Predicting Consumer Behavior in VR Gaming by Integrating AI Driven Predictive Analytics and Behavioral Economics

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DOCTORAL RESEARCH PLAN

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ABSTRACT

As the gaming world rapidly changes, thanks to advancements in AI like deep learning and reinforcement learning, there's a growing need for tools that can forecast player engagement, retention, and spending habits with more accuracy.

How can AI driven predictive analytics combined with behaviour economics be used to predict and explain player behaviour in VR gaming? This research will aim to explore how AI driven predictive analytics can work with behavioural economics to better predict and understand player behaviour in the VR gaming industry, which in turn can help predict player retention, in game purchases, and engagement patterns. The AI models will be trained on real world data from VR gaming companies (such as VRKiwi that the author is currently working on), which might offer actionable insights to optimise game design, player experience, and revenue generation.

Behavioural economics helps explain why people often make irrational decisions, like avoiding losses more than they seek gains or sticking with a game they've already invested in, even if they're no longer enjoying it. This study will look at whether these behavioural patterns can be used in AI models to improve predictions and make games more engaging and profitable.

By combining behavioural economics and predictive analytics, the research aims to go beyond just analysing what players did in the game before. Instead, it will predict future behaviours and offer practical advice to game developers on how to adjust their strategies. This is to say, this approach might not only predict what players are likely to do next but also help explain why they make those choices in VR context.

Drawing from previous experience in working and studying VR gaming behaviour, this study will use real world data (such as player interaction data, in game purchase data, churn data, in game behavioural data and so on) from gaming companies and analytics app (such as unity analytics) to train and create AI models that predict things like player retention and in game purchases. The aim of creating these models are to give insights to the developers so they might improve game design, enhance the player experience, and increase revenue. Additionally, this research could contribute to the field of AI enhanced predictive analytics by adding a more humane aspect to the models, making them more accurate and relatable when analysing the human behaviour.

In conclusion, this study will aim to connect the dots between AI, behavioural economics, and game analytics. The author hopes that this will give game developers, marketers, and decision makers new tools and methods to engage players more effectively and design experiences that match the results from the data. By using the latest advancements in AI and behavioural science, this research could set the stage for a future where decisions in the gaming industry are guided by both data and a deeper understanding of human psychology and not solely intuition.

1. Introduction

The virtual reality (VR) gaming industry has been in steady growth ever since its invention, which is characterised by its immersive environments and interactive experiences. Especially in dynamic environments like VR, understanding and predicting player behaviour has become more challenging than before. In the past, game developers mainly relied on descriptive analytics, using past data to see what players did and analysed them manually or by guessing. However, with the rise of AI, analytics tools, and predictive analytics, developers can now forecast player behaviour and improve game environments to boost retention and monetization (Lecun et al., 2015).

Recent advancements in AI and machine learning allowed businesses to analyse big data to find patterns and make accurate predictions. Techniques like neural networks and reinforcement learning have been especially useful in gaming, where complex decisions are made by players. For example, companies like DeepMind have successfully used AI to predict human behaviour in games like Go (Silver et al., 2016) and StarCraft (Mnih et al., 2015), showing AI's potential.

While some AI models can effectively learn from complex behaviours, they may require specialised training to account for the non-logical decision making choices often observed in human players. Behavioural economics can help provide insights into these psychological factors, which influence players' decisions, such as loss aversion, or bounded rationality. It explains why players make choices based on emotions, biases, or psychology. They can continue playing or spending even if it's illogical because they've already invested time or money (Arkes et al., 1985). These insights are important because understanding irrational behaviours can help developers design games that engage players and encourage in game purchases.

By combining predictive analytics and behavioural economics, game developers can analyse past data to forecast player churn, retention, and in game purchases. Adding behavioural insights makes these predictions even more useful, as developers will understand not only what players are likely to do but also why they make those choices (Hosanagar et al., 2018).

The author's previous academic work in VR games will be helpful in this study, where consumer behaviour was studied using several theoretical models including behavioural analytics. This study will take a step further and into a slightly different direction and use AI driven predictive analytics to predict player engagement, retention, and monetization based on both historical data and behavioural patterns (Shmueli et al., 2011).

AI has already been transformative in the gaming industry. Techniques like dynamic difficulty adjustment (DDA) have enhanced the player experience by adapting game challenges based on real time player performance, ensuring a balance between engagement and difficulty (Hunicke et al., 2004). AI is also increasingly used for player segmentation, grouping players based on their behaviours to offer personalised in game rewards and experiences (Bakkes et al., 2012). Recent advancements in AI, such as deep learning, have allowed for more precise segmentation and personalisation, enabling developers to predict player lifetime value and optimise monetization strategies (Zhang et al., 2021). Furthermore, reinforcement learning has been applied in real time gameplay adaptation, adjusting strategies to keep players engaged and improving retention (MirzaBabaei et al., 2019).

While these AI applications have advanced the gaming industry, they often focus on rational decision making and do not fully account for the irrational behaviours that players exhibit. By combining AI with behavioural economics, one can presume that developers can gain deeper insights into player decisions influenced by psychological factors such as loss aversion, framing effects, and the sunk cost fallacy. This integration remains relatively underexplored in current AI applications, presenting an opportunity to create models that predict not only what players are likely to do but also why they make certain choices, offering new strategies for optimising both game design and monetization.

This research will merge AI driven predictive analytics with behavioural economics to better understand VR player behaviour. It aims to create models that predict player actions while accounting for behavioural biases, offering strategies to improve game design and monetization.

2. Research Questions

The goal of this research will be to explore how AI driven predictive analytics can help understand and predict player behaviour in the VR gaming industry in combination of behavioural economics. The focus will be on identifying patterns in player engagement, retention, and in game spending, while also considering psychological factors that drives those choices.

The main research question for this study is:

How can AI driven predictive analytics combined with behaviour economics be used to predict and explain player behaviour in VR gaming?

And the supporting questions are:

1. How can AI driven predictive models forecast key player behaviours, such as engagement, retention, and in game purchases?
2. How can behavioural economics improve predictive models to better explain and predict player decisions?
3. How can these models help game developers optimise both game design and monetization strategies?

The results from this study will be useful to game developers and marketers, offering them insights into player behaviour and helping them design more fun, engaging, and profitable games. By incorporating behavioural economics into AI models, the research will provide a more human centred approach to understanding how and why players make decisions, leading to better predictive models.

Once these findings are validated, they can be shared with game studios to fine tune game environments and in game purchase strategies, helping create better gaming experiences and business outcomes.

3. Theoretical Background

Predictive Analytics

Predictive analytics is a method in which you use machine learning or similar methods to generate a model that can predict something to a certain extent. It can use historical data, statistical algorithms, and machine learning techniques to potentially forecast future outcomes of something to an extent. In the gaming industry, predictive analytics has been used for forecasting player behaviour, such as player retention, churn, and in game purchases. By identifying patterns in gameplay data, developers can potentially make data driven decisions to improve player engagement and optimise monetization strategies (Chen et al., 2018).

AI powered predictive analytics enhances traditional statistical methods by incorporating machine learning (ML) algorithms that automatically improve predictions as more data becomes available. Supervised learning techniques, such as regression analysis, decision trees, and random forests, use labelled datasets to predict specific outcomes. Unsupervised learning techniques, like clustering, can be used to discover patterns or group players based on behavioural similarities without predefined labels (Schneider & Gupta, 2017).

For example, in gaming, predictive analytics has been applied to estimate player lifetime value (LTV) and predict churn. Churn measures of how many customers stop using a product, in this case, stop playing the game. Accurate churn prediction allows developers to re-engage players before they stop playing permanently. It was demonstrated that machine learning models could accurately forecast player retention in mobile games, reducing player acquisition costs and improving retention through targeted interventions (Chen et al., 2018)

In game monetization strategies could also benefit from predictive analytics as well. AI models may predict when and why a player is likely to make purchases by analysing player behaviour and spending patterns (Schneider et al., 2017)

There are multiple machine learning techniques but 3 methods will be explored in the research to analyse and predict player behaviour in VR gaming. They are supervised learning, unsupervised learning, and reinforcement learning.

The supervised learning technique involves training the algorithm on a labelled dataset. This means that each training example is paired with an output label. The goal is for the model to learn a mapping from inputs to outputs so it can predict labels for new, unseen data. This could be used in predicting player churn or predicting in game purchase amounts.

The difference between supervised learning from unsupervised is that the algorithm is provided with data that has no labels. A blank slate. The goal of this method is to find hidden patterns or structures in the data, which could go well with behavioural economic theory. The model tries to identify relationships or groupings within the data without prior knowledge of the outcomes. This could be used in grouping players into clusters based on their behaviour (e.g., spenders vs. casual players) without predefined categories. Further research, comprehensive literature reviews, and careful interpretation will be essential for its effective application.

Reinforced learning can be more humane like learning since the algorithm learns by rewards or penalties, or trial and error. The goal is to achieve the most optimal results, or gain the most out of something. This can be used in for example, adjusting in game difficulty dynamically based on how the player is performing in real time to maximise engagement. In VR gaming, reinforcement learning could predict when a player is likely to become frustrated or bored. Adjusting the game's difficulty or offering rewards to keep them engaged may alter this.

The aim will be to develop predictive models that can forecast behaviours of the players, which can be helpful in determining things such as player behaviours, player retention, and monetization.

Behavioral Economics

Behavioural economics mixes economics and psychological aspects together to understand why some people do certain things in the real world. That's to say, it explores how psychological, emotional, and cognitive biases influence decision-making of humans. These biases can make individuals act irrationally compared to the rational decision making assumed in most classical economics. This approach is particularly relevant in gaming, where players frequently make decisions based on emotions and the framing of options rather than objective utility maximisation.

For instance, players might exhibit loss aversion, as defined by Prospect Theory, where the pain of losing in-game progress or assets is felt more acutely than the pleasure of equivalent gains (Kahneman et al., 1979). For example, games often provide an option to the players to "continue" a lost game by paying a small fee or using an in game currency. Because of loss aversion, players are more likely to pay to avoid losing their progress due to not liking the idea of losing said progress, even if the cost of restarting is relatively small compared to the effort they've already put in.

Another factor that will be looked into is the sunk cost fallacy. This phenomenon happens when the players or people will continue investing time or money into a game due to investments made previously (Arkes et al., 1985). Although it is similar to loss aversion, the sunk cost fallacy involves justifying continued investment due to prior commitments, whereas loss aversion is about avoiding potential loss. A good example is MMO game series, such as Diablo, Lineage, or World of Warcraft. Even after finishing all the missions and exhausting the contents, the players will continue playing the game and doing repetitive tasks due to their time sunk into the game. This tendency to sink in resources despite diminishing returns in enjoyment is a key behavioural factor in gaming, particularly in retention models where developers aim to keep players engaged over time.

Framing effect is another crucial element of behavioural economics. This effect demonstrates how the presentation of choices can significantly influence the decision making of humans. For example, the framing of having an option impacts consumer perceptions and could apply to limited-time offers or exclusive in-game rewards, encouraging players to make impulsive purchases (Lichtenstein et al., 2006).

By integrating these behavioural principles into AI-driven predictive models, it might enhance the accuracy of predictions regarding factors such as player retention, engagement, and monetisation. Giving the developers the reason behind certain decisions could help them develop a more economically successful game. Predictive models that combine quantitative data (e.g., playtime, spending patterns) with qualitative insights (e.g., cognitive biases) provide a more comprehensive view of player behaviour, which could make developers to design better strategies for increasing retention and monetization (Schneider et al., 2017).

4. Data, ethical considerations, and methodology

This research will aim to blend both qualitative and quantitative methods to develop AI driven predictive models. Focusing on behavioural economics aspect to explore and predict how players behave in VR gaming.

Data Collection and Sources

The primary data will be sourced from VR gaming companies and analytics platforms, such as VRKiwi and Unity Analytics. These data sets gathered will cover key aspects of player behaviour, including:

- Player interaction data: In game activities, time spent, player actions
- In game purchase data: Details of transactions, frequency of purchases, types of purchases (e.g., microtransactions), and purchasing trends.
- Churn data: Information on when players leave the game or reduce their engagement and the potential reasons for their exit.
- Behavioural data: Capturing how players make decisions in response to in game incentives, rewards, penalties, and challenges.

These datasets will be used for training machine learning models and developing predictive insights to optimise game design and monetization.

Machine Learning Techniques

This research will test out and apply a variety of machine learning techniques since each learning model has their own different uses. The methods that are considered to be used are:

- Supervised Learning: Algorithms such as decision trees, random forests, and support vector machines will be employed to predict outcomes like player churn or in game purchases. These models will be trained using labelled historical data to predict future player behaviours based on past interactions.

- Unsupervised Learning: Clustering technique could help group players based on behavioural similarities. Identifying patterns in player behaviour without predefined labels could allow for the segmentation of players (e.g., spenders versus casual players).
- Reinforcement Learning: Reinforcement learning is basically a trial and error based approach where models learn optimal behaviours through rewards and penalties. This could be used to adjust in game features dynamically. In VR gaming, this could be used to simulate real time gameplay adaptation, such as dynamic difficulty adjustment (DDA), which modifies game difficulty to maintain player engagement and reduce churn. It's more complex set of strategies that requires efforts from the developers of the game to integrate, which could be hard to request in their busy schedule.

Integration of Behavioral Economics

Behavioural economics principles will be integrated into the AI models to test out and account for the psychological biases that influence player decisions.

- Loss Aversion: This research will test how the potential for losses (e.g., losing in game progress or items) will influence player behaviour, particularly around retention and spending.
- Sunk Cost Fallacy: The study will model how players' prior investments of time or money influence their continued engagement, even when the enjoyment of the game decreases (when they have either achieved all endings, got all the achievements from the game, etc).
- Framing Effects: Data on player responses to in game offers, such as time limited rewards, bundle deals, or exclusive items, will be used to model how the presentation of choices affects purchasing decisions.

By incorporating these insights (and other aspects if applicable), the AI models could be able to predict not just what players will do, but also why they are likely to behave in certain ways, providing a deeper understanding of player motivations.

Model Training and Validation

The AI models will be trained using a portion of the collected data, with the remainder used for validation. The training process will involve:

- Data preprocessing: Cleaning, normalising, and handling missing data to ensure consistency.
- Feature selection: Identifying key variables (e.g., time spent in the game, purchasing trends) that contribute to player behaviour.
- Model training and testing: Models will be trained using cross validation techniques to assess how well they generalise to unseen data.

Standard evaluation metrics such as accuracy, precision, recall, and the F1 score will be used to evaluate the models' predictive performance.

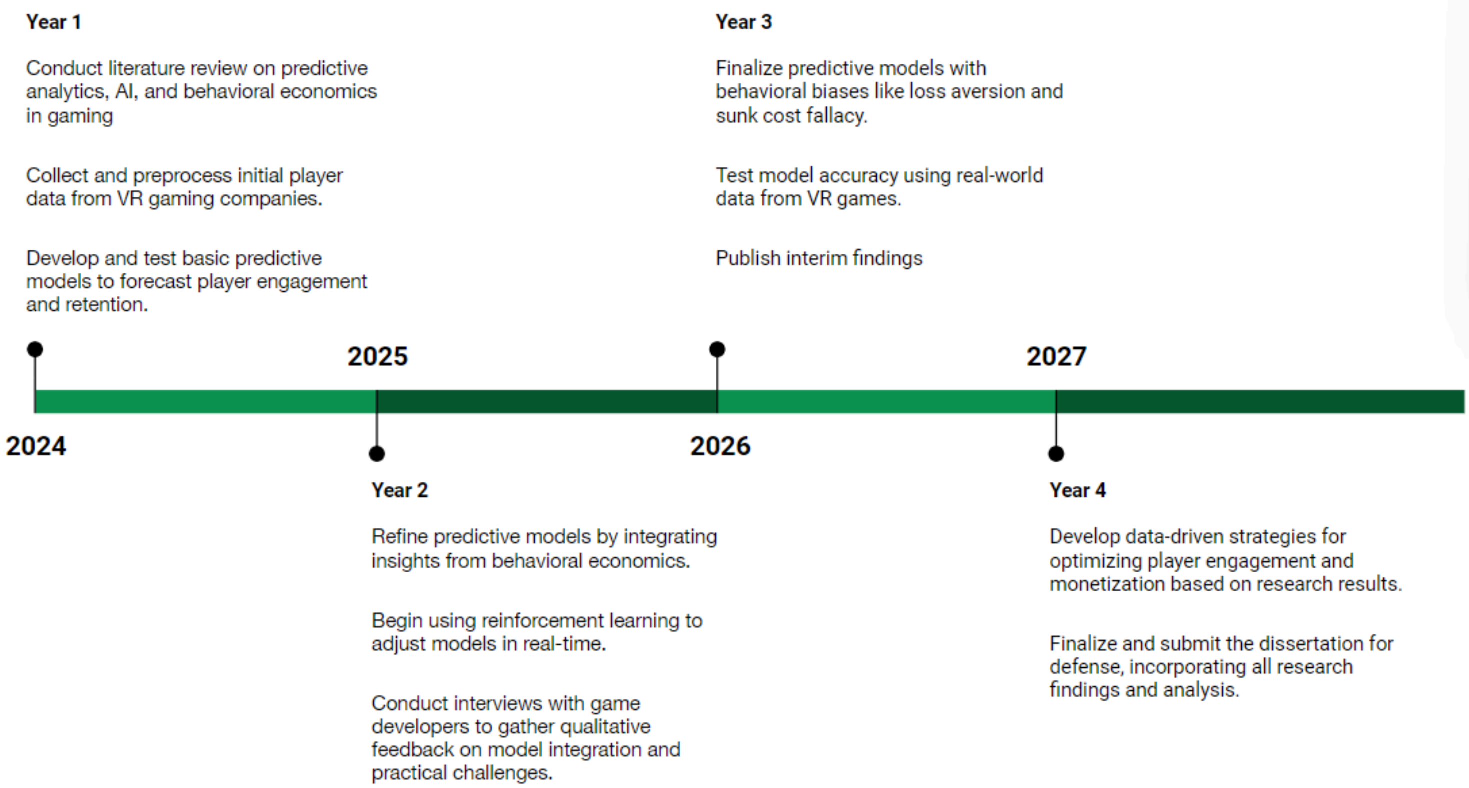
Ethical Considerations

This research will strictly follow ethical guidelines and the General Data Protection Regulation (GDPR). All player data will be anonymised, and informed consent will be obtained from game developers and companies contributing data. The study will also assess potential biases in the AI models to ensure fairness and prevent unintended negative impacts on player engagement or monetization.

Qualitative Approach

In addition to the quantitative analysis, qualitative interviews will be conducted with game developers and industry experts. These interviews will explore practical challenges in implementing AI driven predictive analytics and how behavioural economics insights are currently applied in game development. The qualitative findings could help validate the quantitative results and provide real world relevance to the AI models being developed.

5. Implementation and Timeline



Research funding plan:

The doctoral research will be conducted on a part-time basis alongside my current professional commitments. This arrangement provides flexibility in managing both responsibilities while ensuring progress in research activities. As a result, no specific doctoral research funding is required at this stage, as my employment will support the necessary resources for carrying out the research.

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