The Human Resource Management challenge of predicting employee turnover using machine learning and system dynamics

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Abstract. The turnover rate is an indicator of the company situation (health), a high turnover may indicate dissatisfaction with the work conditions, conflicts with the management or lack of career opportunities, etc. The unexpected loss of high skilled employees will lead to less productivity and less quality which can threaten the company's competitive advantage in the market. The turnover rate is difficult to predict and challenging to manage, therefore, having a warning system or tool that predicts possible resignations at an early stage may help HR managers improve their retention strategies and maintain a stable rate.

The main target for this research proposal is to build a model based on HR managers observations and knowledge alongside theoretical assumptions using historical data to assist decision-making. The model will be built, constructed, and developed using machine learning and system dynamics to act as a predictive tool. Therefore, HR managers will be able to predict the turnover rate and most importantly to identify the reasons behind it, thus, they will have more flexibility in adjusting and improving retention strategies. To build this predictive model, mixed methods qualitative and quantitative will be used taking into consideration the ethical approval process of data gathering by the university of Worcester.

Keywords: employee turnover, human resources management, machine learning, system dynamics.

1 Introduction

The term 'turnover' means that the employee leaves the company permanently and ends the relationship with the organization. Scholars in this field correctly defined it as the rotation of employees around the market; between the firms, jobs, and occupations; and between the states of employment and unemployment [1,17]. The main target for companies is to maintain a stable turnover rate since high turnover may be considered as an indicator of an issue with the organization [5,33].

A proper administration of human resources management (HRM) practices is crucial in retaining employees in organizations. HR professionals and line managers need to work closely to ensure all key practices such as managing performance and employee relations are executed in an effective manner. The importance of managing human resources has been growing over the past years in academia and in practice. The perceptions of human resources practices are more important than the actual practices in developing employee commitment. Management scholars and practitioners have exerted continuous efforts in learning more about human resources practices and how these practices enhance employees' performance and achieve organizational goals [17,20].

Data mining, an effective means of obtaining useful information by identifying trends and patterns [21], has been one of the ways to demonstrate how HRM practices can affect the organisation. Human resources in the enterprise generate various data which can be used in the formulation of corporate strategies and the selection of employees. In recent years, the number of research contributions that aim at supporting the practical adoption of HRM data mining has been rapidly growing. These contributions refer to various HRM activities and processes, such as predicting and evaluating employee performance, predicting employee turnover, etc. [35,21].

Intelligent algorithms based on machine learning (ML), a subset of artificial intelligence that incorporates the principles of data mining to predict business and possible outcomes using historical data [22,3], can help in resolving some of the mentioned challenges as well as in increasing efficiency and effectiveness of HRM. However, organisations should be mindful that the purpose of integrating these technological capabilities is not to replace humans, but rather to improve the decision making around people [8,10].

2 Related research

Several features were highlighted in previous studies as drivers for the turnover rate depending on the selected field, the followed methodology and the analysis methods. The research by [5] showed that gender followed by age then education level were the first variables affecting the turnover prediction in a manufacturing company. [37] also indicated that gender is one of the most relevant features to consider in predicting the turnover rate beside economic indicators such as GDP. [25] highlighted the impact of withdrawal behaviours such as lateness and absenteeism on predicting the turnover in a large software company. Contrary to some previous studies, the research by [33] showed that features such as social interaction ability, age and marital status were insignificant to predict the turnover in a manufacturing company. However, the number of previous job changes and the knowledge about the working conditions were highly correlated to the turnover rate.

For Machine learning and data mining methods, several studies conducted their research to predict the turnover rate in the most accurate way combining different techniques. A variety of machine learning approaches have been applied to prediction of turnover rate. Common approaches include decision tree classification [6,41] and ensemble learning [42,43]. However, applications of machine learning combined with novel computational models has led to further improvements. A study by [37] proposed a new method to predict the turnover including the time factor by combining ensemble learning and survival analysis (statistical approach). The results proved that this combination improved the accuracy of the model compared with the others machine learning algorithms. Moreover, dealing with the turnover rate from a dynamic perspective [7] developed a predictive model using a system dynamics approach. System Dynamics is an approach that allows the creation of micro-worlds where space and time can be compressed and slowed, so you can experience the long-term side effects of your decisions [34]. Different retention strategies were tested with this model which led to conclude that the fact of understanding the reasons causing high turnover may be more important to set an effective retention strategy, taking other factors into consideration.

Having an accurate model that predicts the turnover rate can help HR managers set a suitable retention strategy in time. Few interventions that have been proven successful to manage the turnover are through improving the recruitment strategy [4,6], improving the candidate selection [16,14], providing various self-development opportunities through trainings [15], and by providing various incentives such as bonus, rewards, and competitive compensation [40]. For example, [25] mentioned in their study that young engineers are more interested in having experience in different domains rather than in one specialisation. Therefore, offering a better technology or domain can attract engineers more than compensation. Hence, knowing the cause of high turnover is important to improve decision making since it is different from one field to another, and it depends on the current situations of the company itself.

Interventions through human resource management puts its focus on two indicators for organisations, first is the turnover rate in a period that is deemed acceptable. Another indicator is to see the turnover cost that can be saved by implementing the strategy, whether it is tolerable or intolerable. These two indicators can be the basis for evaluating the best strategy to manage turnover [7].

Based on previous research, it can be can concluded that predicting the turnover rate is an important issue for organisations, several models were built with good, achieved performance, but the majority was not developed starting from real-world observations specifically causal relationships between different variables to consider while building the model. The authors were mainly focusing on proving a good theoretical accuracy based only on historical data. Therefore, the fact of building a model closer to reality by starting from real-world causality, captured from interviews with HR and line managers alongside literature to support the theoretical development of a predictive tool can help HR managers analyse the turnover rate in a different way by highlighting the real reasons behind it, and by testing the outcome of different scenarios/retention strategies before taking any decision.

3 Outline of the research questions and objectives

3.1 Research questions

RQ1: What quantifiable features can be identified by HR experts, line managers and from the literature, that are considered practical cause-effect or causal links to predict the turnover?

RQ2: What is the most effective combination of machine learning algorithms and dynamic/causal modelling approaches to build a predictive model based on real-world causality?

RQ3: How can the outcomes of a predictive model be used to evaluate the efficiency of different retention strategies?

3.2 Research Aim

The aim of this study is to provide a data-driven predictive tool to enable HR managers analyse the turnover rate in a different way by capturing the most important variables causing the fluctuation and testing the outcome of different scenarios. This tool will be focused on real-world causality concluded from interviews and previous research to enable HR managers take into consideration the impact of each variables including the long-term interest of the company before taking any decision.

3.3 Research Objectives

O1:Identify the field of interest to consider in this research based on networking and data accessibility (which industry/sectors to consider).

O2:Identify the most relevant features and the most important causal links that relate to the turnover rate based on HR experts' and line managers point of view, and previous research.

O3:Select the most effective approach between system dynamics and ML to predict the turnover based on real-world causality.

O4:Analyse the results from a theoretical (technical) perspective.

O5: Evaluate the performance of the system from a perspective of a professional practice.

O6: Establish different scenarios to predict the turnover rate and test the efficiency of different scenarios/retention strategies (Consider a specific use case).

4 METHODOLOGY

This topic will be mainly focused on predicting the future, therefore, the research onion for future studies by [23] inspired from the original research onion by [32] will be followed. The research onion is a way to organise and structure the research methodology following consecutive layers step by step starting from the main philosophy until choosing the techniques and procedures of data collection and analysis [32,23], (See figure 1).

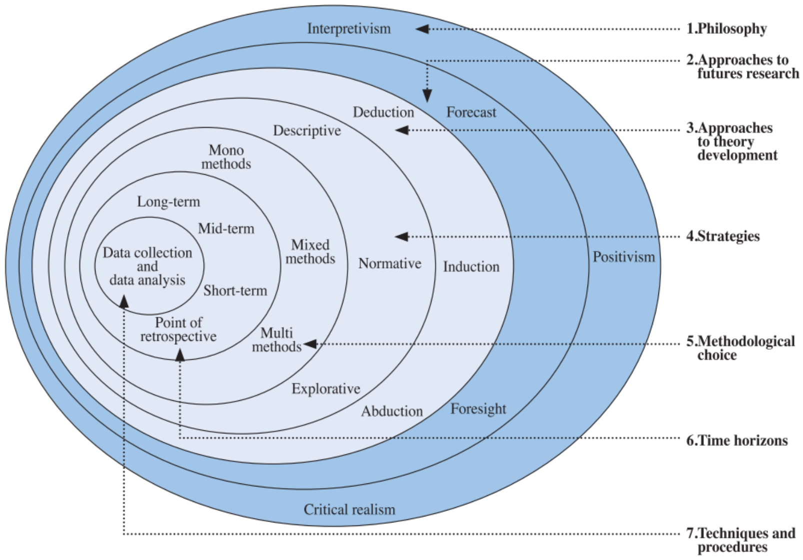

Fig. 1. Research onion for futures studies [23]

4.1 Philosophy

Usually, researchers aim to follow a positivism philosophy for prediction studies using specific statistics and algorithms to predict one possible scenario and have accurate results only from a technical perspective. For this study a more realistic model is investigated with a focus on the employee turnover as a variable and its causality with the other variables in a dynamic way. The main target of this topic is to predict the turnover rate and analyse how it can be affected by other observable variables and vice versa. Hence, multiple scenarios are considered for the future based on adjusting the most relevant observable features correlated to the turnover in order to test the outcome of different scenarios, taking into consideration the company's interest. Therefore, critical realism is the right philosophy for this research [23].

4.2 Approaches to futures research

According to [18], two approaches may be considered forecasting and foresight. The first approach forecasting is mainly applied in areas in which tangible quantitative data is available, such as demography, economic development, while the second approach foresight which leads to have a complex cognitive-analytical view of multiple futures, is used in areas such as institutions, culture, and politics. Therefore, forecasting will be used in this research to evaluate the outcome of each scenario by feeding the model the required data to learn the logic of the selected scenario (causal relationships), [23].

4.3 Approaches to theory development

Abductive reasoning starts with the observation of weak signals in a specific area, it is mainly applied to draw a conclusion from low knowledge. The fact of considering real-world causality to predict different scenarios is still a new area in which several theories and hypotheses are not established yet. Thus, abductive reasoning will be considered when the causal loop diagram will be developed and inductive reasoning will be used to set general conclusions before moving to the development of a clear theoretical position to build the model [27,19,23].

4.4 Strategies

Three main research strategies can be distinguished in this area: descriptive, normative, and explorative. Descriptive methods aim to have a precise description of future events, normative methods aim to shape the desirable and undesirable future in order to establish pathways or chain of events to reach the desirable one, and explorative methods aim to study multiple futures and explore possible developments. This research will be mainly focused on exploring different scenarios for the future based on adjusting different features to analyse their impact on the turnover rate. Hence, explorative methods will be used to investigate multiple scenarios and descriptive methods will be used to examine and explain the observed outcomes [28,18,23].

4.5 Methodological choice

Research methods can be distinguished into quantitative methods, such as time series analysis, causal analysis, etc, qualitative such as Delphi surveys, and mixed methods which are classified as quantitative and qualitative such as scenario construction and modelling. Thus, mixed methods; qualitative and quantitative will be followed in this study to generate hypotheses then build the predictive model based on them [31,23].

4.6 Time horizon

Three basic time horizons are defined in future studies (time scale of prediction): short-term which is up to 10 years, medium-term, up to 25 years, and long-term which can be more than 25 years. This time horizon refers to the period that will be studied or to the chronological horizon of varying breadth. For this research, short term will be considered [18,23].

4.7 Techniques and procedures

In the last layer "techniques and procedures" , the research design will move towards data collection and analysis. As mentioned in previous steps, mixed methods is considered, hence, qualitative and quantitative data collection and analysis will be followed [23].

Qualitative data collection and analysis

. The main purpose for this research is to develop a robust prediction model closer to reality and link the theoretical research to the professional requirement by focusing on causality between different features that are relevant to predict the turnover rate. Therefore, two sources will be considered to identify these features; previous research and primary qualitative data which are semi-structured interviews with HR experts and line managers. For previous research, articles and papers are selected based on their number of citations, quality of their journals and authors, then structured in descriptive tables. For the semi-structured interviews, several interviews will be conducted with HR managers and line managers for a better understanding of the strongest causal connections to consider in predicting the turnover rate based on their experience and knowledge. The number of interviews cannot be defined therefore when the saturation in the amount of information needed is reached (no new information is concluded from the interviews), the interviews will stop [11].

Thematic analysis will be used to have a critical review of responses by determining appropriate coding and creating themes from those codes. This method will be conducted during the entire interview process, which will provide structure and integrate reflexivity to the research [44,9].

Theoretical framework will be considered too, it is a structure that can hold or support a theory of a research study by introducing and describing the theory that explains why the research problem under study exists [2,39]. Hence, it will be used to establish hypotheses based on causality around the turnover rate from interviews and previous research.

Causal loops diagrams summarizing the findings from the interviews alongside previous research will be developed to be integrated later in a predictive model (causal or a cause-effect relationship, it depends on how much details we can capture from interviews and previous research). A field will be selected when building the causal loops diagrams such as IT, Higher education, etc, and a precise use case (an industry in that field) will be investigated in the quantitative part.

Quantitative data collection and analysis

. In this study, a hybrid approach combining the logic of the system dynamics methodology (dynamic causality) and ML algorithms in the context of predicting the employee turnover will be investigated.

Solutions will be represented in the form of a larger graph of causal loops inspired from the first step of system dynamics [34], different sets of non-linear dynamic equations can be tested. Causal-comparative research method will be considered to analyse the results. This quantitative method is used to identify a causal relationship between an independent variable and a dependent variable. The relationships between dependent and independent variables are usually suggested (not proven) because the researcher does not have a complete control over the independent ones [38,29].

A machine learning approach will be followed to optimise this graph representation of the dynamic causality or cause-effect relationships. This approach will allow prediction of the turnover rate and enable analysing the reasons causing the turnover to be high or low. Secondary data from an HR department (individual organisation) will be gathered at this stage to analyse a precise case. The standard HR datasets provided by IBM and Kaggle can be used too for technical testing and analysing [12,13].

This combination of data- and knowledge-based solution by integrating causality in the model will allow HR managers to have more than one scenario to manage the turnover rate by adjusting different variables based on the company interest [30].

The CRISP-DM methodology will be followed to build the model, it is a reference that can provide an overview of the life cycle for data mining projects. It includes six sequential phases, shown in Figure 2 [36].

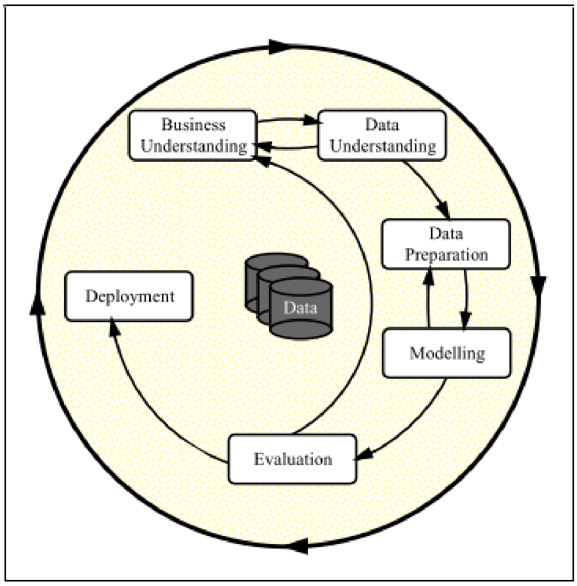

Fig. 2. Phases of the Current CRISP-DM Process Model for Data Mining [36]

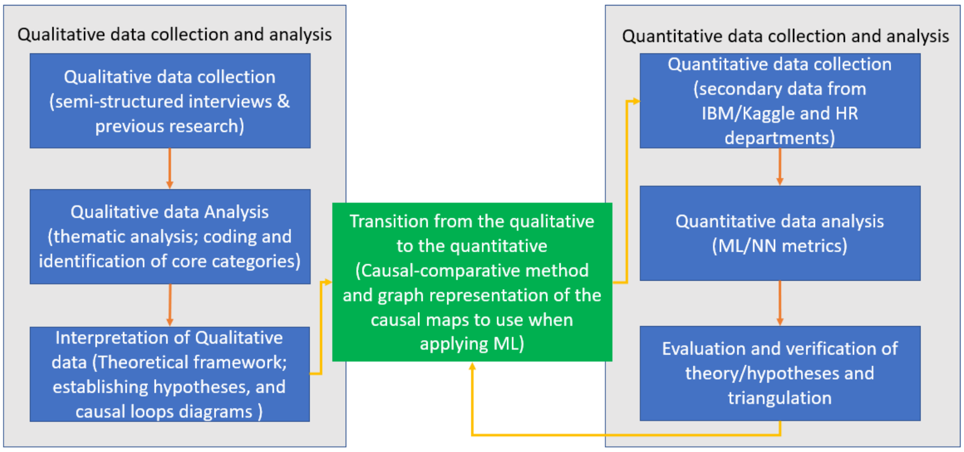

Fig. 3. Research methods framework

5 Expected contribution

This research contribution will be a confirmation, replication of a theory within the area of employee turnover prediction, precisely, confirming the validity of applying a graph representation approach to combine the logic of the system dynamics methodology with machine learning algorithms, to the prediction of turnover rate focused on real-world causality.

6 Stage of the research

At this stage of the research, the semi-structured interviews are still in progress with HR managers and line managers. As mentioned earlier , thematic analysis is considered during the entire process of the interviews. Moreover, causal loops diagrams are developed using VENSIM PLE based on observations throughout data collection and analysis. Purposeful and snowballing sampling have been considered in selecting participants: Purposeful sampling is a technique widely used in qualitative research for the identification and selection of information-rich cases for the most effective use of limited resources. This involves identifying and selecting individuals or groups of individuals that are especially knowledgeable about or experienced with a phenomenon of interest which is employee turnover in this case. It is highly subjective and determined to generate the qualifying criteria each participant must meet to be considered for this research study [26]. The most important criteria to select participants is being an HR manager or a line manager for at least two years. In Snowball sampling, the existing study subjects recruit future subjects among their acquaintances. Sampling continues until data saturation is reached (no new information concluded or added from the interviews), [24].

7 Acknowledgment

Supervisors:

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References

1. Abbasi, S. M., & Hollman, K. W. (2000), Turnover: The Real Bottom Line, Public Personnel Management, 29(3), 333-342.
2. Abend, G. (2008) 'The Meaning of Theory', *Theology*, 54(374), pp. 304–304. doi: 10.1177/0040571x5105437406.

3. Arora, S. (2019) 'Data Mining Vs. Machine Learning: What Is the Difference?', *Simplilearn Solutions*, pp. 1–9. Available at: https://www.simplilearn.com/data-mining-vs-machine-learning-article.
4. Breaugh, J. A. and Starke, M. (2000) 'Research on employee recruitment: So many studies, so many remaining questions', *Journal of Management*, 26(3), pp. 405–434. doi: 10.1177/014920630002600303.
5. Chang, H. (2009) 'Employee Turnover : A Novel Prediction Solution with Effective Feature Selection 2 Turnover and Turnover Intention A Novel Approach to Hybrid 4-1 Feature Selection Based on Taguchi 3 Feature Selection Model', 6(3), pp. 252–256.
6. Chien, C. F. and Chen, L. F. (2008) 'Data mining to improve personnel selection and enhance human capital: A case study in high-technology industry', *Expert Systems with Applications*, 34(1), pp. 280–290. doi: 10.1016/j.eswa.2006.09.003.
7. Destyanto, A. R. *et al.* (2017) 'System Dynamics Approach for Managing Turnover Problem in Professional Service Firm', *2nd International System Dynamic Conferences Asia Pacific Regions*, (February). Available at: https://www.researchgate.net/profile/Akhmad_Hidayatno/publication/315680576_System_Dynamics_Approach_for_Managing_Turnover_Problem_in_Professional_Service_Firm/links/58db033ba6fdccca1c79eb4b/System-Dynamics-Approach-for-Managing-Turnover-Problem-in-Profes.
8. Dogan, A. and Birant, D. (2021) 'Machine learning and data mining in manufacturing', *Expert Systems with Applications*, 166(September 2020), p. 114060. doi: 10.1016/j.eswa.2020.114060.
9. Evans, C. and Lewis, J. (2017) 'Analysing Semi-Structured Interviews Using Thematic Analysis: Exploring Voluntary Civic Participation Among Adults', *Analysing Semi-Structured Interviews Using Thematic Analysis: Exploring Voluntary Civic Participation Among Adults*. doi: 10.4135/9781526439284.
10. Garg, S. *et al.* (2021) 'A review of machine learning applications in human resource management', *International Journal of Productivity and Performance Management*. doi: 10.1108/IJPPM-08-2020-0427.
11. Guest, G., Bunce, A. and Johnson, L. (2006) 'How Many Interviews Are Enough?: An Experiment with Data Saturation and Variability', *Field Methods*, 18(1), pp. 59–82. doi: 10.1177/1525822X05279903.
12. Hamilton, W. L. (2020) 'Graph Representation Learning Hamilton', *Synthesis Lectures on Artificial Intelligence and Machine Learning*, 14(3), pp. 1–159. doi: 10.2200/S01045ED1V01Y202009AIM046.
13. Hamilton, W. L., Ying, R. and Leskovec, J. (2017) 'Representation Learning on Graphs: Methods and Applications', pp. 1–24. Available at: http://arxiv.org/abs/1709.05584.
14. Hom, P. W. *et al.* (2012) 'Reviewing employee turnover: Focusing on proximal withdrawal States and an expanded criterion', *Psychological Bulletin*, 138(5), pp. 831–858. doi: 10.1037/a0027983.
15. Hom, P. W. *et al.* (2017) 'One hundred years of employee turnover theory and research', *Journal of Applied Psychology*, 102(3), pp. 530–545. doi: 10.1037/apl0000103.
16. Hunter, J. E. and Hunter, R. F. (1984) 'Validity and utility of alternative predictors of job performance', *Psychological Bulletin*, 96(1), pp. 72–98. doi: 10.1037/0033-2909.96.1.72.
17. Joarder, M. H. R. (2012) 'The Role of HRM Practices in Predicting Faculty Turnover Intention: Empirical Evidence from Private Universities in Bangladesh', *The South East Asian Journal of Management*, 5(2), pp. 159–178. doi: 10.21002/seam.v5i2.979.
18. Kosow, H. and Gaßner, R. (2008) *Methods of Future and Scenario Analysis*, *Deutsches Institut für Entwicklungspolitik*. Available at: http://www.isn.ethz.ch/Digital-

Library/Publications/Detail/?ots591=0c54e3b3-1e9c-be1e-2c24-a6a8c7060233&lng=en&id=95979.

19. Kuosa, T. (2011) 'Evolution of futures studies', *Futures*, 43(3), pp. 327–336. doi: 10.1016/j.futures.2010.04.001.
20. Long, C. S., Ajagbe, M. A. and Kowang, T. O. (2014) 'Addressing the Issues on Employees' Turnover Intention in the Perspective of HRM Practices in SME', *Procedia - Social and Behavioral Sciences*, 129, pp. 99–104. doi: 10.1016/j.sbspro.2014.03.653.
21. Ma, X. *et al.* (2017) 'Application of Data Mining in the Field of Human Resource Management: A Review', 91(Edmi), pp. 222–227. doi: 10.2991/icwcsn-16.2017.111.
22. Marr, B. (2014) 'What is the difference between data mining, statistics, machine learning and AI?', *StackExchange*, pp. 1–8. Available at: http://stats.stackexchange.com/questions/5026/what-is-the-difference-between-data-mining-statistics-machine-learning-and-ai.
23. Melnikovas, A. (2018) 'Towards an explicit research methodology: Adapting research onion model for futures studies', *Journal of Futures Studies*, 23(2), pp. 29–44. doi: 10.6531/JFS.201812_23(2).0003.
24. Naderifar, M., Goli, H. and Ghaljaie, F. (2017) 'Snowball Sampling: A Purposeful Method of Sampling in Qualitative Research', *Strides in Development of Medical Education*, 14(3). doi: 10.5812/sdme.67670.
25. Nagadevara, V., Srinivasan, V. and Valk, R. (2010) 'Establishing a Link between Employee Turnover and Withdrawal Behaviours: Application of Data Mining Techniques', 16(2), pp. 81–99.
26. Palinkas, L. A. *et al.* (2016) 'Purposeful sampling for qualitative data collection and analysis in mixed method implementation research', 42(5), pp. 533–544. doi: 10.1007/s10488-013-0528-y.Purposeful.
27. Patokorpi, E. and Ahvenainen, M. (2009) 'Developing an abduction-based method for futures research', *Futures*, 41(3), pp. 126–139. doi: 10.1016/j.futures.2008.09.019.
28. Puglisi, M. (2001) 'The study of the futures: an overview of futures studies methodologies', *Ciheam*, 463(44), pp. 439–463. Available at: http://om.ciheam.org/article.php?IDPDF=2001611http://www.ciheam.org/.
29. Raissi, M., Perdikaris, P. and Karniadakis, G. E. (2018) 'Multistep Neural Networks for Data-driven Discovery of Nonlinear Dynamical Systems', pp. 1–19. Available at: http://arxiv.org/abs/1801.01236.
30. von Rueden, L. *et al.* (2020) *Combining Machine Learning and Simulation to a Hybrid Modelling Approach: Current and Future Directions*, *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Springer International Publishing. doi: 10.1007/978-3-030-44584-3_43.
31. Saleh, M. *et al.* (2008) 'A Survey on Futures Studies Methods', *Infos2008*, pp. 38–46. Available at: http://www.researchgate.net/profile/Mohamed_Saleh15/publication/238737064_A_Survey_on_Futures_Studies_Methods/links/02e7e527f8f9013947000000.pdf.
32. Saunders, M., Lewis, P. and Thornhill, A. (2016) *Research Methods for Business Students*. 7th Editio. Pearson. Available at: https://www.pearson.com/uk/educators/higher-education-educators/program/Saunders-Research-Methods-for-Business-Students-7th-Edition/PGM1089011.html.
33. Sikaroudi, A. M. E., RouzbehGhousi and EsmaieeliSikaroudi, A. (2015) 'A data mining approach to employee turnover prediction (case study: Arak automotive parts manufacturing)', *Journal of Industrial and Systems Engineering*, 8(4), pp. 106–121.

34. Sterman, J. D. (2000) *Business dynamics ,Systems thinking and modeling for a complex world*, *Boston*. Available at: http://www.lavoisier.fr/notice/frJWOAR6SA23WLOO.html.
35. Strohmeier, S. and Piazza, F. (2013) 'Domain driven data mining in human resource management: A review of current research', *Expert Systems with Applications*, 40(7), pp. 2410–2420. doi: 10.1016/j.eswa.2012.10.059.
36. Wirth, R. (2000) 'CRISP-DM : Towards a Standard Process Model for Data Mining', *Proceedings of the Fourth International Conference on the Practical Application of Knowledge Discovery and Data Mining*, (24959), pp. 29–39.
37. Zhu, Q. *et al.* (2019) 'CoxRF: Employee turnover prediction based on survival analysis', *Proceedings - 2019 IEEE SmartWorld, Ubiquitous Intelligence and Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Internet of People and Smart City Innovation, SmartWorld/UIC/ATC/SCALCOM/IOP/SCI 2019*, pp. 1123–1130. doi: 10.1109/SmartWorld-UIC-ATC-SCALCOM-IOP-SCI.2019.00212.
38. V.K. Maheshwari, 2018 , Causal-comparative Research, Philosophical commentary on issues of today , viewed 9th April, 2021, < http://www.vkmaheshwari.com/WP/>
39. Swanson, Richard A. Theory Building in Applied Disciplines. San Francisco, CA: Berrett-Koehler Publishers 2013
40. Heneman, H. G., & Judge, T. A. (2006). Staffing Organization (5th ed.). Middleton, WI: Mendota House, Inc.
41. Al-Radaideh, Qasem Al Nagi, Eman , 2012. Using Data Mining Techniques to Build a Classification Model for Predicting Employees Performance. International Journal of Advanced Computer Science and Applications, pp144-151.
42. Zhao, Yue, Hryniewicki, Maciej K. Cheng, FrancescaFu, Boyang, Zhu, Xiaoyu. 2018 Employee turnover prediction with machine learning: A reliable approach, Advances in Intelligent Systems and Computing, pp 737-758.
43. Jain, Rachna, Nayyar, Anand, predicting employee attrition using xgboost machine learning approach, 2018 , Proceedings of the 2018 International Conference on System Modeling and Advancement in Research Trends, SMART 2018, pp113-120.
44. Mackieson, P Shlonsky, A and Connolly, M (2019) 'Increasing rigor and reducing bias in qualitative research: A document analysis of parliamentary debates using applied thematic analysis', Qualitative Social Work. 18(6), pp. 965-980. DOI: 10.1177/1473325018786996.