Agent-Based Gamified Learning Environments for Data Science Education

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Abstract *- Because of the rapid advancement of technology and the increasing importance of the inferences that can be drawn from the big data available in organizations, modern organizations require managers and data Analysts who are capable of data-driven decision-making. But data science students need a natural environment when it comes to learning data-driven decision-making, especially when it comes to predictive and prescriptive analytics. Due to costs and other associated risks in a natural organisation setting, it is hard for educational institutions to teach these aspects of decision-making for data science students. Even Though gamification has been implemented in the data analysis domain in various forms, the field still requires a suitable environment to learn predictive analytics interactively for the students. Even though Researchers have identified that Gamified learning environments can improve Predictive analytics learning can be improved by 15.8%, still there is the lack of proper implementation of a suitable gamified learning environment. This research focused on identifying drawbacks of existing learning environments and whether Agent-Based Modeling can be used in modelling a suitable gamified learning environment. Therefore, an agent-based prototype model of a parameterized environment that enables data-driven decision-making in a simulated environment was modeled using Agent-based modeling, which depicts real-life donor interactions. Results suggest that fill in blanks This Agent-based model can be used as a learning environment for data analysis. Upon further modification, A game that applies this Agent-based model can be developed.*

Keywords**:** Agent-Based Modeling, Gamification, Predictive Analytics, Data Science, Big Data Analytics and Software Agents.

I. INTRODUCTION

In today's fast-paced business world, it's crucial for modern organizations to harness the insights hidden within the vast sea of big data they have access to. As technology continues to advance rapidly, being able to make sense of this data is a key part of making important decisions. According to a study by Accenture (Analytics, n.d.), companies that don't make use of big data in their growth plans risk falling behind. The global big data market is predicted to grow from $42 billion to an astonishing $103 billion by 2027 (Columbus, 2028). To stay competitive, organizations need managers and data analysts who can make the most of data analysis.

However, for aspiring data scientists, there's a challenge when it comes to learning data-driven decision-making, particularly in predictive and prescriptive analytics. Creating a real-world learning environment is difficult due to cost and associated risks in actual organizations. While gamification has been tried in data analysis, there's still a need for a suitable environment for interactive learning, especially in predictive analytics. Research has shown that gamified learning can improve predictive analytics understanding by 15.8%, yet there's a lack of proper implementation. This study focuses on finding the shortcomings of current learning setups and explores the use of Agent-Based Modeling to create a suitable gamified learning environment.

Data scientists, the key players in this data-driven revolution, hail from diverse backgrounds, ranging from information technology to science and engineering

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management. Their skill sets encompass domain expertise, coding proficiency, and a strong foundation in statistics and mathematics, enabling them to unearth valuable insights from data. This requirement for domain expertise sets data scientists apart from their counterparts in fields like machine learning engineering, highlighting the dynamic nature of this profession. In response to these evolving demands, the concept of gamification has gained prominence, bridging the gap between education and engagement for data science learners.

Figure 1. Top technical skills needed for data science jobs

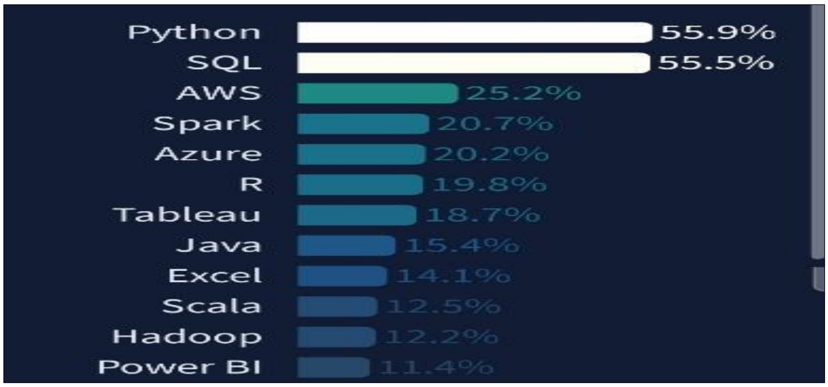
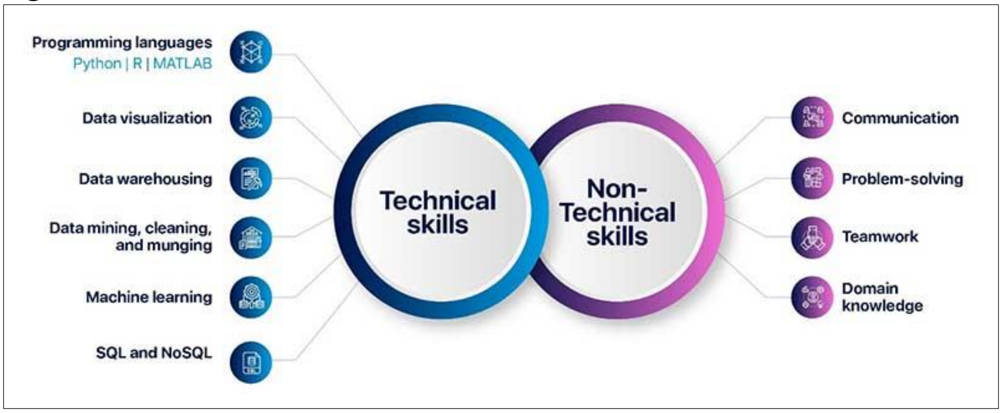


Figure 2. Technical and non-technical skills needed in data science



Amidst these evolving demands, a novel approach has taken the center stage: gamification. Gamification involves the infusion of game design elements and mechanics into contexts beyond the realm of entertainment. Its primary purpose is to engage and motivate individuals to complete tasks or achieve specific objectives. This concept has found relevance in numerous domains, ranging from education to healthcare, marketing, and even employee training. In the realm of data science education, we witness a proliferation of gamified learning platforms like Cortex, Learn2Mine, and Microsoft Learn's latest data feeds (Microsoft Learn Cloud Games | Microsoft Learn, n.d.). These platforms are reshaping the way data science is taught and learned, presenting a unique bridge between the world of data and the excitement of gaming.

Research of Legaki et al., (n.d.) underscores the effectiveness of gamification in improving students' performance in forecasting topics by up to 15.8% compared to traditional teaching methods. Moreover, studies suggest that computer-based simulations can create immersive and engaging learning environments. However, there is a noticeable gap in addressing the limitations of existing gamified data science learning environments, especially concerning decision-making skills for business school students.

A. The Need for Agent-Based Modeling (ABM)

The ability to bridge the gap between data analysis and real-world decision-making poses a formidable challenge. Simulating an artificial market environment using Agent-Based Modeling (ABM) provides a compelling solution. ABM offers the means to construct a simulated environment that mimics real-world donor interactions, enabling learners to experiment with and enhance their data-driven decision-making skills in predictive analytics.

To address this gap and provide an interactive learning environment for data science students, our research endeavors to create an Agent-Based Model (ABM) prototype. This ABM-based environment offers a novel approach to learning data-driven decision-making through immersive experiences, potentially revolutionizing data science education. While previous studies have explored the effectiveness of gamification in data science disciplines and developed platforms for effective data science learning ("Microsoft Learn Cloud Games | Microsoft Learn," n.d; Turner, 2014). This research aims to bridge the gap by introducing an innovative ABM-based learning environment that directly addresses the challenges in practicing decision-making within the context of business education.

The goal is to develop an agent-based prototype model that simulates a data-driven decision-making environment, much like real-life interactions. Decisions that are made based on data analysis can be sent to the parameterized environment, and we can observe the behavior of the agents according to the input from the analysis. The initial results suggest that this agent-based model can serve as a valuable learning tool for data analysis. With further refinement, a game based on this model can be created, providing an effective platform for learning data-driven decision-making.

II. BACKGROUND AND RELATED WORKS

A. Article Selection

When identifying research based on donor behavior and charity, search strings like "Data Science", "Gamification", "Agent-Based Modeling", and "Education" were used. The papers that appeared on Google Scholar's fourth page or later in response to a search query were immediately disqualified. Only the articles on the use of gamifthetion to teach big data analytics were taken into consideration from the papers on the first three pages for this debate. The papers on subjects like utilizing gamification to educate other courses like computer science and business management, using gamification to support machine learning systems, using machine learning for gamification analytics, etc. were removed from the debate. The papers that have cited any of the papers that were thought to be relevant for this topic were also checked for relevance as a final inclusion technique.

Several studies suggest that gamification can be an effective tool for improving business education outcomes. The study of Hamari et al., (2014) found that the learning outcomes of gamification have a positive impact in terms of increased motivation, engagement, and enjoyment in gamified learning contexts. Similarly, a study by Papastergiou, (2009) also suggests the increased motivation and engagement from digital game-based learning environments with the increased effectiveness in learning the concepts and shows games can promote problem-solving skills, critical thinking, and creativity. The Study has also concluded that there is no significant impact from gender for motivation levels in gamified learning of boys and girls involved in that Study despite the boys' higher involvement in gaming. A study by Melissa Thériault et al., (2021) also found a similar higher engagement from students in the context of gamified learning platforms for learning data science concepts.

The studies collectively suggest that gamified data science learning environments are a promising approach for teaching business school students’ data science education. Anderson et al. (2015) and Demchenko et al. (2017), (both address the emergence of cloud-based environments for teaching data science, with positive feedback from students and experts. Hee et al. (2016) propose a tailored learning path for data science using gamification to increase engagement. Liu (2020) proposes a gamified online learning management system for business students, intending to make learning more enjoyable and efficient. Anderson et al. (2015) developed Learn2Mine, a cloud-based environment for teaching data science, and found that student opinion about the usefulness of the tool for learning course content was positive. However, students provided constructive feedback on how the system might be improved. Overall, the papers suggest that gamification can be used effectively to teach data science to business school students.

A study by Legaki et al., (n.d.) found that gamification improved students' performance in forecasting topics by up to 15.8% compared to traditional teaching methods in data science education specifically. Reiners and Wood (n.d.) suggests that computer-based simulations can be an effective way to create an immersive and engaging learning environment. According to Rajapakse et al. (2022), the cortex environment is the state-of-the-art gamified learning platform (Cortex Analytics Game | SAS, n.d.). However, the advantages and disadvantages of the cortex platform vs. the Traditional learning environment have yet to be discovered.

According to Dobson et al. (n.d.), a business strategy game that uses Agent-Based Modeling has identified several drawbacks of existing business strategy games. They are. Lack of timely feedback on the learner's actions. and that the game's feedback is delayed; poor emotional engagement; lengthy durations of training; the information visualisation features in business games are limited to data presentation in the spreadsheet format; the lack of support for after-play debriefing; training business executives/ managers will have less sufficient time to get trained because of their tight schedules.

Even though this research is focusing on broadly business strategy games these same drawbacks are seen on gamified Data Science platforms as well. As there is a significant time gap between this research and the cortex platform, which is the state-of-the-art platform, some of the drawbacks can already be improved. In that research Agent-Based Modeling has been used as an improved solution to those drawbacks.

B. Agent-Based Modeling (ABM)

A model can be described as an abstract description of a process, object, or event that exaggerates certain aspects at the expense of others (Bill Rand (n.d). In Agent-Based Modeling (ABM), a system is modeled as a collection of autonomous decision-making entities called agents. At the most superficial level, an agent-based model consists of a system of agents and the relationships between them (Bonabeau, 2002). According to a famous quote by George Box, essentially all models are wrong, but some are useful. Similarly, the Agent-based model also exaggerates certain aspects but can help gain insights that cannot be seen otherwise.

1) Agent: An agent is an autonomous individual element with properties and actions in a computer-simulated environment. (Bill Rand, n.d.).In this simulation environment, an agent has some properties common to all agents and rules which an agent obeys (makes decisions) when interacting with the simulation environment.

2) Agent-Based Model: Agent-Based Modeling (ABM) is the idea that the world can be modelled using agents, an environment, and a description of agent-agent and agent-environment interactions (Bill Rand, n.d.) An example of a popular Agent-Based Modeling environment is Netlogo (Bill Rand, n.d.).

C. Agent-Based Modeling and Gamification Applications

In another research, Kobayashi and Terano (2005) developed a business game using Agent-Based Modeling to teach students how to make good management decisions by developing business models, decision support tools, and business information systems.

In this study, an Agent-based model was developed, mimicking the fundraising scenario in a charity organization. In this scenario, the charity organization and the donors who would donate money to the charity are modeled using Netlogo. (Bill Rand, n.d.). Therefore, to identify the advantages and drawbacks of the cortex platform, an experiment was done, and through that feedback, a prototypic data science learning environment was built using Agent-Based Modeling. (Cortex Analytics Game | SAS, n.d.).

As a summary, the papers evaluated collectively highlight gamification's potential as a successful approach for improving business education outcomes, particularly in the domain of data science. These research, which included Hamari et al. (2014), Papastergiou (2009), and Melissa Thériault et al. (2021), found that gamification had a beneficial impact on motivation, engagement, and learning effectiveness. Gender did not have a major impact on motivation levels in gamified learning, fostering inclusion. Anderson et al. (2015), Demchenko et al. (2017), Hee et al. (2016), and Liu (2020) also demonstrated the efficacy of gamification in teaching data science to business school students, with cloud-based environments and tailored learning paths contributing to improved engagement and learning experiences.

Legaki et al. (n.d.) provided insights into the significant performance improvement noticed when gamifying data science education, whilst Reiners and Wood (n.d.) demonstrated the effectiveness of computer-based simulations in establishing immersive learning environments. Rajapakse et al. (2022) acknowledged the advent of the Cortex platform ("Cortex Analytics Game | SAS," n.d.), while a complete review of its advantages and limitations in comparison to traditional learning settings is still awaited.

Dobson et al. (n.d.) found many flaws in existing business strategy games, which are also visible in gamified data science platforms. Given the amount of time that has passed since this study, it is possible that some of these shortcomings have been solved, and Agent-Based Modeling has been presented as a solution.

III. METHOD

The experiment consists of a workshop with a traditional learning environment consisting of a session and the other participants learning the same data analysis scenario in the cortex platform.

A. Game's Scenario

Predictive analytics is used to determine how many and which individuals to target in a fundraising campaign for a 12-year-old, not-for-profit charitable organization with a million members. The objective is to fundraise the most donation amount considering the costs of calling members. Prebuilt templates will train, and fit models based on previous behavior of donors and score donors to predict this year's donation. The list of scored donors will be exported to an output file/report and uploaded to a leaderboard based on operating surplus.

The cortex game consists of two rounds, round 1 involves predicting the donation amount and round 2 involves the 2-stage modeling approach to calculate the uplift. The software used to analyse the dataset in the cortex platform was SAS enterprise miner.

In this study, only round 1 was used. The first group participants were given the donor data set, which is used in the cortex platform as well, and they were taught how to analyse the data set. The software that they were using is the Microsoft Machine Learning Studio, which has a similar interface to SAS Enterprise Miner. The participants gave overall positive feedback on the gamification environment.

Table 1. Cortex environment advantages and disadvantages according to participants.

Advantages	Drawbacks
Engaging	Delay in setup time
Easy to learn	Better UI in Microsoft Machine Learning Studio Compared to SAS enterprise miner software.
	Not having user guidelines inside the game

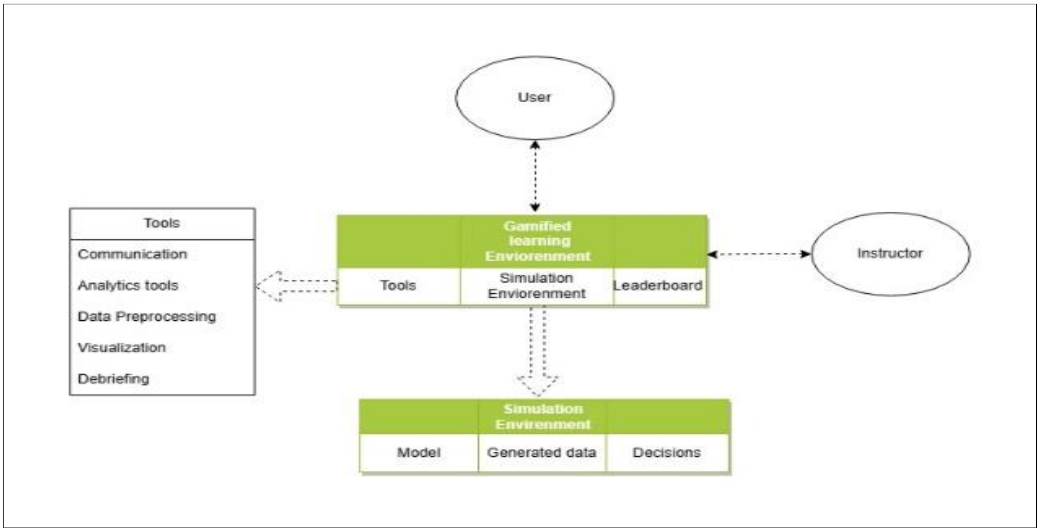
Source: Authors' compilation.

From the drawbacks identified in similar environments by Dobson et al., (n.d), poor emotional engagement and lengthy durations of training is satisfied by the cortex. However, in cortex, there is a time lag until the game environment sets up, but it is a significant improvement. However, the lack of timely feedback on the learner's actions of gamification is somewhat addressed through the cortex's leaderboard because the participants can see how well they have performed against one another., But it is still not a very interactive environment with prebuilt answers from the input datasets.

The information visualisation features in business games are limited to data presented in the spreadsheet format is still a problem not addressed in the cortex. However, the participants couldn't identify the need for such a feature. The lack of support for after-play debriefing. Even Though the platform doesn't have such built-in features for debriefing, the lecturer/instructor conducting a game session can successfully conduct a debriefing session after a competition. After identifying the drawbacks of existing learning environments, a Gamified learning environment which fulfils such drawbacks were proposed.

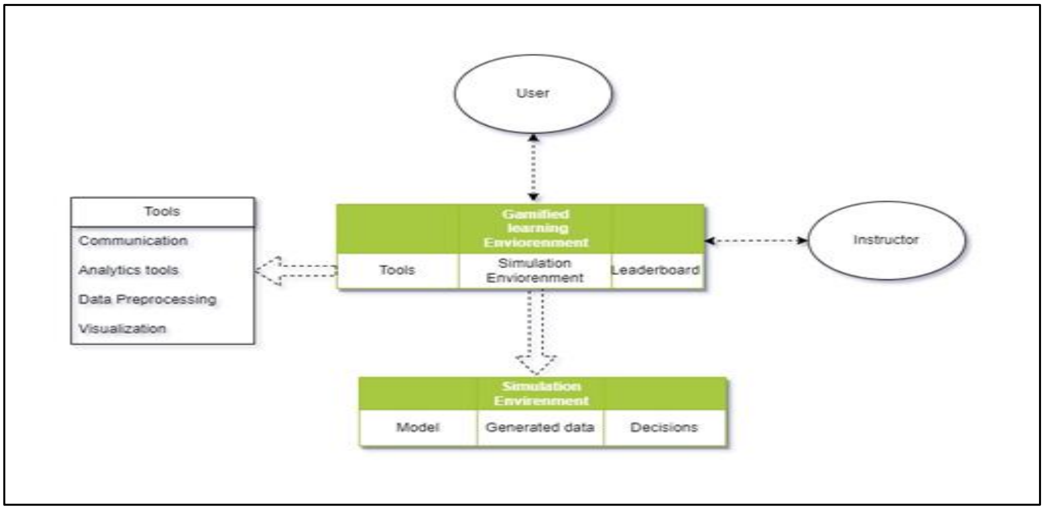
B. System Design of Proposed Gamified Learning Environments

Figure 3. Proposed learning platform 1



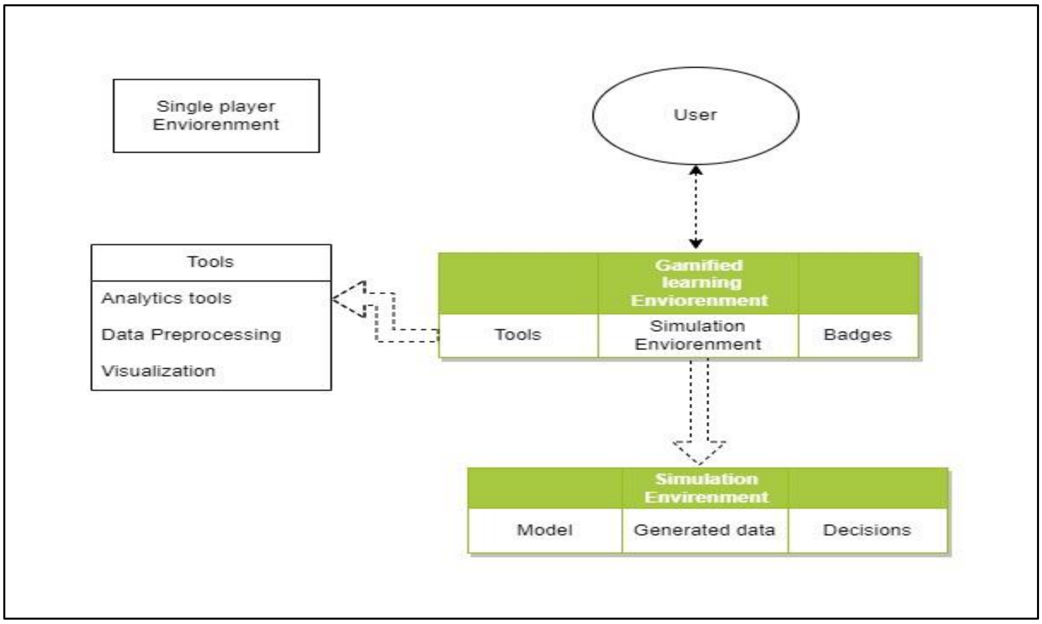
Source: Authors' compilation.

Figure 4. Proposed learning platform 2



Source: Authors' compilation.

Figure 5. Proposed learning platform 3



Source: Authors' compilation.

From these proposed designs, the first design (Figure 1) was chosen as a viable solution which solves the above drawbacks, and the simulation environment of this platform could be designed from Agent-Based Modelling as per the solution environment suggested by research (Dobson et al., n.d.)

In these Dobson et al. (n.d.), the suggested simulation environments are being created using Agent-Based Modelling, and so does Arai et al. (2005). For the proposed gamified learning environment, a similar scenario as the cortex environment is used, i.e., the fundraising scenario for the Agent-based model, and the KNN algorithm was chosen as a starting point for implementation, which identifies whether the agents will be donors or not. To develop the rules about this fundraising scenario, another literature review was conducted.

Many studies categorize donor behaviors in our society. According to these studies, fundraising and charity involve three different actors, namely the donor, the charity (fundraiser), and the benefitted party (beneficiary) (Kim et al., 2022). From these three key parties, donors are the most crucial part of the modeling purposes.

According to Kumar and Chakrabarti (2021), donor behavior can be related to three dimensions: the Donor dimension, the charity and non-profit organisation dimension, and the external environment dimension.

Donor (internal) characteristics affecting donor behavior include:

- Socio-demographic variables-Age/Gender/Income/Education/Occupation/Social class/Marital Status/ Religiosity/ Government vs. Private Jobs
- Intrinsic motivation- Pure altruism with warm glow and impure altruism- joy of giving
- Intrinsic Motivation-Empathy/Guilt

- Extrinsic motivation- Reputational concern/Social reputation/Self-respect/Recognition/Image/Reward motivation
- Moral identity of donors- internalization and Symbolisation
- Strategic fit of donor's political identity and charity's moral foundation
- Personal and social identity
- Past donation behavior – Recency, Frequency, and Monetary value

Charity or non-profit organizational factors affecting donor behavior include:
- Type of charity
- Voluntary disclosure of financial and performance information/Web disclosure
- Charity brand image and positioning and reputation
- Donation appeal – Entitativity/ Identified intervention effect
- Relationship marketing- charity with its donors
- Commitment and satisfaction provided by a charity to its donors
- Charity rating
- Matching the donation campaigns by charities

Factors from the external environment that affect donor behavior include,
- Religious causes and donation
- Social Norms and donor behavior
- Social pressure/ Peer pressure
- Social comparison information
- Tax benefits for a charity donation

As stated by Kim et al. (2022), In a study conducted in Australia, the donors are categorised into five donor archetypes (with the percentages in the sample) Cancer-Carers (24%), 'Effective Altruists' (19%), 'Animal and Nature Lovers' (16%), 'Emergency Responders' (23%), and 'Feel-good Do-gooders' (18%)(Kim et al., 2022).

In another categorization, as per "Six types of donor - which type are you? - CHARITY SCIENCE FOUNDATION," (n.d.), the donors are categorised into 6 types as the procrastinator type, the charity nerd type, The peer-pressured donor type, The rationaliser type, The time-effective donor type, The first-time donor type. According to these categories of "Six types of donor - which type are you? - CHARITY SCIENCE FOUNDATION," (n.d.), the procrastinator donor is the one who postpones the donations. The charity nerd refers to the donors who research about a charity and know more information about charity than other donors. The peer-pressured donor, on the other hand, is the one who donates money if there is peer pressure or the one who goes with the majority's idea about a particular charity. The rationaliser donor type rationalises the reasons for not donating to a particular charity. The time-effective donor is also like the charity nerd donor but more concerned about the research times. The first-time donor is the one who is new to donations.

This study aimed to develop an Agent-based model resulting in a dataset like the Donor data set in the second international knowledge Discovery and data mining tools competition, which is already used in the SAS enterprise miner and Cortex game. ("UCI Machine Learning Repository: KDD Cup 1998 Data Data Set," n.d.). This fundraising Charity organization model has resulted from the interactions between the donor and charity organization agents. The Donor agents have different behavioural rules which determine how, how much and when they donate to the charity organization. The teacher or the lecturer can adjust the model According to their preferences and change the overall behaviours of the donors in the model. These parameterized attributes can be used to provide a suitable learning environment for the students according to the learner's needs.

In the study by Andreoni (1990), the donors' motivations are categorized as pure altruists, impure altruists, and pure egoists. In the study by Andreoni (1990), an individual's economy is modelled with only one private good and one public good for simplicity.

And the individual's utility is represented as:

$$U_i = U_i(x_i, G, g_i) \tag{1}$$

Where individuals have wealth, they can allocate between consumption as a private good and their gift to the public good.

The total amount of public goods is represented in Andreoni (1990) as:

$$G = \sum_{i-1}^{n} g_i \tag{2}$$

In this research (Andreoni, 1990), a purely altruistic person, i.e., a selfless person and concern for the well-being of others, is modelled as:

$$U_i = U_i(x_i, G) \tag{3}$$

Similarly, in Andreoni, (1990), a purely egoistic, i.e., a person who is only motivated to give only by warm glow modelled as:

$$U_i = U_i(x_i, g_i) \tag{4}$$

Moreover, according to (Andreoni, 1990), an impure altruistic person's utility is as follows.

$$U_i = U_i(x_i, G, g_i) \tag{5}$$

But in the Agent-Based Modeling scenario, individuals' economic capacity can be modeled as wealth and donation attributes in an agent, which determines the economic capability of an individual in the artificial society and the amount donated to the charity.

In the agent-based model, an impurely altruistic person can be modelled as someone who donates to the charity if the charity's cause is aligned with the donor's intentions. Assuming the donor believes the total amount of public good increases when the charity's cause is aligned with donor intentions.

On the other hand, a purely egoistic doner can be modelled as a person who only cares about the donation amount, they donate to the charity. In this scenario, a purely altruistic person is modelled as the default donor who donates a random amount of money for a donation.

The concept of warm glow giving is considered as an economic theory that describes the emotional reward of donating to others. But as it is challenging to model the exact complex emotions in an agent, only one type of Agent who does care about the charity cause is modelled, i.e., the rationalized donor.

According to the article by Green and Webb, (2008), donation behavior is based on several factors, including attitudes toward helping others, attitudes toward the charitable organization, and various intrapersonal, social, and economic motives.

According to research by Kim et al. (2022), even though the donor archetypes identified among Australian citizens are of various percentages, distributed around 20% (one-fifth) of the population, it is safely assumed that those donor categories are evenly distributed in the population. Archetypes 2 and 5 (effective altruists and feel-good-do-gooders) are the altruists and egoists in the research (Andreoni, 1990). Archetypes 1 and 3 (cancer carers and nature lovers) are representative of their beneficiary preferences. Even Though there are many different charity types, in this model, only these 2 types of beneficiaries are represented.

Archetype 4 is representative of emergency responders. But as this Study focuses only on a specific charity, those aspects are not represented in the Agent-Based Model. Furthermore, the donor dataset (cite donor) was analysed to identify the most suitable attributes from the dataset. Then the donor behaviour in general and the Findings of the data set was combined to obtain a better rule set for the Agent based model. The process for model building is as follows (Figure 4).

In this artificial fundraising Charity organisation scenario, there are 2 types of agents as charity and donors. The market has 10000 number of donors and maximum 10 (y) no of charity member agents. And the simulation time increments in discrete time amount usually accounts for a year. The model parameters are in Table 2.

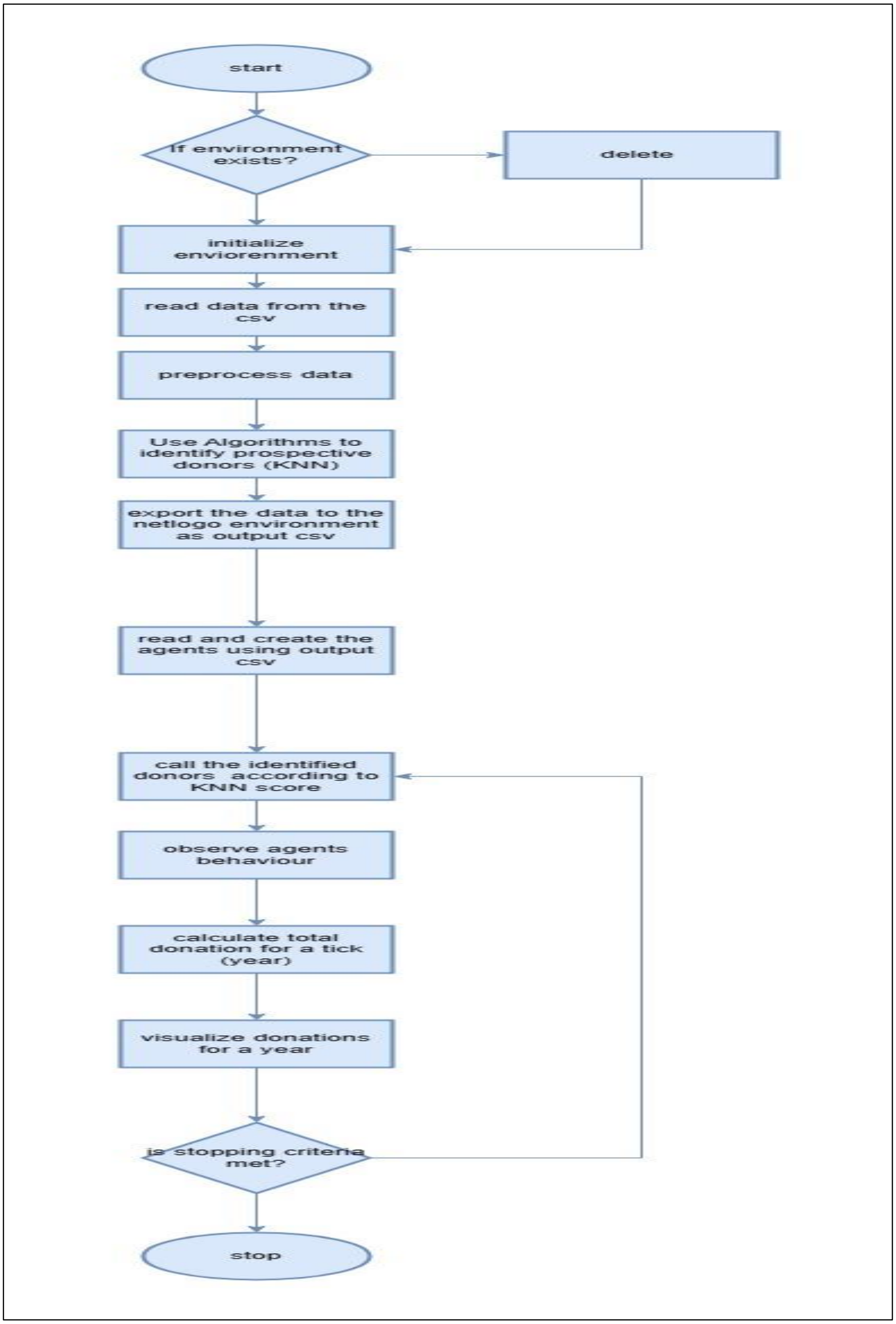
C. Model Parameters

Table 2. Model Parameters

Parameter Name	Description
No-of-charities	Number of charity agents in the simulated world
No-of-calls	The no of calls made by the charity to donors
Max wealth-increment	Maximum income level an agent can possess in
Min-donation-limit	Minimum donation amount an agent can donate
No-of -charity-members	Number of charity members
k-no-of-neighbors	The no of closest neighbors used for KNN
d-matrix	The distance measure used for the KNN
Time steps	Number of discrete time steps

Source: Authors' compilation.

Figure 6. Model flow chart



Source: Authors' compilation.

IV. RESULTS AND DISCUSSION

A sensitivity analysis was done to assess the model's stability, and the results are shown below. Furthermore, to assess the model's results with the actual donor behaviour in the donor kid 98 data set, the results from 10000 agents and their actual output was compared. And the Precision, recall, accuracy and f1 values were compared.

Table 3. Confusion matrix with the output of agent-based model (one iteration) vs. actual behaviour

		predicted		
		donor	non donor	Total
actual	donor	1031	1362	2393
	non donor	2331	5276	7607
	Total	3362	6638	10000

Source: Authors' compilation.

Table 4. Model evaluation

Measures	Value
Precision	03066
Recall	0.4308
Accuracy	0.607
F1	0.3582

Source: Authors' compilation.

For the first iteration, the model's values show a similar result to the actual donor behavior, but it depends on the Agent's knowledge on the charity organization has called them. Still, as a data analysis algorithm, only KNN is used for prospective donor identification. This model can be further enhanced to accurately capture the donation amount by modifying agent rules. Upon further modification, this kind of a parameterized environment can be used in a gamified learning platform as a gamified learning environment. Which eliminates the drawbacks identified in research (Dobson et al., n.d.)

Furthermore, the research by Chen and Venkatachalam (2017) suggests identifying micro-level patterns that can be seen in big data analytics as well. Upon further development, these kinds of platforms can be used in identifying micro-level patterns seen in big data analytics.

V. CONCLUSION

In this study, a fundraising charity organization model was proposed as a scenario for a gamified learning environment aimed at teaching predictive analytics to students. However, a gamified learning platform has not been developed yet. Nevertheless, it's worth noting that this model does not fully capture the socio-cultural aspects of donations, such as the gender-related variations in donations and the influence of donor age on contribution levels. Hence, there is a clear need for further refinement of the model.

Throughout this study, drawbacks of existing gamified data analysis platforms were identified, and an agent-based parameterized learning environment was suggested as a solution for the drawbacks identified. A parameterized Agent-Based Model, which can be used in a data science learning environment, was developed in this research. This kind of gamified learning environment with Agent-Based Modelling can be used in a gamified learning environment. This Agent-Based Model only focuses on one algorithm specifically (KNN), but this can be further improved to include other types of algorithms as well. Furthermore, an improved gamified platform is yet to be developed. This agent-based model can be used to develop an improved gamified learning platform upon further improvements. If a high-capacity simulation environment is used, these environments can also be used in big data analytics learning.

REFERENCES

Analytics, A. (n.d.). *Big Success With Big Data - Executive Summary*

Anderson, P. E., Turner, C., Dierksheide, J., & McCauley, R. (2015). An extensible online environment for teaching data science concepts through gamification. *Proceedings – Frontiers in Education Conference, FIE 2015-February.* https://doi.org/10.1109/FIE.2014.7044205

Andreoni, J. (1990). Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving. *The Economic Journal.*

Arai, K., Deguchi, H., Matsui, H., & International Simulation and Gaming Association. International Conference (34th : 2003 : Kisarazu-shi, J. (2005).Agent-based modeling meets gaming simulation, 151.

Bill Rand. (n.d.). *Fundamentals of NetLogo.* Retrieved from https://s3.amazonaws.com/complexityexplorer/NetLogoTutorial/FundamentalsfNetlogo.pdf (accessed 2.8.23).

Bonabeau, E. (2002). Agent-Based Modeling: Methods and techniques for simulating human systems. *Proc Natl Acad Sci U S A, 99,* 7280–7287 https://doi.org/10.1073/PNAS.082080899/ASSET/15AB2074-729491AB9E6292A9C40AE31/ASSETS/GRAPHIC/PQ0820808004.JPEG

Chen, S.H., & Venkatachalam, R. (2017). Agent-Based modeling as a foundation for big data. *http://dx.doi.org/10.1080/1350178X.2017.1388964, 24*(362–383).

Columbus, L., (2018). *10 Charts That Will Change Your Perspective of Big Data's Growth*.Forbes Retrieved from https://www.forbes.com/sites/louiscolumbus/2018/05/23/10-charts-that-will-change-your-perspective-of-big-datas-growth/?sh=460ecf752926 (Accessed: April 23, 2023)

Cortex Analytics Game | SAS. (n.d.). Retrieved from https://www.sas.com/en_us/training/programs/cortex-analytics-simulation-ame.html (accessed 4.1.23).

Demchenko, Y., Belloum, A., Laat, C. De, Loomis, C., Wiktorski, T., Spekschoor, E. (2017). Customisable data science educational environment: From competences management and curriculum design to virtual labs on-demand. *Proceedings of the International Conference on Cloud Computing Technology and Science, Cloud.Com 2017-December, 363–368.* https://doi.org/10.1109/CLOUDCOM.2017.59

Dobson, M., Kyrylov, V., Kyrylova, T. (n.d.). Decision training using agent-based business strategy games. Green, C.L., & Webb, D.J. (2008). Factors Influencing Monetary Donations to Charitable Organizations. *http://dx.doi.org/10.1300/J054v05n03_03*, *5*(19–40).

Hamari, J., Koivisto, J., Sarsa, H. (2014). Does gamification work? - A literature review of empirical studies on gamification, in *Proceedings of the Annual Hawaii International Conference on System Sciences.* IEEE Computer Society, pp. 3025–3034. https://doi.org/10.1109/HICSS.2014.377

Hee, K., Zicari, R. V., Tolle, K., Manieri, A. (2016). Tailored data science education using gamification. *Proceedings of the International Conference on Cloud Computing Technology and Science, CloudCom 0, 627–632.* https://doi.org/10.1109/CLOUDCOM.2016.0108

Kim, H., Chapman, C., Haruvy, E., Popkowski Leszczyc, P.T.L., & Allenby, G.M. (2022). Fundraising Design in a Competitive Market. *SSRN Electronic Journal.* https://doi.org/10.2139/SSRN.4113694

Kobayashi, M., Terano, T. (2005). Exploring Business Gaming Strategies by Learning Agents, 49–58. https://doi.org/10.1007/4-431-29427-9_6/COVER

Kumar, A., & Chakrabarti, S. (2021). Charity Donor Behavior: A Systematic Literature Review and Research Agenda. https://doi.org/10.1080/10495142.2021.1905134

Legaki, N.Z., Xi, N., Hamari, J., Assimakopoulos, V. (n.d.). Gamification of The Future: An Experiment on Gamifying Education of Forecasting.

Liu, S. (2020). Developing a Gamified Online Learning Management System for Business Students.

Melissa Thériault, Léger, P.-M., Plante, J.-F. (2021). *HEC MONTRÉAL Impacts of Gamification on Learning and Engagement in the Context of Learning Data Analytics par Melissa Thériault Sous la codirection de.*

Microsoft Learn Cloud Games | Microsoft Learn. (n.d.). Retrieved from https://learn.microsoft.com/en-us/training/cloud-games (accessed 4.1.23).

Papastergiou, M. (2009). Digital Game-Based Learning in high school Computer Science education: Impact on educational effectiveness and student motivation. *Comput Educ*, *52*, 1–12. https://doi.org/10.1016/j.compedu.2008.06.004

Rajapakse, C., Takahashi, M., & Matsuura, Y. (2022). USING GAMIFIED LEARNING ENVIRONMENTS FOR TEACHING BIG DATA ANALYTICS IN BUSINESS SCHOOLS: A CONSTRUCTIVE REVIEW. 9996-10001. https://doi.org/10.21125/inted.2022.2639

Six types of donor - which type are you? - CHARITY SCIENCE FOUNDATION. (n.d.). Retrieved from https://www.charityscience.com/blog/six-types-of-donor-which-type-are-you (accessed 4.1.23).

Torsten Reiners, Lincoln C. Wood. (n.d.). *Gamification in Education and Business*

Turner, C. (2014). Learn2Mine: Data Science Practice and Education through Gameful Experiences. *International Journal of e-Education, e-Business, e-Management and e-Learning, 4*. https://doi.org/10.7763/ijeeee.2014.v4.338

UCI Machine Learning Repository: KDD Cup 1998 Data Data Set. (n.d.). Retrieved from https://archive.ics.uci.edu/ml/datasets/KDD+Cup+1998+Data (accessed 4.2.23)