].

Customer complaint analysis in banks has been extensively investigated in the recent past, proving the significance of text processing technology in enhancing service delivery and operations in the banking sector. Earlier approaches to customer complaint categorization were mainly rule-based or keyword-matching, which were limited both in terms of effectiveness and scalability [1], [2]. The importance of using automated text processing techniques to categorize complaints in the banking industry and the significant benefits of doing so using basic machine learning models were outlined by Pallavi et al [3], [8].

Natural language processing techniques have become crucial for complaint analysis since then. Kaur [9], pointed out that the implementation of sentiment analysis of e-banking customers' complaints will enable financial institutions to uncover emerging customer dissatisfaction trends and operational issues, and modify their business approach accordingly. Furthermore, Pangaribuan et al.[5], introduced a novel text categorization method utilizing LSTM, which proves significantly more accurate than traditional machine learning approaches and demonstrates the potential of deep learning in text processing [5].

It has been proven in many studies that the importance of sentiment analysis in understanding customer complaints should be stressed. Bhuiyan et al. [7] showed that sentiment analysis enables organizations to assess customer satisfaction and make informed decisions to reduce service-related problems. Furthermore, automated complaint analysis systems classify and prioritize customer complaints, thereby improving decision-making and customer service efficiency [8].

The use of data mining and clustering methods for analyzing the structure of datasets has been widely proposed. In particular, Nikitha et al. [1] demonstrated that data mining techniques applied to banking customer complaints can help improve service quality and identify recurring problem areas. Furthermore, Mutesi et al. [8] emphasized that automated complaint management systems should integrate complaint classification, sentiment analysis, and visualization to support more effective decision-making [8].

LSTM and other neural network models prove promising tools for classifying sophisticated banking texts. According to Baskaran [6], these models yield better results compared to conventional rule-based and statistical approaches, particularly in large environments comprising various types of complaints. Moreover, Mitta [11] demonstrated the value of AI-based sentiment analysis for capturing subtle nuances in customer opinions and supporting more accurate decision-making [11].

Furthermore, the topic modeling approach and feature extraction have also been tested on complaint classification using thematic approaches. In particular, Bastani et al. [12] employed Latent Dirichlet Allocation (LDA) to identify recurring complaint themes, while García-Méndez et al. [4] successfully applied a Support Vector Machine (SVM) approach to transaction-related text classification.

In summary, it is evident from the literature that the integration of NLP, ML, and DL techniques facilitates the automatic and precise analysis of complaints received by banks on a massive scale. However, most of the approaches used today still do not incorporate a common platform that incorporates such steps as data preprocessing, feature extraction, classification, sentiment analysis, and visualization [10]. This deficiency prompted the development of the present study and its proposal for a conceptual software model of complaint management.

In particular, the methodology employed in this paper seeks to create a conceptual software model that can facilitate the analysis of inquiries received by financial institutions based on the use of modern NLP technologies together with ML and DL for effective classification and visualization of complaints. The methodology comprises the following five steps: data collection, data preprocessing, feature extraction and classification, and data visualization and decision support.

1. Data Gathering

The system gathers data about customer complaints and feedback through various digital channels such as mobile banking applications, email, web-based forms, and social media sites [1]. The model uses historical complaint datasets to be trained, while incoming datasets will continuously undergo processing for classification purposes. Quality data and a complete dataset are needed for the successful operation of the model [8].

2. Data Preprocessing

There are different ways to preprocess the raw data that will be fed into the machine learning model to classify complaints. Such methods are listed below:

1. Text normalization: lowering case and eliminating punctuation marks, digits, or other unnecessary characters [2].
2. Tokenization: breaking text into tokens or relevant chunks [9].
3. Stopword elimination: taking out words not applicable to the classifications [9].
4. Stemming and lemmatization: bringing down the words into their base or root form [11].

These procedures are used to filter noise in the data as well as increase the effectiveness of extracting features and training the model.

3. Feature Extraction and Classification

Having preprocessed the data, features can be extracted via both classical techniques and new advancements, which include:

Bag of Words (BoW) and TF-IDF: conventional ways of converting text data into numbers by taking into account the frequency and significance of words [1].
Word vector representations (Word2Vec, FastText): embedding words as dense vectors indicating their meaning.
Contextual representation via neural networks (LSTM, Bi-LSTM): considering the sequential nature of complaints as well as their meanings [5], [6].
Techniques for classification involve multiple models, both machine and deep learning-based, such as:
SVM algorithms are a strong classifier [13].
Ensembles of random forests and gradient boosting trees [8].
LSTM and Bi-LSTM models capture textual sequences [5], [6]. Machine learning and deep learning models are trained using datasets consisting of complaints and then evaluated in terms of metrics like precision, accuracy, recall, and F1 score [2], [3].

4. Sentiment Analysis

Alongside classification, sentiment analysis is done to evaluate the emotional polarity of customer messages: positive, neutral, or negative. This helps banks to understand trends of customer dissatisfaction and handle complaints promptly [7], [11]. The use of advanced NLP techniques allows combining semantic and emotional aspects in order to improve the classification of complaints.

5. Visualization and Decision Support

Ultimately, all analyzed data is presented visually through dashboards and reporting solutions. Visual analytics may involve the following indicators: number of complaints per category, changes in sentiments over time, and urgency [8], [10]. These insights will help managers of banks make decisions based on data and manage complaints effectively.

Overall, this methodology offers a complete theoretical framework for complaint classification automation in banking companies. Combining data processing, feature extraction, classification, sentiment analysis, and visualization, this approach makes complaint analysis scalable, accurate, and effective [2], [12].
The conceptual software model designed for analyzing automated inquiries of customers of banks is built around a modular architecture that consists of several modules, such as data acquisition, data processing,

feature extraction, classification, sentiment analysis, and visualization. The proposed system contains five major modules that contribute to efficient complaints management and decision-making.

1. Data Collection Module

This module gathers customer complaints received through multiple channels, such as mobile banking applications, emails, online forms, and social networking sites [1]. Historical databases are used as training data, and live complaint feeds are constantly monitored for prompt processing. This module guarantees the quality of collected data by eliminating duplicates and preparing the collected data for pre-processing [8].

2. Data Preprocessing Module

The data pre-processing module converts unstructured text data into structured data ready for machine learning and NLP techniques. Tokenization, elimination of stopwords, stemming, lemmatization, and normalization are some of the processes included in data pre-processing [2], [9], [11]. This module ensures that text data is prepared for feature extraction and classification.

3. Feature Extraction and Classification Module

The basic functionality of this module is to represent text data numerically and categorize complaints based on predefined categories:

Techniques used for feature extraction: BoW (Bag-of-Words), TF-IDF, Word2Vec, FastText, contextual embedding for use in deep learning models [1], [14].
Algorithms for classification: SVM (Support Vector Machine), Random Forest, Gradient Boosting, and LSTM/Bi-LSTM networks [5], [6].
The output from classification includes the category of the complaint, priority level, and related features.

4. Sentiment Analysis Module

This module combines with the classification process to evaluate the emotional nature of the complaint made by the customer. The system determines whether a complaint contains positive, neutral, or negative emotions [7], [11]. Assessment of emotional states is then integrated with classification outcomes.

5. Module for Visualization and Reporting

This module generates dashboards and reports that give the following data:

1. Complaint classification;
2. Trends of sentiment by time;
3. Priority analysis;
4. Department workload overview [8],[10].

The visualization of complaint data aids in strategic decision-making and performance tracking. The suggested system operates like a pipeline that collects, pre-processes, extracts features from, classifies, analyzes the sentiment of, and visualizes data. This way of creating a system provides flexibility and modularity, which allow it to scale and make the system resilient to changes. New approaches for classification and sentiment analysis can be easily implemented into the system without breaking anything [2], [12].

Automation will help decrease manual labor and shorten response time. Accuracy will improve thanks to the application of deep learning for classification and sentiment analysis tasks [5], [6]. Making decisions based on data will be facilitated by using dashboards and reporting tools. Scalability makes it possible to integrate more data from different bank channels.

Such an architecture shows how one intelligent system is able to make the process of managing customer complaints more effective, accurate, and strategic in banks, thus enhancing the quality of services and the level of customer satisfaction [3], [12],[14].

The proposed software architecture was theoretically assessed based on findings reported in previous studies. Existing research suggests that LSTM models can achieve competitive performance in customer complaint classification compared with conventional machine learning methods such as SVM and Random Forest [5], [6]. Based on the findings reported in the literature, sentiment analysis can help identify negative customer feedback and support improvements in customer satisfaction [7], [11].

By using visual tools, information about complaints could be obtained, including their sentiment analysis and the workload of certain departments [8], [10]. In general, the combination of NLP techniques, machine learning algorithms, and visualization made the proposed software solution effective and scalable. Thus, the results of the theoretical evaluation prove the viability of the proposed intelligent system [2], [3], [12].

Conclusion

This paper develops an abstract software model for automatic analysis of customer complaints in banks using natural language processing (NLP), machine learning, deep learning, and visualization algorithms. With the help of data processing, classification, and analysis of textual information in an unstructured form, this system will be able to minimize manual labor, optimize processing time, and enhance efficiency [3], [5], [6], [7], [8].

According to previous research and the proposed conceptual framework, NLP models based on LSTM networks may provide effective performance in classifying and prioritizing customer complaints [5], [6], [7]. The use of visualizations facilitates data-based decision-making and strategy development by ensuring a deeper insight into patterns, types, and sentiments found in complaints [5, 6].

Thus, the developed model appears to be effective, intelligent, and applicable for solving issues of customer service and management at financial organizations. Future research may be aimed at investigating the performance of this model on real-life datasets [2], [12], [14]

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Automation of patentability for utility models

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Abstract: Automating the process of finding patentability for utility models would involve using technology and tools to assist in patent search and analysis. Levels of automation could depend on how much human interaction a system needs. The automation systems would be fully automated systems, semi-automated systems, and partially automated systems. The utility models only require novelty and industrial application. The process would involve checking patentability requirements and conducting a patentability search. First, the automation will thoroughly inspect industrial applications. Then, it will check the novelty of the device. The automation would involve AI to learn some real-world logic and natural sciences, such as physics, chemistry, etc. The field of science would depend on the operational field of the utility models. The AI would be implemented with OCR capabilities. From that, AI would do some data mining to find some keywords, key terms, and classifications. Since the AI would be implemented in Azerbaijan, the found keywords and key terms would be in Azerbaijani and Russian. But since we are also searching for some English-implemented databases, AI would also have a translation function. We would use the API of patent databases, which would give access to the databases. AI would find a few documents and, based on its training from search reports and search strategies, it could judge those documents (depending on the type of automation).

Keywords: Patentability, patent search, patent law, utility models, automated search, AI, artificial intelligence, patents, inventions, machine learning, text mining, automation

1.Introduction

Automating the process of finding patentability for utility models would involve using technology and tools to assist in patent search and analysis. Patentability searches are usually performed to determine whether an invention is novel, non-obvious, and has an industrial application or utility, which are key criteria for obtaining a patent. However, it is worth mentioning that utility model law differs from country to country. In some countries or Patent Offices, utility models are not considered patentable. Some Patent Offices, on the other hand, consider utility models as the subject of patent law and therefore patentable as utility models. A few of the offices that consider utility models as the subject of patent law give a patent without a patent search, while other offices that consider utility models as the subject of patent law require a patent search to determine the patentability of utility models. There are many ways to automate the process of finding patentability. It would depend on the level of automation of the patent search, since there are many different ways of the patent search process.

One of the ways would be to use keyword-based searches. During the patent search, human examiners could open patent databases and search for patents using the keywords. The examiner examines the given application and finds the keywords. After that, the examiner searches with keywords in the patent databases like PATENTSCOPE or USPTO. Most of the time, the search gives many documents, and the examiner needs to open and inspect them one by one. This only creates partial automation.

Another option would be using more advanced patent search software or AI. There are many patent search software tools. Examples would be PatSeer, InnovationQ, TotalPatent, etc. AI (artificial intelligence) and machine learning algorithms can help automate the process further. Some AI-driven platforms, such as PatSnap and Innography, can analyse large patent datasets to identify relevant prior art and assess patentability. Those methods would create better automation because they would make patent searches simpler and less time-consuming.

I believe automation of patent search would make the process of finding patentability more efficient. When automating patentability searches, it is also important to know that while technology can assist in the search process, human expertise is often essential to interpret search results and make the final determination of patentability. Automating patentability searches would also benefit Azerbaijan. This could make the examination easier and less time-consuming. This could increase the efficiency of the organization.

2. Literature review

According to the patent law of the Republic of Azerbaijan, the subjects of patents can be inventions, utility models, and industrial designs. In the Republic of Azerbaijan, utility models can only be devices. While inventions have three patentability requirements, utility models have only two. Those are novelty and industrial applications. The devices for novelty conditions must have new characteristics. If the device can be made or used in any field of industry or economy, then the invention is considered applicable [1]

Unlike some other national or regional patent legislations, in the Republic of Azerbaijan, examiners also provide supplementary examinations for utility models. The publication of the utility model occurs only after the patent search. Depending on the patent search, the examiner decides whether to grant or reject the application [1].

In many aspects, national patent laws in Azerbaijan and Russia are similar. According to the Civil Code of the Russian Federation, patents are granted for three subjects: inventions, utility models, and industrial designs [2].

Similar conditions can be found for utility models. In the Russian Federation, as it is in Azerbaijan, utility models can only be devices. Here, they again have two patentability conditions. What are novelty and industrial applications? [2].

According to the Civil Code of the Russian Federation, examiners also provide supplementary examination to utility models. This means that, again, a patent for the utility model could only be granted after the patent search [2].

In the Eurasian Patent Office, the protected subjects of patents are inventions and industrial designs. According to the Eurasian Patent Convention, patentability requirements are novelty, inventive step, and industrial applicability. Therefore, utility models cannot be protected since they mostly do not have inventive steps [3].

Like the different regional Patent Office – European Patent Office (EPO) patentability requirements are novelty, inventive step, and industrial applicability. Therefore, utility models cannot be protected since they mostly do not have inventive steps. The difference from the Eurasian Patent Office is EPO only protects inventions [4].

Utility models could also be protected in the contracting states of the EPO individually. According to Article 140 of the European Patent Convention, Articles 66, 124, 135, 137, and 139 shall apply to utility models and utility certificates and to applications for utility models and utility certificates registered or deposited in the Contracting States whose laws make provision for such models or certificates [5].

In the Republic of Belarus, utility model applications may only be a technical solution. Patentability requirements for utility models here are novelty and industrial applicability. However, utility model applications shall not be subject to verification of compliance with the patentability requirements. Examination must be conducted within three months, and after that, the utility model shall be granted. In case, during the examination, it is found that the application is for a utility model that does not relate to patentable subject matter, the Patent Office shall decide to refuse the grant of a patent. After preliminary examination, utility models are granted without substantive examination [6].

In some countries, a utility model system protects "minor inventions" through a system like the patent system. Compared with patents, utility model systems require compliance with less stringent requirements (for example, a lower level of inventive step), have simpler procedures, and offer shorter terms of protection [7].

According to the German Patent and Trademark Office, utility models are considered a fast IP right. However, there is no examination of novelty, inventive step, and industrial application. However, there is a greater risk for a utility model to be challenged and cancelled. Like the Republic of Belarus, in Germany, after preliminary examination, utility models are granted without substantive examination [8].

In Japan, the process for granting a patent right differs from that for granting a utility model right. In the patent system, an examiner performs a substantive examination for a patent application upon receiving a "request for examination," which must be submitted by the patent applicant or any person other than the applicant within three years of the filing date of the patent application. On the other hand, a utility model is registered without a substantive examination if it meets the basic requirements of the Utility Model Act. According to the law, utility models can only be devices in Japan, too. Utility models must fulfil patentability requirements such as novelty and inventive steps. However, these substantive requirements are not examined. Here again, after preliminary examination, utility models are granted without substantive examination [9].

Other data show conditions of patentability. For a device to be patentable, the invention must: consist of patentable subject matter; be novel and have utility. A patent application must sufficiently describe the device in enough detail to enable a person skilled in the invention's field to make, construct, compound, or use the invention [10].

As mentioned above, the subject of patents and conditions could differ from country to country. However, overall, the national laws of most countries are similar. The main conditions for utility models are that the subject of patents should be new and capable of industrial application. The subjects of the patent are also similar in most countries. Those depend on the national law. Discovery, Scientific theories, mathematical methods; Aesthetic creations; Inventions contrary to morality or public order; Therapeutic and diagnostic methods; and Plant or animal varieties. Plants or animals (other than microorganisms) are usually not considered subjects of the patent [11].

Sometimes, as exceptions to patentability, they also involve software. However, software-implemented inventions might be patentable. The software can also be patentable in some countries, such as the USA, Canada, and some European countries. However, it is not patentable in some other countries, such as the Russian Federation, the Republic of Azerbaijan, etc [1], [2], [11].

To overcome some of these disadvantageous aspects of current keyword-based search approaches, it is necessary to decrease the manual work of the examiner. It is also essential to increase the quality of the search results by avoiding irrelevant patents from being returned, as well as automatically accounting for synonyms to reduce false negatives. This could be achieved by comparing the patent application with existing publications based on their entire texts rather than searching for specific keywords. By considering the entire texts of the documents, much more information, including the context of keywords used within the respective documents, is considered. For humans, it is, of course, infeasible to read the whole text of each relevant document. Instead, state-of-the-art text processing techniques can be used for this task [12].

The search for prior art for a given patent application is, in general, conducted by a single person using keyword searches, which might result in false positives as well as false negatives. Furthermore, as different patent applications are managed by different patent examiners, it is difficult to obtain a consistently labelled dataset. A more reliably labelled dataset would therefore be desirable to rigorously evaluate our automatic search approach [12].

Search for prior art for a given patent application, and thereby the citation process, can be enhanced by a precursory similarity scoring of the patents based on their full texts. With a natural language processing (NLP) based approach, we would not only greatly accelerate the search process, but, as shown in their empirical analysis, our method could also improve the quality of the results by reducing the number of omitted yet relevant documents [12].

The search for a patent's prior art is a particularly difficult problem, as patent applications are purposefully written in a way that creates little overlap with other patents, as only by distinguishing the invention from others does a patent application have a chance of being granted. By showing that the automated full-text similarity search approach successfully improves the search for a patent's prior art, these methods are also promising candidates for enhancing other document searches, such as identifying relevant scientific literature [12].

The work in [13] by K. M. Richmond et al. describes the XAI survey in the field of legal systems, which considers the evidential reasoning needs and other requirements needed to apply AI to law. It is claimed that legal decision-making involves the storage of expert knowledge, precedent, and evidential reasoning; thus, transparency and accountability are vital when it comes to automating the process. The authors note that the current AI systems are often black-box algorithms, which complicates the process of justifying decisions and explaining their reasons to lawyers.

Moreover, a taxonomy of AI methods in legal reasoning is introduced by the authors. They distinguish the following types of AI in legal reasoning: rule-based reasoning, case-based reasoning, argumentation-based reasoning, evidential reasoning, and hybrid approaches. These types connect certain models of legal reasoning to certain AI methods and evaluate the level of explainability of the approaches. Earlier AI systems were based on symbolic AI approaches (such as expert systems), which involved clear rule-based reasoning [13].

One significant contribution of this article lies in the explanation of the trade-off between interpretability and performance. The authors observe that even though deep neural networks are known for delivering important levels of prediction accuracy, they lack interpretability compared to the symbolic approaches. However, this article asserts that interpretability in the legal field is a necessity because of the reasoning needed for making judicial and administrative decisions, which can be understood and reviewed by the involved parties. As such, this research explores the existing XAI methods that seek to increase interpretability but still face numerous challenges [13].

Whereas the study by Richmond et al [13]. It stresses the importance of explainability as a key principle in the application of AI to automate the law; their approach still focuses on decision-making systems and does not classify several types of automation used for patent searches. In contrast, the suggested study attempts to overcome this limitation by developing a system for classifying patent search automation as fully automated, semiautomated, and partially automated, stressing the possibility of automation through deterministic means.

Several countries are already implementing AI tools for examination. For example, in Australia, Data Science techniques are being used to analyse profiles of a patent within the current stockpile and predict the level of manual intervention required from the examiner to progress a patent application to the outcome. The model is used to predict the effort required to conduct a high-quality examination. This approach facilitates the allocation of appropriate resourcing for each examination task, thereby improving examination efficiency [14].

IP Australia's Family Member Analyser (FMA) tool provides patent examiners with direct links to family members and documents from their electronic dossiers (where available) during patent examination. Examiners would often consider observations made in Foreign Examination Reports (FERs) of closely related patent family members to improve examination quality and avoid duplication of work where appropriate [14].

Other countries, such as Austria, Brazil, and China, also use AI for classifying patents. In Canada, they use semantic AI search engines. Semantic search is a set of search engine capabilities that includes understanding words from the searcher's intent and their search context [14].

Some regional Patent Offices, such as the European Patent Office (EPO), also use AI. The EPO has been active in developing business solutions using Machine Learning and AI to manage patent files at various degrees of implementation: Automatic annotation of patent literature; Automatic detection of problem/solution in the patent document; Automatic detection of exclusion from patentability [14].

We could also use text mining tools to investigate patentability. Text mining is also known as text data mining. It is a process of transforming unstructured text into a structured format to identify meaningful patterns. The tools apply advanced analytical techniques, such as Naïve Bayes, Support Vector Machines (SVM), and other deep learning algorithms. In this way, companies can explore and discover some relationships within their unstructured data [15].

Text mining is a process of getting high-quality information from text. With text mining tools like Angoss, DigitalMR, IBM SPSS, and others, the patent examiner might analyse the document much faster. Patent documents usually have significant study results. The documents are usually lengthy and rich in technical terminology. That takes a lot of human effort to analyse. Automatic tools like text mining might make the process faster and more efficient.

Text mining could be done in this order: Firstly, we could use text mining to identify other terms that define the universe of things in which we are interested. Then we could identify the relevant areas and find where those terms fall in the patent classification. After that, we could filter the data by the terms and the patent classifications in the document. Later, we could measure how frequently those terms and classifications appear in the text. In the end, we could use experimental visualisation along the way to evaluate and refine our analysis [16].

Another option we could use for automating the determination of patentability would be machine learning. In recent years, Artificial Intelligence (AI) has been the focus of discussion. In recent years, AI has improved and started to be used widely around the globe. Machine learning libraries will typically make a significant difference in patent analytics. Identifying packages and models that are well-documented and have active communities will allow us to get things done rather than navigating complex layers of documentation or puzzling over what the statistics from a model run mean [16].

Many advanced technologies might help to automate the process of finding patentability. One of the tools could be text mining. Text mining is a process of transforming unstructured text into structured data. With the data, the application performs an easy analysis. It uses natural language processing (NLP), allowing machines to understand human language and process it automatically. With its help, patentability could be automated [17].

Any company, Patent Office, or academic institution that works with patents would benefit from doing patent analytics and machine learning. Patents represent great business value to many organizations, with corporations spending a great deal of money each year developing patentable technology and transacting their rights, and Patent Offices around the world spend a great deal of money each year reviewing patent applications. AI or machine learning might help Patent Offices and companies working with patents [18].

Patent document collections are an immense source of knowledge for research worldwide. The rapid growth of the number of patent documents creates challenges for retrieving and analysing information. There are different patent analysis tasks that have been automated at least partially in the past [19].

The paper [20] introduces an XAI-human collaborative approach to the research of patent novelty. The purpose of the research is to enhance the analysis of patent novelty through the integration of deep learning text classification with human expert feedback due to the inefficiencies of the current black-box approach to patent analysis based on AI. Specifically, the authors state that the current approach to patent evaluation based on AI is concentrated mostly on performance and does not consider the aspect of usability and collaboration.

Three major components of the framework are considered. First, a self-explanatory neural network is trained to classify patent novelty based on historical data. Then, the XAI model is used to make a prediction about novelty and explain it. As a result, a user, especially a technical one, can examine the prediction and give feedback that is further utilized in the training process. According to the experimental results obtained by the authors, the collaborative approach was proven to be effective since the accuracy reached 0.890 and the F1-score was 0.916 [20].

One of the important contributions of the research is the attempt to fill the gap between completely automated AI systems and human knowledge and experience, thus building an intermediate semi-automated approach. As opposed to a complete replacement of human examiners, in this study, the AI is considered as an auxiliary tool for novelty evaluation. According to the authors, explainability promotes trust and applicability, which is particularly important for applications like patent examination [20].

The approach suggested by Jang and Yoon [20], who developed a collaboration-oriented XAI-based model for patent novelty analysis, facilitating human-machine interaction, still lacks full automation due to the necessity of iterative human feedback and retraining of the machine learning algorithm. The present research contributes to the existing literature on the topic by suggesting a formal classification of different approaches to patent search automation into fully, semi-, and partially automated ones, indicating that automation can be reached deterministically as well.

The integration of automation in the patent process can reduce the occurrence of human errors, help to optimize time, and enable more efficient operations. Patent professionals often need to submit an Information Disclosure Statement (IDS) to the United States Patent and Trademark Office (USPTO), along with their patent application, to fulfil their "duty of candour." This duty requires patent applicants to provide their patent examiners with any information they have come across that could affect patentability. Completing an IDS form is just a matter of data entry; it can be quite daunting and time-consuming to input information for each material prior art reference that is known. The development of patent prosecution strategies will never be a completely automated activity. With automation in the patent process, patent professionals can research to find viable office action rebuttals and produce drafts of office action responses in less time without sacrificing quality [21].

In [22], R. Setchi et al. explore the potential use of artificial intelligence tools in patent prior art searches, examining how AI could help patent examiners in the search phase of the examination process. In the research work, the authors propose a proof-of-concept platform, which is created in partnership with the UK Intellectual Property Office and aimed at testing different AI approaches for solving various important tasks in patent prior art search, such as query expansion, document categorization, clustering, semantic similarity identification, ranking, and topic modelling. The authors describe prior art searches as extraordinarily complex, iterative, and human-focused tasks, during which patent examiners continually modify their search strategy according to new terminology and prior art information.

Another great benefit of the paper is the formal breakdown of the patent prior art search process into several technical subprocesses. The researchers use interviews with skilled patent examiners to identify technical requirements, such as improved query expansion (TR1), improved classification of documents into coding schemes (TR2), recognition of semantically similar patents (TR3), and ranking of the most similar documents (TR4). To perform these tasks, the research employs supervised and unsupervised AI approaches like SVM, clustering, and topic modelling to check their applicability for the patent retrieval process [22].

AI is concluded to be useful when used for reducing the time and costs involved in examining patent documents retrieved, particularly when it comes to analysis and ranking. But one of the key findings of this paper is that AI is ineffective in generating queries since this task requires more contextual knowledge of the examiners. Therefore, the human-in-the-loop approach is recommended in which AI serves as the support tool but not a substitute for the examiners [22].

Although Setchi et al. [22], have proven that the use of AI technology helps to enhance the efficiency of prior art search due to its capacity to help with ranking, classification, and semantic similarity detection. The research also proves that AI technologies are still poor in query generation and are highly dependent on the skills of the examiners. That is why it is clear that most of the present patent retrieval systems are still semi-automatic but not fully automatic.

In [23], An assessment study is performed for the problem of AI-enabled prior art search in patents; it further elaborates on earlier research in applying AI to patent searching processes. The research focuses on the question of whether AI can be used in the patent examination process to help reduce the number of irrelevant items and improve search efficiency. The research views the problem of prior art search in patents from the point of view of being knowledge-intensive and iterative, including the construction of queries, definition of terms, determination of relevant IPC classes, and evaluation of retrieved data.

This study explores the use of artificial intelligence throughout various stages in the retrieval process, including but not limited to semantic similarity analysis, ranking, clustering, and classification. Like previous studies, the researchers conducted tests using diverse types of machine learning techniques to find out which approach would work well in helping the examiners locate pertinent prior art. The proposed methodology cannot replace the role of human examiners but rather functions as a decision-making support tool in enhancing efficiency when analysing results after the queries have been made. According to the feasibility study, the use of AI in the analysis phase can reduce the manual efforts required by the examiners to sift through large volumes of results [23].

The most important finding from this study is that AI works best at the downstream stage of searching, which includes ranking and similarity detection, among others, as compared to upstream stages like formulating search queries and choosing appropriate terminologies. The researchers acknowledge that search query formulation is very knowledge-intensive and heavily relies on the technical expertise of the human examiners [23].

Although some researchers [23], have proven that AI-based approaches to patent searching can enhance the effectiveness of search using ranking, clustering, and similarity algorithms; the research has proven that the main search formulation process still relies heavily on human intelligence. This means that these systems are not completely automated but only semi-automated. The proposed research is going to build further on this topic by categorizing patent searches into full, semi-, and partial automation depending on the level of dependency on examiners.

As we can see, automation of patentability would bring its benefits. However, not every national or regional office considers utility models as the subject of patents. Moreover, some countries that consider utility models as the subject of patents do not conduct patentability searches for utility models. But automation would be helpful for Patent Offices (such as the Republic of Azerbaijan, the Russian Federation, etc.) that conduct patentability searches for utility models.

3. Methodology

The paper suggests a theoretical and simulation-based model of the automation of the examination of utility model patentability. This model relies on three scenarios of automation of patent examination: complete automation, semi-automation, and partial automation. The goal of the methodology is not to substitute the official function of the patent examiner, but to create an explicit representation of diverse types of automation that could be utilized in the examination of utility models concerning their industrial applicability and novelty.

The methodological approach is rule-based and process-oriented. It involves (i) legal criteria of patentability of utility models, (ii) searching logic that is used during patent examination, (iii) retrieval techniques based on keyword searches and patent classification, and (iv) the examiner's validation of the results of processing by the system. This model is designed specifically to take into account the practice of examination of patentability of utility models according to Azerbaijani patent legislation, where utility models include only devices examined against the same set of patentability criteria as inventions, with the exception that the subject matter must belong to the object of the utility model.
The proposed framework will be designed in five steps as follows:

1. Input and claim acquisition. The system gets an application that includes its title, claims, descriptions, and other relevant data, such as examiners' search parameters.

2. Technical features extraction. The system extracts technical features, relevant keywords, significant phrases, and other parameters of classification according to IPC/CPC from applications or search parameters provided by examiners.

3. Search and filtering for patentability. The system conducts one or several patentability searches based on combinations of keywords, IPC classes, and semantic/phrase similarity. The scope of this search varies depending on how this framework will be used: as a fully, semi-, or partially automated framework.

4. Decision-making on novelty. The system analyzes the list of prior art documents found and rates them according to their relevance. Depending on the automation type, novelty decisions are made either automatically, reviewed by human examiners, or made only by human examiners.

5. Human validation and decision making. The final decision of patentability is the responsibility of the patent examiner/patent office. The level of human involvement is different according to automation types.

Thus, the described methodological approach treats automation as a range between fully human and fully automatic frameworks.

4. Formal representation of the proposed framework

To put forward the formalized framework, we will consider that a utility model application can be described as:

[U = {T, C, D, K, I]

where: (T) – title of the application; (C) – set of claims; (D) – set of descriptions and other text components of the application; (K) – extracted set of keywords, key terms, and phrases; (I) – identified patent classification set (for example, IPC).

The process of patentability examination will be considered as a function:

[PE(U) = {IA, N]

Where: (IA) – industrial applicability assessment; (N) – novelty assessment.

The automation framework offered does not consider all three elements equal. On the contrary, it separates them into two analytical levels:

1. Rule-based legal/technical assessment level, mainly related to industrial applicability and admissibility of the subject matter of the utility model;
2. Searching and similarity assessment level, mainly related to novelty.

Therefore, the utility model examination model will be presented as follows:

[PE(U) = {R(U), S(U)]

with the following components: (R(U)) is the output of the rule-based assessment; (S(U)) is the output of the search-based patentability.

The output of the rule-based assessment (R(U)) could include whether the claimed invention belongs to the category of utility model objects; whether the claimed technical solution is industrially applicable; and whether the technical content of the application is sufficiently structured for automated search.

The output of the search-based assessment (S(U)) could include retrieved prior art documents, similarity score rankings, labels A, Y, or X, and novelty suggestions based on automation level.

5. Automation systems

According to the Patent Law of the Republic of Azerbaijan, the utility models only require novelty and industrial application. That would mean the inventions lacking the inventive step could also be protected as utility model patents. This would be the core information for creating the automation [1].

One of the first things a human examiner would do to find patentability is to check industrial applications. This is usually done before the patentability search. Regarding the automation would first check if the device is applicable in the industry. Only after that, the automation would check the second patentability requirement, which is novelty.

The automation systems could have different automation levels. Levels of automation could depend on how much human interaction a system needs. With that, we could divide the automated systems into three parts. Those three parts are the fully automated systems, which require little to no human interaction, semi-automated systems, which require some human interaction, and partially automated systems, where the system requires more human interaction than other systems.

Automated systems:

Depending on the type of automation, the algorithm process would be different. However, the systems would also have a similar configuration.

Algorithm of automated systems:

1. Start the process.
2. Scan the input information about the utility model.
3. Find relevant keywords from the scanned input.
4. Identify corresponding CPC or IPC classifications based on the input's content.
5. Check if the device is applicable in the industry:
    a. If yes, proceed to Step 6.
    b. If not, issue a "Refusal of Grant" and terminate the process.

6. Perform a combined patentability search using the identified keywords and classifications.
7. Locate relevant documents from the patentability search.
8. Evaluate if the device has novelty based on the found documents:
    a. If yes, proceed to Step 9.
    b. If not, issue a "Refusal of Grant" and terminate the process.
9. Grant the device as a utility model if all conditions are met.
10. End the process.

The problem with this algorithm arises because it does not let applicants prove a negative decision otherwise. We will need to upgrade Steps 5 and 8.

5. Check if the device is applicable in the industry:
    a. If yes, proceed to Step 6.
    If not, check if the applicant can prove otherwise:
        i. If yes, accept the proof and proceed to Step 6.
        ii. If no, issue a "Refusal of Grant" and terminate the process.
8. Evaluate if the device has novelty based on the found documents:
    a. If yes, proceed to Step 9.
    b. If no, check if the applicant can prove otherwise:
        i. If yes, accept the proof and proceed to Step 9.
        ii. If no, issue a "Refusal of Grant" and terminate the process.

Fully automated system:

Here, the system would scan the application documents and, according to that, conduct a patent search. AI or machine learning would pick useful information from documents and search by them. Later, the system itself would create a patent search report. That search report would be according to the conducted search by a fully automated system. This search system would need zero to no human interaction.

To automate the process of a patent search or substantive examination, firstly, we need to understand the patent search and substantive examination. Usually, the first step during the substantive examination is to determine whether the application is usable in the said industry. The human examiner reviews the application. Later, they decide if the device is functional according to the laws of nature and logic. For example, many Patent Offices immediately decline any "perpetual motion machine" applications. The reason for that is that it is impossible according to the laws of physics. After finding that the device could be used, the examiner conducts a patentability search. During the search, the examiner finds some documents. Those documents could be relevant or irrelevant. That would be decided by the examiner. After deciding which documents are relevant to the topic of the application, the examiner checks the relevant documents. After inspecting them, the examiner decides if any of the found documents harm the novelty of the device. Following this, the examiner creates the search report. Then, according to the search report, the examiner declines or grants a utility model. In accordance with all of that, we could create automation.

The automation of patentability for utility models would first start with scanning the document. After the scan, the automation would find keywords and would identify IPC or CPC classifications. However, this will not be the next step. That is due to the examination process. During the examination, we need to check the industrial application before we check any other patentability requirements. Prior to conducting the patentability search, it is crucial to ensure that the industrial application has been thoroughly evaluated. Therefore, the next step is to find out whether the device could be useful or not. In case it is not applicable in the said industry, the application would be denied. If it is applicable, the automation would conduct a combined patentability search. By combined search, we mean the system would use both keywords and IPC or CPC classifications. During the patentability search, the system would find some documents. After that, the automation would decide if the device was novel. At the same time, the automation would create a patentability search report. If it is not novel, it will be refused. In case the device has novelty, then it would be granted as a utility model.

Now that we have a working system, we must figure out how every process would work. The first process is "Scanning the document". Here, the system would scan the description, the claims, the abstract, and the drawings. The automation would use advanced tools like text mining and image search. With that, the system would identify the topic of the application.

The important part of the identification is that the automation will not just find some words but will find some phrases and concept-based terms. With this, the system would understand the context of the documentation.

After identifying what the application is about, automation will decide if the device is applicable in the said industry. The automation will check the laws of nature and use logical deduction to determine the applicability.

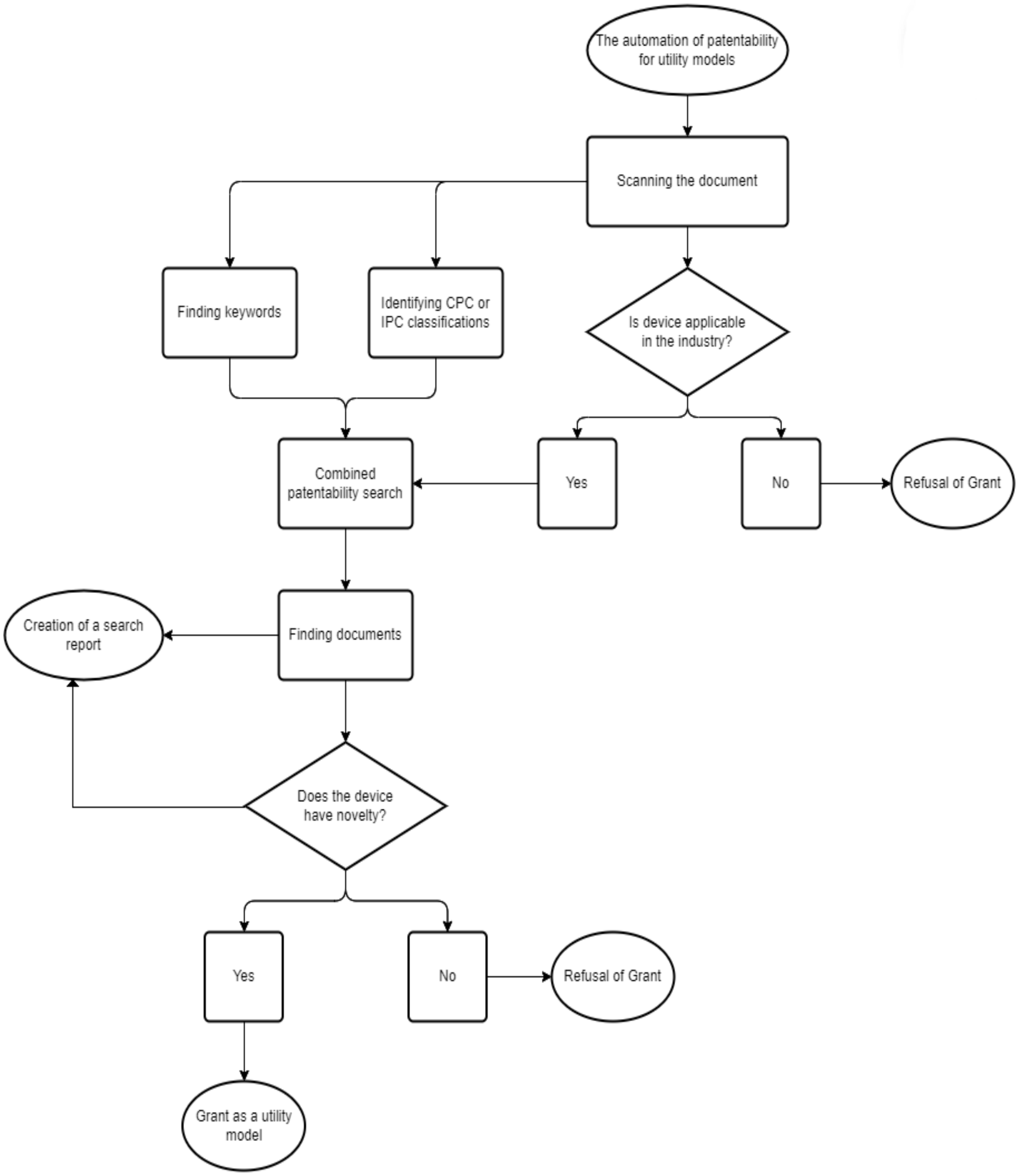
The next step after scanning the document would be finding suitable keywords and patent classifications. With an understanding of the context of the document, the system would identify the appropriate classification and keywords.

After deciding that the device has applicability in the said industry or after the applicant proves industrial applicability, the automation would conduct a combined patentability search. A combined search consists of using keywords and classifications.

The system would find a number of documents after searching. Those would be closest to the application examined according to the automation. The next steps would be finding if the device is novel and, according to that, creating a search report. If the application is not novel and the applicant cannot provide the necessary proof of novelty, the utility model would be refused. Otherwise, it would be granted.

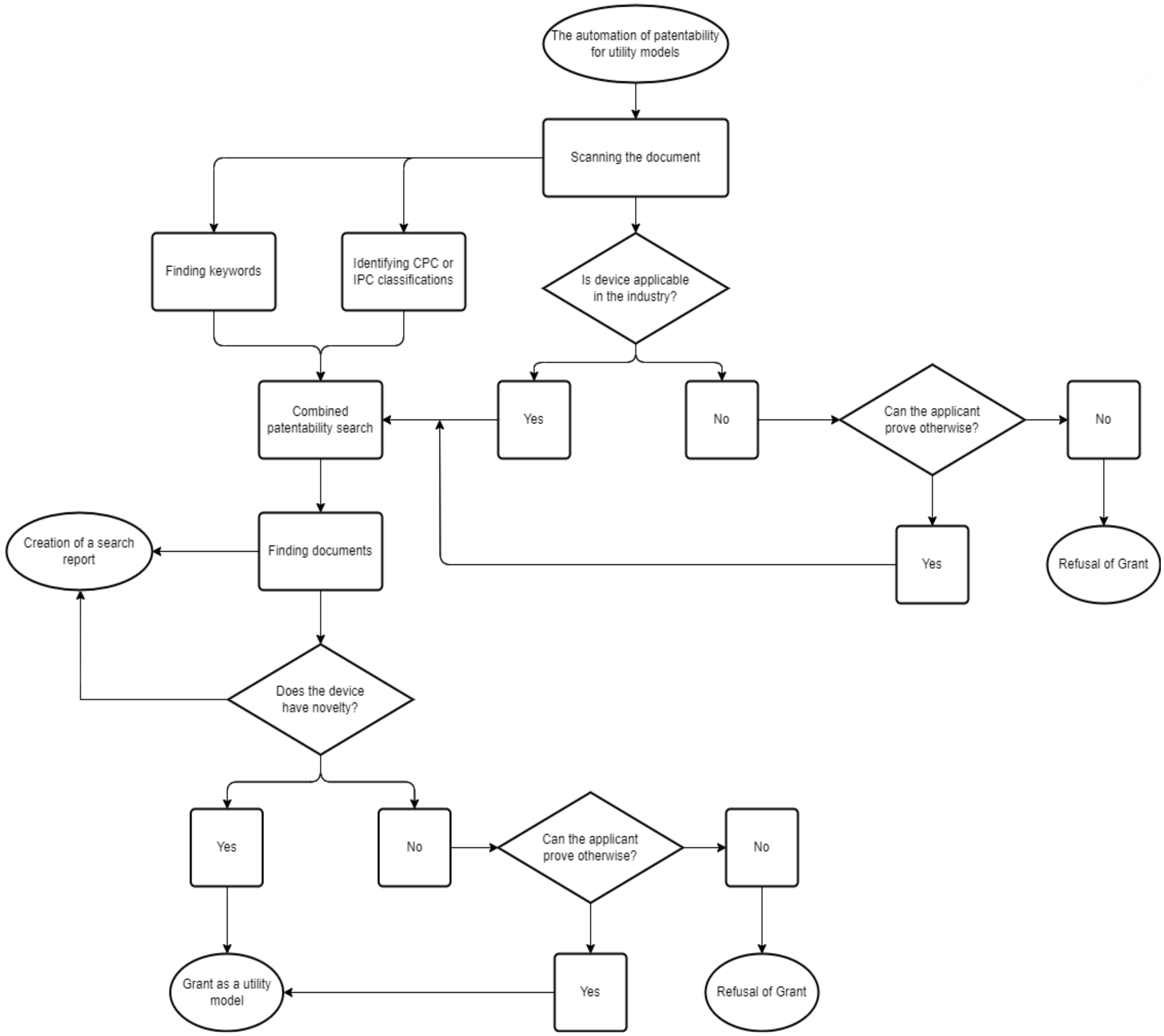
The automation also creates a patent search report, and depending on the national or regional law of the Patent Office, the system could send the report to the applicant. That would save time and prevent exhaustion of the human examiners. By doing this, we can also minimize the likelihood of human error. On the other hand, no inspection by the human examiners could lead to programming or computer errors. AI might find non-harmful documents for the application. It might also misjudge the documents. For example, the system might find that "The application doesn't have novelty", while the application does have novelty.

Another problem of a fully automated system is that it has zero to no human interaction. A patent examiner's view on a subject is essential. It does not matter how good AI or machine learning can be; I believe the view of a human expert will always be important. Another problem that could occur during the process of full automation is that automation might not be perfect, and it might find some wrong, unrelated documents.



Scheme 1 – Block scheme (flowchart) of finding patentability for a utility model (fully automated)

The automation might seem complicated. However, it is almost perfect. The only problem is it makes the human or artificial examiner's decision final. That is mostly right, but it means there is no room for appeal. That means we need to let the applicant try to explain and prove why the examiner's decision is incorrect. That means whenever a patentability requirement is not present, we need to let the applicant try to prove otherwise. Meaning the algorithm would look more like this.



Scheme 2 – Block scheme (flowchart) of finding patentability for a utility model with possible appeal (fully

Algorithm of the fully automated system:

For most of it, the algorithm of a fully automated system would be like the algorithm of general automation. However, it would have a few distinctive characteristics. In comparison to the general algorithm, the fully automated system would have slightly different Steps for Steps 2, 3, 4, and 8.

2. Scan the document to extract necessary information about the utility model.
3. Find relevant keywords from the scanned document.
4. Identify corresponding CPC or IPC classifications based on the document's content.
8. Evaluate if the device has novelty based on the retrieved documents:
    a. If yes, proceed to Step 9.
    b. If no, check if the applicant can prove otherwise:
        i. If yes, accept the proof and proceed to Step 9.

   ii. If no, issue a "Refusal of Grant" and terminate the process.
  c. Create a search report for the evaluation.

The difference in Step 2 in the fully automated system is that it scans the documents and gets the information from them. In the general algorithm, we have input information that could be provided by the human examiner.

Similarly, in Steps 3 and 4, the fully automated system finds relevant keywords and classification from scanned documents.

In Step 8, we have an extra "create a search report" feature.

Semi-automated system:

Here, the system would again scan the application documents and, according to that, will conduct a patent search. AI or machine learning would pick useful information from documents and search for it. However, this is where the automation would stop. The automation would not create a search report. After inspecting the found documents, the human expert would create a patent search report. That search report would be according to the conducted search by a semi-automated system. This search system would need some human interaction. In basic terms, the semi-automated system is a fully automated system that requires human verification for important decisions.

The sequence of the process is shown in the scheme above. Now we must figure out how every shown process would work in a semi-automated system. As mentioned above, a semi-automated system is remarkably similar to a fully automated system. The difference is that a semi-automated system requires human verification or control.

The first process in the sequence is "Scanning the document". Here, the system would scan the description, the claims, the abstract, and the drawings. The automation would use advanced tools like text mining and image search. With that, the system would identify the topic of the application. The system would find some phrases and concept-based terms, which would help the automation understand the context of the documentation. The next step after scanning the document would be finding suitable keywords and patent classifications.

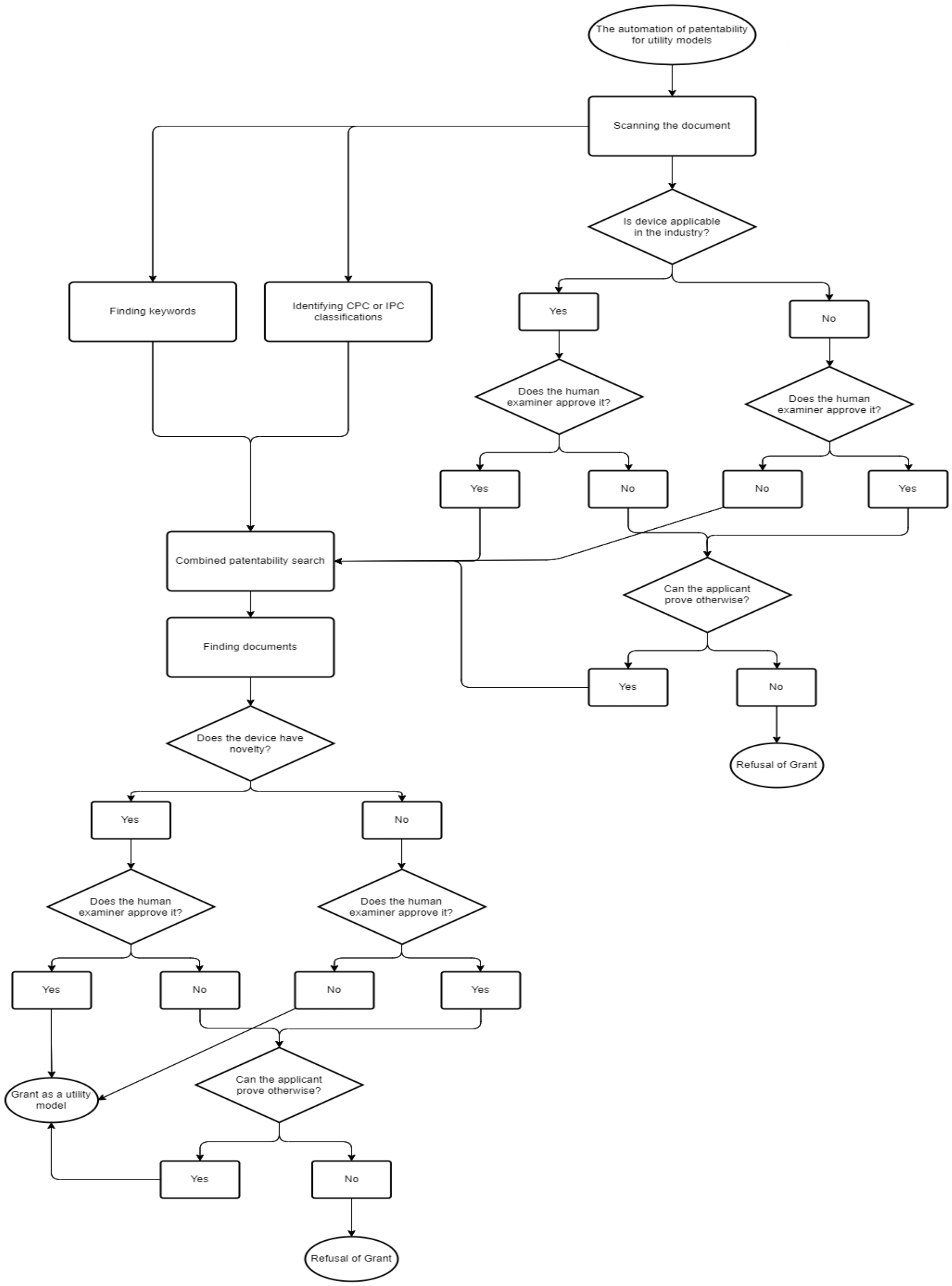
Then the automation will decide if the device is applicable in the said industry. The automation will check the laws of nature and use logical deduction to determine the applicability. However, whether it is right or wrong would be checked by the human examiner.

After deciding that the device has applicability in the said industry or after the applicant proves industrial applicability, the automation would conduct a combined patentability search. A combined search consists of using keywords and classifications.

The system would find a number of documents after searching. Those would be closest to the application examined according to the automation. The next step would be finding if the device is novel. This process would be conducted by automation and checked by the human examiner. Here, the system would not create the search report. It could later be created by the human examiner. If the application is not novel and the applicant cannot provide the necessary proof of novelty, the utility model would be refused. Otherwise, it would be granted as a utility model.

The semi-automated system would be perfect for conducting a patent search. Here, we get a large amount of automation and inspection by a human examiner. The only problem that could occur during a semi-automated system is that the automation might not be perfect. Therefore, it might find the wrong documents.

During the substantive examination, the human examiner conducts a patentability search. The semi-automated system will streamline and enhance the patent search process. However, in this system, there would be some human interaction. The system would conduct a patent search amazingly fast. It would not create a patent search report. The search report would be created by the human examiner. That would again save time and prevent some fatigue for the human examiners. By doing this, we can decrease the likelihood of human error. There could be some programming or computer errors. However, those errors would be inspected and corrected by the human examiner. On the other hand, this might lead to human errors. Since the results of a patent search depend on the opinion and are not fully definite, we cannot fully say whether humans, and AI would make a better decision.



Scheme 3 – Block scheme (flowchart) of finding patentability for a utility model with possible appeal (semi-automated)

Algorithm of the semi-automated system:

The algorithm of the semi-automated system has two main differences from the algorithm of a fully automated system. The differences are in Steps 5 and 8.

5. Check if the device is applicable in the industry:
    a. If yes, ask the human examiner for approval:
        i. If the human examiner approves, proceed to Step 6.
        ii. If no, check if the applicant can prove otherwise:
            1. If yes, accept the proof and proceed to Step 6.
            2. If no, issue a "Refusal of Grant" and terminate the process.
    b. If no, ask the human examiner for approval:
        i. If the human examiner approves, check if the applicant can prove otherwise:
            1. If yes, accept the proof and proceed to Step 6.
            2. If no, issue a "Refusal of Grant" and terminate the process.
        ii. If the human examiner disapproves, proceed to Step 6.
8. Evaluate if the device has novelty based on the retrieved documents:
    a. If yes, ask the human examiner for approval:
        i. If the human examiner approves, proceed to Step 9.
        ii. If no, check if the applicant can prove otherwise:
            1. If yes, accept the proof and proceed to Step 9.
            2. If no, issue a "Refusal of Grant" and terminate the process.
    b. If no, ask the human examiner for approval:
        i. If the human examiner approves, check if the applicant can prove otherwise:
            1. If yes, accept the proof and proceed to Step 9.
            2. If no, issue a "Refusal of Grant" and terminate the process.
        ii. If the human examiner disapproves, proceed to Step 9.

In both steps, the system asks for clarification from a human examination. Different from the fully automated system, this system needs human examiners' opinions. In addition to step 8, the system would not create a search report. The search report would be created by the human examiner.

Partially automated system

Here, the system would not scan the application documents. It would conduct a patent search according to the search information provided by the human examiner, or the system would scan a specific document provided by the human examiner. AI or machine learning would use that search information and conduct a search. This is again where the automation would stop. The automation would not create a search report; it would only find some documents, and the human examiner would need to check them. Here, the automation would not decide the novelty. It would strictly be done by the human examiner. After inspecting the documents found, the human expert will create a patent search report. That search report would be according to the conducted search by a partially automated system. This search system would need more human interaction than other systems. In a way, a partially automated system is a semi-automated system that requires more human verification and control.

The sequence of the process is shown in the scheme above. The first step in the sequence is "The information provided by the human examiner". Here, a human examiner can write some search information, like keywords, patent classifications, the name of the device, etc. Or a human examiner could provide a document for scanning. For example, the examiner could provide the claims documents only. In this case, the system would scan the claims and use the necessary information.
The next step is "Scanning the information". Here, the system would scan the information provided by the human examiner. The automation would use advanced tools like text mining and image search. With that, the system would identify the topic of the application. The system would find some phrases and concept-

based terms, which would help the automation understand the context of the documentation. The next step after scanning the document would be finding suitable keywords and patent classifications. The search information could be delivered by the examiner, or the system could scan a specific document for that.

Then the automation will decide if the device is applicable in the said industry. The automation will check the laws of nature and use logical deduction to determine the applicability. However, whether it is right or wrong would be checked by the human examiner.

After deciding that the device has applicability in the said industry or after the applicant proves industrial applicability, the automation would conduct a combined patentability search. A combined search consists of using keywords and classifications.

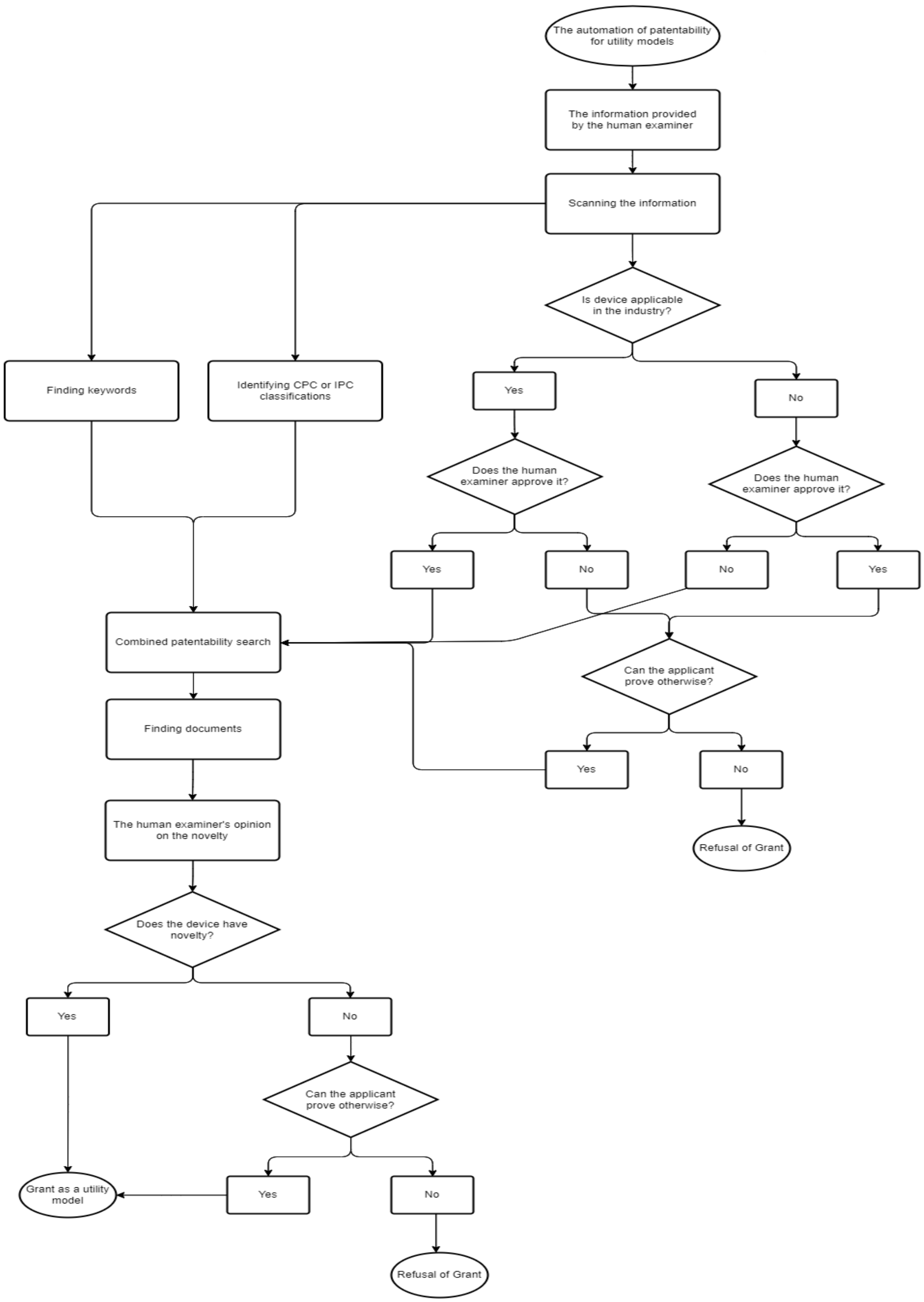
The system would find a number of documents after searching. Those would be closest to the application examined according to the automation. Then the human examiner would analyse them. The automation would not give any opinion regarding the novelty of the device.

The next step would be figuring out if the device is novel. This process would be conducted by a human. The system would not create the search report. It could later be created by the human examiner. If the application is not novel and the applicant cannot provide the necessary proof of novelty, the utility model would be refused. Otherwise, it would be granted as a utility model.

The partially automated system would be perfect for conducting a patent search for some Patent Offices. Not every Patent Office has open patent databases to everyone. Therefore, they might want to use a partially automated system to keep the examined application more secretive. Here, we get some amount of automation and inspection by a human examiner. The problem that could occur during a partially automated system is that a human examiner would need to do most of the work. Therefore, there might not be much automation. Also, we need to note that automation might not be perfect, and it might find the wrong documents. Because of the limited information, the conducted search might be incomplete.

In this system, there would be more human interaction than in the other systems. The system would conduct a patent search. Regardless of the automation, the patent search will not be fast and could be unreliable. This is due to the lesser automation. The system would have limited automation and would not have access to the whole document. It would conduct a patent search regarding some keywords, or it would scan a specific document provided by the human examiner. The found documents would be inspected by the human examiner. That might save time. However, it would not prevent fatigue for human examiners. Because the human examiner would need to check the documentation to create a patent search report. The limitation of automation would mean that the system would find more documents. There could again be some programming or computer errors. However, those errors would be inspected and corrected by the human examiner. On the other hand, this might lead to human errors. Since the results of a patent search depend on the opinion and are not fully definite. Those systems would not be much different from key-based searches on patent databases. That makes those systems less helpful since it creates a slight difference.

The important thing to remember is that not every Patent Office will implement this automation. That is because not every Patent Office has utility models as a subject of a patent. Moreover, in some Patent Offices, utility models are granted without a patentability search. Therefore, implementing this automation would be unnecessary for some Patent Offices. Another point is that Patent Offices that grant utility models without a patentability search could implement this automation. The automation is simple and mostly requires little to no human interaction. Therefore, implementing automation could improve the quality of a grant of utility models. We can also see many countries already implementing AI and modern technologies in their national and regional offices for examination of patentability. This increases efficiency and saves time. The automation of finding patentability for utility models would use an AI with techniques like machine learning algorithms, natural language processing (NLP), or others. Important tools it would use are text mining, search by image, search by significant phrases, sentences, or concept-based terms, etc. It would imitate the process done by the human examiner. The process would involve checking patentability requirements and conducting a patentability search. First, the automation will thoroughly inspect industrial applications. Then, it will check the novelty of the device.



Scheme 4 – Block scheme (flowchart) of finding patentability for utility model with possible appeal (partially automated)

Algorithm of the partially automated system:

The algorithm of the partially automated system is like the general algorithm of automation and to the algorithm of the semi-automated system. The said algorithm has some extra steps in comparison to the other systems.

1. Start the process.
2. Get the input information provided by the human examiner.
3. Scan the input information to extract necessary information about the utility model.
4. Find relevant keywords from the scanned input information.
5. Identify corresponding CPC or IPC classifications based on the input information's content.
6. Check if the device is applicable in the industry:
    a. If yes, ask the human examiner for approval:
        i. If the human examiner approves, proceed to Step 7.
        ii. If no, check if the applicant can prove otherwise:
            1. If yes, accept the proof and proceed to Step 7.
            2. If no, issue a "Refusal of Grant" and terminate the process.
    b. If no, ask the human examiner for approval:
        i. If the human examiner approves, check if the applicant can prove otherwise:
            1. If yes, accept the proof and proceed to Step 7.
            2. If no, issue a "Refusal of Grant" and terminate the process.
        ii. If the human examiner disapproves, proceed to Step 7.
7. Perform a combined patentability search using the identified keywords and classifications.
8. Locate relevant documents from the patentability search.
9. Wait for the input of human examiner regarding the novelty.
10. Evaluate if the device has novelty based on the human examiner's opinion:
    a. If yes, proceed to Step 11.
    b. If no, check if the applicant can prove otherwise:
        i. If yes, accept the proof and proceed to Step 11.
        ii. If no, issue a "Refusal of Grant" and terminate the process.
11. Grant the device as a utility model if all conditions are met.
12. End the process.

The algorithm takes limited input information from the general automation and human examiner's opinion from the semi-automated system.

Principle of operation:

Now that we understand a system, let us discuss how it would work. NLP machine learning-based AI is one of the foundations of any automotive (fully, semi, and partially automated) system.

Please note that we are reviewing the legislation of Azerbaijani Patent Law, and therefore, the AI will operate according to Azerbaijani Patent Law.

Training:

The first important part is training AI. AI training would consist of using human-made patent search reports.

The process of training:

Firstly, we would select human-made patent searches. Then, we would introduce the claim documents and a search report of the application to AI. The claim documents are the most important part of patent documentation, as they hold the most significant elements of the utility model. From this AI would start to understand how to do a patent search. With search reports, we would also use search strategies, which would hold the information of the patent search process. Here, AI would learn how to classify the application based on previous searches. The main classification the AI would use is IPC since it is the most used one in the Republic of Azerbaijan. Later, AI would learn which keywords and key terms to use during the patent search. In addition, AI would also learn from search reports how human examiners determined the documents found. The main elements used during the search are "A", "Y" and "X". "A" means the found document is close to the examined application without damaging any patentability requirements. "Y" means the found document is close to the examined application and is damaging the inventive step requirement of the patent. "X" means the found document is close to the examined application and is damaging the inventive step and novelty requirement of the patent. In this case, “Y” will not be important as inventive step is not a requirement for a utility model. Using how human examiners made decisions, AI could identify and make decisions from the found documents. However, this will not be the end of the training as there is always room for improvement. The AI conducting a patent search would be tightly controlled by the human examiner, who would check if the AI's reasoning were right or not. In addition, the AI would also be taught how to use some logical operations such as "AND", "OR", etc. This would help AI to operate in various databases. Also, if the said AI would check the industrial application of the invention, it would need training in logic and related scientific fields. For this, we would use a structured knowledge base. Here, you will find significant information such as scientific and technical databases, patent databases, regulations, and standards, etc.

The process of decision-making:

The decision-making process primarily consists of two key components: assessing the industrial application and determining novelty.

Industrial application: Usually human examiners check industrial application before conducting a patent search. There are two main ways to approach this: a human examiner can check for industrial applications, or the process can be automated. The automation would involve AI to learn some real-world logic and natural sciences such as physics, chemistry, etc. The field of science would depend on the operational field of the utility models. For instance, the utility model could involve engines, which would require knowledge of mechanics. Alternatively, it could pertain to a new chemical compound, necessitating expertise in chemistry. Although in the Republic of Azerbaijan utility models could only be devices. That means in our case AI would need and expertise on the field of physics and mechanics. In general, the AI here would have data and knowledge bases that would have the necessary information. From what the AI would be able to decide whether the utility model is applicable in the said industry or not. If it is found not applicable, then the human examiner or the AI would create a notification related to it. This process is done to decrease errors and give a chance to the applicant to prove otherwise.

Novelty: This is the last patentability requirement checked by the examiner. During this phase, the examiner conducts a patentability search. According to the search results human examiner decides whether the utility model is novel or not. For automation, we could again use AI. How would AI conduct a patent search? Firstly, the AI would need access to the keywords, key terms, classification (IPC), and databases. The keywords, key terms and classifications could be given in two ways. It could be given by the human examiner or by AI that would scan the claim documents. How would the scanning of the document work? The AI would be implemented by OCR capabilities, which would give access to AI to read the claim documents. From that, AI would do some data mining to find some keywords, key terms, and classifications. According to the Azerbaijani Patent Law, the claim documents are written in two languages. Since the AI would be implemented in Azerbaijan the found keywords and key terms would be in Azerbaijani and Russian. But since we are also searching some English-implemented databases such as PATENTSCOPE, Espacenet and USPTO, AI would also have a translating function. The translation function would also be based on machine learning and would be monitored to ensure the right translation. We would use the API of patent databases. Having APIs of databases would give access to those databases, therefore, AI could use keywords, key terms, and classifications or a combination of them. Lastly, AI would find a few documents at the end, and then it could judge (depending on the type of automation). If it is found not to have a novelty, then the human examiner or the AI would create a notification. The process would be done to decrease errors and give a chance to the applicant to prove otherwise.

Search model and retrieval logic:

The search model uses a mixture of title terms, noun keywords, adjective keywords, configuration keywords, and IPC classes. Let the search query be denoted as:

[Q = {Q_T, Q_N, Q_A, Q_C, Q_{IPC}}]

where (Q_T) is the title-based query component; (Q_N) is the noun keyword component; (Q_A) is the adjective/qualifying feature component; (Q_C) is the configuration or relation-based component; (Q_{IPC}) is the patent classification component.

The total similarity score can be separated into two categories:

[S_Y = f (S_T, S_N, S_A, S_{IPC})]

[S_X = f (S_T, S_N, S_A, S_{IPC}, S_C)]

where (S_T) is title similarity; (S_N) is noun keyword similarity; (S_A) is adjective/feature similarity; (S_{IPC}) is IPC similarity; (S_C) is configuration similarity.

The former one (S_Y) is used to check the closeness of the found document to decide about its suitability for novelty or inventive step relevance. The latter one (S_X) includes the similarity at the configuration level and is expected to have an anticipation or inventive step damage effect.

Threshold values can be assigned as follows: Label A if ($5.5 < S_Y$); Label Y if ($S_Y > 7.5$); Label X if ($S_X > 9$); Ignore if ($S_Y < 5.5$). These threshold values are conceptual and can later be adjusted through empirical testing.

Rule-based methodology for utility model examination:

As utility models apply only to devices, there is a set of preliminary subject-matter rules in the framework. The stage is not aimed at novelty assessment, but at legal and technical feasibility filtering.

Examples of such rules include:

Rule 1 - Device determination

IF the subject matter of the claim refers to a technical device, apparatus, mechanical structure, physical combination, or arrangement of parts,

Then, proceed to the utility model examination.

Rule 2 - Non-device exclusion

IF the subject matter of the claim refers exclusively to a method, process, algorithm, or non-device solution,

Then, utility model protection shall not be applied within the utility model framework.

Rule 3 - Presence of technical features

IF the claim contains technical features that can be correlated to structural or functional parts of the solution,

THEN conduct a patentability search.

Rule 4 - Industrial applicability

IF the technical solution disclosed by the claim can be produced, assembled, used, and applied in an industry,

THEN industrial applicability = YES.

Rule 5 - Industrial applicability failure

IF the technical solution disclosed by the claim is impossible to reproduce, violates physical laws, or has no technologically feasible industrial application,

THEN industrial applicability = NO.

Thus, the rule-based phase plays the role of a gate from the technical and legal points of view prior to or along with the novelty search.

Comparison with existing frameworks:

In this sense, the proposed framework diverges from existing frameworks for analysing patents using AI and search technologies in multiple ways.

Firstly, most current frameworks using AI in patent analysis are aimed at faster prior art searches, semantic similarity assessment, or patent landscape analysis. On the other hand, the current framework relies on the legal process of patentability examination, which includes industrial applicability, novelty, and inventive step of the invention.

Secondly, many current research papers deal with inventions in general rather than specifically with the legal concept of utility models. Examination of utility models implies an extra filter as the subject matter should be a device. For this reason, a preliminary rule-based step is included in the proposed framework that will determine whether the object is suitable for utility model protection.

Thirdly, the proposed framework divides all automation processes into fully automated, semi-automated, and partially automated, while existing frameworks usually speak about AI usage in general.

Fourth, the proposed framework is based on combining rule-based and similarity search approaches. In patent AI literature, there is a strong focus on using machine learning or semantic search techniques, but not on integrating law reasoning and searching logic as well as human checking, into one examination-oriented system.

The comparison could be formulated in the following way:

1. Classical tools for searching information in patent databases. Advantage: good availability of the prior art and structured searching fields. Drawback: requires high qualifications of an examiner and does not consider the patentability issues.
2. AI-supported prior art retrieval systems. Advantage: good capabilities in semantic searching, keyword expansion, ranking, and similarity retrieval. Drawback: can be limited only to the retrieval phase and are not integrated into the decision-making about patentability.
3. Patent novelty prediction models. Advantage: They are useful for evaluating novelty scores. Drawback: usually limited by the claim-document comparison and does not consider industrial applicability, legal responsibility, or utility model subject matter filtering.
4. Proposed framework. Advantage: integrates all the above aspects in one system dedicated to the utility model examination process.

Discussion: legal responsibility, explainability, and AI governance:

Legal liability in connection with the outcome of patentability examination represents one of the fundamental problems in the automation of this procedure. In the case when the automated system conducts a search, scoring, or preliminary patentability evaluation, the legal action of granting or denying a patent or utility model still lies within the competence of the respective patent office and, in fact, of the human examiner.

That is why the suggested architecture must be considered a system for decision-making assistance, not an independent legal entity. This aspect is especially important for those cases where: the system cannot find the appropriate prior art; the system gives the wrong recommendation about novelty or inventive step; the system generates an inaccurate explanation or rating.

In these situations, legal responsibility must lie with the human-driven examination procedure, not with the software.

Explanation capability is critical in the process of patentability examination for three main reasons. The first reason is that patentability judgments must be well-reasoned and replicable. In case there is any retrieval of a prior art document that poses harm to novelty and inventive step, the examiner must be able to comprehend the reason that the document was retrieved, and what claims were matched.

The second reason is that an explanation capability is needed for the examiner's trust. Patent examiners are not likely to use a system that provides a relevance score but does not disclose the role of title, IPC classification, noun keywords, adjective features, or configuration components.

The third reason is that explanation capability is required for legal defensibility. In case of any objection from the applicant regarding the rejection or the relevance of the cited document, the office should be able to explain the grounds for using the system in support of the examiner's judgment.

Hence, it is reasonable to prefer the architecture for the proposed system that includes visualized keywords and IPC extraction; weighted search terms; threshold values; distinct title, noun keywords, adjective keywords, and configuration similarities; and human evaluation of the output.

The requirement for explainability also promotes the employment of semi-automated or partially automated algorithms because these algorithms inherently maintain an interpretable logic chain.

AI's employment for purposes of patent examination presents issues regarding governance related to transparency, confidentiality, data quality, bias, reproducibility, and oversight. The Patent Office's work involves applications that have not been published, confidential information about the applicants, and make important decisions. Therefore, any AI-supported system employed for patent examination needs to be governed.

At least the following requirements of governance should be considered: one. Human supervision. The examiner should have the power to accept, refuse, or correct the work of the system. 2. Traceability. Search strategy, weights, documents retrieved, as well as intermediate scoring, should be saved to restore the process of reasoning in case of need. 3. Confidentiality and security. If the system operates on unpublished applications, the patent office should ensure that the data of applications is not accessible to any external AI system or to third parties. 4. Control over bias and validation. Periodical testing of the system on patentability cases from various areas or in various languages should be conducted to ensure that the quality of retrieval is not too low for some areas or languages. 5. Governance of updates. In case the system uses machine learning or dynamic weighting, any updates to the model should be documented and versioned since a future update can affect the processing of similar applications. Therefore, the governance issue does not lie in the technicality of the issue. It has more to do with the embedding of the automated process within the institutional framework of the patent office's decision-making process.

Limitations

It is important to note that automation would specifically streamline the process of conducting patent searches and speed up the substantive examination process. It would not automate any other part of the examination. For example, it will not be useful during the preliminary examination. For utility models, the system would check patentability requirements. It would not automate anything other than that. The system would be a great tool for speeding up the process of granting or refusing a utility model.

Conclusion

Automating the process of finding patentability offers several advantages, making the search more efficient and effective. Automation reduces the time required for patent searches. It is also necessary to point out that automation would great tool for patent examiners. They could be searching for a single patent or conducting extensive patent landscaping, much easier with the help of automated systems.

AI or machine learning, with the help of advanced tools like text mining, could find relevant documents and could conduct a patent search for the application. The automation of finding patentability for utility models would use an AI with techniques like machine learning algorithms, natural language processing (NLP), or others. Important tools it would use are text mining, search by image, search by significant phrases, sentences, or concept-based terms, etc. It would imitate the process done by the human examiner. The utility models only require novelty and industrial application. The process would involve checking patentability requirements and conducting a patentability search. First, the automation will thoroughly inspect industrial applications. Then, it will check the novelty of the device.

Levels of automation could depend on how much human interaction a system needs. With that, we could divide the automated systems into three parts. Those three parts are the fully automated systems, which require little to no human interaction, semi-automated systems, which require some human interaction and partially automated systems, where the system requires more human interaction than other systems.

Usually, the first step during the substantive examination is to determine whether the application is usable in the said industry. Human examiners check industrial applications before conducting a patent search. The automation would involve AI to learn some real-world logic and natural sciences, such as physics, chemistry, etc. The field of science would depend on the operational field of the utility models. In the Republic of Azerbaijan, utility models could only be devices. That means in our case, AI would need expertise in the field of physics and mechanics. In general, the AI here would have data and knowledge bases that would have the necessary information. From what the AI would be able to decide whether the utility model is applicable in the said industry or not. If it is found not applicable, then the human examiner or the AI would create a notification related to it. This process is done to decrease errors and give the applicant a chance to prove otherwise.

Novelty is the last patentability requirement checked by the examiner. During this phase, the examiner conducts a patentability search. According to the search results, a human examiner decides whether the utility model is novel or not. For automation, we could again use AI. Firstly, the AI would need access to the keywords, key terms, classification (IPC), and databases. It could be given by a human examiner or by AI that would scan the claim documents. The AI would be implemented with OCR capabilities, which would give the AI access to read the claim documents. From that, AI would do some data mining to find some keywords, key terms, and classifications. According to the Azerbaijani Patent Law, the claim documents are written in two languages. Since the AI would be implemented in Azerbaijan, the found keywords and key terms would be in Azerbaijani and Russian. But since we are also searching some English-implemented databases such as PATENTSCOPE, Espacenet, and USPTO, AI would also have a translating function. The translation function would also be based on machine learning and would be monitored to ensure the right translation. We would use the API of patent databases. Having APIs of databases would give access to those databases; therefore, AI could use keywords, key terms, and classifications, or a combination of them. Lastly, AI would find a few documents at the end, and then it could judge (depending on the type of automation). If it is found not to have novelty, then the human examiner or the AI would create a notification. The process would be done to decrease errors and give the applicant a chance to prove otherwise.

The important thing to remember is that not every Patent Office will implement this automation system. That is because not every Patent Office has utility models as a subject of a patent. Moreover, in some Patent Offices, utility models are granted without a patentability search. Therefore, implementing this automation would be unnecessary for some Patent Offices. Another consideration is that Patent Offices that grant utility models without conducting patentability searches could incorporate this automation. The process is straightforward and requires minimal human intervention. Therefore, integrating automation could enhance the quality of utility model grants.

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The Role of Artificial Intelligence in Human Resource Management

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Abstract: AI technology has greatly helped improve the accuracy of talent acquisition, predictive performance analytics, as well as developing effective HR strategy and human resource management (HRM). However, challenges remain, for instance, fears over data privacy, potential algorithm bias in AI, and the retention of human-centeredness against the backdrop of technological advancements. This paper analyzes the diverse applications of AI technology in human resource management (HRM), ranging from recruiting to employee engagement and innovative HR planning. In order to develop clear, ethical, and unbiased AI solutions that are efficient in terms of technology yet intuitive from a human perspective, organizations have to take into consideration the ethical dimensions of the new technologies.

Keywords: human resource management, artificial intelligence, recruitment, employee performance, HR analytics

1. Introduction

Artificial intelligence (AI) has emerged as a major driver of digital transformation across various sectors, including human resource management (HRM). One such field is HRM. HRM activities such as recruitment, selection, training, and employee development have traditionally been time-consuming and prone to human error or discrimination.. But with developments in AI, these processes are getting smarter and more efficient. Through artificial intelligence, large volumes of job applications can be analyzed and selected as per predetermined standards of suitability

Studies carried out under the umbrella of Human Resource Management have significantly contributed to the comprehension of AI's applicability and importance. The main objective of this study lies in revealing concrete cases of utilizing AI technologies in order to automate tasks that are usually handled by HR experts. Indeed, nowadays, algorithms are capable of conducting preliminary interviews with candidates, evaluating their qualifications, and predicting their future performance [1], [2]. One may state that there are some gaps in relation to existing research on the topic, which focuses on the practical aspect and, thus, does not provide any theoretical basis. Furthermore, even in the case of tangible advantages of using AI in Human Resource Management, there are no clear solutions concerning the ethics of AI application [3], [4].

However, an important gap remains in the existing literature regarding the ethical implications and human-centered challenges associated with the adoption of AI in HRM. Although the current studies have made it clear that the use of AI in HRM does have several benefits, it must also be recognized that there is no information about the implications of its use. This is what the present study intends to bridge. This research

aims to provide a comprehensive perspective on the role of AI in HRM by adopting diverse viewpoints and methodologies.
This research aims to provide a comprehensive perspective on the role of AI in HRM by adopting diverse viewpoints and methodologies. Accordingly, this study addresses the following research question: How is AI used to drive strategic change in human resource management, and what risks and challenges are associated with its implementation?

2. Methodology

This study adopts a qualitative and conceptual research approach based on a review and synthesis of existing academic literature on the application of artificial intelligence in human resource management. The analysis focuses on the major applications of AI in HRM, including recruitment and selection, employee training and development, performance management, and HR analytics. It also examines the key challenges associated with AI adoption, particularly data privacy, algorithmic bias, fairness, transparency, and the potential over-reliance on automated decision-making. The reviewed literature is synthesized to provide a comprehensive understanding of the opportunities and challenges of integrating AI into HRM and to highlight the importance of maintaining a human-centered approach to AI-driven HR practices.

3. Literature Review

Analysis of the interconnections between Artificial Intelligence and Human Resource Management has become more and more common recently, and continues its evolution. The initial studies in this field tended to be more instrumental and viewed the role of AI in HRM as a kind of tool that helps streamline HRM operations. The paper by Sithambaram and Tajudeen (2022), which is dedicated to using AI in HRM operations, can serve as an illustration [5]. According to Sithambaram and Tajudeen, artificial intelligence was able to complete various routine tasks typical for HRM, including resume analysis and interview scheduling, thus saving HR professionals' time and energy [5].

In view of the advancements in AI technologies, attention has been paid to AI's predictive capabilities. It was observed that AI would not only be capable of performing routine tasks, but also help in the interpretation of a vast amount of information to draw out some significant conclusions. This is best exemplified by the work done by Kakulapati et al. (2020) using long-term HR data. According to them, AI could be used for matching employees with suitable job roles [6], [7]. Nevertheless, recent trends are taking into account the use of AI from a much broader perspective when it comes to HRM. For instance, according to Agarwal et al. (2023), AI has been transforming the nature of HRM structurally [8]. In light of the interviews taken with the managers of the international corporations, one can understand that AI has not just been considered as a tool, but a partner too [9], [10].

4. System Architecture

The proposed AI-based HR framework operates as an integrated system. First, the data collection module collects information about the employee and the candidate. In the second stage, an NLP-based processing engine analyzes unstructured texts and identifies patterns. Finally, a decision support system provides HR managers with analytical data, such as ranking candidates or predicting performance trends.

5. Main Applications of AI in HRM

Indeed, the discourse concerning the use of AI as a means to enhance the operations of organizations is currently shifting from the notion of utilizing the technology merely to boost efficiency to implementing it as a technique capable of affecting the entire process of HRM [8]. To begin with, despite a number of existing studies related to the use of AI in HRM, which have contributed to the understanding of the problem, there are still some areas that need more exploration.[4] Firstly, most of the papers dealing with this question are based on cases where AI is used in certain particular aspects of organizational life without taking into account the way in which it facilitates the process of HRM. Secondly, the methodology used by the researchers is another gap in the field under consideration. Namely, many qualitative studies have been produced in the area, but few quantitative findings have emerged.

6. Challenges and Ethical Issues

6.1 Data Privacy and Security

Finally, while the benefits offered by AI in HRM have been considerably discussed, the negatives connected with the use of artificial intelligence in human resource management are usually overlooked. Issues such as data security, ethical problems, and discrimination are not as frequently discussed as their importance would suggest. To compensate for this lack, the present study intends to provide a more comprehensive investigation, which would pay attention to the use of AI in strategic HRM. Accordingly, this study addresses the following research question: How is AI used to drive strategic change in human resource management, and what risks and challenges are associated with its implementation? The advent of artificial intelligence technology represents a major paradigm shift within many different industries, among which HRM [12]. While in the past, HRM focused on performing administrative tasks, today, thanks to artificial intelligence, HRM has transformed itself from an administrative to a strategic function.

This could be seen from observing the processes of talent management in firms. Processes such as recruitment, training, development, and retention, among others, no longer occur independently but rather together due to advancements in technology, specifically artificial intelligence, which enables firms to foresee and utilize their human capital resources effectively in order to achieve their strategic goals. Another emerging aspect has been an increasing focus on improving the experience of employees in terms of well-being and inclusiveness, among others [13].

Moreover, there has been much advancement with regard to the basic roles of HRM in the era of AI. This includes aspects like recruiting, training, and developing employees, evaluating the performance of workers, compensation and benefits programs, managing labor relations, and strategic staffing, among others. Not only has the use of AI helped to enhance efficiency in these functions, but it has also made HRM professionals assume a more proactive role in organizations [7].

Recruiting used to be a very tedious and time-wasting task that involved human error. However, through the implementation of AI technology, this function has undergone a lot of transformation. Currently, computer software powered by AI is able to screen thousands of resumes for applicants who are competent enough for the vacant positions [2].

For example, sites such as LinkedIn employ AI in ranking applicants according to their compatibility with certain jobs. Likewise, Google for Jobs makes use of AI technologies in delivering the most appropriate results regarding job openings according to a user's profile and search history.

Moreover, companies are employing AI-based technologies in other aspects related to the recruitment process. ByteDance is one of those firms that utilizes AI technologies in identifying potential applicants for certain positions. In the same manner, Liepin uses artificial intelligence to match applicants with jobs that would suit their credentials. On the other hand, Tencent incorporates artificial intelligence in the HR operations of its organization, ranging from recruiting activities to employee engagement. Apart from increasing efficiency, these recruitment techniques also aid in reducing biases in the recruitment process.

The application of Artificial Intelligence (AI) has had a tremendous impact on the role of HRM in training and development by offering customized learning experiences to learners. Rather than following a conventional and uniform style of teaching, learners are able to access adaptive learning programs tailored to fit their unique preferences, styles of learning, and even speed of learning.

Apart from that, VR and AR are being used for training purposes in many organizations. The adoption of these technologies has made the training process much more practical. It creates a simulated environment, thus making learning much more effective for employees whose jobs are very practical in nature.

6.2 Algorithmic Bias and Fairness

The concept of annual performance evaluations is steadily being phased out. Thanks to the implementation of AI in performance management, the process of monitoring employees has evolved into a more dynamic one. An AI-based performance appraisal system can evaluate different elements of work, such as tasks performed on a day-to-day basis, projects carried out by employees, and collaborations with other colleagues, thus producing continuous feedback.

Continuous feedback leads to better performance understanding on the part of workers themselves and shows them areas where there should be improvements. On the other hand, the process of working itself becomes more goal-oriented.

Today, artificial intelligence is gaining popularity in the field of HRM. With the appearance of new AI technologies, numerous opportunities arise. Nevertheless, as with any innovation, numerous challenges arise with the introduction of artificial intelligence.

One of the primary concerns involves data protection and privacy. As for AI technologies, the amount of necessary data is enormous, and it contains personal information that is often confidential. Therefore, there may be issues related to the leakage of such data, its unauthorized usage, or even theft. Furthermore, when using AI technologies for HR processes, companies expose themselves to more sophisticated types of cyber attacks.

In addition, one needs to consider another crucial issue, namely, that of biased AI. Due to their reliance on historical data, AI programs may acquire and even enhance the presence of bias in the data [3]. In turn, this could lead to various discriminatory practices in recruiting, promotion, and evaluation processes, causing further injustice within society. Not only would it perpetuate inequality, but it would also deprive companies of potentially talented employees.

6.3 Over-dependence on AI

Another issue involves the problem of over-dependence on AI technologies. Although AI helps to make sense of data and provides valuable insights, it is not able to replace the expertise of humans. HR specialists have a unique ability to use their knowledge, experience, and other qualities that allow them to understand people. AI cannot provide all of these benefits. It is especially important when dealing with employees, as interpersonal relationships require a lot of emotions and communication.

Finally, there might be some technical difficulties associated with the implementation of such tools. As with other technologies, AI tools could also suffer from some technical difficulties, such as software malfunctions or downtime. Using these tools might require additional skills and knowledge that HR specialists do not possess.

In general, even if AI can help revolutionize HRM like no technology before, it should be introduced into the process of HRM very cautiously so that both efficiency and the ethical side of the issue are considered.

Adoption of an AI-based HR system is quite a heavy investment for any business entity because several economic aspects have to be addressed, including expensive upfront implementation costs, further costs for continuous maintenance, and the need for costly employee training.

Even though an AI-based system gives access to a lot of useful data and provides insightful analytics, which significantly facilitate many HR processes, the adoption process is complicated, as it includes a lot of steps, and the involvement of humans and their skills and knowledge is critical. The abilities gained by people over many years of their life experience and knowledge are invaluable and cannot be replaced by anything, as they give a person an opportunity to understand how others behave better than software does.

That is the reason for the necessity to develop a strategy that will combine the use of possibilities offered by artificial intelligence as well as human knowledge and experience. The firms that are planning to make an efficient and sustainable HR transformation need to make sure that there is no attempt at neglecting the use of the human factor. Despite all the benefits that the application of AI gives to firms and HR management, one should not overlook the challenges that are connected with their combination.

The involvement of AI technologies in HRM practices has really revolutionized everything; HR departments now have great chances and possibilities that were not there before. Thanks to AI, HR specialists have been able to automate all those processes that were performed manually and took lots of time to do properly, such as applicant screening or evaluation of engagement metrics. Thus, HR management became considerably simplified in many ways. But there are still some issues arising with all these innovations and improvements.

As regards the future development of AI-enhanced HRM in general, it must be noted that it will certainly be quite difficult. The involvement of AI in HR management processes is a definite step forward and helps enhance efficiency and use the data for decision-making. Nonetheless, the value of human experience, reasoning, and intuition should never be underestimated in this case.

First of all, human intuition relies upon many years of experience, cultural environment, and emotional intelligence. Human intuition becomes particularly significant for getting acquainted with an individual emotionally. Of course, artificial intelligence will be able to easily analyze any patterns, process huge quantities of information, and detect correlations; nevertheless, AI technology cannot read people's minds, understand their feelings, emotions, or even inner doubts. Human resource managers can interpret complex interpersonal and emotional factors through experience, communication, and contextual understanding. Consequently, human resource managers can become particularly helpful in performing different kinds of activities in human resource management.

6.4 Implementation costs and technical barriers

The next evolution step in the HR transformation with the help of artificial intelligence is unlikely to consist of using more sophisticated AI tools or greater automation. The key is going to be finding out how to achieve a higher level of integration between artificial and human intelligence. The goal should not be the replacement of human decision-making but rather its augmentation through the help of intelligent algorithms capable of delivering analytics.

In turn, the increased usage of artificial intelligence by HRM implies a variety of ethical questions that should be answered to use technology safely. Transparency, accountability, fairness, and the problem of preventing bias are some of the main questions concerning the application of AI in human resources management. It is necessary for HR specialists to understand the principles according to which the system makes decisions.

A third issue worth considering is the existence of algorithmic bias. With artificial intelligence learning from past experiences, it becomes highly possible that they inadvertently pick up on any biases already present within that data, which means that the process would end up being discriminatory against one particular group. It might show when making decisions regarding hiring, promotion, performance reviews, and other HR-related procedures, so companies should constantly test these systems to avoid such problems.

7. Discussion: human-centered AI in HRM

It is also crucial to note that AI in the HR department will not take away from the necessity of maintaining human connections. With the growing levels of technological advancement in our society, the need for maintaining an equal level of human and artificial intelligence in the working environment is inevitable. While AI proves to be extremely efficient in some fields, there are certain functions that can be done only by humans, which include, among others, the capacity to offer emotional support to staff members and show empathy in hard times.

To achieve a similar balance, it is crucial to ensure constant training of the professionals working in the field of Human Resource Management. With the growing interaction between AI and HRM systems, employees dealing with such technologies should obtain some new skills to be able to handle them properly.

The factor that should be discussed regarding the development of artificial intelligence in HRM is interdisciplinary cooperation between different specialists. The specialists working in the areas of computer science, psychology, sociology, ethics, and management, as well as other sciences, will need to cooperate in order to create technologies that could be considered both effective and socially responsible at the same time.

8. Conclusion

On the whole, there is no doubt that using artificial intelligence in HRM may have a number of positive impacts on organizations that choose to implement the technology [7], [11]. However, at the same time, it should be said that introducing such technologies implies the transformation of the processes involved in conducting HRM activities. It seems important to note that this process should not mean losing certain abilities.

In conclusion, what the advent of artificial intelligence-based HRM has made clear is that in any case, the human must take precedence over technology. If a company wants to establish the optimal HRM, then artificial intelligence and human intelligence have to be seamlessly integrated [9], [10]. In simpler terms, a company must give the same weight to data analytics as they do to human emotion.

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An Investigation of Artificial Intelligence and the Future World of Work

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Abstract: Modern artificial intelligence (AI) represents an innovation that is drastically reshaping the corporate landscape, thus serving as the basis for a new era of economics. The main advantage of AI is that this technology ensures the efficiency and speed of business operations by automating the most routine activities. In the future, many routine and repetitive tasks may be automated, allowing human workers to focus more on effective decision-making and strategic activities. Data analytics will provide businesses with an opportunity to predict the behavior of customers and use their assets more efficiently. Although AI-driven automation may contribute to the displacement of certain jobs, it has also created new employment opportunities, particularly in the IT industry. The education system needs to change as well, as it should provide future workers with technical literacy and critical thinking skills. With the help of machine learning algorithms, errors in production processes can be reduced, while quality control and standards can be improved. Remote and hybrid working models can be managed more effectively through AI-based management systems. Collaboration between humans and artificial intelligence may contribute to addressing complex challenges at the global level. But along with that come some ethical questions about the use of AI as well as problems regarding data privacy and algorithmic biases. Workers who will prosper in the future are those who are willing to constantly learn and work together with artificial intelligence. From an economic perspective, AI has the potential to reduce operational costs and contribute to economic growth. To sum up, artificial intelligence is influencing business in many ways, not just technologically but also philosophically and socially.

Keywords: Automation, digital transformation, neural networks, data analytics, machine learning

1. Introduction

Artificial intelligence is regarded as one of the biggest technological revolutions in human history and is now penetrating every sector of society. With the start of the XXI century, the improvement of computing capacity and the emergence of big data have contributed to breakthroughs in the sphere. Nowadays, artificial intelligence is not only an object described in science fiction movies but also an element of our daily routine and economy [1]. As businesses are at the heart of this innovation process, the traditional dynamics of the labour market are also being transformed.

Unlike traditional approaches to data analysis, AI can identify complex and hidden patterns within massive volumes of data [2]. Digital transformation of organizations is seen as the key component of future working environments. The use of artificial intelligence aims at increasing effectiveness in every sphere of human activity, whether it concerns production or services. For many specialists, the modern period can be viewed as the golden age of the fourth industrial revolution [3]. The future working world would involve a combination of human imagination and the analytical capacities of artificial intelligence. Work process automation is associated with prospects and socio-economic problems. The emergence of new technologies affects the evolution of professional roles and the formation of new professions [4]. At present, the use of artificial intelligence technologies is generating significant economic value across the global economy.. Advanced data processing capabilities may facilitate more objective decision-making.

Nevertheless, issues related to ethics in connection with artificial intelligence, and responsibility in particular, continue to be a matter of discussion. The new trends demand flexibility and adaptability as the most crucial capabilities for success. Educational and personnel training programs have to undergo a major transformation accordingly. Artificial intelligence and the future work environment represent a topical theme worth exploring both theoretically and practically. To summarize, we can observe an unprecedented turning point when technologies drastically transform working life [5].

The relevance of the topic: The transition of enterprises to artificial intelligence-based systems is further increasing the relevance of the topic in order not to fall behind in the global competitive environment [3]. The fundamental shift in the skills required in the labour market necessitates that specialists and educational institutions focus on this area. In terms of increasing economic efficiency and optimising resources, artificial intelligence presents unique opportunities. The exponential growth in the volume of data (Big Data) makes its processing by the human brain impossible, which underscores the relevance of intelligent systems. The minimisation of errors and the automation of quality control in manufacturing processes make this topic vitally important for industry. The enrichment of modern management methodologies with artificial intelligence algorithms makes decision-making processes more scientific and precise [2].

In the post-pandemic era, the expansion of remote and hybrid working models has brought the need for intellectual management tools to a peak. The fact that the ethical, legal, and security aspects of artificial intelligence are not yet fully regulated maintains the relevance of research in this field. The transformation of workplaces and the threat of the disappearance of certain professions necessitate the restructuring of social protection systems [4]. Artificial intelligence plays an indispensable role in establishing production chains that comply with international standards and ISO norms. The analytical capabilities of artificial intelligence are widely used in the protection of ecological standards and the transition to a “green economy”.

Issues of technological independence and national economic security have made the development of artificial intelligence strategies a pressing state priority [6]. Increasing customer satisfaction through personalised services is the main factor keeping this topic on the agenda in the business sector. The application of artificial intelligence in strategic areas such as education and medicine is of great importance for enhancing the general well-being of society. The role of the human factor and models of intellectual collaboration in the future world of work are being widely discussed in academic circles [7]. The establishment of an innovative economy is directly dependent on the level of adoption of artificial intelligence technologies [6]. Global calls to increase productivity and reduce costs continually keep this topic in the spotlight. Consequently, the subject of artificial intelligence and the future of the business world is one of the most cutting-edge areas of modern science, both theoretically and practically.

The aim of the study: The primary aim of the research is to investigate the mechanisms by which artificial intelligence technologies impact the modern business world, to forecast the structural changes that will occur in the future labour market, and to identify ways of enhancing economic efficiency in this process.

Subject of the study: The subject of the research is the management structures of modern enterprises, the digital economy environment, and future labour market relations, which are being transformed by the application of artificial intelligence technologies.

Research methods: The impacts of artificial intelligence on the business world have been evaluated from both theoretical and practical perspectives, using systematic analysis, comparative analysis, and statistical forecasting methods during the research process. At the same time, future development trends were summarised by applying qualitative analysis and econometric modelling methods to study international experience.

2. Materials and discussions

The integration of artificial intelligence into the business world is shaping the most important material basis and discussion platform of the modern economy. International technology reports, statistical data, and the digital metrics of enterprises serve as the primary materials for the research. This section provides a comprehensive analysis of the innovations that artificial intelligence has brought to work processes. Firstly, the advantages of automation over physical and intellectual labour are a matter for debate. Materials indicate that delegating routine tasks to algorithms allows human resources to be directed towards more creative fields. Economic efficiency is taken as the main criterion during the processing of materials.

Using artificial intelligence software saves a lot of money in terms of operations for businesses. While talking about artificial intelligence, its role in the decision-making processes is especially stressed. Proactive identification of risks using data analysis makes businesses resilient [8].

The use of artificial intelligence in the industrial sphere leads to quality enhancement [9]. Digital instruments are necessary to manage international environmental standards, including ISO 14040 and 14044. The analysis of the materials shows that artificial intelligence can be extremely useful in saving resources. Artificial intelligence will become a personal assistant to each person in the future world of work. One of the most popular issues mentioned is the formation of new occupations. Such spheres as data engineering, artificial intelligence ethics, and algorithm regulation are becoming very important in the current context. This implies that the educational system needs reorganization.

In addition to this, artificial intelligence is revolutionizing the area of customer service. Use of chatbots and virtual assistants enhances the quality of service delivery since they work 24/7. It has been argued that artificial intelligence will not be able to emulate human emotions, but can make technical support more effective. Incorporation of artificial intelligence in logistics and supply chain management reduces any time wastage. Real-time monitoring of the data helps in speeding up the process of international trading. In finance, artificial intelligence helps to prevent any fraudulent activity.

Another strand of the discussions is ethical issues and data privacy. The potential for artificial intelligence to make biased decisions is causing serious concern in scientific circles. The materials show that artificial intelligence can also be a tool for eliminating inequality in the workplace. However, for this, it is necessary for the algorithms to be transparent and explicable. Remote work and digital nomadism are taking on a more organised form thanks to artificial intelligence. The integration of cloud technologies and artificial intelligence frees the work environment from geographical boundaries.

In the modern business world, competition is no longer just about human intelligence, but also about technological advantages. The share of artificial intelligence in companies' R&D (Research and Development) budgets is increasing each year. The materials in this field demonstrate the role of artificial intelligence in creating innovative products. In the field of design, particularly industrial design, artificial intelligence can present thousands of variations in a short space of time. The discussions emphasise that artificial intelligence is a tool that complements human labour [10]. Employees' ability to collaborate with artificial intelligence (AI literacy) is the most important competency of the future.

The economic impacts of artificial intelligence are also analyzed at a macro level. The contribution of artificial intelligence to global GDP growth is forecast to increase sharply by 2030. The materials indicate that countries that complete the digital transformation will lead the economy. Social welfare issues are also not forgotten in the discussions. New mechanisms are proposed for the risks of unemployment that could arise from the automation of workplaces. Reskilling programmes are critical during this transition period.

The predictive capabilities of artificial intelligence are completely changing marketing strategies. It is now possible to anticipate customer needs before they even arise. Discussions require that this process be balanced with the privacy of personal life. Artificial intelligence-based management systems objectively assess employee productivity. This also serves to strengthen the principles of meritocracy in enterprises. Analysis of the materials shows that artificial intelligence also opens up great opportunities for small and medium-sized businesses. Cloud-based artificial intelligence solutions allow you to leverage technology without building expensive infrastructure.

In the future world of work, the synergy of artificial intelligence and human intelligence will be directed towards solving global problems. Energy efficiency, tackling climate change, and the fair distribution of resources will be accelerated with the help of this technology. In conclusion, it is noted that artificial intelligence is inevitable, and adapting to it is the key to success. The materials confirm that artificial intelligence is making the business world more agile, smarter, and more effective. As a result, artificial intelligence is a catalyst for not only a technical but also a social transformation. In this new era, the human factor will gain value in the areas of empathy, leadership, and strategic vision. The future of the business world will continue to be shaped in the light of the vast materials offered by artificial intelligence and the scientific discussions these materials give rise to.

The table below summarises the impact of artificial intelligence on various sectors of the business world and the innovations it has brought:

Table 1. The Impact of Artificial Intelligence on the Business World: A Sector-by-Sector Comparison

Field	Traditional Methods	The Future with Artificial Intelligence	Main Advantage
Management	Decisions based on experience	Decisions based on data analytics	Accuracy and risk reduction
Production	Mechanical lines and human control	Autonomous robots and AI control	Speed and reduced error rates
Customer Service	Live support limited to business hours	24/7 Virtual Assistants (Chatbots)	Constant availability and responsiveness
Human Resources	Mechanical review of CVs	Algorithmic choices and forecasting	Objectivity and time-saving
Marketing	General mass advertising	Personalised offers	High sales conversion
Finance and Audit	Periodic inspections	Periodic inspections	Immediate detection of fraud
Logistics	Static route planning	Dynamic and optimised paths	Saves fuel and time
Education and Training	Standard programmes	Individual learning trajectories	Effective staff training

This table shows that artificial intelligence is a force in the workplace that is not only a substitute but also a complement.

3. Conclusion

The study concluded that artificial intelligence is not merely an auxiliary tool in the modern business world, but also the primary driving force behind fundamental changes. As a result of the implementation of this technology, the economic efficiency of enterprises has been raised to a new level, and operational costs have been significantly reduced. Artificial intelligence-based systems are predicted to make decision-making processes at all management levels more objective and accurate in the future. Through automation, the risk of human error can be reduced in tasks that are suitable for automated processing. Yet, the capability of human intelligence to generate, understand, and strategize is irreplaceable in the corporate sector.

The ability of employees to collaborate with artificial intelligence becomes the defining skill of the future workplace. Even though the changes occurring within the labour market cause the extinction of some older jobs, at the same time, they open up opportunities to establish new professions, which demand higher qualifications. In order to ensure competitiveness, the digital strategy of organizations should comply with global standards, including ISO standards. Big data analysis will become an essential element influencing the future corporate direction of businesses. Observing ethical principles and protecting data privacy during the implementation of artificial intelligence is an indispensable condition of its credibility.

Economically, artificial intelligence has the potential to contribute to global economic growth and improve resource efficiency. Education systems must prioritise technological literacy and flexible adaptation skills when preparing the specialists of the future. The integration of artificial intelligence in businesses will allow for a better work-life balance, alongside an increase in employee productivity. Algorithmic governance models remove bureaucratic obstacles, making governance more transparent and agile [11]. Artificial intelligence also plays a crucial role in the transition to a green economy and in protecting environmental standards.

Intelligent solutions applied in logistics and the supply chain increase the speed and sustainability of global trade. A personalised customer experience is becoming a key criterion for business success, and this is made possible by artificial intelligence. Social protection systems must develop new and innovative mechanisms to counter the risks of technological unemployment [12]. Artificial intelligence and human collaboration are the most effective mechanisms for solving the complex global problems facing humanity. The digital future brought by this technology promises a smarter, faster, and more inclusive world of work.

In conclusion, the main objective should not be to oppose artificial intelligence, but to manage it properly and integrate it successfully into business processes. The innovation potential of enterprises depends directly on their speed of adopting artificial intelligence technologies. The future world of work is no longer a distant dream, but a present-day reality shaped by artificial intelligence. In this new era, leaders will not be those who merely apply technology, but those who steer it ethically and strategically. The changes that artificial intelligence has brought to the world of work are irreversible and open up great prospects for the well-being of society. Finally, it can be noted that the harmony between artificial intelligence and human intelligence constitutes the most solid foundation for future economic progress.

Novelty of the research work: The novelty of the research lies in the comprehensive evaluation of new management paradigms created by human-machine synergy, not merely as an automation tool, but within the framework of international ISO standards and economic efficiency criteria.

Practical significance of the research: The practical significance of the research lies in providing practical mechanisms for enterprises to reduce operational costs and increase the accuracy of management decisions by using artificial intelligence technologies in their digital transformation process. At the same time, the results obtained serve as a methodological basis for the development of personnel training programmes and the preparation of strategic roadmaps to meet the new demands of the labour market.

The economic efficiency of the research: The economic efficiency of the research is reflected in the potential reduction of operational costs and the optimisation of resource utilisation resulting from the automation of routine processes through the application of artificial intelligence.

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Development Prospects of Alternative Energy Sources

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Abstract: The article examines current trends in the field of renewable energy and discusses Azerbaijan's development prospects in this field in an international context. The study used descriptive and comparative analysis methods to examine global trends and Azerbaijan's prospects in renewable energy development. The main data sources are based on official reports from the International Energy Agency (IEA) and other relevant international and national energy institutions. The study findings could be useful for alternative energy policymakers and energy planners. The recommendations provide practical advice for developing countries seeking to balance economic growth goals with environmental responsibilities. The study highlights the growing importance of wind and solar power in renewable energy development. The study shows that IT is not just an auxiliary tool, but a fundamental enabler of alternative energy sustainability, while also creating new system vulnerabilities that require active cyber-management. The article presents a critical, synthesised analysis of the convergence of IT and energy in the Azerbaijani context, including regional barriers to energy transition and a comparative analysis with developed alternative energy markets.

Keywords: alternative energy, smart grids, artificial intelligence, IoT, energy transition

1.Introduction

The article analyzes trends in renewable energy production. Unlike the traditional model, solar and wind energy are more accessible to people and cause less harm to the environment. In Azerbaijan, the development of clean energy is also supported by various incentive programs, the most obvious examples of which are SOCAR Green and MASDAR. Other developing countries are also taking steps in this area.

The main problem in the field of alternative energy is not related to production, but to storage. Since this energy, unlike traditional energy, is dependent on variable climate conditions, it requires special large storage systems. Nevertheless, work in this area continues, as it is an important step for the energy independence of countries. Azerbaijan is also in this process. As a country seeking to reduce its dependence on energy imports, the transition to a "green" infrastructure is on the agenda here.

2. Global Trends and Technological Development

In the 1990s, renewable energy accounted for 3% of total energy [1]. Since then, countries around the world have been working to decarbonize their energy systems to combat climate change. In the past five years, this figure has reached a record high. In 2023, renewable electricity accounted for 30.3% of global electricity generation, with most of the net growth coming from hydro and wind power [2]. But that doesn't tell the whole story. The main issue is how these systems are managed. Unlike traditional systems, solar power plants and wind turbines generate electricity based on weather conditions. Managing such a network was simply impossible twenty years ago. It requires forecasting, adaptation, and distributed decision-making on a scale that only digital systems can support.

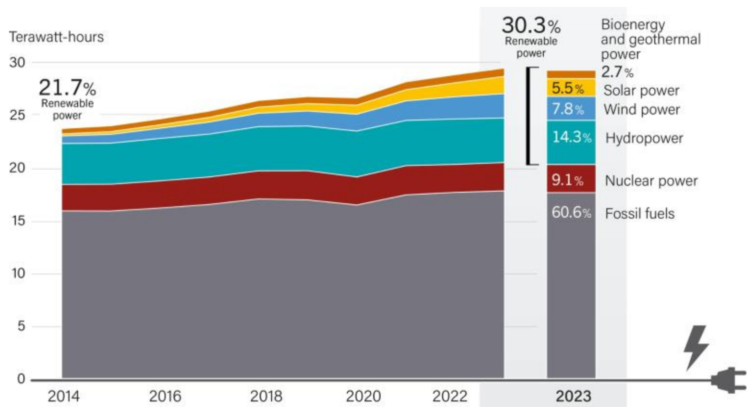


Figure 1. Global Electricity Generation by Source (2014–2023)

During 2020, global solar power capacity exceeded 142 GW, an increase of one-fifth. At the same time, while in 2010 there were only 7 countries in the world with solar power plants, in 2020 this figure increased to 43. China is still the leader in this field, but in recent years, other countries have managed to reduce the gap. The areas suitable for the development of solar energy are mainly desert areas, while for wind energy, these are coastal areas. Tables 1 and 2 show the largest solar power plants and wind farms in the world.

Table 1. Largest Solar Power Plants Globally by Installed Capacity

Solar Park	Country	Capacity (MW)
Talatan Solar Park	China	21,000
Ningdong Solar Park	China	18,320
Hobq Solar Park	China	10,020
Urtmorin Solar Park	China	5,440
Midong Solar Park	China	5,000
Ruoqiang Solar Park	China	4,000
Otog Front Banner Solar Park	China	4,000

Table 2. Largest Wind Farms Globally by Installed Capacity

Wind Farm	Country	Capacity (MW)
Gansu Wind Farm	China	30,000
Zhang Jiakou	China	21,235
Urat Zhongqi, Bayannur City	China	2,100

Mintyre & Herries Range, QLD	Australia	2,023
Markbygden Wind Farm	Sweden	2,000
Hami Wind Farm	China	2,000
Damao Qi, Baotou City	China	2,000

In Europe, wind and solar together accounted for more than a quarter of electricity generation in 2020 [3]. In Europe as a whole, including all alternative sources, such as hydroelectric power plants, the share of renewable energy sources has increased by almost half, overtaking fossil fuel-based electricity generation for the first time. The figure is even higher in Germany, the United Kingdom, Norway, Switzerland, and Sweden.

Alternative energy sources are of particular importance for Azerbaijan, whose economy has long been dependent on hydrocarbon exports. The Southern Gas Corridor is a prime example of this [4]. Azerbaijan's hosting of COP29 in 2024 is an indication that the country has taken important steps in this area.

3. IT as a Driver of Development

Information technology has greatly increased the efficiency of alternative energy through forecasting. Solar radiation and wind speed are weather-dependent and uncertain, but they are not random. Studies have shown that neural network-based forecasting models can reduce forecast errors by 20–40% [5].

The Internet of Things (IoT) brings this capability from the network level directly to devices. Hundreds of sensors installed on a modern wind turbine can transmit data such as vibration, temperature, and rotational speed. Studies show that these sensors can reduce the operating time of a wind turbine by 30–50% [6].

The integration of data collected from sensors poses a serious challenge in itself. A simple solar power plant generates terabytes of data every year. Central servers are not enough to process this data. Smart grid technology is the only solution to this problem [7]. In essence, a smart grid is an electrical network in which information flows in both directions simultaneously between the generator, the grid operator, and the consumer. Thanks to this, users can monitor electricity consumption in real time.

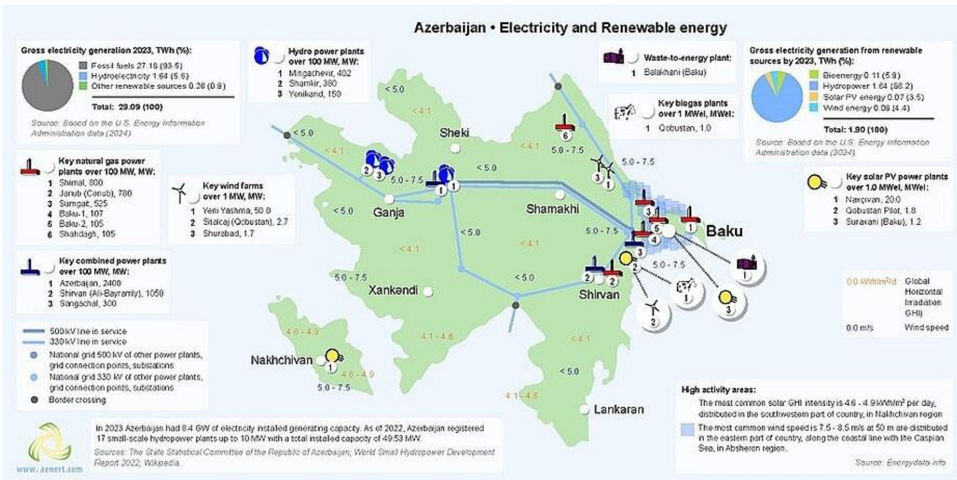
The value of renewable energy also depends on the intelligence of the grid it is connected to. This is an overlooked but fundamental problem. A solar panel on a simple grid is economically poor. The same panel on a smart grid with real-time assessment creates more value for both the user and the system. Some countries that invest in energy production without investing in digital infrastructure are wasting money.

4. Development Prospects: Global Trends and Azerbaijan's Position

In recent years, the global development of alternative energy sources has exceeded expectations. The rapid decline in the cost of solar panels has led the International Energy Agency to revise its forecasts. Based on current trends, renewable energy is expected to account for almost half of global electricity production by 2030 [8]. The main drivers of this development have been the steps taken globally. The EU's REPowerEU program and the US Inflation Reduction Act of 2022 have pumped hundreds of billions of dollars into this sector [8]. Technology costs have fallen, and production chains have been restructured.

Azerbaijan is both a gas exporter and a country with significant renewable energy resources. The country also has significant wind resources along the Caspian coast. According to AREA figures, the technical potential is 27,000 MW: the main share is solar, with a small share from wind, and the rest from bioenergy and river energy [10]. Solar energy in the country has the largest technical potential. The government's goal is to obtain the majority of electricity from renewable sources by 2030 [11]. Hydropower plants also remain an untapped resource. The country's technical potential in this area is estimated at 520 MW. However, only a small part of this capacity is currently used, and a large part of the potential remains untapped.

Figure 2



According to the Azerbaijan Renewable Energy Agency's 2023 data, one in six kilowatt-hours of total energy comes from renewable sources. The majority of this is hydropower. The majority of hydroelectric power comes from the two largest hydroelectric power plants located on the Kura River. The largest wind power system is installed in the Khizi district.

The creation of SOCAR Green is connected with the arrival of COP29 in Baku. Strategic partnerships with major energy companies such as 'Masdar' and 'ACWA Power' show that this step is taken with serious intention [12]. The result will be known in practice.

5. Challenges and Critical Gaps

The biggest technical challenge with renewable energy is its variability. Solar panels work in clear skies, while wind turbines work in windy conditions. When the weather changes, production drops. Traditional power grids are not designed to handle this kind of variability. As the share of renewable energy increases, storage systems and grid management systems are becoming increasingly important.

Solar farms and wind farms require large areas of land. This is becoming a serious competition for agricultural land. As a solution, some projects are looking to combine both uses. It has not yet been tested on a large scale, but the idea is interesting.

Cybersecurity is the least talked-about but most worrisome aspect of the energy transition. An example of this is the ransomware attack on the Colonial Pipeline in 2021. To prevent this, the company simply shut down its fuel distribution system. Some states in the eastern United States were unable to find fuel during the day. Although the incident affected a fuel pipeline, it demonstrated the potential consequences of cyberattacks on critical energy infrastructure. The smart grid is much more complex. A successful cyberattack on a digitally connected energy grid could potentially disrupt electricity supply across a large geographic area.

This represents a serious cybersecurity concern. Dozens of power grid intrusions have been reported in Europe and North America in recent years. This is a particularly serious concern for Azerbaijan, where the grid infrastructure is still in its infancy [13]. Systems built without a cybersecurity architecture are a huge risk.

The second issue that receives little attention is the digital divide. Artificial intelligence-based energy systems need a lot of data to operate. Countries that manage modern grid infrastructure have been collecting this data for decades. Countries that build new systems must collect this data from scratch. This means that simply "copying" AI algorithms that have been successfully tested, such as in European or North American contexts, and using them in different climates and infrastructure conditions, will not produce the same results in Azerbaijan or similar settings.

6. Conclusion

The transition to alternative energy has moved from a topic on the agenda to a real policy issue. This is an important step towards ensuring energy independence and restructuring national economies towards a greener economic model. It is good that Azerbaijan is joining this process. But "joining" is a start, not a goal. Conducted research and analysis show that the development of the alternative energy sector in Azerbaijan directly depends on the implementation of Information Systems in Management. The digitalization of the energy system, the inclusion of "Smart Grid" elements in a centralized system, brings with it several critical solutions:

1. Minimizes technical risks arising during the synchronization of renewable energy to the grid;
2. Ensures the active involvement of consumers in the energy management process (prosumer model);
3. It forms a reliable analytical and statistical database to help the state achieve its green energy goals.

Finally, it is advisable to develop automated reactive control algorithms that can be directly integrated with the local energy grid in future research

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