Multiplayer Online Battle Arena (MOBA) games create immersive virtual gaming worlds in which two teams compete with each other to take down the opponent's base. Existing MOBA games such as *DOTA*, *League of Legends (LoL)*, *King of Glory*, etc. attract millions of players to invest their time and money, making MOBA one of the most profititable markets in the digital game industry. To succeed in fifierce business competitions, game designers strive by all means to attract and keep players in the game to ensure its playability [17], which, in a multiplayer setting, particularly relates to teamwork satisfaction, a sense of fair competition, and mastery of complex gameplay interactions [19]. This motivates game designers to identify the critical factors that may inflfluence game dynamics by closely inspecting individual and team gameplay behaviors.

While game outcomes (*Win* or *Lose*) indicate the level of players' gaming skill and the effectiveness of gaming strategies, game occurrences capture game dynamics as the changes of a team's advantage (or disadvantage) over its opponent [25].In this paper, we focus on three major occurrences: *snowballing*, *comeback*, *back and forth*. *Snowballing* occurs when a team easily achieves and maintains dominating advantages over its adversary throughout a match. *Comeback* occurs when a team overcomes a substantial disadvantage and eventually wins the battle. *Back and forth*, in comparison, defifines the situations in which there is no clear winner until the end. To a great extent, the distribution of different occurrences of a game reflflects its playability [23]. A game dominated by *snowballing* (or *comeback*) occurrences may inevitably raise concerns about its fairness. If the majority of the matches are *back and forth*, players may feel that there is no adequate differentiation or the sense of mastery. In either situation, the game engagement is at stake. Therefore, it is critical for game designers to identify and understand common patterns of key gaming behaviors that contribute to each type of game occurrences. They can modify game design settings accordingly to balance different types of game occurrences and optimize playability and engagement.

Conventionally, game experts classify game occurrences based on designed rules and then manually inspect a selected halfhour match for gameplay behaviors and events that possibly lead to its occurrence [25]. Nevertheless, manually designing rules to distinguish occurrences and inspecting individual matches are both time- and labor-intensive, and the experts have conceived ML to help them conduct game occurrence analysis. Previous research on game analytics employs ML as an effective means to predict the game outcomes, or extract the patterns that lead to such outcomes from aggregated data [2, 9, 14, 34, 36]. Particularly, for game designers intending to improve an existing game or even conceive a new one for better experiences, ML can enable the game to automatically customize its offers to the players and gaming context. However, given the characteristics of gameplay data, game designers may struggle to directly communicate with ML. Adapting general-purpose ML methods to solve a particular application problem, such as game occurrence reasoning, often requires signifificant domain knowledge. Furthermore, there has been little empirical study on the extent to which a design process can resolve the breakdowns in game designers' communication with ML analysis, bridge the expert knowledge with the investigation of MOBA game occurrences in large-scale data.

In this paper, through a close collaboration with a game team, we explore how their conversation with our proposed visual occurrence analytics system evolves. We begin with an

observational study of their current approaches, and identify their initial needs and concerns. Then, we build a single-match module of the system to familiarize the team with interactive analytics and co-design the input and output data representations to be inherited in the full system. Based on their feedback and derived insights, we further incorporate ML models in the full system to facilitate result reasoning and in-depth analysis based on multiple game matches. This system contributes to a commercial game that is already in the market and attracts the interest of the other MOBA game developing teams in the company. Our primary contributions include: 1) an interactive game occurrence analytics system that supports human-ML collaboration, and 2) insights derived from the stepwise codesign process into how to establish better communication with ML. The remainder of the paper is structured as follows. After providing the background about the game and reviewing related work, we present the three phases of our co-design process: Phase I about the observational study, Phase II about the co-design of the single match module, and Phase III about full system with a ML model incorporated. Finally, we detail our exploratory case study and conclude with the takeaways of designers and our reflection on the entire process.

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