

Economic Determinants and Social Influences on Gambling in South Africa: A Mathematical Modeling Approach

Tichaona Chikore* and Farai Nyabadza^{}

Abstract

Gambling in South Africa, propelled by casinos, sports betting, and a growing online sector, is increasingly influenced by economic pressures and accessibility. This study presents a partially data-informed mathematical model to analyze gambling participation, focusing on the impact of economic indicators (unemployment, inflation, GDP per capita, and poverty) on gambling behaviours. Integrating these factors with social influences, we employ a non-linear differential equation framework to evaluate the perceived utility of gambling in varying economic scenarios. Using Monte Carlo simulations and scenario analysis, our results reveal a significant association between high unemployment, poverty, and increased gambling participation, particularly in socially cohesive environments. Results indicate that higher unemployment and poverty levels significantly correlate with increased gambling, with social influence amplifying this trend. Unemployment and peer effects emerge as primary predictors, highlighting economic hardship's role in gambling behaviour. These findings suggest targeted interventions for economically vulnerable populations, such as educational campaigns and support services, to mitigate gambling-related risks during economic downturns.

Keywords: Gambling dynamics, Economic conditions, Predictive modeling, Utility function, Social influences.

2020 Mathematics Subject Classification: 91B42, 91D10, 34C60, 91B16.

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1. Introduction

Gambling has evolved into a prominent feature of economic and social landscapes worldwide, functioning as both a popular leisure activity and a significant revenue source for governments. As global economies experience volatility, there is growing interest in understanding how gambling behaviour adapts in response to economic changes. According to [1], the gambling industry in South Africa, with an estimated 2022 population of 62 million people [2], has witnessed unprecedented growth, projected to reach a trillion rand in 2024. Over the past 28 years, from 1995 to 2023, total gambling turnover has surged from R8 billion to R815 billion, marking an astounding increase of 10,087%. This remarkable escalation has been particularly pronounced following the COVID-19 pandemic, with the sector expanding from R326 billion to R815 billion in just two years (see also [3, 4]). Such growth prompts an exploration into the underlying socio-economic dynamics that have shaped this trajectory. To contextualize this phenomenon, a comparative analysis with mature gambling markets reveals significant insights. In Great Britain, which boasts a population of approximately 68 million, the total gambling market was valued at £15.1 billion (R384 billion) in 2023 [5], less than half that of South Africa's total gambling turnover. Notably, the GDP per capita in Great Britain stands at \$45,000, which is six times higher than South Africa's \$7,000. The high per-capita gambling expenditure relative to income levels raises critical questions about the socio-economic drivers of gambling behaviour within the South African population. Further, Australia reported a national gambling aggregate of A\$25.49 billion (R312 billion) in 2021, despite its smaller population of 25 million [6]. This translates to an average gambling spend of R12,450 per Australian, compared to R13,583 per South African, indicating a striking similarity in average expenditures despite vast differences in income levels. In the broader African context, South Africa's gambling turnover constitutes more than half of the aggregate of all other 53 African nations, underscoring its prominent role as a gambling nation.

This unprecedented growth and comparative analysis call for a comprehensive mathematical model to explore the socio-economic dynamics influencing gambling behaviour in South Africa. By integrating economic indicators, social factors, and consumer behaviour, this research aims to investigate the complex relationships among these variables and contribute to the broader understanding of gambling within the socio-economic arena [7]. Numerous studies suggest that economic downturns, marked by factors such as rising unemployment, inflation, and poverty, often correlate with increased gambling activity [8–11]. During times of financial stress, individuals may be drawn to gambling as a form of escapism or as a per-

ceived opportunity for financial relief. Prior research has examined the connections between economic hardship and gambling behaviour, revealing that betting activity often surges when economies enter a recession (see also [12–14]). Additional studies have investigated the psychological factors influencing gambling, such as addiction or the perceived utility derived from gambling, as well as social influences, such as peer behaviour [15]. The social consequences of gambling, including the effects on vulnerable populations, have also been widely studied, with particular attention to problem gambling and its economic repercussions on families and communities [9, 16]. Despite these insights, there remains a need for predictive models that incorporate multiple economic and social factors to reflect the complex dynamics driving gambling behaviour in society.

According to the report in [17], the gambling industry in South Africa has evolved significantly since its inception in 1997, transitioning from a developing market to a more mature industry. Structural changes have occurred, including the introduction of electronic devices and online betting, along with the establishment of new gambling facilities. Over the years, the incidence of gambling among South Africans aged 18 and older has decreased from 56.8% in 2002 to 30.6% in 2017, with the majority of the population, 69.4%, abstaining from gambling, highlighting a notable decline in participation. The National Lottery remains the most popular mode of gambling, with 67.8% of respondents indicating it as their preferred option. From [17], other forms of gambling include illegal activities, licensed horse and sports betting, and casinos, each exhibiting varying levels of participation. The report also examines the socio-economic effects of gambling, including its influence on household welfare, expenditure displacement, and budgetary behaviour. Financial motivations are significant for many gamblers, as 79.6% cite financial reasons for their participation. Also, there is a focus on problem gambling, addressing the prevalence of issues related to it and assessing the effectiveness of rehabilitation programs, while also discussing the factors contributing to problematic gambling behaviour, including financial stress, mental health issues, and social influences. The report also addresses the associated social harms, such as financial difficulties, strained relationships, and negative impacts on mental health.

Mathematical models on the gambling problem exist in the literature, including [18] in which the author proposes techniques to prevent excessive gambling. In [19], the authors use ordinary differential equations in an epidemiological model to help prevent addictive gambling. Using a simplified epidemiological mathematical model, it was established in [20] that the prevalence of gambling exists among young adults at different scales. The Mathematical Principles of Reinforcement (MPR) were used to understand human behaviour as far as gambling is concerned in [21] using human experiments simulated with an electronic gaming machine. Results support the effectiveness of the MPR in forecasting human behaviour under Random Ratio (RR) schedules.

Although significant progress has been made, notable gaps persist within the current body of literature on gambling dynamics. First, while numerous studies have examined correlations between gambling behaviour and individual economic

factors (such as unemployment or inflation), few have integrated these variables within a multi-factorial model capable of capturing their combined influence on gambling activity. The absence of such holistic modelling limits the capacity to understand how various economic indicators interact to affect gambling behaviour on a societal level. Furthermore, psychological and social factors, though often acknowledged as critical drivers, are rarely studied in conjunction with economic conditions. There is considerable value in combining these domains to account for the influence of peer pressure, utility perception, and social networks, which may intensify or mitigate gambling behaviour under different economic circumstances. Also, most existing models employ linear assumptions, which may overlook the potentially non-linear relationships that exist between economic conditions and gambling trends. For instance, when economic factors reach critical thresholds, individuals may alter their risk tolerance, leading to non-linear increases in gambling participation. This gap in modelling techniques neglects the complex ways in which economic hardship may amplify societal gambling behaviour, suggesting a need for more dynamic, multi-factorial models to accurately capture these relationships.

In this study, we develop a mathematical model to analyze gambling participation dynamics in response to economic conditions. The novelty of our approach lies in three specific contributions: (1) a non-linear conformity structure that captures asymmetric social influence on gambling adoption versus cessation, (2) a utility-based formulation that integrates multiple economic indicators to reflect the perceived benefit of gambling, and (3) the introduction of differentiated conformity parameters (a_1 and a_2) that allow social influence on adoption and cessation to vary independently. By integrating these elements, the model provides a framework for simulating the complex interplay between economic conditions and social dynamics in gambling behavior. We employ sensitivity and scenario analyses to identify key economic predictors and assess the robustness of the modeled dynamics. The results offer insights into the societal factors that drive gambling trends, with potential implications for stakeholders in regulatory and economic policy spheres.

The introduction is in Section 1, followed by a comprehensive methodology in Section 2, which covers the ordinary differential equation, its properties, a utility function to model behaviour, data manipulation, and various simulations. The results are discussed in Section 3, and the discussion of the results and conclusion are found in Section 4.

2. Methodology

Following a formulation in [22], this model defines several key variables and parameters to analyze the dynamics of gambling behaviour by considering some economic indicators. Throughout the paper, $g(t)$ represents the proportion of the total adult population who are *active gamblers* at time t ; it does not include lifetime or occa-

sional gamblers. Clarifying this interpretation avoids ambiguity when discussing equilibrium values such as $g = 1$.

The variable $g(t)$ denotes the fraction of the population that is into gambling at time t . The unemployment rate μ reflects how economic instability may influence gambling; higher unemployment often correlates with increased gambling as individuals seek alternative income sources [9]. The inflation rate ϕ captures the impact of rising prices on consumers' purchasing power, potentially leading to increased gambling as individuals pursue financial gains. The overall GDP, denoted as γ , represents the economic prosperity of a region, where higher GDP typically correlates with greater discretionary spending on gambling activities [23]. The poverty level π is critical, as elevated poverty rates may drive individuals toward gambling as a means to improve their financial situations [8, 24], thus increasing participation.

Utility derived from gambling is denoted by $u_g(t) \in [0, 1]$ and varies with economic and social conditions [25, 26], illustrating how individuals' perceived value of gambling shifts according to their circumstances. We note that the theoretical formulation in (2) does not automatically guarantee that $u_g(t) \in [0, 1]$; therefore, normalization is applied during calibration to ensure interpretability as an index. The parameter q serves as a rate constant that quantifies the responsiveness of the gambling population to changes in utility [27]; a higher q indicates that small changes in perceived utility can lead to significant variations in the gambling population. The choice of q is therefore not behavioural in origin but represents a scaling of reaction speed, which is explored through sensitivity experiments. In the absence of empirical longitudinal data for reaction rates, q is chosen heuristically to demonstrate model sensitivity.

The primary equation governing the dynamics of the gambling population describes the rate of change of the gambling population ratio as a function of utility, following [22]. It is given as:

$$\frac{dg}{dt} = q \left((1 - g)g^a u_g - g(1 - g)^{1-a} (1 - u_g) \right), \quad (1)$$

where all the model parameters q, u_g, a , and the variable g are non-negative, with the initial condition $g(0) \geq 0$ imposed. The exponent structure $(a, 1 - a)$ encodes asymmetric conformity in which adoption is influenced by the proportion of gamblers, whereas cessation is influenced by the proportion of non-gamblers. This is consistent with relative conformity theory, in which individuals weigh the behaviour of both groups rather than responding symmetrically to prevalence.

The asymmetry in the exponents, using a for adoption and $1 - a$ for cessation, is a deliberate modeling choice based on the framework of relative conformity [28, 29]. The parameter $a \in [0, 1]$ captures the extent to which individuals are influenced by the behavior of others. The term g^a models the strength of social influence from gamblers during adoption, while $(1 - g)^{1-a}$ models the influence from non-gamblers during cessation. This formulation ensures that a single parameter a governs the relative weight of social utility from both behavioral groups (gamblers and

non-gamblers). When $a = 1$, individuals are maximally influenced by gamblers; when $a = 0$, they are maximally influenced by non-gamblers. Later sensitivity experiments illustrate how varying a reshapes the trajectories of $g(t)$.

2.1 Gambling adoption, cessation, and utility prevalence

The model can be interpreted in terms of two main processes, which are gambling adoption and gambling cessation. In gambling adoption, the positive term $(1 - g)g^a u_g$ represents the rate at which non-gamblers $(1 - g)$ start gambling. This rate is proportional to the combined utility from gambling, represented by $g^a u_g$, where u_g is the individual utility or benefit derived from gambling. The term g^a reflects the influence of social interactions with other gamblers, with the parameter a serving as a weighting factor for how much social utility impacts the decision to start gambling.

In gambling cessation, the negative term $g(1 - g)^{1-a}(1 - u_g)$ represents the rate at which gamblers stop gambling. The term $(1 - u_g)$ represents the utility or benefit derived from not gambling, while $(1 - g)^{1-a}$ captures the social utility from interactions with non-gamblers. Thus, the same conformity parameter governs both initiation and cessation, but with opposite reference groups. The parameter a , known as the *relative conformity parameter* [28, 29], determines how strongly social influences impact gambling behaviour. In societies with a larger a , which are more collectivistic, social utility has a stronger influence on behavior, meaning the social environment (such as a high prevalence of gambling) could significantly drive individuals' decisions to start or continue gambling. Conversely, in more individualistic settings, where $a < 1$, personal attitudes and individual utility play a more dominant role than social factors in influencing gambling behavior.

2.2 Utility formulation

The utility function $u_g(t)$ at any time t reflects the perceived benefits of gambling, incorporating various economic and social factors such as unemployment ($\mu(t)$), gross domestic product ($\gamma(t)$), inflation ($\phi(t)$), gambling revenue ($\rho(t)$), poverty level ($\pi(t)$), ease of access (ψ) (see [30, 31]), and the baseline utility (Λ) (see [32]), to obtain:

$$u_g(t) = f(\phi(t), \mu(t), \gamma(t), \pi(t), \psi, \rho(t), \Lambda) = c \frac{\mu}{1 + \phi} + d \frac{\pi}{\gamma + e} + f\rho + h\psi + \Lambda. \quad (2)$$

The terms are constructed as normalized indices rather than literal economic quantities, because the indicators have different natural scales. The constants c, d, f, h therefore act as weights, while e prevents division by zero and stabilizes the influence of GDP when values are small. The additive structure assumes that these factors contribute to gambling utility independently, which provides a tractable baseline for evaluating the relative impact of economic stress versus accessibility.

The terms f and e represent the weights of gambling revenue and online accessibility [30, 33], respectively. The parameter $f\rho$ enhances utility in line with market profitability, suggesting that higher revenue may increase the gambling appeal (an indicator of the growing availability of gambling [34]). The term $h\psi$ captures online gambling's ease of access. The expression $\frac{\mu}{1+\phi}$ captures how higher unemployment heightens gambling utility. The term $\frac{\pi}{\gamma+e}$ similarly conveys how poverty, relative to GDP, may enhance gambling's perceived value in financially stressed settings. The constant Λ represents baseline utility from gambling, including fixed preferences and social factors [35]. This functional form is heuristic but transparent since each factor contributes additively, allowing sensitivity analysis rather than claiming causal interpretation. Temporal discrepancies in data (for example, Table 1) are resolved by using normalized 2020–2022 trends for the primary calibration phase.

2.3 Relative utility ratio

The terms

$$\frac{d(g^a u_g)}{dg} \quad \text{and} \quad \frac{d(g^a u_g)}{du_g},$$

represent how the total utility changes as the fraction of the population engaged in gambling changes and how the total utility varies with changes in individual utility, respectively. Then we obtain:

$$r = \frac{d(g^a u_g)}{dg} \bigg/ \frac{d(g^a u_g)}{du_g} = a \left(\frac{u_g}{g} \right), \quad (3)$$

indicating how the utility from gambling compares to its prevalence in the population. If this ratio is relatively high such that $0 < a < 1 < r$, it suggests that individuals derive substantial utility from gambling relative to the proportion of gamblers, which could signal a strong attraction to gambling as a social activity. Because r diverges as $g \rightarrow 0$, simulations employ lower bounds on g to avoid numerical artifacts, and this behaviour is explicitly acknowledged in interpretation.

2.4 Solution boundedness, positivity, and stability of equilibria

Proposition 2.1 (Boundedness and positivity). *Let the initial condition satisfy $g(0) \in [0, 1]$. Then the solution $g(t)$ of (1) remains in the interval $[0, 1]$ for all $t \geq 0$. Moreover, if $g(0) \in (0, 1)$ and $u_g > 0$, then $g(t) \in (0, 1)$ for all $t \geq 0$.*

Proof. Let $F(g) = q((1-g)g^a u_g - g(1-g)^{1-a}(1-u_g))$. The function $F(g)$ is continuously differentiable on the open interval $(0, 1)$, and therefore locally Lipschitz. By standard existence and uniqueness theorems, the initial value problem has a unique solution for as long as it remains bounded. Since $F(0) = 0$ and $F(1) = 0$, the constant functions $g(t) \equiv 0$ and $g(t) \equiv 1$ are solutions. Uniqueness

implies that no other solution can cross these equilibrium solutions. Consequently, any solution starting in $[0, 1]$ cannot leave this interval. These arguments ensure that the model remains biologically meaningful, since proportions of gamblers cannot become negative or exceed unity justifying the theoretical validity of the feasible region.

For the positivity claim, suppose $g(0) \in (0, 1)$ and $u_g > 0$. If the trajectory were to approach $g = 0$, then for sufficiently small $g > 0$ we have $F(g) \approx qg^a u_g > 0$, which would push the solution away from zero. Thus, the solution cannot reach zero. A similar argument near $g = 1$ shows that if $u_g < 1$, then for g close to 1, $F(g) < 0$, preventing the solution from reaching one. If $u_g = 1$, then $F(g) = q(1-g)g^a \geq 0$, with equality only at $g = 1$, so the solution approaches but does not exceed 1. This behavior reflects the intuitive interpretation that, in the absence of external interventions, the population cannot evolve toward unrealistic states such as negative participation or total gambling saturation. $\square$

Proposition 2.2 (Boundary equilibria and their linear stability). *Assume $u_g \in [0, 1]$ is constant and $a \in (0, 1)$. The boundary equilibria of (1) satisfy:*

1. *The equilibrium $\bar{g} = 0$ is locally asymptotically stable if $u_g = 0$ and unstable if $u_g > 0$.*
2. *The equilibrium $\bar{g} = 1$ is locally asymptotically stable if $u_g = 1$ and unstable if $u_g < 1$.*

Proof. We analyze stability by examining the sign of $F(g)$ near each equilibrium.

For $\bar{g} = 0$, consider small $g > 0$. If $u_g = 0$, then $F(g) = -qg(1-g)^{1-a} < 0$ for all $g \in (0, 1)$, so trajectories move toward zero. If $u_g > 0$, then for sufficiently small g , the dominant term is $qg^a u_g > 0$, so trajectories move away from zero. For $\bar{g} = 1$, let $h = 1 - g$ with h small and positive. If $u_g = 1$, then $F(1-h) = qh(1-h)^a > 0$, so trajectories approach $g = 1$ from below. If $u_g < 1$, then

$$F(1-h) = q[h(1-h)^a u_g - (1-h)h^{1-a}(1-u_g)] \approx -qh^{1-a}(1-u_g) < 0,$$

so trajectories move away from $g = 1$. Hence, the stability of the boundary states is governed entirely by whether the utility favors gambling or abstaining.

Thus, the stability conditions are as stated. $\square$

Proposition 2.3 (Existence of an interior equilibrium). *Let $u_g \in (0, 1)$ be constant. Then there exists at least one interior equilibrium $g^* \in (0, 1)$ satisfying*

$$g^{a-1}u_g = (1-g)^{-a}(1-u_g). \quad (4)$$

If the function $\Phi(g) = g^{a-1}u_g - (1-g)^{-a}(1-u_g)$ is strictly decreasing on $(0, 1)$, then g^* is unique.

Proof. Define $\Phi(g) = g^{a-1}u_g - (1-g)^{-a}(1-u_g)$. Observe that $\lim_{g \rightarrow 0^+} \Phi(g) = +\infty$ and $\lim_{g \rightarrow 1^-} \Phi(g) = -\infty$. By continuity, there exists at least one $g^* \in (0, 1)$ such that $\Phi(g^*) = 0$, which is equivalent to (4). If $\Phi'(g) < 0$ for all $g \in (0, 1)$, then Φ is strictly decreasing and the root is unique. This guarantees a single coexistence point between gamblers and non-gamblers when preferences are balanced. Numerical evaluation across our parameter space confirms this monotonicity. $\square$

Proposition 2.4 (Stability of the interior equilibrium). *Assume that an interior equilibrium $g^* \in (0, 1)$ exists for constant $u_g \in (0, 1)$ and $a \in (0, 1)$. Then g^* is always locally asymptotically stable.*

Proof. We compute the derivative $F'(g)$ explicitly:

$$F'(g) = q \left[-g^a u_g + a(1-g)g^{a-1}u_g - (1-g)^{1-a}(1-u_g) + (1-a)g(1-g)^{-a}(1-u_g) \right].$$

At the interior equilibrium g^* , we use the condition $g^{*a-1}u_g = (1-g^*)^{-a}(1-u_g)$. Denote $K = g^{*a-1}u_g = (1-g^*)^{-a}(1-u_g) > 0$. Substituting $u_g = Kg^{*1-a}$ and $(1-u_g) = K(1-g^*)^a$ into $F'(g^*)$ and simplifying yields:

$$F'(g^*) = qK[(a-1) + g^*(1-2a)].$$

Since $q > 0$ and $K > 0$, the sign of $F'(g^*)$ is determined by $S(a, g^*) = (a-1) + g^*(1-2a)$. We now show $S(a, g^*) < 0$ for all $a \in (0, 1)$ and $g^* \in (0, 1)$.

Consider two cases:

1. If $a \leq 0.5$, then $1-2a \geq 0$. Since $g^* < 1$, we have:

$$S(a, g^*) \leq (a-1) + (1-2a) = -a \leq 0.$$

Equality occurs only when $a = 0$ and $g^* = 1$, which is impossible in our parameter regime.

2. If $a > 0.5$, then $1-2a < 0$. Since $g^* > 0$, we have:

$$S(a, g^*) < (a-1) + 0 \cdot (1-2a) = a-1 < 0.$$

Therefore, the coexistence equilibrium attracts nearby trajectories for all admissible parameters, supporting the interpretation that gambling persists at a stable level even without shocks or interventions. Thus $S(a, g^*) < 0$ always, implying $F'(g^*) < 0$. Therefore, any interior equilibrium is locally asymptotically stable. $\square$

Remark 1. The interior equilibrium represents a coexistence state where gamblers and non-gamblers balance social and economic incentives. The stability proof confirms that this balance is attracting under constant conditions. In simulations with time-varying utility $u_g(t)$, the system tracks a moving equilibrium, explaining the persistent gambling levels observed. This provides the analytical foundation for the interpretation used later in the results section.

2.5 The data

We make use of South African economic indicators covering the period 2000–2022 to construct an empirical approximation of the utility derived from gambling. To empirically estimate $u_g(t)$ for South Africa from 2000–2022, we construct a simplified proxy version of the theoretical utility function in Equation (2). This proxy is formed as a normalized, equally weighted linear combination of key economic indicators:

$$u_g(t) = w_1 \cdot \text{Unemployment} + w_2 \cdot \text{GDP} + w_3 \cdot \text{Poverty} + w_4 \cdot \text{Inflation} + w_5 \cdot \text{Gambling revenue} \quad (5)$$

where, in the absence of prior information about the relative importance of each economic factor, we initially assign equal weights to all components, setting $w_1 = w_2 = w_3 = w_4 = w_5 = 0.2$. This provides a neutral baseline assumption in which each indicator contributes equally to the proxy. The use of equal weights ensures that no single economic factor unduly biases the utility proxy before the non-linear regression process determines the functional coefficients. Future work could refine these weights using data-driven methods such as regression-based calibration or expert elicitation. Thus, the proxy acts as a practical empirical substitute for the full theoretical specification used during model estimation. Analogous to constructing a composite socioeconomic index, we use the weighted sum model as a proxy for utility derived from gambling. This is reasonable since economic indicators represent dimensions of macroeconomic performance and household welfare that influence risk-taking behavior and financial decision-making.

Each economic indicator is normalized independently to the range $[0,1]$ using min-max normalization:

$$x_{\text{norm}}(t) = \frac{x(t) - x_{\min}}{x_{\max} - x_{\min}},$$

where $x(t)$ is the raw value of an indicator at time t , and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of that indicator across the entire observation period (2000–2022). This independent normalization ensures comparability across different measurement scales while preserving relative trends within each series. We acknowledge that long-term drift in variables like unemployment can affect normalized trends; however, this approach provides a consistent baseline for constructing the utility proxy.

The resulting proxy values from (5) thus lie in the interval $[0,1]$ and serve as the observed utility index for the calibration of the theoretical utility function in (2). To fit the data to the utility function model, we set up a non-linear regression process to estimate the parameters c , d , f , h , e , and Λ based on the formula for $u_g(t)$. We first implement the functional form of $u_g(t)$ in Python and allow the parameters to vary during optimization. We then employ non-linear curve fitting using `scipy.optimize.curve_fit`, which estimates the parameters by minimizing the difference between observed values of $u_g(t)$ (the proxy from (5))

and the predicted values generated by the function. To ensure that the fitted utility function yields values in the interpretable range $[0,1]$, we apply a post-hoc min-max rescaling to the predictions of (2) after parameter estimation. This rescaling maps the fitted values to the $[0,1]$ interval, preserving their ordinal relationships while guaranteeing compatibility with the dynamic model's requirements. The optimization utilizes the Levenberg-Marquardt algorithm to ensure convergence given the non-linear nature of the quotients in Equation (2). Table 1 presents the normalized indicator values together with the resulting utility proxy:

Table 1: Economic and social indicators with gambling utility proxy $u_g(t)$. All values are normalized to $[0,1]$ for consistency.

Year	Hunger	GDP	Unemployment	Inflation	Gambling Rev	Utility proxy
2000	0.1087	0.0689	0.0765	0.5602	0.0000	0.1629
2001	0.0869	0.0193	0.0574	0.5939	0.0387	0.1592
2002	0.0652	0.0000	0.0462	0.9461	0.0774	0.2270
2003	0.0435	0.2064	0.0569	0.5918	0.1161	0.2029
2004	0.0000	0.3850	0.0411	0.0000	0.1547	0.1162
2005	0.0000	0.4855	0.0280	0.2559	0.1934	0.1926
2006	0.0217	0.5310	0.0062	0.3656	0.2321	0.2313
2007	0.0435	0.6198	0.0000	0.6381	0.2708	0.3144
2008	0.0435	0.5683	0.0177	1.0000	0.3095	0.3878
2009	0.1522	0.6097	0.1230	0.7344	0.3482	0.3935
2010	0.2826	0.8759	0.4041	0.4441	0.3868	0.4787
2011	0.3696	1.0000	0.2188	0.5286	0.4255	0.5085
2012	0.3913	0.9277	0.2577	0.5960	0.4642	0.5274
2013	0.4565	0.8259	0.2841	0.6015	0.5029	0.5342
2014	0.6304	0.7660	0.3441	0.6336	0.5416	0.5831
2015	0.6739	0.6612	0.3714	0.4860	0.5804	0.5546
2016	0.6087	0.5910	0.4925	0.6746	0.6247	0.5983
2017	0.5000	0.7668	0.4894	0.5458	0.6750	0.5954
2018	0.5000	0.8391	0.5136	0.4838	0.7379	0.6149
2019	0.5869	0.7907	0.6526	0.4470	0.8007	0.6556
2020	0.7609	0.6357	0.5262	0.3624	0.8685	0.6307
2021	0.9783	0.8843	0.9926	0.4926	0.9374	0.8570
2022	1.0000	0.8392	1.0000	0.7181	1.0000	0.9115

Without loss of generality, we assume an equal weight of 0.2 across all indicators and from the fit in Figure 1, we get the parameter values:

Table 2: Fitted parameter values for the South African gambling utility model.

	c	d	f	h	e	Λ
Value	0.069	0.266	0.545	0.071	1.000	0.071

To evaluate model performance, we compute the coefficient of determination R^2 and the root mean square error (RMSE). The R^2 value indicates how well the fitted model captures the variance in the observed data, with a value close to 1 indicating a good fit and in our case $R^2 = 0.9394$ as shown in Figure 2. The RMSE gives an idea of the average residual size, with the smaller value 0.0538 suggesting a closer fit. These metrics confirm that the chosen heuristic functional form for $u_g(t)$ is statistically robust for the purpose of dynamic simulation.

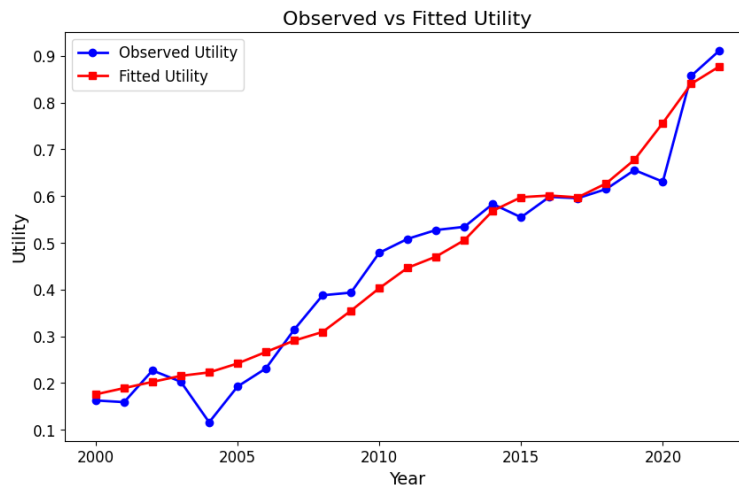


Figure 1: Illustration of how well the model captures the observed trend in utility over time.

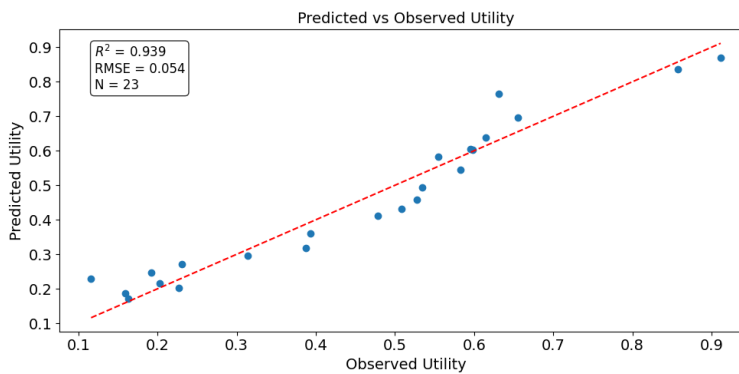


Figure 2: Illustration of the relationship between the predicted and observed utility values, showing that the model predictions closely track the observed data.

These parameter estimates form the foundation for all subsequent simulations across the full observation period (2000–2022). The correlation between hunger and GDP (0.61) suggests a potential link between economic growth and reduced hunger, though this may also reflect inequalities. A high correlation between hunger and unemployment (0.94) indicates that rising unemployment is associated with increased hunger, consistent with economic theory. The correlation between GDP and unemployment (0.59) further emphasizes the economic interplay at work. also, a significant positive correlation between GDP and utility (0.77) indicates that economic growth is associated with increased gambling participation, while the very strong correlation between gambling revenue and utility (0.96) suggests that greater perceived utility is associated with higher gambling activity. Conversely, the weak correlation between unemployment and utility (0.15) indicates limited association with gambling behavior, while the strong negative correlation between unemployment and gambling revenue (-0.89) suggests that economic distress is associated with lower gambling participation. Taken together, these relationships highlight the multifaceted and sometimes counterintuitive interactions between macroeconomic conditions and gambling dynamics.

2.6 Impact of social influences

We explore the dynamics of gambling behavior by examining the influence of social interactions on individuals' decisions to engage in gambling for parameter values $q = 0.5$ and $s = 1.0$, with the initial value $g(0) = 0.1$. Specifically, we vary the parameter a , which quantifies the degree of social influence in the model. Values of a range from 0, indicating an individualistic society where personal preferences dominate decision-making, to 1, representing a collectivistic society where social interactions significantly shape behavior. The resulting trajectories are displayed in Figure 3.

To further assess robustness, we provide a Monte Carlo simulation, allowing for a robust exploration of parameter uncertainty. To ensure reproducibility and rigor, Monte Carlo simulations are conducted using $N = 10,000$ iterations. Parameters q , a , and components of u_g are sampled from Uniform distributions $\mathcal{U}(\min, \max)$ based on the ranges provided in Table 2. Outcome variability is reported using 95% confidence intervals to quantify parameter uncertainty. By randomly sampling multiple parameter values, including q , s , and u_g , from specified distributions, it generates a range of potential outcomes for $g(t)$, assessing the model sensitivity to fluctuations in a , which is crucial for understanding behavior under uncertainty. For the Monte Carlo framework, we execute $N = 10,000$ iterations with $q \sim \mathcal{U}(0, 1)$ and $u_g \sim \mathcal{U}(0, 1)$, ensuring that the conclusions regarding social influence are not artifacts of a specific parameter set. The results are shown in Figure 4 that follows:

Both q (the rate of influence) and a (the social influence parameter) play crucial roles in determining the dynamics of the gambling population. q governs how strongly external factors affect gambling behavior, while a characterizes the nature of these influences, ranging from individualistic to collectivistic. When q is large

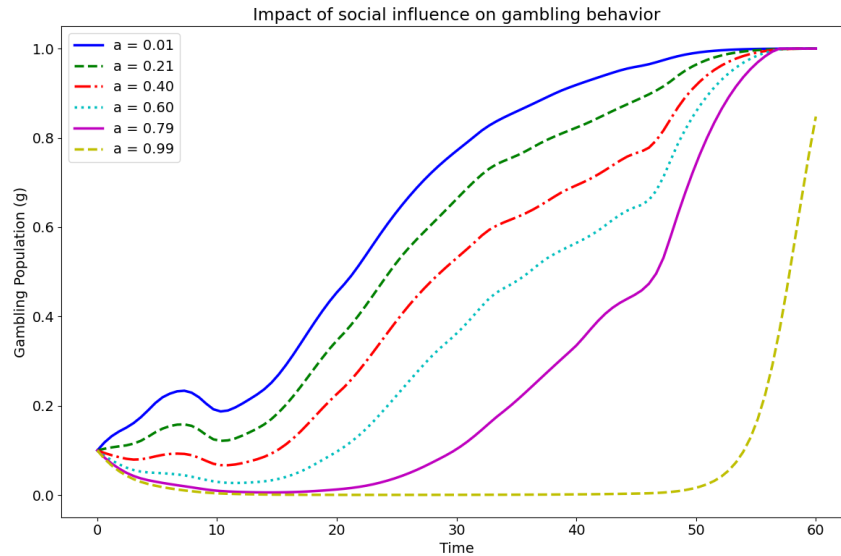


Figure 3: This plot visually shows how well the model captures the observed trend in utility over time.

(for example, $q = 0.99$), even modest social pressures propagate rapidly through the population, producing pronounced fluctuations. Conversely, a low value of q , (when $q = 0.01$), dampens the influence of these external factors, making a more significant in determining gambling behavior. Under low q , systems with more individualistic structures ($a \rightarrow 0$) appear comparatively stable, as illustrated in Figure 5.

2.7 Differentiated conformity for adoption and cessation

The original formulation used a single parameter a to govern social influence, with symmetric exponents a and $1 - a$ applied to the adoption and cessation terms, respectively. This implied that increases in conformity toward adoption necessarily reduced conformity toward cessation. While elegant, this constraint may oversimplify real-world behavioral dynamics, particularly in contexts where social influence does not operate in a zero-sum fashion across opposing behaviors. To address this limitation, we generalize the model by decoupling social conformity into two distinct parameters: a_1 for gambling adoption and a_2 for cessation. This allows the model to account for asymmetric social pressures. In many environments, peer encouragement to gamble is visible and public, whereas the decision to stop gambling is often private or stigmatized. The revised dynamic equation

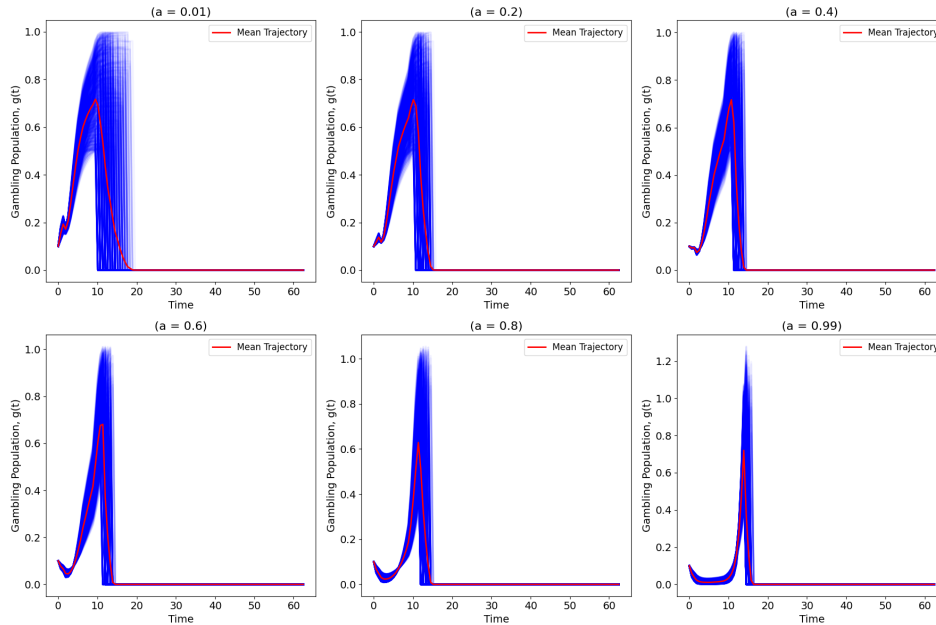


Figure 4: Results of Monte Carlo simulation depicting the model sensitivity to fluctuations in a .

becomes:

$$\frac{dg}{dt} = q \left(\left(1 - \frac{g}{s}\right) g^{a_1} u_g - g \left(1 - \frac{g}{s}\right)^{a_2} (1 - u_g) \right). \quad (6)$$

This two-parameter structure adds flexibility, improves empirical realism, and enables better alignment with sociocultural data on behavioral conformity. By introducing a_1 and a_2 , we explicitly model the possibility that social pressure to enter a behavior may be significantly stronger (or weaker) than the pressure to stop it, which is central to understanding the persistence of gambling in South Africa. By distinguishing between a_1 and a_2 , the model effectively captures the differential responses of individuals to social influences when initiating versus ceasing gambling behaviors. We begin by exploring combinations of these parameters through simulation, as illustrated in Figure 6.

The sigmoidal growth curves show that in the early stages, the population grows rapidly until saturation of potential gamblers or social changes limit further growth. Eventually, the population reaches a stable state, where the growth rate becomes very small, and the fraction of gamblers stabilizes around the carrying capacity. In some scenarios, however, the system approaches the maximum value determined by the influence parameters rather than exhibiting classic logistic behavior. Other deterministic dynamics when $q = 0.45$ (medium) and $q = 0.99$ (high) are shown in Figures 7 and 8, respectively.

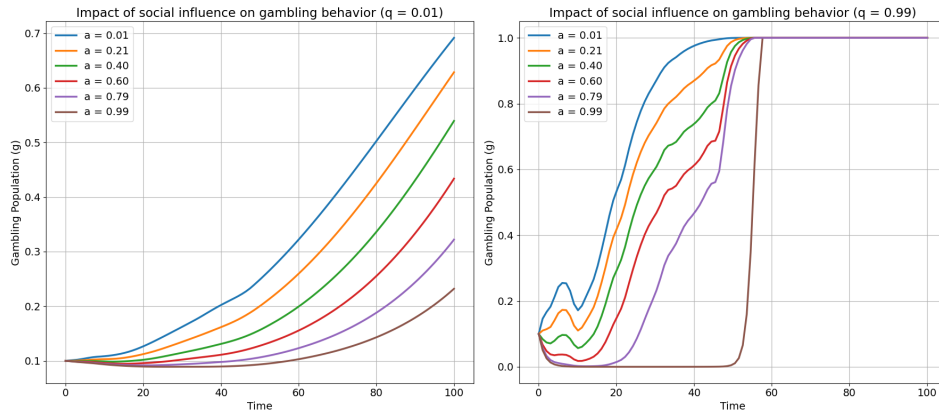


Figure 5: The interplay between q and a for $s = 1.0$ with the initial value $g(0) = 0.1$.

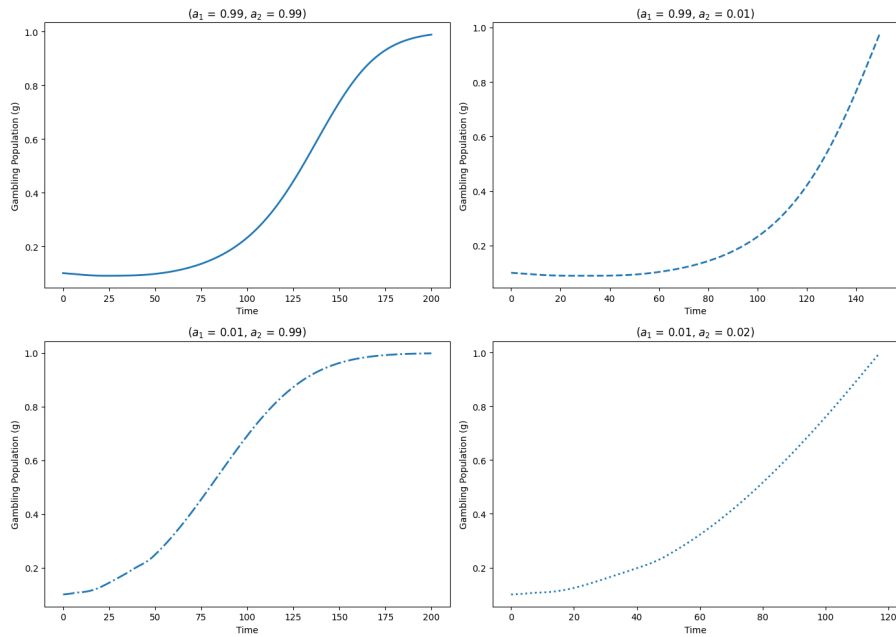


Figure 6: The interplay between a_1 and a_2 for $s = 1.0$ with the initial value $g(0) = 0.1$ when $q = 0.01$.

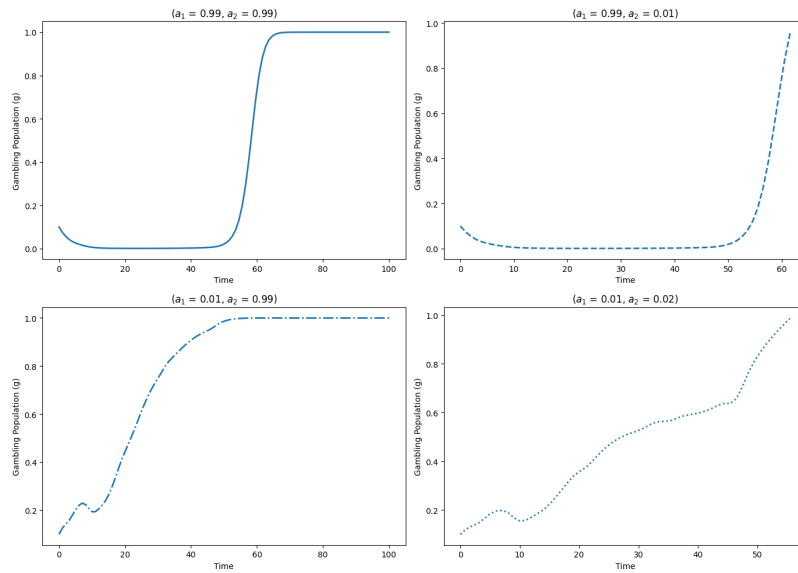


Figure 7: The interplay between a_1 and a_2 for $s = 1.0$ with the initial value $g(0) = 0.1$ when $q = 0.45$.

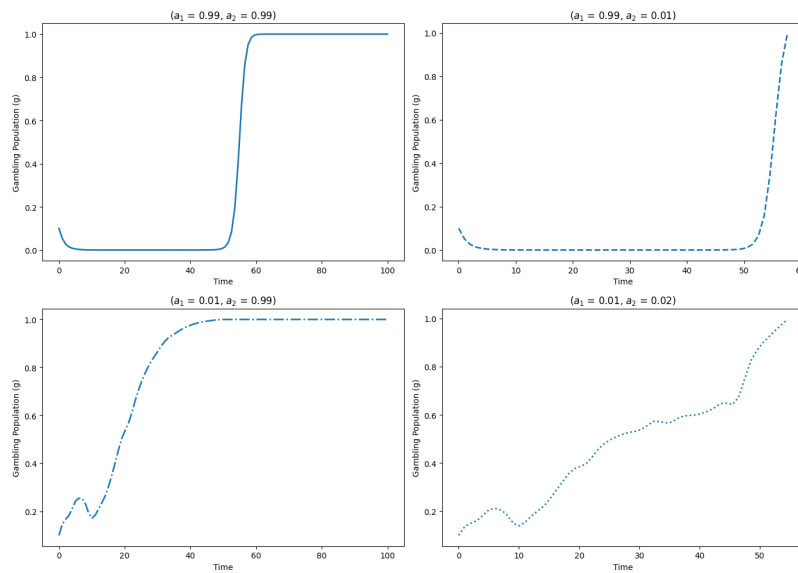


Figure 8: The interplay between a_1 and a_2 for $s = 1.0$ with the initial value $g(0) = 0.1$ when $q = 0.99$.

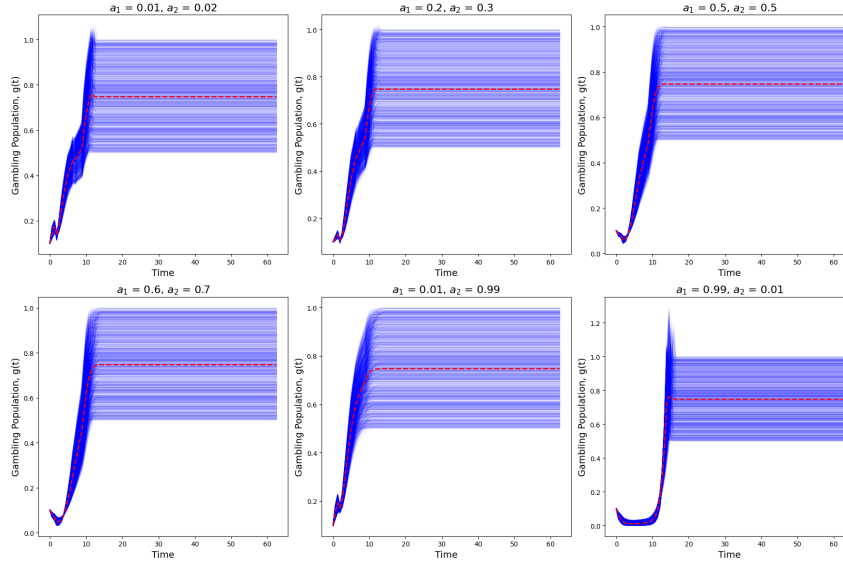


Figure 9: Results of Monte Carlo simulation depicting the model sensitivity to fluctuations in a_1 and a_2 .

The Monte Carlo simulations reveal that, unlike the single-parameter case, the gambling fraction does not collapse to zero. Instead, the system converges to an equilibrium between 0.7 and 0.8, reflecting persistent social reinforcement of gambling participation. This convergence suggests that social influence in South Africa acts as a stabilizing mechanism for high-level participation, even when economic utility fluctuates. The differentiated conformity parameters capture a persistent gambling population, indicating sustained social influence on both gambling initiation and cessation.

3. Results

The study investigates the effects of economic and social factors (specifically unemployment, inflation, GDP, poverty, and gambling revenue) on the dynamics of gambling behavior. The analysis utilizes empirical data derived from South African economic indicators from 2000–2022. These factors are incorporated into a utility function $u_g(t)$, which quantifies the attractiveness of gambling and its fluctuations in response to varying economic conditions. The key results and insights are as follows:

Based on the structure of our utility function, economic factors significantly influence gambling behavior through $u_g(t)$. Based on the definition of r in Equation (3), high unemployment or poverty enhances the appeal of gambling as a

perceived financial remedy, increasing u_g and, consequently, $\frac{dq}{dt}$, which accelerates gambling adoption. Conversely, robust economic conditions (reflected by high GDP and low poverty) lower u_g , reducing the appeal of gambling and slowing the growth in gambling rates. This relationship illustrates how economic distress can drive gambling behaviors, while economic stability generally discourages them. The sensitivity of the adoption rate to the ratio r confirms that economic variables act as a catalyst for participation when baseline survival utility is threatened.

Social conformity, represented by the parameter a_1 in the gambling adoption term g^{a_1} , indicates that a higher a_1 reflects strong social influence in driving gambling adoption, causing gambling rates to rise more quickly in settings where gambling is common among peers when q is small as shown in Figure 6 albeit, at a slower pace compared to other scenarios, followed by rapid increase. This typifies societies with high collectivism, where individuals are inclined to engage in socially accepted behaviors. In contrast, a lower a_1 suggests an individualistic environment where decisions are less influenced by peer behavior, and personal factors, encapsulated in u_g , primarily drive gambling choices. These have rapid increases as the values of q increase as illustrated in Figures 6, 8 and 9. This suggests that people in such an environment are more self-directed in their gambling decisions and normally occurs in tight-knit communities where gambling is visible and socially rewarding.

The rate constant q further influences the sensitivity of gambling rates to changes in u_g , modulating how strongly gambling behavior responds to shifts in economic conditions. A higher q amplifies the effect of u_g on $\frac{dq}{dt}$, meaning that even small economic changes lead to marked shifts in gambling rates, thus highlighting how gambling might become more prevalent when external economic conditions fluctuate. In contrast, a lower q dampens this responsiveness, reflecting environments where gambling behaviors are relatively stable and less reactive to economic factors. Phase-plane analysis reveals that q does not change the position of the equilibria but dictates the speed of convergence to the steady state.

Monte Carlo simulations in Figure 9, conducted with varying values for a_1 and a_2 reveal how gambling rates respond under different conformity conditions. Lower values of a_1 and a_2 suggest strong social influence, making gambling rates more volatile and amplifying both the adoption and cessation processes in response to changes in u_g . Higher values, by contrast, indicate that gambling behaviors are driven more by individual decision-making than social influence, resulting in less dramatic fluctuations in gambling rates. This distinction illustrates the effect of social settings on gambling behaviors, with individualistic environments exhibiting pronounced shifts in gambling participation, while high-conformity settings demonstrate steadier rates.

Monte Carlo simulations in Figure 9 conducted with varying values for a show that eventually the fraction of the gambling population vanishes after hitting the range 0.6 – 0.8. This shows that when a single conformity parameter a is used as opposed to differentiated parameters a_1 and a_2 , the model fails to sustain a per-

sistent gambling population over time. Instead, the fraction of gamblers initially rises but eventually vanishes, highlighting the limitation of assuming symmetric social influence. In contrast, the introduction of differentiated conformity parameters captures more nuanced behavioral dynamics and allows for equilibrium states that reflect persistent social reinforcement in both gambling adoption and cessation. We note that the use of differentiated parameters a_1 and a_2 aligns the model more closely with observed social behaviors, as empirical studies suggest that initiation and cessation of gambling are influenced differently by peer and social pressures [31, 36].

The model highlights the sensitivity of gambling behaviors to economic uncertainty. The utility function u_g incorporates the effects of economic indicators, such that fluctuations in variables like unemployment or GDP impact gambling adoption and cessation. High values of both q and u_g predict rapid increases in gambling rates, as individuals may turn to gambling in response to financial instability or due to accessible online alternatives. Conversely, in stable economic environments with lower q and a steady u_g , gambling rates show reduced sensitivity to economic shifts. Overall, the model captures the interplay of economic and social factors, demonstrating both the rapid rise in gambling during economic hardship or high social conformity and the stability observed in individualistic or economically secure settings.

In addition, these results underscore that policy interventions targeting social influence (for example, public awareness campaigns or community programs) could effectively modulate gambling rates alongside economic measures, particularly in collectivistic settings where social conformity strongly drives behavior. Our analysis suggests that interventions are most effective when q is high, as the population responsiveness allows for a faster decline in participation following policy implementation.

4. Discussion and conclusion

This study highlights the complex interplay between economic conditions, social conformity, and individual decision-making in shaping gambling behaviors. By focusing on these interactions, the model provides insights into gambling participation dynamics and the potential for effective policy interventions. As societal contexts evolve, continued research is crucial for adapting models to accurately represent the changing landscape of gambling and its implications for individuals and communities.

Social interactions significantly shape individual gambling behaviors. In collectivistic societies, strong social cohesion and peer influence make individuals more likely to gamble due to peer pressure. Conversely, in individualistic societies, personal attitudes and decisions are more decisive in gambling behavior. From the simulations in Figure 3, individual decisions largely drive gambling, as the fraction of gamblers increases as $a \rightarrow 0$. Simulations in Figure 5 illustrate that with low

q , if a is closer to 0, gambling behavior remains more stable and responsive to social influence. This stability emerges because a low rate of influence reduces the gambling population's sensitivity to external factors. However, when a approaches 0, social influence shifts to an individualistic focus, where personal decisions drive gambling behavior more strongly [37]. Even slight variations in social influence can thus provoke substantial shifts in the gambling population, underscoring a hidden relationship between parameters that shape gambling dynamics.

Note that in our simulations, the fraction of gamblers represents the active gambling population, which may differ from lifetime or occasional participation. This distinction clarifies the interpretation of equilibrium values such as $g = 1$. If q is small and a_1 is high, yet gambling grows rapidly, this suggests that social conformity is the main driver of adoption. Normally, a low q would slow growth, but the high a_1 amplifies peer influence, making individuals strongly influenced by others' behavior. This means even a modest gambling presence can attract many new gamblers, with social pressure compensating for the lower baseline growth rate. Such rapid adoption despite low q might occur in close communities where gambling is visible and socially rewarding, showing how peer influence can drive gambling trends. Mathematically, this highlights that the social influence term g^{a_1} can overcome low kinetic rates q when the behavior is already established in the community.

Monte Carlo simulations enhance the model's robustness by examining how variability in a influences predicted gambling behavior over time, $g(t)$. By sampling from distributions for parameters such as the rate constant q , market saturation s , or social influence a , these simulations produce a range of possible trajectories. For reproducibility, the specific sampling ranges and distribution parameters were chosen to reflect plausible variations in social and economic factors; future work could include confidence intervals or variance reporting to strengthen interpretability. This approach emphasizes the gambling population's sensitivity to economic and social influences, particularly useful when parameters are uncertain or dynamic. The results indicate that over time, the gambling population fraction in the single-parameter model tends toward zero, suggesting that symmetric dynamics drive a natural decline in participation rates. Factors like diminishing social influence or shifts in external conditions contribute to this trend. Despite short-term fluctuations, simulations point to a long-term stabilization at lower levels, reinforcing the notion that sustainable gambling behavior may not persist indefinitely as societal influences and individual choices evolve [38].

Monte Carlo simulations with varying values of a_1 and a_2 clarify the role of social conformity in influencing gambling rates. Lower values for these parameters suggest strong social influence, making gambling rates highly responsive to changes in gambling utility, u_g , as individuals are more prone to adopt or cease gambling based on observed behaviors. This heightened sensitivity leads to greater volatility in gambling rates, with minor shifts in u_g producing amplified effects. Conversely, higher a_1 and a_2 values indicate that individual decision-making dominates, reducing the impact of social trends and resulting in a steadier gambling

rate that reflects personal rather than social factors.

The Monte Carlo simulations in Figure 9 reveal that with a fixed a , the fraction of the gambling population initially increases, reaching 0.6–0.8, before declining over time. However, across combinations of a_1 and a_2 , the mean fraction of gamblers stabilizes between 0.7 and 0.8, suggesting that these parameters collectively sustain gambling behavior. This demonstrates that using differentiated conformity parameters allows the model to maintain a persistent gambling population, unlike the single-conformity scenario where fractions eventually vanish. The survival of the gambling population in the decoupled model ($a_1 \neq a_2$) suggests that the asymmetry of peer pressure (where the pressure to join may outweigh the pressure to quit) is a critical factor in the "stickiness" of gambling as a social phenomenon. Stability around the mean fraction implies resilience, where societal or intervention efforts may require greater force to alter gambling rates. If the fraction diminishes, it suggests that certain social or individual conditions could effectively reduce gambling behaviors. Thus, adjusting a_1 and a_2 could support interventions either by leveraging social conformity to discourage gambling or by emphasizing individual decision-making to reduce prevalence.

The findings emphasize the necessity of incorporating social and economic factors into gambling behavior models. By elucidating the interactions among social conformity, economic conditions, and individual decision-making, this model offers a robust framework for understanding gambling dynamics. The sensitivity of gambling behavior to social influence variations indicates that targeted interventions can effectively modify gambling rates, particularly in contexts with high peer pressure. It should be noted that while the model incorporates some empirical data, key parameters (for example, a_1 , a_2 , q) are chosen heuristically and are not fully empirically estimated. Thus, the conclusions are partially data-informed. This limitation underscores the qualitative nature of our findings, which serve to identify dynamical regimes rather than provide precise numerical forecasts. Policymakers can utilize these insights to devise strategies that mitigate gambling-related harms, especially in collectivistic societies where peer influence is significant.

To evaluate whether our conclusions genuinely arise from the model structure rather than from narrowly chosen parameter values, we implemented a series of robustness exercises and interpreted the resulting behaviour patterns. In the first step, Monte Carlo simulations were used to repeatedly perturb parameters such as the responsiveness rate q , social conformity a , and the utility u_g , drawing them from predefined probability distributions. Each draw generated a new trajectory of $g(t)$, allowing us to observe the spread of possible outcomes. The fact that these trajectories consistently clustered around stable ranges rather than diverging widely forms the basis for interpreting the model as structurally stable and the same qualitative outcomes reappeared even under stochastic variability, indicating that the decline or persistence of gambling participation is not dependent on a single calibrated parameter set. A complementary robustness exercise compared a model with one conformity parameter a against a model with differentiated parameters a_1 and a_2 . The single-parameter system repeatedly produced eventual

declines toward low gambling prevalence, whereas the differentiated system generated persistent interior equilibria. This contrast provides the foundation for our interpretation that asymmetric social pressures are necessary for sustained gambling participation, an observation emerging directly from replicated simulation patterns rather than assumption alone.

Sensitivity testing of the parameter q , which governs behavioural responsiveness to utility, further clarifies contextual differences since high values of q repeatedly produced amplified swings in gambling participation whenever economic conditions shifted, while low values resulted in smoother trajectories driven primarily by social conformity. This pattern justifies the conclusion that economic environments accelerate volatility while socially anchored environments generate slower, more gradual adjustments. Finally, the economic component of the model was evaluated through goodness-of-fit diagnostics, where the proxy utility achieved an R^2 of 0.9394 and an RMSE of 0.0538. These statistics provide empirical support for linking observed macroeconomic trends to the constructed utility measure, strengthening the interpretation that economic signals meaningfully influence the modelled behavioural responses. Together, these robustness outcomes show that the model's interpretive conclusions (regarding economic pressure, social reinforcement, and persistence versus decline) are supported not only by narrative reasoning but by repeated simulation evidence and statistical consistency.

Future research should include additional variables, such as the effects of online gambling platforms and their distinct social dynamics. The influence of digital interactions and virtual communities on gambling behavior is increasingly pertinent, given the rise of online gambling. Exploring how these factors interplay with existing social and economic influences could clarify the complexities of gambling behavior. Moreover, future work could attempt empirical calibration of social conformity parameters and further quantify the effect of economic conditions on utility $u_g(t)$ to improve model-data alignment. Also, the inclusion of age-structured compartments could reveal how these economic utilities shift across different demographic cohorts.

Conflicts of Interest. The authors declare that they have no conflicts of interest regarding the publication of this article.

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