A Case for Skill-based Matchmaking in Regulating India's Online Real Money Games

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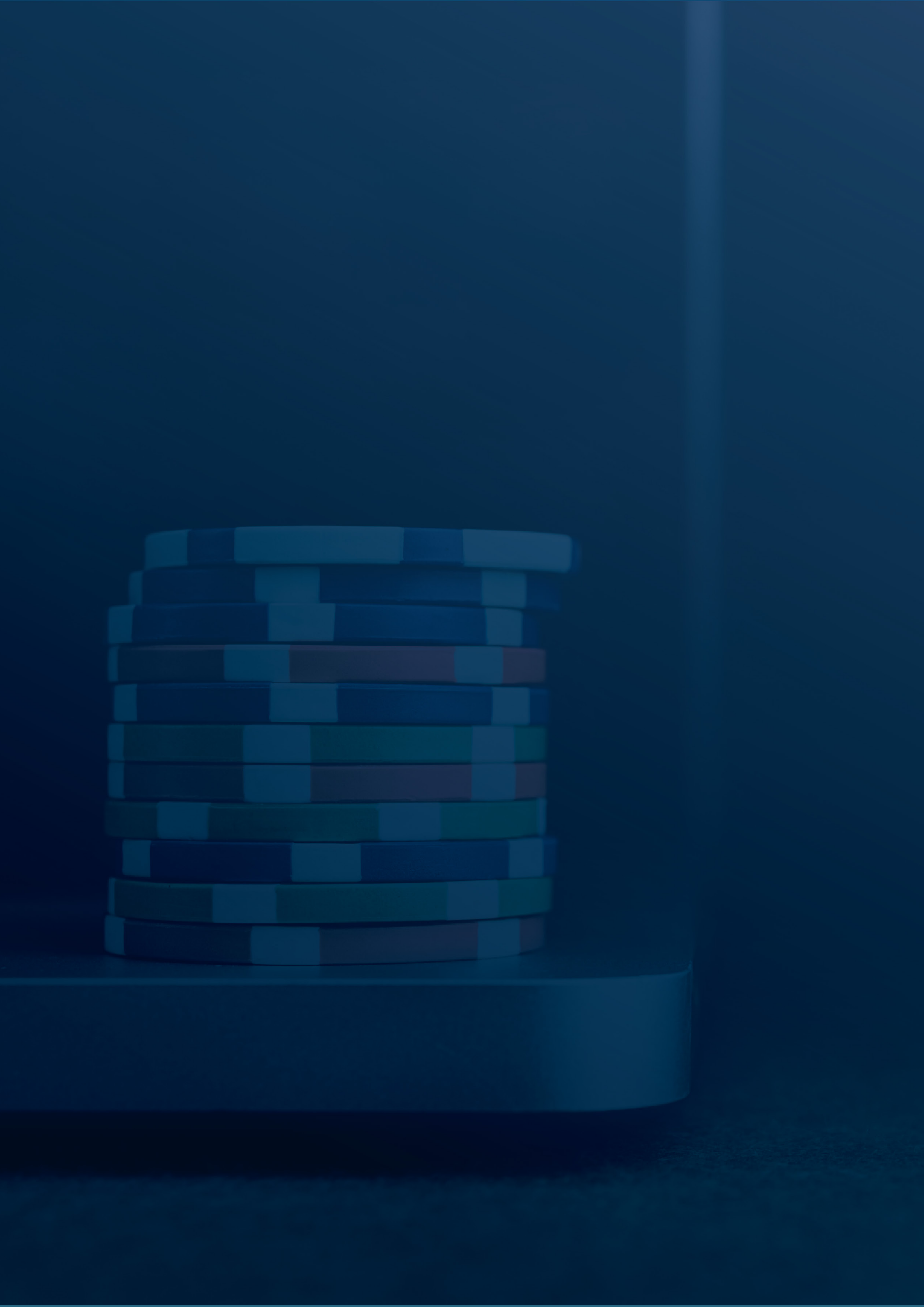

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1. Background

The global gaming industry has witnessed staggering growth in the past decade. Emerging markets such as India have especially thrived in recent years. Between 2020 and 2023, the Indian online gaming sector expanded at a Compound Annual Growth Rate (CAGR) of 28 %,[1] generating revenues worth INR 16,428 crores in 2023,[2] with RMGs accounting for nearly 60 percent of market share, followed by in-app purchases and advertisements.[3] In part, this is attributable to the years of the Covid-19 pandemic, which afforded the industry with favourable conditions for growth. However, more fundamentally, the positive trend witnessed by the gaming industry in the past decade is a product of the global shift towards increased digitalisation. This is especially true of India. The popularity of online gaming in India is inextricably linked to the growing affordability of smartphones and internet data plans,[4] rise in adoption of digital payments,[5] as well as the opportunities it presents for winning monetary gains through online Real Money Games (RMGs).

The impressive volumes realised by the industry have, however, brought with them acute concerns surrounding the lack of a regulatory regime for governing online RMGs in India. As a first step, on 6th April, 2023, the Central Government had notified a set of rules to regulate online RMGs, but is likely to soon supplement them with a more concrete course of action. At the same time, various State Governments have begun cracking down on online RMGs by introducing amendments to their respective gaming legislations, which in effect, equate such games with the illegal practice of gambling.[6] Legal tussles that have consequently ensued between States and various online gaming platforms also highlight the need for a comprehensive regulatory framework for assessing the legality of online RMGs.

Such a regulatory framework would have to necessarily be centered around the determination of online RMGs as *'games of skill,'* which has been a long-standing test for distinguishing RMGs from gambling within Indian jurisprudence. This paper argues that the use of Skill-Based Matchmaking (SBMM) by online RMGs be taken into consideration by policymakers in such determination of games of skill. Over the course of the following sections, the paper critically analyses concerns within India's current regulatory landscape for online RMGs, argues for the legal and policy necessity of integrating SBMM in gameplay, expands on a number of skill-rating models used today, and finally presents a baseline framework for implementing SBMM in online RMGs.

1 Lohchab, Himanshi. "Playing on Numbers: Making Sense of India's Gaming Boom." The Economic Times, December 10, 2023. https://economictimes.indiatimes.com/tech/technology/playing-on-numbers-making-sense-of-indias-gaming-boom/articleshow/105864435.cms?from=mdr.

2 "New Frontiers: Navigating the Evolving Landscape for Online Gaming in India." EY, December 2023. https://assets.ey.com/content/dam/ey-sites/ey-com/en_in/news/2023/12/ey-new-frontier-online-gaming-report.pdfM.

3 TeamG2G. "Real-Money Games Largest Source of Revenue for India's Online Gaming Market: Report." G2G News, October 27, 2021. https://g2g.news/gaming/real-money-games-largest-source-of-revenue-for-indias-online-gaming-market-report/.

4 Livemint. "Mobile Data Price in India among Cheapest. Where It Is Less Costly than India?" Mint, July 28, 2022, sec. Technology. https://www.livemint.com/technology/tech-news/mobile-data-price-in-india-among-cheapest-where-it-is-less-costly-than-india-11658991755978.html.

5 Ojha, Sangeeta. "The Rise and Rise of UPI: A Forecast for Unified Payments Interface for 2024." Mint, December 7, 2023, sec. Money. https://www.livemint.com/money/personal-finance/the-rise-and-rise-of-upi-a-forecast-for-unified-payments-interface-for-2024-11701937367022.html.

6 Bhalla, Vineet. "Why the Centre Must Step in to Regulate Online Gaming in India." Scroll.In, December 8, 2023. https://scroll.in/article/1060209/why-the-centre-must-step-in-to-regulate-online-gaming-in-india.

2. Inside India's RMG Regulatory Landscape

RMGs are games where players stake money by making deposits of either cash or kind, with the expectation of earning monetary winnings on such deposits. The industry in India is subject to laws prohibiting gambling, such that RMGs are excluded from their ambit only if such games can be classified as 'games of mere skill;' a term that has not been defined in any Indian legislation.

Under the Indian Constitution, the subject of 'Gambling and Betting' falls within the legislative purview of states, thereby allowing them to regulate it through state laws within their own territories.[7] At the same time, a pre-Constitutional Central law, the Public Gambling Act 1867, has been adopted by various states, insofar as it lays down the 'Games of mere Skill' exception.[8] While a few State legislations have explicitly referred to certain games as 'games of mere skill,' it has largely fallen upon Indian courts to clarify the nature of a 'game of mere skill' through litigation – an exercise that has been both, cumbersome for the industry and somewhat devoid of a technical inquiry into the elements of skill and chance present in games.

In 1957, the Indian Supreme Court, in the State of Bombay v. RMD Chamarbaugwala,[9] adopted the 'Preponderance of Skill' test, stating that a game of 'mere skill' is one that is preponderantly, or predominantly, a game of skill. This means that a game whose winning outcome is determined more by skill than chance, will not fall into the category of gambling, despite there being an element of chance involved. The test has subsequently been used by courts to determine the skill classification of specific games when played with stakes, most notably rummy[10] and betting on horse racing.[11]

However, such a case-to-case basis determination of 'games of skill' has been a cause of concern for two key reasons. Firstly, the absence of a policy framework regulating RMGs has not only forced the industry to exist in a legal grey area, but has also allowed gambling and betting websites to come up, thereby endangering the regulatory certainty for legitimate skill-based games. Secondly, there is now a need for a policy framework that takes into account the 'online' nature of RMGs while determining their legality.

Echoing some of these very concerns, in April 2023, the Union Ministry for Electronics and Information Technology (MeitY) amended the IT Rules (Intermediary Guidelines and Digital Media Code) of 2021, allowing for self-regulating bodies (SRBs) from within the industry to be notified and tasked by the MeitY to verify online RMGs as "permissible," basis a minimum criteria laid down in the Rules, in addition to

7 Constitution of India, 1950, List 2, Entry 34. http://constitutionofindia.etal.in/schedule_7_2/.

8 The Public Gambling Act, 1867. https://www.indiacode.nic.in/bitstream/12345.pdf.

9 State of Bombay v. RMD Chamarbaugwala (1957) AIR SC 699.

10 State of Andhra Pradesh v. K. Satyanarayana, (1968) 2 SCR 387.

11 Dr. KR Lakshmanan v. State of Tamil Nadu, (1996) 2 SCC 226.

any other requirements that the SRBs may deem fit.[12] The single most important criterion for verification of an online RMG is that it should not involve wagering on any outcome. However, no SRBs have been notified under the Rules thus far. Furthermore, the MeitY is reportedly re-deliberating the entire self-regulatory framework laid down under the Rules.[13]

In the meantime, Indian courts have been grappling with whether the *online* nature of RMGs can alter the preponderance of skill in determining outcome such that it affects the very legality of online RMGs in India. This question has, in particular, been raised with reference to the game of online rummy, in the aftermath of various State governments, including Karnataka, Kerala, Tamil Nadu, and most recently, Andhra Pradesh, introducing bans on the online variant of the game.[14] Barring Andhra Pradesh, the high courts of all the above-mentioned states have held that a game of skill does not become a game of chance merely by being played online, and retains its preponderance of skill. On the other hand, the Andhra Pradesh High Court has acknowledged the lack of factual material to decide on this question, and has directed the State of Andhra Pradesh to set up a committee — constituting independent technical and non-technical members — to carry out a detailed analysis of online rummy gameplay and infrastructure, and is currently waiting for the same.

At present, neither Indian courts nor policymakers have come to a common understanding of the online aspect of online RMGs, and how best to regulate them. At the same time, the potential for further monetisation in the Indian market has incentivised players within the RMG ecosystem to engage in game development such that the market is now full of not only online RMG variants of offline games, but sometimes even entirely new games that may not have offline counterparts. These developments have the potential to further muddy our understanding of how to measure skill and chance in games.

Given the relative and intrinsic nature of 'skill,' it is clear that lawmakers will have to supplement their present understanding on the matter with more technically and empirically sound methods of measuring skill and chance in an online game. Further, the meteoric rise in accessibility and affordability of smartphones in India, and their rising popularity to engage in online RMGs, combined with the very promise of monetary winnings from such games, is unprecedented for India. The sheer number of people engaging in online RMGs today, along with the financial and social implications involved, underscores the need for guardrails that not only ensure against gambling, but also promote responsible and fair gaming. Skill-based Matchmaking is one measure that can be implemented within online RMGs to help address both these concerns.

12 "Information Technology (Intermediary Guidelines and Digital Media Ethics Code) Rules, 2021 (Updated 06.04.2023)" Accessed August 17, 2023. https://www.meity.gov.in/writereaddata/files/Information%20Technology%20%28Intermediary%20Guidelines%20and%20Digital%20Media%20Ethics%20Code%29%20Rules%2C%202021%20%28updated%2006.04.2023%29-.pdf.

13 Das, Shouvik. "It's over to Govt Now in Gaming Regulation." Mint, January 1, 2024, sec. Industry. https://www.livemint.com/industry/online-gaming-self-regulation-hits-roadblock-meity-weighs-direct-control-11704104343456.html.

14 "2023 RMG Litigation Round-up: Flurry of GST Notices and Laws Banning Online Money Games Keep Gaming Lawyers Busy, G2G News." https://g2g.news/online-gaming-laws/2023-rmg-litigation-round-up-flurry-of-gst-notices-and-laws-banning-online-money-games-keep-gaming-lawyers-busy/.

3. Skill-based Matchmaking Mechanisms

In game design, 'Matchmaking' refers to the process of selecting two or more opponents to take part in a single match, round, or session, depending on the terminologies used in the game.[15] Typically, whenever individual players wish to join a game, they are first placed in a pool of eligible players, after which, the underlying matchmaking mechanism of the game determines who they should be matched against.

The goal of a matchmaking system is to ensure online gameplay[16] that is optimal, enjoyable, but also fair and balanced. The quality and fairness in gameplay achieved through this process is, however, entirely dependent on the degree of importance assigned to various factors which are taken into consideration by the mechanism. Matchmaking systems today consider factors including location, connectivity, wait time (the time spent by a player waiting to be matched) and crucially, the skill level of players as is the case with Skill-Based Matchmaking (SBMM).

The SBMM process assigns greater importance to the relative-skill level of players in comparison to other factors, and strives to match players, as closely as possible, with those players who are at a similar skill level as them. Although 'skill' is a qualitative concept, it is capable of being expressed in measurable terms. For this purpose, SBMM implementations in online games today use skill-rating models which compute the 'skill ratings' of individual players. These skill ratings are statistically-derived numerical values inferred from the past performances of players in previous matches. After computing such ratings, SBMM systems determine the compatibility between a player and a match on the basis of similarity between the skill ratings of the player in question, and that of other players in the match.

For the Indian RMG sector, there are two critical reasons why the use of SBMM could potentially assume increasing importance. Firstly, from a legal standpoint, the absence of an SBMM mechanism in online RMGs introduces elements of chance within the gameplay such that the outcome of winning is no longer preponderantly a function of skill. On the flipside, the use of an SBMM mechanism aids in expressing 'skill' within a game in quantitative terms. Secondly, from a policy standpoint, the use of SBMM mechanisms in online RMGs is necessary to ensure fair and responsible gaming.

3.1 Significance of SBMM in determining 'Games of Skill'

Much of the legal uncertainty surrounding RMGs in India stems from the fact that very few games can be classified as games of "pure skill" or "pure chance," and that in reality, games tend to be of a *mixed* nature such that, *both*, skill and chance elements have a bearing on the outcome of success.[17] This complexity of fact has given rise to a legal conundrum for courts; compelling them to draw a line *somewhere* between the two categories of games, so as to treat them differ-

15 Jiménez-Rodrıguez, Jorge, Guillermo Jiménez-Dıaz, and Belén Dıaz-Agudo. "Matchmaking and Case-Based Recommendations." In the 19th International Conference on Case Based Reasoning, 2011. http://sce.carleton.ca/~mfloyd/iccbr11games/papers/Jimenez-Rodriguez.pdf.

16 Gameplay is a term used to describe the structures which characterise the manner in which a game is played. The term, therefore, includes both the rules of the game, but also includes the conditions in which players experience the game, and interact with one another. See Bjork, Staffan, and Jussi Holopainen, Patterns in Game Design (Game Development Series). Charles River Media, Inc., 2004. https://dl.acm.org/doi/abs/10.5555/1044921.

17 Lakshmanan, supra note 11 at para 3.

ently under the law. Such a line has historically been drawn by invoking the 'Preponderance of Skill' test.

As per the test, a game of skill is one whose *final* winning outcome is determined by a *preponderance* of skill over chance, regardless of whether the game otherwise involves elements of chance. For example, in the case of State of Andhra Pradesh v. K. Satyanarayana & Ors,[18] the Supreme Court held that the game of rummy involves a preponderance of skill over chance, because winning depends on memorising the fall of the cards and the building up of the game, which in turn, requires considerable skill on the part of the player, in both, holding and discarding cards.[19]

Furthermore, the court observed that the elements of chance involved in rummy are identical across games which involve the shuffling and dealing of cards, and that the pattern in which cards find themselves within a shuffled pack is purely up to chance.[20] In the subsequent matter of K.R. Lakshmanan v. State of Tamil Nadu ("*Lakshmanan*")[21] — whilst classifying the game of betting on horse races as a game of skill — the Supreme Court also observed that it is the *dominant* element, either skill or chance, which determines the very *character* of a game.[22]

In essence, in order to be considered a game of skill, the *probability* of a player winning the game must be determined predominantly by elements of skill, and not chance. However, it is critical to realise that the very question of *who* a player is paired against is an important determinant of the player's chances of winning.

Take, for example, two gameplay scenarios for A; a complete novice player in an online rummy RMG match. In the first scenario, A is matched with a similarly-skilled novice, whereas in the second scenario, A is matched with an expert or a highly-experienced player. Upon comparing the two given scenarios, it is clear that, the outcome of "success" for A in the two scenarios is not solely driven by the substantive aspects of how rummy is played (i.e. memorising the fall of the cards and the building up of the game, and holding and discarding cards) but is also determined by *who* A's opponent is in the game. The Elo rating system — widely used in a range of traditional games of skill, most popularly Chess — presents some evidence.

In the Elo rating system, the difference in the Elo 'skill ratings' of two individual players serves as a predictor of the outcome of a match. Developed in the 1960s by Arpad Elo, an American-Hungarian physicist and accomplished chess player, the Elo system models the probability of possible outcome in a match based on the skill ratings of two players, such that it is expected that two players with equal skill rating, when playing against each other, will score an equal number of wins.[23]

Under the Elo system, all players are assigned a 'skill rating' — a numerical value that denotes their skill level relative to their opponents. The performance of players within the system is inferred from their wins, losses, and draws against their opponents, and their ratings are dependent on the ratings of their opponents, and the results scored against them. The reason why a player's skill level in a game of skill is inferred from their past performance is because of an underlying assumption made by the system that, while a player might perform better or worse from one game to the next, the mean value of their performance – which is a true reflection of her skill — remains the same, and only changes slowly over time. This allows for the difference in the Elo ratings between two players to serve as a predictor of the outcome

18 Satyanarayana, supra note 10.

19 Ibid, para 12.

20 Ibid.

21 Lakshmanan, supra note 11.

22 Ibid, para 3.

23 Elo, Arpad E., and Sam Sloan. "The Rating of Chessplayers: Past and Present." FIDE , 1978. https://cir.nii.ac.jp/crid/1130282270181653248.

of a match.

If players at vastly different skill levels are placed in the same match of an online RMG, especially frequently, the online gameplay or conditions of gaming will push the preponderance of probability in the territory of chance, such that players' success in a game will no longer be a function of their skill, but their luck in who they were matched with. Differently put, if the elements of chance present at the starting point of a match are *so* dominant — such that the skill showcased over the course of the match becomes immaterial to the final outcome — then, it would be impracticable to classify such a game as a 'game of skill.' In this regard, an SBMM mechanism controls for such dominant elements of chance at the beginning of a match.

Relatedly, the 'Draft Guidelines for Online Fantasy Sports Platforms in India' of December 2020, released by the NITI Aayog — India's apex public policy think tank — recommend that fantasy sports contest relate to, and *emulate* real world officially-sanctioned sports contests *as closely as possible*, and not *infuse* elements of chance not present in the real-world contest.[24] Again, giving effect to this principle would require that platforms use a skill-ranking system for creating matches, as is the case in a range of real world officially-sanctioned games of skill.

Lastly, an SBMM mechanism is a good method of measuring skill of individual players when using more objective criteria for determining games of skill. For example, the element of predictability implicit in the outcome of games of skill can be used as an objective criterion to distinguish games of skill from games of chance. Games of chance are determined by luck, and have outcomes which are wholly *uncertain* and doubtful.[25] In contrast, games of skill must necessarily be somewhat predictable in that the past performance of players must be indicative of their future performance. In some ways, this was touched upon in *Lakshmanan*, where the Supreme Court observed that the game of betting on horse races is determined by the bettor's judgement pertaining to the special ability of the horse and jockey,[26] and that such ability is discernible from public *information* such as breed, upbringing, training, and past records of races.[27]

However, if information about past performance and ability is to form the basis of a bettor's judgement, then it must also necessarily be true that past performance in a game of skill is, in fact, indicative of future performance. The use of this test of predictability in determining games of skill can be best facilitated by integrating an SBMM mechanism within RMGs.

3.2 Significance of SBMM in ensuring Fair & Responsible Play

Derived from the 'Preponderance of Skill' test is the additional requirement that RMGs also be *fair* to play. In game design theory, player(s) versus player(s) matches are deemed fair so long as opponent players have roughly an equal chance of winning at the beginning of a match, regardless of what subsequent options are chosen.[28] In the absence of fairness in play, it would be infeasible for individual players to showcase their skill to the best extent possible, also making it infeasible for the winning outcome to be principally determined by skill elements. Moreover, a fair and balanced game enhances player experience,[29] which in turn enhances engagement and the game's replayability from the user's perspective.[30]

24 NITI Aayog, "Guiding Principles For The Uniform National-Level Regulation Of Online Fantasy Sports Platforms in India." (December 2020).

25 Lakshmanan, supra note 11 at para 3.

26 Lakshmanan, supra note 11 at para 30.

27 Lakshmanan, supra note 11 at para 24-26.

28 Becker, Alexander, and Daniel Görlich. "What Is Game Balancing? - An Examination of Concepts." ParadigmPlus 1, no. 1 (April 21, 2020): 22–41. https://doi.org/10.55969/paradigmplus.v1n1a2.

29 Olivier Delalleau et al., "Beyond Skill Rating: Advanced Matchmaking in Ghost Recon Online," IEEE Transactions on Computational Intelligence and AI in Games 4, no. 3 (September 2012): 167–77, https://doi.org/10.1109/TCIAIG.2012.2188833

30 Graepel, Thore, and Ralf Herbrich. "Ranking and Matchmaking." Game Developer Magazine 25 (2006): 34.
https://www.microsoft.com/en-us/research/wp-content/uploads/2006/10/Game-Developer-Feature-Article-Graepel-Herbrich.pdf.

Fairness, however, is not always a quality that is inherently present in the way games are played, and often, it is for platforms to actively *grant* a state of fairness in the game by introducing balancing measures;[31] SBMM being one such critical measure. SBMM mechanisms strive to create *even* matches by pairing competitors who are at skill *parity* with each other, and refrain from matching competitors at vastly different skill levels, thereby allowing players to showcase their skill to the best extent possible in a 'fair' game. To this end, SBMM mechanisms ensure fairness at the very beginning of a match by actively controlling for those elements of chance which would have otherwise been dominant enough to make skill immaterial to the final outcome.

SBMM mechanisms are also fair in that they treat players at similar skill levels similarly and players at different skill levels differently. While Indian courts and legislatures have said little on the matter, some States in the US have recognised the need to distinguish players along skill lines within their gaming law regulations.[32] Most notably, in 2016, the Office of the Attorney General to the State of Massachusetts issued regulations (*"DFS regulations"*) that direct daily fantasy sports (DFS) contest operators to develop some games that are limited to *beginners*, and restrict non-beginners from participating in them either directly or indirectly.[33] Additionally, they also direct operators to develop games that exclude *highly-experienced players* from participating.[34] The underlying purpose of such directions is to ensure 'fair DFS contests,'[35] and to protect the consumers of DFS contests and their families from unfair practices in the gaming process which could lead to "unaffordable losses" for these parties.[36]

Moreover, in the context of competitive play carrying real financial implications, platforms must assume a greater role in the promotion of responsible gaming, and ensure that the criterion to participate still hinges on skill, and not simply on the amount of money that players can stake. Take, for example, the case where the only determining factor considered by a card-based RMG while placing a player at a particular virtual table is the player's *willingness* to stake a particular amount of real money. Here, players would not be subjected to any constraints that could have otherwise ensured the staking of money in a responsible manner, i.e., taking monetary decisions that are commensurate with players' skills. In failing to integrate such constraints into the game, platforms would be making the assumption that individual players are both *capable of* and *interested in* arriving at objective assessments in this regard, and would consequently place such constraints on themselves. This assumption, however, would be antithetical to the Indian regulator's perspective on the need to introduce strict regulation to safeguard the population from the harmful and addictive nature of gambling.

The necessity of SBMM in online RMGs is, therefore, derived from the necessity of determining 'games of skill' — which must be, both somewhat predictable in that the past performance of players should be indicative of their future performance, and fair to play. At the same time, their rules should proactively promote responsible gaming.

31 Adams, Ernest. Fundamentals of Game Design. Pearson Education, (2014) Pages 404-416.

32 MS Code § 97-33-303 (2020) https://sos.ms.gov//00022732b.pdf, 940 MA Code of Regs 940.34 (2016) https://www.mass.gov/doc/940-cmr-34.

33 MA Code, Regulation 34.12 (6) 'Beginner Games' https://www.mass.gov/doc/940-cmr-34.

34 MA Code, 34.12 (7) 'Games that Exclude Highly-Experienced Players' https://www.mass.gov/doc/940-cmr-34.

35 MA Code, 34.12 (1) 'Purpose' https://www.mass.gov/doc/940-cmr-34.

36 Ibid.

4. Skill Rating Models for Implementing SBMM

The most widely-understood skill rating models used for SBMM in online gaming today are the Elo rating system, the Glicko system,[37] and TrueSkill.[38] A number of online games, for example, team-based video games such as Dota-2[39] and Counter-Strike: Global Offensive,[40] also use custom models. Although largely opaque given their proprietary nature, often, such customised models are tweaked versions of standard models such as the Elo, or its subsequent improvements.

As is the case with all statistical models, skill rating models must necessarily make certain statistical assumptions that allow for a relationship between various variables to be specified. To this end, skill rating models make certain assumptions which help correlate game outcomes to underlying variables that represent players' skill. These assumptions in turn inform how ratings are assigned and further updated. A skill rating model is, therefore, only as good as its underlying assumptions.

The Elo system is widely regarded as the first skill rating model to have strong underpinnings of probability theory. It received official recognition as far back as the 1970s, when it was adopted by two professional chess federation bodies, namely, United States Chess Federation (USCF) and the World Chess Federation (FIDE).[41] Today, the Elo continues to be used in any number of sports including chess, table tennis, association football, golf, basketball, baseball, and e-sports.[42] At the same time, the Elo is not without its limitations, and over time, a number of models have sought to improve upon it, most notably, the Glicko system in 1995 – developed by Dr. Mark E Glickman, Chairman of the USCF and a statistician at Harvard University[43] – and the TrueSkill system in 2005 – developed by Microsoft Research for use on its Xbox Live network.[44]

Moreover, a common aphorism used for statistical models – 'All models are wrong, but some are useful' – also applies to skill rating models.[45] What this means is that while all skill rating models fall short of perfectly modelling the complexities of reality, they are nevertheless useful for making estimations of what is most probable. At the same time, it is important to be cognisant of the limitations of such models, so as to make informed inferences. This is the context in which the Elo and its subsequent improvements must be understood.

4.1 The ELO Rating System

The Elo system is a method used to calculate the relative skill level of individual players. As per the system, all individual players are assigned a 'skill rating' denoted by a numerical

37 Glickman, Mark E. "The Glicko System." Boston University 16, no. 8 (1995): 9.

38 Graepel, Thore, and Ralf Herbrich, supra note 30.

39 Dota 2 Wiki. "Matchmaking." Accessed March 11, 2024. https://dota2.fandom.com/wiki/Matchmaking.

40 "Matchmaking | Counter Strike Online Wiki | Fandom." Accessed March 11, 2024. https://cso.fandom.com/wiki/Matchmaking.

41 Elo, Arpad E., and Sam Sloan, supra note 23.

42 Barrow, Daniel, Ian Drayer, Peter Elliott, Garren Gaut, and Braxton Osting. "Ranking Rankings: An Empirical Comparison of the Predictive Power of Sports Ranking Methods." Journal of Quantitative Analysis in Sports 9, no. 2 (January 1, 2013). https://doi.org/10.1515/jqas-2013-0013.

43 Glickman, supra note 37.

44 Graepel, Thore, and Ralf Herbrich, supra note 30.

45 Clear, James. "All Models Are Wrong, Some Are Useful." James Clear (blog), July 11, 2016. https://jamesclear.com/all-models-are-wrong.

value. Such a value does not express skill in absolute terms, but relative to opponents, and is inferred from wins, losses, and draws. The ratings of individual players are informed both by the ratings of their opponents, as well as game outcomes. The system also follows a self-correcting mechanism such that early estimations of skill ratings are modified over time with the observation of more outcomes. After each match, there is a transfer of a certain number of points from the player who lost to the player who won. This transfer can be understood as the system responding to the skill level of opponents, by first estimating what will happen, and then adjusting based on what actually happened. This way, with more games played, assigned ratings converge with more accurate skill estimations.[46]

The Elo model rests on *three key assumptions*. First, that a player's performance can be denoted by a single variable – a value that varies along the path of a normally-distributed bell-shaped curve. This curve denotes all possibilities for the player's performance; however, every possibility is not equally likely. Instead, the most likely possibilities for the player's performance are concentrated around the mean, or what is colloquially referred to as the "average". This mean value is considered the true reflection of a player's skill. Second, that the mean performance of a player only changes slowly over time. Third, for the sake of simplicity, the model assumes a constant standard deviation for all players. This means that the model assumes itself to be just as accurate or sure about a player's skill rating as it is of any other player's.

In essence, the model gives rise to the idea that while an individual player might perform significantly better or worse in one match to the next, the mean value of their performance will remain the same. When two players compete, the difference in ratings predicts that the one with the higher rating is expected to win more often than the lower-rated player. Also, the more marked the difference in ratings, the greater the likelihood that the higher rated player will win.[47]

However, a few limitations of the model have been identified over time. Firstly, as a model originally designed for ranking chess players, the applicability of the Elo, at least in its classic form, is limited to two-player games that end in either a win or a loss. Secondly, it takes a long time for the Elo ratings of new players to converge to a player's actual skill rating.[48] Thirdly, its use of a constant standard deviation for all players ignores the fact that the ratings of some players are going to be estimated more poorly than others. For example, player ratings based on only a small number of games will likely be more imprecise than of players whose ratings are based on a large number of games. The model also makes no distinction between regular players and those who compete sporadically. This is a concern because, the skill ratings of players who have not played for a considerable period of time will most likely be less reflective of their present mean skill.[49]

4.2 Improvements to the Elo Rating System: Glicko and TrueSkill

The Glicko and TrueSkill systems have sought to address the limitations of the Elo model by improving on two key aspects – *reliability* of skill ratings and general *applicability* of the model to different game formats.

Similar to the Elo model, the Glicko rating system assumes that players' skills are represented by the value of mean skill, however, it assumes that a player's skill must also be represented by a second value called the rating deviation (RD) which measures the reliability of said player's skill ratings. In other words, the RD denotes an interval for how confident the model is of the player's rating. As more and more games are played, the model becomes more and

46 Elo, Arpad E., and Sam Sloan, supra note 23.

47 Glickman, Mark E. "A Comprehensive Guide to Chess Ratings" http://www.glicko.net/research/acjpaper.pdf

48 Glickman, supra note 37.

49 Ibid.

more confident of the player rating assigned by it, and the RD gets lower. Additionally, the uncertainty in a player's skill rating grows linearly with time not played, which is reflected in the RD also increasing over such time. This is because in the time that the player has not played, they may have gotten better or worse; only now, in the absence of having observed the same, the model becomes less sure of the player's actual rating.

However, since Glicko was designed to serve as an extension to the Elo model, its applicability continues to be limited to two-player matches.[50] As a result, Glicko is not capable of computing and updating the skill levels of players in multiplayer or team-based game formats.

In contrast to its predecessors, the TrueSkill system generalises Elo's applicability to matches between any number of players and team-based games.[51] Similar to Glicko, TrueSkill monitors two variables for each player: average skill (Mean) and the degree of uncertainty (Sigma); the latter referred to as 'RD' in Glicko. The model, therefore, tracks not just player skill level, but also the degree to which it believes it to be so. After each match, the system calculates new updated values for both variables, but does not show players both. Instead, it computes them into a single conservative rating. Mathematically expressed as *Mean – 3 Sigma*, a TrueSkill rating is deemed conservative in that it is 98% likely that the player's actual rating is higher than the visible rating.[52]

Furthermore, relative to Elo and Glicko, TrueSkill is known to identify skill levels of individual players from a smaller number of games.[53] For this purpose, the model makes use of 'Free-for-all' – an important gameplay mode where several players simultaneously compete against one another in the same match. According to Microsoft Research's own assessments, TrueSkill can accurately rate a player in 3 matches of a free-for-all mode with 8 players.[54]

However, the TrueSkill model has been critiqued for some of its assumptions, best explained through the case of online shooter games. In the case of an online shooter match where two teams/players are competing, the model only learns from win, loss, or draw outcomes, and uses no additional in-game information such as 'kills' and 'deaths' scored by individual players, their tendency to quit, and their membership in a team. Additionally, the model assumes that the performances of individual players within a team is independent of one another.[55] Subsequent developments, such as Microsoft's TrueSkill 2.0, have sought to address some of these issues.[56]

50 Graepel, Thore, and Ralf Herbrich, supra note 30.

51 Ibid.

52 Ibid.

53 Ranking Systems: Elo, TrueSkill and Your Own, 2019, https://www.youtube.com/watch?v=VnOVLBbYlU0.

54 Graepel, Thore, and Ralf Herbrich, supra note 30.

55 Dehpanah, Arman, Muheeb Faizan Ghori, Jonathan Gemmell, and Bamshad Mobasher. "The Evaluation of Rating Systems in Online Free-for-All Games." arXiv, August 15, 2020. http://arxiv.org/abs/2008.06787.

56 Minka, Tom, Ryan Cleven, and Yordan Zaykov. "TrueSkill 2: An Improved Bayesian Skill Rating System." Technical Report, 2018. https://www.microsoft.com/en-us/research/uploads/prod/2018/03/TrueSkill2.pdf.

5. Baseline Considerations for an SBMM Mechanism

As discussed in previous sections, the underlying goal of integrating SBMM in online games is to create fair, balanced, and engaging matches by prioritising matching players of a similar skill level, over other factors. The critical information required to achieve this goal, i.e., skill levels of individual players, is extracted from matches, and computed with the help of skill-rating models or algorithms. Therefore, to a large extent, the quality of an SBMM implementation depends on the efficiency of its underlying skill-rating model.

Broadly speaking, an *efficient* skill-rating system is characterised by its ability to measure player's skill ratings, both, accurately and expediently.[57] In this regard, the similarities in how Elo, Glicko, and TrueSkill model players' skill levels and predict game outcomes provide a number of baseline considerations for developing skill-rating models underlying SBMM implementations. We list some of these below:

1. Skill ratings of individual players must necessarily be computed *relative* to other players.

2. Skill level of individual players must be represented by the *mean value* of their performances.

3. Regardless of the number of variables considered in its computation, the skill level or skill rating of a player must be expressed in a *single numerical value*. As seen in the case of Elo, Glicko, and TrueSkill, a single value for a player's ratings provides players with a simple and tangible point of reference to compare their skill level with that of their competitors.

4. The model must be *self-correcting* such that, after every match, skill ratings are updated on the basis of the difference between the predicted and the observed outcome. Additionally, in computing and updating skill ratings, the model must take into consideration whether the player in question competes sporadically or consistently.

5. The model should strive for *short convergence periods*; i.e., the time it takes for the model's skill approximations to converge towards more accurate skill ratings of players. This is critical to ensure that the initial period for which players have to engage in unbalanced matches is kept at a bare minimum, and user engagement is not consequently disincentivized.

6. Lastly, the model should strive to achieve a balance between *accuracy* and *simplicity*. While computationally-heavy models such as Glicko and TrueSkill are deemed more accurate, they are not as widely understood and therefore accepted as the classic Elo model is, which was intentionally designed to be simple enough such that chess players could calculate their Elo ratings with the use of only pen and paper. This inherent tradeoff between accuracy and comprehensibility is important to consider from the point of view of user perception and experience of 'fairness,' and in turn user engagement.

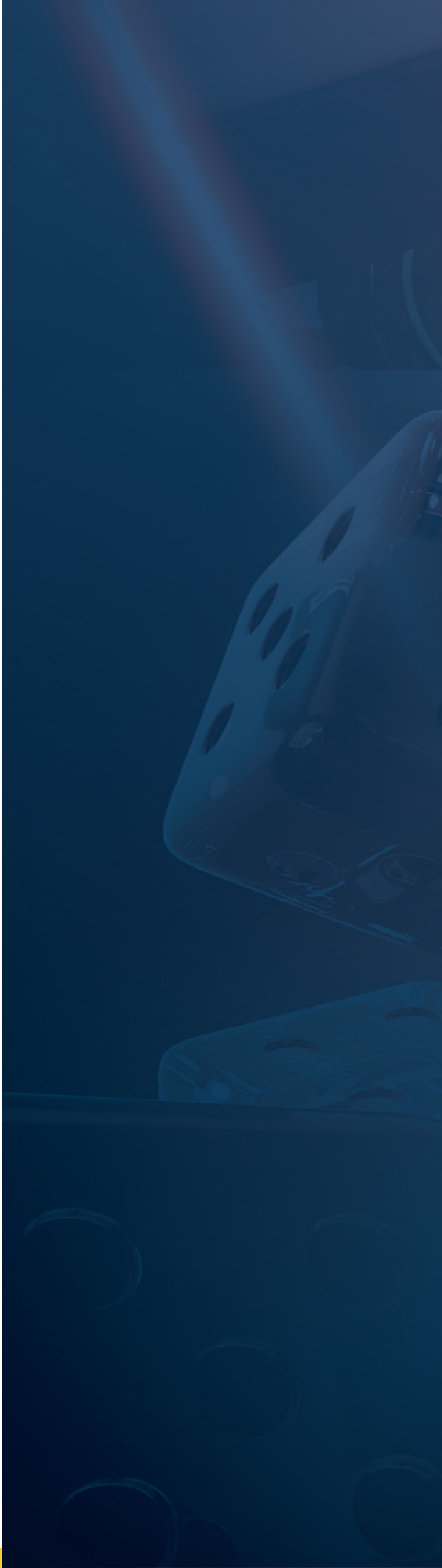
57 Josh Menke; Skill, Matchmaking, and Ranking Systems Design, 2017, https://www.youtube.com/watch?v=-pglxege-gU.

6. Conclusion

The need to regulate online RMGs in India has never been more urgent, and India's push for comprehensive regulation has come not a moment too soon. However, within this context, regulators must take into consideration the necessity for SBMM in online RMGs, both from a legal and policy standpoint, as has been argued over the course of the paper.

Underlying SBMM mechanisms are skill-rating models that use probability theory to quantify the 'skill' of individual players, and pair players of a similar skill level, ultimately creating fair and even matches for players. An efficient skill-rating model is characterised by its accuracy and expediency in assessing skill, and while the Elo model is widely accepted and used, TrueSkill and Glicko enhance its accuracy and applicability.

In this context, by identifying the characteristics common to all three models, along with desired improvements vis-a-vis regulation, we end this paper with a baseline framework for online RMGs to consider when devising their own SBMM mechanisms.



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