Using Digital Twin (DT) Technology for Workforce Demand Forecasting in the Post-War Reconstruction of Ukraine

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Abstract

This article explores the application of Digital Twin (DT) technology for forecasting workforce demand during the post-war reconstruction of Ukraine. The use of digital twins enables the analysis of demographic changes, assessment of labor shortages, and planning of workforce allocation across various economic sectors. The proposed Digital Twin Workforce Navigator in Post-War Ukraine Reconstruction Planning model takes into account migration dynamics, demobilization, educational initiatives, and shifts in regional workforce availability. Integrating Digital Twin technology into workforce planning enhances labor management efficiency, minimizes labor market imbalances, and improves the accuracy of workforce demand forecasting. The use of machine learning algorithms, particularly LSTM and Random Forest, facilitates predictions of workforce fluctuations across regions, supports optimal resource allocation, and aids in developing adaptive strategies for the reintegration of demobilized workers. Such models enable the construction of potential economic development scenarios, making them valuable tools for workforce demand forecasting in post-war recovery. The implementation of digital twins in both public and private human resource management strategies can significantly accelerate reconstruction efforts and stabilize Ukraine's labor market. Moreover, the proposed approach has been demonstrated through workforce forecasting for the years 2012-2030, providing a first approximation of labor demand trends and offering valuable insights for the practical implementation of Digital Twin models in workforce planning during post-war reconstruction.

Keywords

Digital Twin, technology, workforce forecasting, personnel, post-war reconstruction, model, efficient management

1. Introduction

On February 24, 2022, russia launched a full-scale invasion of Ukraine, resulting in widespread destruction, civilian casualties, and a massive exodus of the workforce. A significant portion of Ukraine's working-age population was forced to seek safety abroad, leading to severe labor shortages

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across multiple economic sectors. At the same time, millions of Ukrainians became internally displaced persons (IDPs), which disrupted the regional balance of the labor force. While relatively safe regions experienced labor oversaturation, areas requiring extensive reconstruction now face a critical shortage of skilled workers, complicating workforce management across the country.

Another major challenge has been the substantial loss of economically active individuals due to shelling and missile strikes, which devastated residential areas, infrastructure, industrial facilities, and utilities. These losses have further exacerbated the workforce deficit.

The mass mobilization of Ukrainians into the Armed Forces of Ukraine has also complicated workforce management. Many mobilized workers remain officially employed at their previous jobs but are actively serving in the military. This dual status distorts employment statistics and hinders effective reconstruction planning, as formally registered workers are unavailable for economic recovery efforts.

As of early 2025, Ukraine's demographic and labor situation remains critical due to the prolonged impact of war-related factors. According to forecasts by the Ptoukha Institute for Demography and Social Studies of the National Academy of Sciences of Ukraine, the population continues to decline due to low birth rates, high mortality, mass emigration, and casualties from military actions. In addition, the war has caused significant outflows of working-age individuals abroad, internal migration, and the deaths of many civilians [1–3].

Rebuilding Ukraine's economy will require targeted workforce management strategies and national programs that encourage the return of Ukrainians from abroad, support population growth, and facilitate the integration of IDPs and war veterans into the labor market. Integrating advanced technologies, such as Digital Twin (DT) systems, can play a crucial role in analyzing and forecasting workforce demands during reconstruction.

Digital Twins can serve as powerful tools for workforce demand forecasting and optimizing labor management in Ukraine's post-war recovery. By leveraging real-time data analysis, DT technology can assess current labor market conditions and predict future shifts by considering demographic changes, economic trends, and the scale of reconstruction efforts.

Research on intelligent personnel management systems lays the foundation for developing workforce forecasting models based on DT technology. Shpak et al. [4] explore the use of intelligent systems for employee evaluation and development, highlighting the integration of mentoring programs within DT frameworks to support workforce management in reconstruction scenarios.

Additionally, Shpak et al. [5] examine the transformation of HR roles due to digitalization, offering valuable insights for adapting workforce forecasting approaches to the evolving post-war labor market.

Maznyk et al. [6] further contribute by analyzing data mining applications in people analytics to balance employer and employee interests. These methods are particularly relevant for modeling recruitment and integration strategies using DT technology during the reconstruction planning process.

Digital Twin technology offers significant potential for addressing Ukraine's workforce challenges during post-war reconstruction. By analyzing data from government and private databases, DT systems can accurately assess labor demands for specific projects while considering regional characteristics. This approach enables the precise allocation of labor resources and supports effective forecasting of workforce needs across key economic sectors, including construction, logistics, industry, and infrastructure.

A crucial aspect of workforce planning is aligning educational programs with real labor market demands. By using DT technology, it is possible to forecast which specializations will be most in demand, enabling educational institutions to adjust curricula accordingly. This proactive adaptation helps accelerate the integration of skilled professionals into reconstruction efforts and bridges gaps between labor supply and demand.

Moreover, DT technology can simulate various development scenarios, which is essential for making flexible decisions in the volatile post-war environment. By modeling potential outcomes, decision-makers can better manage risks related to labor shortages, inefficient resource use, and changing economic conditions. This adaptability is critical for optimizing workforce strategies and ensuring a smoother, more efficient reconstruction process.

Digital twins can significantly improve the forecasting of material and workforce needs through integration with machine learning technologies and simulation models. For example, in the context of warehouse operations, digital twins can be used to predict labor requirements, especially for labor-intensive processes such as order picking. This is achieved by analyzing historical data on demand and working hours, enabling the creation of a workforce forecasting model [7].

In manufacturing systems, digital twins can utilize physical simulations to model material flows, allowing the prediction and prevention of physical disruptions that could lead to accidents or reduced productivity [8]. This ensures adaptability and flexibility in production, particularly when manufacturing customized products in small batches.

Digital twins can also be integrated with automated systems, such as Automated Guided Vehicles (AGVs), to optimize material planning and routing [9]. This enhances forecasting accuracy and reduces transportation costs.

Despite their significant advantages, there are challenges related to the excessive complexity of digital twin models, which can lead to unnecessary efforts and prolonged computation times [10]. Future research may focus on optimizing the level of model detail to ensure efficiency and ease of use.

In the broader context, the integration of digital twins into workforce forecasting processes will help Ukraine achieve a more effective and rapid reconstruction. It will prevent the chaotic distribution of labor, reduce costs for training and recruitment, and create an adaptive and resilient personnel management system that will foster economic recovery and ensure social stability. The aim of the study is to analyze the potential of using Digital Twin technology to forecast personnel needs during Ukraine's post-war reconstruction. The research focuses on developing a model for the Digital Twin Workforce Navigator in the Post-War Ukraine Reconstruction Planning System.

2. Literature review

The Digital Twin technology is gaining popularity as a tool for creating virtual models of real systems and processes, allowing the analysis of their functioning and the forecasting of possible future changes. Recently, numerous scientific publications and studies have demonstrated the successful application of digital twins for forecasting personnel needs in various countries for strategic development planning. Specifically, in the article [7], the authors explore the role of digital twins in enhancing the efficiency of future warehouses. They analyze how the use of digital twins combined with machine learning allows for forecasting workforce requirements, optimizing resource allocation, and improving overall productivity. The research also discusses the implementation of sensor technologies, autonomous vehicles, and robots for warehouse automation, which significantly reduces operational costs and improves inventory management.

In another study [8], the focus is on the creation and implementation of a digital twin for managing material flows in production systems. The authors apply physical modeling for accurate forecasting of material movement and monitoring and diagnostics of processes. The use of this approach helps identify inefficiencies in logistics, forecast potential disruptions, and optimize resource utilization.

Zhang et al. [11] explore a hybrid approach to forecasting the performance of manufacturing systems, combining traditional theoretical models with data-driven methods. The proposed approach significantly enhances the management of production processes, leading to increased manufacturing efficiency. According to the authors, the key advantage of this approach lies in the adaptability of the Digital Twin (DT) model to dynamic changes in manufacturing processes, enabling more accurate analysis and forecasting. The study emphasizes the importance of integrating digital twins into industrial systems to optimize resources and improve enterprise competitiveness.

The authors of publication [12] analyzed the capabilities of digital twins in coordinating supply chains in modular construction. They concluded that the digital twin model helps predict logistical risks and determine precise delivery times for modules, thereby improving the productivity of construction projects.

A separate group of authors [13] examined the role of DTs in accelerating the development of new materials. By using n-point spatial correlation and surrogate models, they optimized the structure, processes, and performance of materials across various industries.

The study on the application of digital twins in material distribution systems is presented in article [14]. The authors developed a model that optimizes logistics, reduces costs, and improves the regularity of material supplies to production facilities. The proposed solution ensures flexibility in production planning and adaptation to fluctuations in demand.

Research on forecasting the demand for manufacturing resources is highlighted in study [15], which investigates the use of DTs to predict spare parts demand in modern enterprises. The authors proposed a model capable of accurately forecasting spare parts needs, helping optimize supply chains and reduce costs. The integration of artificial neural networks with DTs improves forecasting accuracy, which is crucial for maintaining stable production processes and enhancing customer service levels.

Study [9] presents a concept of digital twins for automated transportation within the Industry 4.0 framework. Automated guided vehicles (AGVs) utilize digital twins to simulate movement and accurately predict routes with high precision (97.95%–98.82%). This allows enterprises to minimize logistical delays and ensure efficient use of transport systems in production environments.

An intriguing approach is presented in study [10], which focuses on automatic detection of manufacturing systems and the generation of digital twins based on data log analysis. This method enables automated performance evaluation and supports decision-making for production optimization. The use of this approach improves manufacturing process management and minimizes the impact of human error.

The review [16] systematizes existing studies on Digital Twins in manufacturing and proposes a categorization of physical-digital levels. The authors highlight the potential for optimizing production processes, reducing costs, and forecasting future system states. They also outline directions for further research, covering the integration of Digital Twins into cloud services, their interaction with IoT, and the expansion of analytical capabilities.

A popular area of Digital Twin application is operational planning. In study [17], discrete event modeling is combined with predictive methods, enabling efficient management of production processes, particularly workforce planning and production load optimization.

Some studies focus on demand forecasting using DT technologies. Research [18] is dedicated to developing a Digital Twin that integrates intelligent warehouse and production management with demand forecasting. The use of genetic algorithms improves inventory management accuracy for small manufacturing enterprises.

The authors of [19] proposed the use of a Digital Twin for forecasting production capacity based on the LSTM (Long Short-Term Memory) algorithm. The study shows that this approach achieves a forecasting accuracy of 91.8%, enabling manufacturers to improve efficiency and reduce order fulfillment times.

Another promising application of Digital Twin technology, according to the authors of [20], is predictive maintenance in manufacturing. The methodology relies on simulation models, allowing for accurate predictions of the remaining useful life of equipment and efficient maintenance planning.

Some researchers have explored the use of DT in the field of energy efficiency. For example, the authors of [21] developed an energy consumption forecasting model for buildings using the Prophet algorithm. This technology enables high-accuracy energy consumption predictions, contributing to the optimization of energy costs in buildings.

Theoretical research [22] focuses on the use of Digital Twins for nonlinear dynamic systems. The application of reservoir computing allows for accurate tracking of the state of complex systems, such as infrastructure, ecosystems, and climate models.

A highly promising area for DT technology is in medicine, particularly for disease prevention and treatment. In publication [23], a DT model is presented that utilizes artificial intelligence and mathematical modeling to predict patients' health conditions. The proposed approach leverages graph-based representations of medical data, enabling deeper analysis of the interconnections between various factors affecting a patient's health. This research opens new possibilities for personalized medicine and preventive measures, potentially leading to significantly improved treatment outcomes.

Additionally, the authors of [24] consider DT technology valuable for modeling disease progression in stroke patients. The study demonstrates the effectiveness of a machine learning-based approach for modeling disease trajectories and supporting clinical decision-making. Furthermore, DTs can be used to create virtual control groups in clinical trials, enhancing the efficiency of testing new treatments and assessing their effectiveness.

In conclusion, DT technologies hold significant potential across various industries and needs. They enable the optimization of logistics processes, coordination of supply chains, evaluation of material resources, improvement of medical services, and forecasting of workforce needs. This makes them an exceptionally promising tool for predicting staffing demands during Ukraine's post-war reconstruction.

3. Methods and Materials

In the present study, a range of methods was implemented:

- analysis and synthesis – to explore existing concepts of Digital Twins and to assess the prospects of using Digital Twin (DT) technology for forecasting workforce needs in Ukraine's post-war reconstruction;
- simulation – to develop the conceptual model Digital Twin Workforce Navigator in Post-War Ukraine Reconstruction Planning;
- graphic method – to formalize the Digital Twin Workforce Navigator in Post-War Ukraine Reconstruction Planning model, which was designed using the LucidChart environment.

4. Results

The development of digital technologies opens new opportunities for forecasting and managing human resources, especially in the complex conditions of post-war reconstruction. The use of Digital Twin technology enables not only the analysis of existing labor data but also the modeling of potential scenarios for changes in the labor market. This is particularly important in unstable environments, where workforce needs can shift rapidly under the influence of global challenges, as well as demographic, economic, and social factors.

This study explores methodological approaches to creating a Digital Twin model for forecasting workforce needs in Ukraine's post-war reconstruction. In particular, it analyzes the potential of this technology for assessing labor shortages in key industries, planning workforce reintegration, and adapting personnel to new conditions. The study also highlights the advantages of combining Digital Twins with machine learning methods to improve forecasting accuracy.

The model (Fig. 1) illustrates the workflow of the Digital Twin Workforce Navigator for post-war reconstruction planning in Ukraine. It consists of several key stages, starting from data collection to generating analytical reports and workforce planning recommendations.

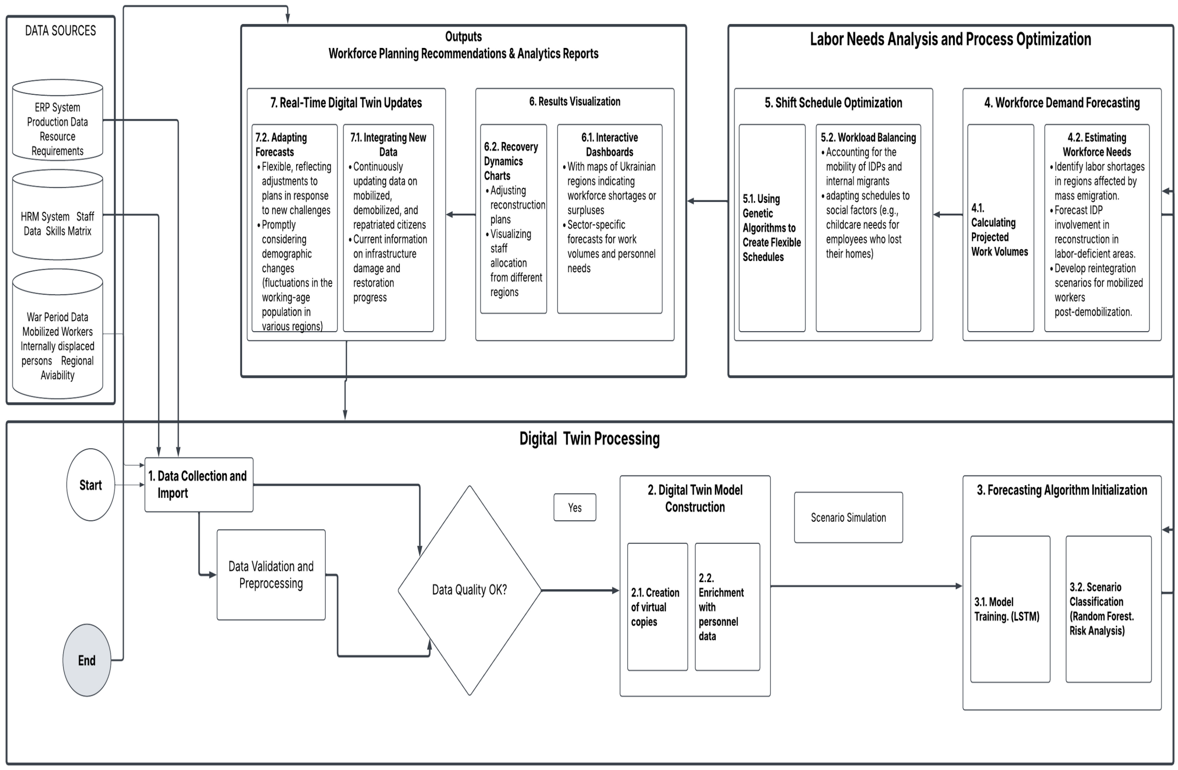

Figure 1: Digital Twin Workforce Navigator in Post-War Ukraine Reconstruction Planning model

At the initial stage, data is collected and integrated from various sources. This includes information from ERP systems (data on production and resource needs), HRM systems (data on personnel and skill matrices), and data from the wartime period (mobilized workers, internally displaced persons, and regional workforce availability). The collected data undergoes verification and preprocessing to ensure quality and compliance with requirements.

Once verified, a data quality control process is conducted. If the data does not meet the standards, it is sent back for further preprocessing and correction. If the data passes the quality checks, the Digital Twin modeling stage begins. At this stage, a virtual model is created that accurately represents existing resources, their current state, and potential capabilities.

The next step involves simulating scenarios using the Digital Twin to forecast possible outcomes of different reconstruction strategies. Based on these simulations, analysis and forecasting are conducted to assess the effectiveness of the scenarios and identify optimal recovery strategies.

In the final stage, the system generates workforce planning recommendations and analytical reports. These results support informed decision-making regarding resource allocation, organization of reconstruction activities, and efficient utilization of human resources in Ukraine's post-war rebuilding efforts.

The proposed model structure consists of the following elements:

1. Data collection and import. Import of data from production systems and HRM: ERP systems (production volumes, resource needs); HRM systems (available personnel, shift schedules, skills, vacations, sick leaves, etc.). The scheme also includes specific data for the post-war period: information about mobilized employees (dual accounting); data on internally displaced persons (IDPs) and their availability for work; registries of unemployed persons and migrants; statistics on losses among the working-age population.

2. Building the Digital Twin model.

2.1. Creation of virtual copies of production facilities, considering damage or destruction of infrastructure (partially or completely destroyed enterprises) and updating logistics chains to supply materials to restored regions.

2.2. Enrichment with personnel data: available workforce (considering regional migration and demographic changes); skills and qualifications of employees (especially for sectors that require restoration – construction, utilities, infrastructure); accounting for mobilized employees (formally employed but actually unavailable).

3. Initialization of the forecasting algorithm.

3.1. Model training. For forecasting changes in the number and structure of personnel using LSTM (Long Short-Term Memory). These models involve training on historical data regarding work shifts, seasonal demand fluctuations, the impact of mobilization waves, and migration processes.

3.2. Scenario classification. It is recommended to use Random Forest to classify regions by the level of personnel demand (reconstruction zones, safe regions, regions with an oversupply of labor) and to analyze risks, taking into account instability factors (e.g., repeated shelling and resulting destruction).

4. Forecasting personnel needs.

4.1. Calculation of forecasted work volumes. It is proposed to assess production plans for infrastructure restoration and determine the required volumes of materials and equipment for the work.

4.2. Assessment of personnel needs. At this stage, it is necessary to consider labor shortages in regions with mass emigration, forecast the involvement of IDPs in reconstruction efforts in labor-deficient regions, and develop scenarios for the reintegration of mobilized employees after demobilization.

5. Optimization of shift schedules.

5.1. Using genetic algorithms to create flexible schedules. It is essential to consider available personnel and their accessibility, as well as the possibility of optimizing shifts to maximize workforce engagement in reconstruction regions.

5.2. Workload balancing. This involves ensuring an even distribution of employees between regions (considering the mobility of IDPs and internal migrants) and adapting schedules to social factors (e.g., childcare for employees who have lost their homes).

6. Visualization of Results.

6.1. Interactive Dashboards. Construction of information panels with maps of Ukraine's regions, displaying indicators of labor shortages or surpluses. Separate forecasts should be made regarding work volumes and personnel needs by industry (construction, energy, logistics, education, healthcare, and other social infrastructure sectors).

6.2. Recovery Dynamics Charts. At this stage, it is advisable to adjust reconstruction plans considering the workforce potential and visualize the process of involving personnel from different regions.

7. Real-Time Digital Twin Updates.

7.1. Integration of new data. This involves updating information on mobilized, demobilized, and citizens returning from abroad, as well as updating data on infrastructure damage and its restoration status.

7.2. Forecast Adaptation. The system is flexible and should reflect adjustments in plans in case of new challenges (e.g., repeated destruction or natural disasters). It is also necessary to promptly account for changes in the demographic structure (reduction or increase in the working-age population in regions).

The Digital Twin Workforce Navigator in Post-War Ukraine Reconstruction Planning model acts as a "digital conductor" that orchestrates the symphony of Ukraine's reconstruction. This innovative algorithm is not just a personnel planning system but a true bridge between the present and the future of our restored nation.

Key features of this system include: adaptive data collection (Integrating "war-time realities" with traditional HR metrics, considering the unique experience of veterans as potential workers, and tracking the movement of internally displaced specialists); intelligent contextual processing (analyzing regional reconstruction specifics, evaluating the impact of demilitarized areas on the labor market, and considering international reconstruction projects); predictive modeling (creating digital twins of various recovery scenarios, forecasting the demand for specialists across different sectors, and generating recommendations for workforce retraining).

The Digital Twin Workforce Navigator in Post-War Ukraine Reconstruction Planning model integrates mathematical forecasting and optimization techniques to provide a robust framework for labor market recovery. The following equations underpin the key components of our model:

Workforce growth projection: the workforce growth over time is modeled using a logistic function:

$$L_t = \frac{K}{1 + \left(\frac{K - L_o}{L_o} \right)^{e^{-rt}}}, \tag{1}$$

where L_t represents the projected workforce at time t, K is the workforce capacity limit, and r is the workforce recovery rate.

Labor resource distribution optimization:

$$S_i = D_i + M_i - R_i, \tag{2}$$

where S_i is the available workforce in region i, considering demand D_i, migration impact M_i, and workforce losses R_i.

Sectoral workforce deficit calculation:

$$Def_i = \sum_{j=1}^{n} \left(W_{ij} - A_{ij} \right), \tag{3}$$

This formula evaluates the workforce gap in region i, where W_{ij} denotes required labor and A_{ij} represents available workers per sector j.

Training program effectiveness in workforce recovery:

$$E_t = E_0 + \alpha \sum_{i=1}^{N} \left(T_i \cdot R_i \right), \tag{4}$$

where E_t is the total trained workforce at time t, T_i represents the number of program graduates per sector, and R_i is the employment probability.

Labor mobility impact on reconstruction:

$$M_{ij} = \beta \cdot P_{ij} \cdot \left(W_j - A_j \right), \tag{5}$$

This equation models workforce movement from region i to region j, incorporating mobility factor β, migration probability P_{ij}, and workforce demand W_j.

Forecast accuracy measurement:

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} \left(L_t^{emp} - L_t^{forecast} \right)^2}, \tag{6}$$

where $RMSE$ – the root mean square error evaluates model forecast accuracy, L_t^{emp} – empirical workeforce number, $L_t^{forecast}$ – forecast workeforce number, ensuring precise workforce planning. The lower the RMSE value, the more accurate the model.

These mathematical models reinforce the predictive capabilities of the Digital Twin Workforce Navigator, facilitating real-time labor allocation and workforce reintegration strategies essential for Ukraine's post-war recovery.

The uniqueness of our proposed approach lies in:

1) military-civilian integration, which takes into account the specifics of the transition of military specialists to civilian projects, assesses the possibilities of applying military experience in reconstruction projects and creates "bridges of competences" between the military and civilian spheres;

2) ensuring regional adaptability through the formation of individual strategies for different regions depending on the level of destruction, taking into account local labor market characteristics and offering flexible solutions for different scenarios of Ukraine's reconstruction;

3) forecasting, which uses digital twin technology to model various scenarios taking into account international experience of post-conflict or post-war reconstruction for further adaptation of best world practices to Ukrainian realities.

To develop a forecast for workforce demand forecasting using Digital Twin Technology under three scenarios (optimistic, realistic, and pessimistic), we apply the logistic recovery equation:

$$W(t)=W_0+\frac{L}{1+\exp(-k*(t-t_0))}, \tag{7}$$

where W(t) – projected workforce size in year t, W0 – initial workforce size at the end of the base year (20__), L – maximum workforce growth (difference between the asymptotic level and the initial value), k – recovery rate, t0 – inflection point, the year when the growth rate is at its maximum, t – forecast year (normalized relative to the base year 20__).

Using the logistic function for workforce recovery forecasting is suitable for different reasons:

1. Alignment with post-war reconstruction phases. The logistic function ideally represents the S-shaped dynamics of post-war labor market recovery, which typically follows three phases:

1) initial phase (t < t0): slow growth due to economic instability, uncertainty, and limited investments;

2) rapid recovery phase (t ≈ t0): the highest rate of workforce expansion due to international investments, infrastructure rebuilding, and the return of displaced workers;

3) stabilization phase (t > t0): saturation of the labor market as employment reaches a sustainable level.

2. Flexibility for different scenarios. This equation allows adjusting parameters for each scenario:

1) optimistic scenario – high L (rapid workforce growth due to strong international support and fast repopulation), high k (fast economic recovery), early t0 (accelerated reconstruction programs);

2) realistic scenario – moderate values of L, k, t0 (gradual, steady recovery);

3) pessimistic scenario – low L (slow workforce growth due to prolonged instability), low k (economic stagnation and limited investments), late t_0 (delayed recovery due to ongoing conflict or policy challenges).

3. Robustness under uncertainty. The logistic function is robust in uncertain conditions because it limits forecasted values to a realistic upper bound, captures delayed effects in workforce recovery, is resistant to anomalies, which is crucial for a country still in a state of war.

The logistic recovery equation provides a well-founded mathematical approach for modeling workforce dynamics during Ukraine's post-war reconstruction. It enables scenario-based forecasting, ensures stability in predictions, and offers flexibility for adaptation as new data becomes available. This approach serves as an initial approximation (a lightweight model) within the Digital Twin framework and can later be refined with more complex models (e.g., stochastic simulations or agent-based modeling) as additional data on Ukraine's reconstruction process becomes available.

To ensure effective forecasting of workforce dynamics in Ukraine during post-war reconstruction, the use of the logistic function has been justified. This approach allows for modeling a three-phase recovery process in the labor market: initial decline, period of rapid growth, and stabilization at a new level. By adjusting the parameters W_0, L, k, t_0, this model adapts to different future recovery scenarios. Optimistic scenario anticipates rapid growth driven by international investments, accelerated infrastructure reconstruction, and effective government policies. Realistic scenario reflects a gradual recovery of the economy and labor market, based on moderate investment inflows and a controlled demographic situation. Pessimistic scenario models a prolonged stagnation period with a slow transition to stability due to delays in reconstruction and low economic activity. The table 1 presents the projected workforce size in Ukraine from 2012 to 2030 for each scenario.

Table 1
Workforce Forecasting in Ukraine by three scenarios, 2012–2030 (ths persons)

Years	Optimistic scenario	Pessimistic scenario	Realistic scenario
2012	19261.4	19261.4	19261.4
2013	19314.2	19314.2	19314.2
2014	18073.3	18073.3	18073.3
2015	16443.2	16443.2	16443.2
2016	16276.9	16276.9	16276.9
2017	16156.4	16156.4	16156.4
2018	16360.9	16360.9	16360.9
2019	16578.3	16578.3	16578.3
2020	15915.3	15915.3	15915.3
2021	15610,0	15610,0	15610,0
2022	14800,0	14200,0	14500,0
2023	14500,0	13500,0	14000,0
2024	15622.9	14222.6	14930.1
2025	16032.4	14385.9	15203.9
2026	16467.6	14563.9	15500,0
2027	16877.1	14750,0	15796.1
2028	17220.5	14936.1	16069.9
2029	17481.8	15114.1	16305.6
2030	17666.3	15277.4	16496.1

The adequacy assessment of the model, based on the Student's t-test and the Durbin-Watson criterion, shows that while the model is partially relevant, there are areas for improvement. The Student's t-test results indicate that the mean forecast error is not statistically significant (p-value = 0.5225), suggesting that the model's contribution to forecasting is not substantial and that the analyzed variable does not significantly explain the dependent variable. However, despite this, the model still offers a reasonable first approximation of workforce demand in Ukraine under the realistic scenario. On the other hand, the Durbin-Watson criterion, with a value of 0.8065, indicates positive autocorrelation of the residuals, meaning that deviations between forecasted and actual values are correlated. This suggests that the model may not fully account for all relevant factors or relationships in the data, leading to a systematic error in the residuals. While this indicates room for improvement, the model can still be considered a valid starting point for forecasting. Therefore, we conclude that while the model is partially relevant, further refinement is necessary to enhance its accuracy and address the autocorrelation issue.

Based on these data, a chart has been created to illustrate the projected trends in Ukraine's labor market during the post-war period (Fig. 2).

Figure 2: Ukraine Workforce Forecast, 2012–2030 (ths persons)

The result of applying this innovative algorithm can be the formation of dynamic maps of specialist needs, the creation of retraining programs taking into account regional needs, the development of strategies for attracting international experts and the optimization of the distribution of labor resources in various reconstruction projects.

The system does not just predict personnel needs – it creates a "smart map" of Ukraine's reconstruction, where each specialist finds his place in the great project of the country's revival. It is a kind of "talent navigator" that helps to connect the needs of reconstruction with available human resources, creating effective teams for the implementation of projects of varying complexity. The proposed innovative algorithm has integration capabilities. It provides the ability to interact with international expert databases, connect to educational platforms for rapid retraining, synchronize with reconstruction projects of various scales, etc. This algorithm is a tool that helps to turn the challenges of reconstruction into opportunities for development, and human potential into the driving force of Ukraine's revival.

5. Conclusion

The application of Digital Twin technology in forecasting personnel needs for the post-war reconstruction of Ukraine allows for the effective resolution of complex challenges related to human resource management. First, digital twins provide the ability to accurately assess existing and forecasted human resources, which enables the optimization of labor distribution across sectors and regions. This ensures even workload distribution and minimizes the risks of specialist shortages in key sectors such as construction, energy, and transportation.

Second, the use of digital twins allows for flexible reconstruction planning by enabling the modeling of different scenarios. This helps to swiftly adapt personnel recruitment strategies to the real conditions of the labor market and the socio-economic situation in the country. Forecasting changes in the workforce structure helps to reduce the shortage of specialists in critically important areas and facilitates the reintegration of mobilized workers after demobilization.

Third, the Digital Twin system allows for the integration of international experience in post-war recovery processes by incorporating the best global practices in labor resource management. This fosters the development of an effective model for retraining personnel according to the changing needs of the economy.

Moreover, digital twins can contribute to the active return of Ukrainians from abroad, as they allow for precise forecasting of in-demand professions and the creation of attractive employment conditions. They also help assess potential risks related to the restoration of destroyed infrastructure and optimize reconstruction costs.

It is also worth noting the possibility of integrating digital twins with modern educational platforms. This enables the rapid adaptation of training programs to labor market needs, which will facilitate the accelerated preparation of specialists for the country's reconstruction.

The proposed approach has been demonstrated through workforce forecasting for the years 2012-2030, offering a first approximation of labor demand trends and providing valuable insights for the practical application of Digital Twin models in workforce planning during the post-war reconstruction of Ukraine. By leveraging this technology, the forecasting process can be enhanced, supporting effective and data-driven decision-making in the planning and management of human resources for the recovery period.

The use of Digital Twin technology in the planning of human resources for post-war reconstruction in Ukraine can become one of the key factors in the successful reconstruction of the economy. It allows for the creation of a flexible, adaptive, and efficient labor resource management system that will promote faster and higher-quality recovery of the country, ensure social stability, and increase the competitiveness of the Ukrainian labor market.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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