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An integrated dual process simulation model of alcohol use behaviours in individuals, with application to US population-level consumption, 1984–2012

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ABSTRACT

Introduction: The Theory of Planned Behaviour (TPB) describes how attitudes, norms and perceived behavioural control guide health behaviour, including alcohol consumption. Dual Process Theories (DPT) suggest that alongside these reasoned pathways, behaviour is influenced by automatic processes that are determined by the frequency of engagement in the health behaviour in the past. We present a computational model integrating TPB and DPT to determine drinking decisions for simulated individuals. We explore whether this model can reproduce historical patterns in US population alcohol use and simulate a hypothetical scenario, "Dry January", to demonstrate the utility of the model for appraising the impact of policy interventions on population alcohol use.
Method: Constructs from the TPB pathway were computed using equations from an existing individual-level dynamic simulation model of alcohol use. The DPT pathway was initialised by simulating individuals' past drinking using data from a large US survey. Individuals in the model were from a US population microsimulation that accounts for births, deaths and migration (1984–2015). On each modelled day, for each individual, we calculated standard drinks consumed using the TPB or DPT pathway. In each year we computed total population alcohol use prevalence, frequency and quantity. The model was calibrated to alcohol use data from the Behavioral Risk Factor Surveillance System (1984–2004).
Results: The model was a good fit to prevalence and frequency but a poorer fit to quantity of alcohol consumption, particularly in males. Simulating Dry January in each year led to a small to moderate reduction in annual population drinking.
Conclusion: This study provides further evidence, at the whole population level, that a combination of reasoned and implicit processes are important for alcohol use. Alcohol misuse interventions should target both processes. The integrated TPB-DPT simulation model is a useful tool for estimating changes in alcohol consumption following hypothetical population interventions.

1. Introduction

Alcohol use is a significant concern for population health, and in 2016 contributed to 3 million global deaths (World Health Organization, 2018). It is important to understand alcohol consumption at a population level because many policies designed to alter alcohol use tend to target the population as a whole, for example by changing the price of alcohol (Babor et al., 2010). Theoretical explanations of drinking behaviour are often validated in smaller populations (e.g. heavy drinkers and college students) and explain individual behaviour

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in specific circumstances (e.g. binge drinking). It is unclear whether these theories can extrapolate to explain alcohol use in wider populations or can be used to make predictions about the expected usefulness of interventions to reduce alcohol-related harm. Simulation modelling may be a cost-effective alternative to primary research that can be used to test whether theoretical predictions can generalise to wider populations and can test hypothesised changes in population level behaviour following policy interventions (Guest, 2021). Simulation modelling can also indicate where future primary research should be directed. In this paper we describe a bottom-up simulation approach using influential theories of alcohol use that can be employed to study alcohol consumption at the population level.

The Theory of Planned Behaviour (TPB) (Ajzen, 1991), is a social-cognitive theory that has been used extensively to model health behaviours including alcohol use (Zemore, 2014). According to the model, subjective intention is the proximal determinant of drinking behaviour, and intentions are determined by attitudes, subjective norms and perceived behavioural control. Attitudes refer to overall positive or negative evaluations of the behaviour and subjective norms represent a perception of others' behaviour and implicit behavioural rules in society. Perceived behavioural control describes individuals' perception of their ability to perform the behaviour, for example how much a person believes they can reduce their drinking. Meta-analyses have confirmed that models using constructs from TPB are able to predict intentions and behaviours for health-related behaviours (McEachan et al., 2011) and for alcohol consumption (Cooke et al., 2016). However, perceived behavioural control has a small and non-significant relationship with both alcohol consumption (Cooke et al., 2016) and intentions (Hagger et al., 2016), which has prompted calls for a theoretical overhaul of TPB that reconsiders the role of PBC to improve its predictive validity. Further research has found the inclusion of past behaviour increased the explanatory capabilities of TPB (Hagger, 2016). Although a general theory, support for TPB has tended to originate from experimental studies of specific populations (e.g. college students) (Cooke et al., 2016).

It has been suggested that social-cognitive theories are not comprehensive explanations due to their inability to represent determinants of behaviour that may not be consciously accessible (Hagger, 2016). Dual process theories (DPT) (Strack & Deutsch, 2004) suggest that behaviours are determined by a conscious, reflective system and a non-conscious impulsive system, and alcohol use is thought to be determined jointly by the strength of the impulsive and reflective systems (Stacy & Wiers, 2010). A recent study demonstrated that heavy episodic drinking was predicted by intentional constructs (Hamilton et al., 2020); (i.e. attitudes and subjective norms) and self-reported drinking habits. Here, habits were defined as behaviours that are evoked automatically in specific contexts (stimulus–response associations) in the absence of, or despite alternative intentions (Orbell & Verplanken, 2010). DPT suggests that past behaviour influences future behaviour at least partially independently of intentions (Stacy & Wiers, 2010; Tiffany, 1990). To date, there have been no studies investigating DPT in the general population.

In our simulation approach we express key components from theories as a series of dynamical equations to generate drinking for simulated individuals in a model built according to a rigorous scientific framework (Vu et al., 2020). This enables us to model individual-level factors that lead to drinking and the social context of individuals. We use a generative approach and subject models to a test of generative sufficiency (Epstein, 1999), which examines whether the assumptions of a theory can generate the behaviour the theory is trying to explain. If a theory can generalise to a population, i.e. adequately reproduce the observed behaviour (indicated by targets calculated from representative data sources), our models can help to disentangle how theoretical components may be operating within a population, and advance theory building in psychological science (Guest, 2021). Simulation also allows individual health behaviour decisions to be linked to policies and interventions designed to change behaviours. These approaches can provide information about the potential impact of policies on alcohol use of individuals and populations, to inform strategies to reduce harm.

A recent review identified 22 existing agent-based models (ABMs) of alcohol use focusing on a range of topics including consumption patterns, injuries and violence and the density of alcohol retail outlets (McGill et al., 2020). Although many of these studies are theoretically grounded, none of them model automatic processes or integrate multiple theories. The TPB has previously been used to study alcohol use in a simulation framework (Purshouse et al., 2014), but with a limited focus on the dynamics of drinking frequency in a cohort of young adults in England. In this paper, we aim to both include automatic processes and take a step towards unifying multiple theories of behaviour for modelling alcohol use. We anticipate that more integrated–or systems-based–perspectives on drinking will improve both explanatory and predictive modelling of alcohol use and alcohol-related harms. The transparent nature of the explanations encoded in an ABM can also directly support policy evaluation and appraisal–by indicating the logic by which interventions have their intended, or unintended effects.

We present an individual-level simulation model that uses TPB and DPT to determine decisions to drink in simulated individuals representative of the adult population of the US. First, we present a calibration of our model to US level observed drinking behaviour (1984–2004), and a validation of the best fitting model parameters (2004–2012). Second, we show the calibrated parameters from theory that provide the best fit to empirical data and discuss how these constructs may be operating at a population level. Finally, we demonstrate an application of this model, to test the impact of a hypothetical scenario whereby a percentage of the population undergoes temporary abstinence from alcohol, as happens during "Dry January", which is increasingly popular in the UK and the US (de Visser & Piper, 2020). For this scenario, we present the expected changes in the population when a percentage of individuals abstain from alcohol for a month.

2. Method

We briefly outline each modelled component below. A detailed description and rationale for each model component is available in supplementary material and has been written according to the Overview, Design concepts and Details (ODD) framework for consistent and logical reporting of individual and agent-based models (Grimm et al., 2020).

2.1. Conceptual design

Fig. 1 provides an overview of the process each modelled individual follows on each day to decide whether and how much to drink. We extracted key components from TPB and expressed them as equations to generate drinking intentions (see Table 1). The decision process begins with the individual probabilistically behaving according to the habitual or intentional pathway. A pathway is triggered according to a parameter in the model that describes the tendency for an individual's drinking to be governed by previous drinking, termed "automaticity" (Bargh, 1994). Automaticity is defined over the range 0 (always intentional) to 1 (always habitual). If a sampled random number between 0 and 1 is lower than an individual's automaticity, they will behave according to their previous drinking patterns on that day. Otherwise, the intention pathway is triggered, and intentions will be calculated to determine the probability of different drinking decisions.

2.2. Behavioural schema

Behavioural schema are discrete behavioural categories that represent the options for drinking behaviour available every day of the simulation. In the model, the probabilities of instantiating each schema are represented using a multinomial logit equation. We defined five

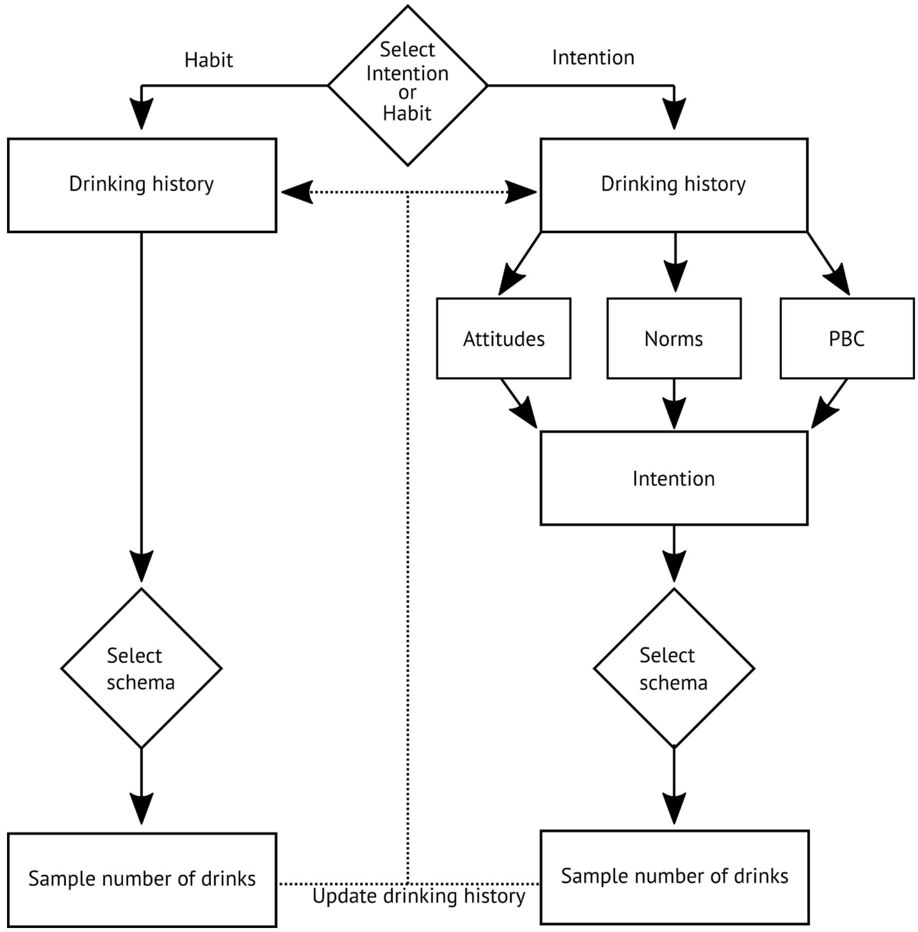

Fig. 1. Overview of the decision framework that each individual in the model follows on each day of the simulation to decide whether to drink and if so, how much to drink.

behavioural schema, derived from World Health Organisation categories of risk based on sex and mean grams of alcohol consumed per day (World Health Organization, 2000). The categories are: (1) abstaining (0 drinks); (2) 1–2 drinks (males) and 1 drink (females); (3) 3–4 drinks (males), 2 drinks (females); (4) 5–7 drinks (males) and 3–4 drinks (females); (5) 8–30 drinks (males) and 5–30 drinks (females). The maximum number of drinks a modelled individual can consume on one day is 30 standard drinks and within each schema, the number of drinks are sampled using distributions informed by US National Alcohol Survey (NAS) data on respondents' number of standard drinks consumed over the previous month (Greenfield et al., 2015) (see Section 5;supplementary material). 1 standard drink is assumed to contain 14 g of ethanol (Substance Abuse and Mental Health Services Administration, 2018).

2.2.1. *The intentional pathway*

When the intentional pathway is triggered, an intention is calculated for each behavioural schema using the equations reported and described in Table 1. We used an existing individual-level simulation model, described in detail in (Probst et al.) to calculate attitudes and norms components of the intentional pathway. In this first implementation we have not specified mechanisms to include perceived behavioural control, as the existing model we used to inform this model only contains constructs for social norms and attitudes (Probst et al.). Additionally, *meta*-analyses have indicated a small and non-significant relationship between perceived behavioral control and intentions to consume alcohol (Cooke et al., 2016; Hagger et al., 2016). Following (Probst et al.) "autonomy" (the weight given to the desire to ignore the norms) is assumed to have different values for non-drinkers, medium, and heavy drinkers. Past behaviour influences the intentional pathway and changes the descriptive norms through a perception bias (Equation 3 in Table 1) whereby individuals perceive the norms to be closer to their own drinking behaviour.

2.2.2. *The habit pathway*

At baseline (simulated year 1984) each individual is allocated a drinking history (section 2.4.2) that describes the percentage of days during each year that their behaviour was classified in each schema category and represents their probability of drinking in that schema on any given day. Each time an individual follows the habitual pathway, a schema is sampled without replacement. Drinking history is updated every n^{th} day, where n represents the number of days taken for a behaviour to become habitual. The value of n can vary between individuals and is allocated a value following the calibration process, with ranges informed by research on habit formation (Lally et al., 2010). Drinking history is updated by calculating the percentage of days that the individual drinks in each of the schema categories over the previous n days in the model.

2.3. *Model parameters*

2.3.1. *Individual properties*

A microsimulation model was used to populate individuals in the model (Brennan et al., 2020). This comprises a population representative of the US between 1984 and 2015 (see supplementary material section 7.1), accounting for births, deaths and migration and changes in

Table 1
A description of concepts and equations used to operationalise the intentional pathway.

No.	Concept	Model equation	Description
1	Descriptive norms	DescriptiveNormRaw[j,g] = MeanPrevalence[j,g]	The raw descriptive norm is the mean prevalence (percentage of days) individuals *i* in each age-sex subgroup *g* behave in each schema category *j*.
2	Descriptive norms	WeightedDescriptiveNorm[j,g] = Σ_h(Shared[j-,g,h] × DescriptiveNormRaw[j,g]) / Σ_hShared[j,g,h]	The weighted descriptive norm is the weighted sum of the raw descriptive norms for all reference groups, *h*, the individual belongs to (calculated using the operator Σ Shared), i.e. if they are an 18–24-year-old man, the norms of 18–24-year-old men are weighted as 2, all other age categories for men are weighted as 1, the 18-24 year-old women category is weighted as 1, and all other age categories for women are weighted as 0.
3	Descriptive norms	DescriptiveNorm$_i$[j] = **Perception_bias** × WeightedDescriptiveNorm[j,g$_i$] + (1-**Perception_bias**) × PrevalenceSchema-$_i$[j]	The weighted descriptive norm is adjusted for perception bias. This adjusts the descriptive norms to be biased towards the current drinking level of the individual. PrevalenceSchema$_i$[j] refers to the percentage of the time individual *i* drinks in schema *j*.
4	Injunctive norms punishment	If HED_proportion[g] > **injunctive_proportion**, InjunctiveNorm[g] = **punish_adjustment** × InjunctiveNorm[g]	If the prevalence of heavy episodic drinking (defined by **injunctive_threshold**) in a particular subgroup *g* rises above a level **injunctive_proportion**, the injunctive norm is tightened by a factor **punish_adjustment** to make it less acceptable to drink.
5	Injunctive norms relaxation	If MeanPrevalence[j,g] > InjunctiveNorm[j,g], InjunctiveNorm[j,g] = (1-**relax_adjustment**) × MeanPrevalence[j,g] + **relax_adjustment** × InjunctiveNorm[j,g]	Mean prevalence refers to the average percentage of the time individuals in reference group *g* spend drinking in schema group *j*. If the average prevalence of individuals having at least one drink is larger than the injunctive norm over **days_relax** days, then the injunctive norm is relaxed by a factor **relax_adjustment**.
6	Autonomy	Autonomy$_i$ = exp(**Autonomy_shift$_i$** × **Autonomy_baseline$_i$** - **Autonomy_shift$_i$**)	Autonomy reflects the proportion of time individuals follow the norms. This is shifted for individuals according to their baseline drinking to reflect that heavier drinkers have different levels of autonomy over their drinking compared to non-drinkers and infrequent drinkers.
7	Norms	Norms$_i$[k,j] = (1-Autonomy$_i$) × (log(DescriptiveNorm$_i$[j] / DescriptiveNorm$_i$[j=0]) + log(InjunctiveNorm[j,g$_i$] / InjunctiveNorm[j=0,g$_i$])) / 2	The norms have two components (1) descriptive norms - describe the prevalence of drinking in each schema, for each population age/sex sub-group and (2) injunctive norms - describe the perceived acceptability of drinking in each schema category *j* for each reference sub-group *g*. These are weighted by individual's **autonomy** which is how much they want to comply with the norms.
8	Attitudes	Attitudes$_i$[k,j]= Autonomy$_i$ × log(desire$_i$[j] / desire$_i$[j=0])	Attitudes refer to the overall positive or negative appraisal of drinking in each schema category. Here this is calculated as the individual's desire to drink (when not following the norms) weighted by their autonomy.
9	Log odds intention	LogOddsIntention$_i$[k,j] = **β_Attitude** × Attitudes$_i$[k,j] + **β_Norms** × Norms$_i$[k,j] + **β_PBC** × PerceivedBehaviouralControl$_i$[k,j]	The log odds of intention for each schema is the weighted sum of attitudes, norms and perceived behavioural control. PerceivedBehaviouralControl$_i$[k,j]=0 in this initial model.
10	Intention	Intention$_i$[k,j] = exp(LogOddsIntention$_i$[k,j] / Σ_jLogOddsIntention$_i$[k,j])	The intention for each schema is converted into a probability of performing the behaviour in each schema category.

Note: These equations contain unobserved parameters (highlighted in bold) which modify the effects of the mechanisms. These are given values following the model calibration process (section 2.5) which searches for the parameters that best fit historical alcohol consumption trends over time. The simulated individuals in the model are indexed by *i* and represent individual inhabitants of the US. Drinking is simulated on each day and is indexed by *k*. There are 5 behavioural schemas that individuals can select, and these are indexed by *j*. Reference groups for social norms are indexed by *g* and indicate the individual's age and sex sub-group

socio-demographic properties (marriage, employment and parenthood status) over time. The microsimulation uses data from the US Census (Manson et al., 2019) and the American Community Survey (Ruggles et al., 2019) and comprises a population of the US aged 18 to 80 for all years of the simulation. Data from the Behavioural Risk Factor Surveillance System (BRFSS) (Centers for Disease Control and Prevention (CDC), 2015) was used to assign individuals with socio-demographic characteristics (age, sex, race/ethnicity, marital employment and parental status, highest educational attainment and household income) and baseline alcohol consumption (12-month drinking status, usual quantity and frequency of drinking).

2.3.2. Drinking history

Each individual is allocated a drinking history at baseline, which is simulated using data from the US National Alcohol Survey. The NAS contains information on how many days per year individuals usually consume 1,2,3–4,5–7, 8–11 and 12 + drinks, alongside mean quantity and frequency of consumption and socio-demographic properties. This information was used to simulate a number of drinks per day in the year prior to the simulation starting for each individual using information about their usual alcohol consumption and age and sex.

2.4. Implementation

The simulation was written in C++ using the Repast HPC toolkit (North et al., 2013) and was run using a 36-core i9 processor. The model is run forward in time for 20 years for calibration (1984-2004) and 8 years for validation (2004–2012). Each model tick represents one simulated day. On each day, a number of drinks for each individual is calculated using the process described in Fig. 1. Daily drinking of each individual was calculated for each year, and annual sex-disaggregated summary statistics were collected for alcohol consumption prevalence (overall percentage of current drinkers), quantity of alcohol consumption (mean grams of alcohol per day) and frequency of alcohol consumption (mean drinking days per month). Due to model run time (up to 2 min per run), models were calibrated using 1,000 individuals sampled from a representative whole population of the US. All model results and experiments reported use the best calibrated settings with a random sample of 10,000 US representative individuals. The source code for the simulation with the best calibrated parameters is available at bitbucket.org/r01cascade/integrated_dual_process_addictive_behaviors and is licensed under the GNU General Public License version 3.

2.5. Model calibration

The model was calibrated by adjusting the values of the unobserved parameters in the model (listed in Table 2) to match the outputs of the model with observed alcohol use data (targets).

Table 2
A description of unobserved parameters in the model and their allocated values following the calibration process.

	Model Parameter	Subgroup	Calibrated value	Description
Individual level				
1	Autonomy_baseline$_i$	Female	Beta($\alpha = 1.37, \beta = 4.94$)	The weighting an individual assigns to what they want to do (compared to the norms). A beta distribution separately calibrated for males and females
		Male	Beta($\alpha = 3.03, \beta = 0.67$)	
2	**Automaticity$_i$**	Low drinkers	Beta($\alpha = 0.91, \beta = 2.08$)	The tendency for individuals to follow their habits over their intentions. A beta distribution separately calibrated for low (<20 g), medium-heavy (20 g-99 g) and very heavy (100 g +) drinkers.
		Medium drinkers	Beta($\alpha = 2.57, \beta = 2.53$)	
		Heavy drinkers	Beta($\alpha = 2.79, \beta = 2.23$)	
3	**Habit_interval$_i$**		N(m = 99.5, s^2 = 44.2)	The length of time habits take to update in the simulation over time. This is different for each individual but fixed over time. Assumed to be normally distributed in the population. Note standard deviation is not calibrated in this version of the model but informed from prior research about individual differences in habit formation (Lally et al., 2010)
Population level				
4	Autonomy_shift	Abstainers	0.40	Autonomy is shifted to account for differences in drinking patterns. Abstainers are individuals that have not consumed any alcohol in the previous 30 days. Infrequent drinkers are defined as drinkers that have consumed alcohol on up to 4 days in the previous month. Heavy drinkers are defined as individuals that have consumed alcohol on 28 or more days, or have consumed over 100 drinks in the previous month. Medium drinkers are defined as drinkers that consume alcohol on more than 4, but less than 28 days and are assumed to represent an "average drinker" and do not have their autonomy shifted.
		Medium drinkers	0.36	
		Heavy drinkers	0.12	
5	Injunctive_proportion		0.49	The proportion of individuals that need to be considered as heavy episodic drinkers to trigger punishment of the injunctive norms
6	Injunctive_threshold		14.2	The number of drinks in one occasion considered as heavy episodic drinking in this model
7	Punish_adjustment		0.81	The percentage the injunctive norms are tightened by, when they are punished
8	Relax_adjustment		1.00	The percentage the injunctive norms are relaxed by when they are relaxed
9	Days_punish		30	The number of days behaviour is considered over when calculating whether norms should be punished
10	Days_relax		365	The number of days behaviour is considered over when calculating whether the norms should be relaxed
11	Interval_punish		30	How often equation 5 is triggered to calculate whether the norms are punished
12	Interval_relax		90	How often equation 4 is triggered to calculate whether the norms are relaxed
13	Perception_bias		0.54	How much the descriptive norm is adjusted by to make it more similar to the individuals own drinking
14	**β_Attitude**		0.89	The weighting given to attitudes when calculating intentions
15	**β_Norms**		0.98	The weighting given to norms when calculating intentions
16	**β_PBC**		0	The weighting given to perceived behavioural control when calculating intentions (switched off in this model)

Note: Parameters of theoretical importance are highlighted in bold.

2.5.1. Targets

Targets were derived from alcohol use data from the BRFSS for the years 1984–2012, adjusted to per-capita US alcohol sales data for each year using a triangulation method described in (Rehm et al., 2010). In each year, there were three alcohol use targets: (1) prevalence – the overall proportion of individuals reporting consuming an alcoholic beverage at least once during the previous year, (2) quantity – among drinkers the average grams of alcohol consumed per day, (3) frequency – among drinkers the average number of drinking days per month. All targets were split by sex, resulting in 6 calibration targets per year.

2.5.2. Procedure

Equations to calculate the intentional and habitual pathway contain a total of 30 parameters with unobserved values (see Table 1). A Latin-hypercube space-filling design was used to sample 10,000 parameter settings from the joint prior distribution using the lhs R package (Carnell, 2019). For each parameter setting, the model was run once and an error metric was calculated using equation (1), which describes the overall difference between simulated outputs and calibration target data (Vu et al., 2020). N is the number of observations and M is the number of outputs (McEachan et al., 2011). $y^*_m[n]$ is the simulated data for output m at time n; $y_m[n]$is the mean of empirical target data for output m at time n; $(s_m[n])^2$ is the standard error of the empirical target data for output m at time n and $(d_m)^2$ is the variance of the model discrepancy for output m, which is fixed at 10% of the range of each output and captures the fact that the model is not a perfect representation of reality. The parameter settings that produce the minimum value of model error represent the best model settings and were used for all results presented.

$$error = \frac{1}{NM}\sum_{n=1}^{N}\sum_{m=1}^{M}\frac{|y^*_m[n] - y_m[n]|}{\sqrt{(s_m[n])^2 + (d_m)^2}} \tag{1}$$

2.6. Scenario experiment

To demonstrate how the simulation model can be used for policy analysis, we performed an experiment to investigate the hypothetical impact of a percentage of the population undertaking a temporary period of abstinence, "Dry January". We constrained a percentage (20% or 100%) of the eligible population to abstain for the first 30 days of each year from 2010 to 2015. Individuals were eligible if they currently consumed more than 3 drinks per day, as research suggests those that take part in Dry January in the UK tend to have higher AUDIT scores than the general population (de Visser & Piper, 2020). In the remaining months of the year, we calculated drinking prevalence, quantity, and frequency of the whole population.

3. Results

3.1. Model calibration results

Fig. 2 shows the results of running the simulation model and comparing against observed drinking patterns in the US for 1984 – 2012. Observed prevalence of current drinkers has remained stable over the period and the best calibrated model follows these trends well for both males and females. In the observed data, quantity of drinking (grams per day) in males declines between 1984 and 1998 before levelling off and the model is not able to reproduce this trend. In females the decline in drinking quantity is less marked, and the model is closer to the observed data. The model is able to reproduce the changing trend in male frequency of drinking with a steady downward decrease. Female frequency also decreases and then increases over this period and the model is able to fit this trend well with a small steady decrease in frequency over time.

Note: the data between 1984 and 2004 was used to calibrate and 2004 to 2012 was used for validation (separated by dashed vertical line). Results shown for annual drinking *prevalence* (percentage of current drinkers), *frequency* (mean days per month) and *quantity* (mean grams of alcohol per day), separately for males and females.

3.2. Calibrated parameters

Table 2 outlines unobserved parameters in the model alongside a

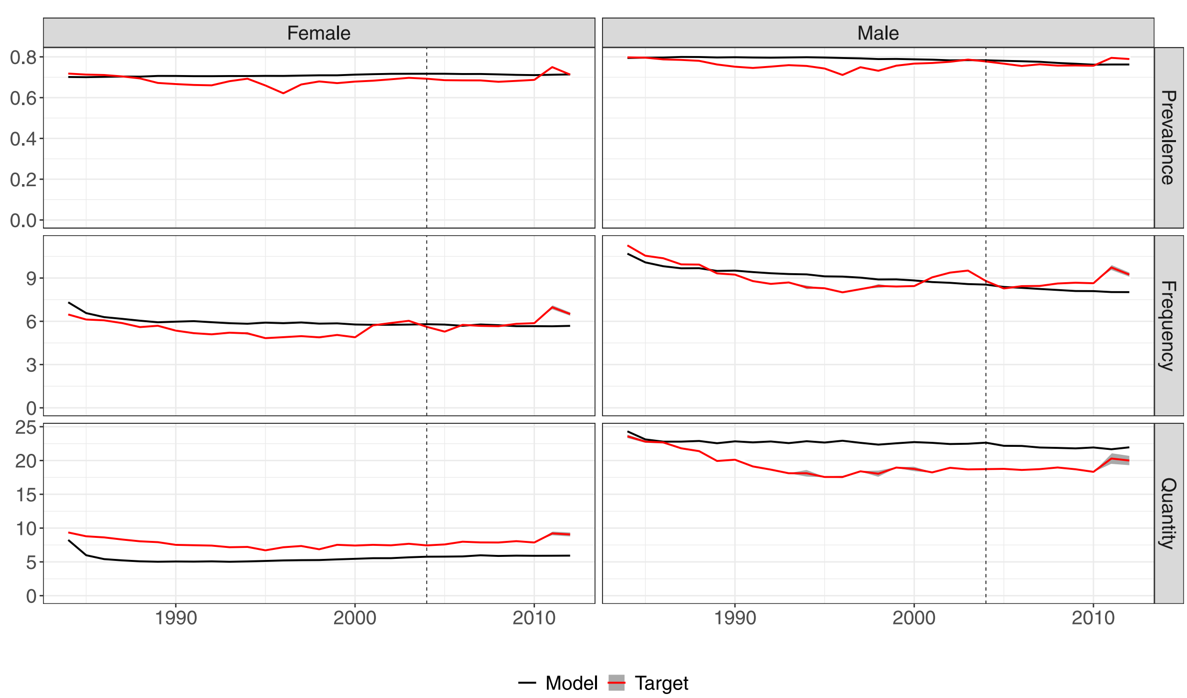

Fig. 2. The best calibrated model compared to alcohol empirical alcohol use data (mean target data ± 95% confidence interval) from the BRFSS. Note: the data between 1984 and 2004 was used to calibrate and 2004 to 2012 was used for validation (separated by dashed vertical line). Results shown for annual drinking *prevalence* (percentage of current drinkers), *frequency* (mean days per month) and *quantity* (mean grams of alcohol per day), separately for males and females.

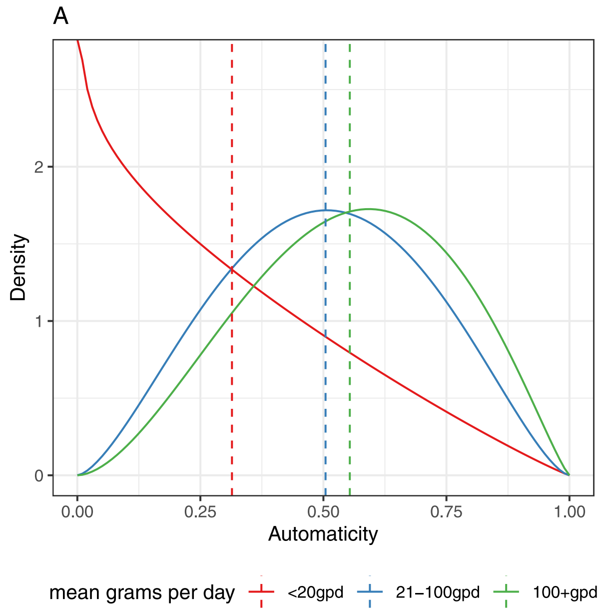

Fig. 3. A. Distribution of automaticity in the model split by mean quantity of alcohol consumption per day. Each dashed line shows the mean automaticity value for each group – i.e. the percentage of the time they follow their habitual behaviour. B. Distribution of time taken to update habits in the population, the dashed line shows the mean habit update time interval and the solid line is the distribution in the population.

description and their value assigned in the best fitting calibrated model. We will focus on parameters of theoretical importance, highlighted in bold in Table 2: automaticity, habit interval, βAttitude, and βNorms. Automaticity describes the percentage of the time an individual behaves according to habit (as opposed to intentions) in the model. Following our calibration, we find the distribution of automaticity shown in Fig. 3A. The lightest drinkers (below 20 g of alcohol per day) have the lowest automaticity and behave according to habits 30% of the time. The medium-heavy drinkers (21–100 g per day) have an increasing level of automaticity and behave according to habits 51% of the time. Automaticity increases to 55% in the heaviest drinkers (over 100 g of alcohol per day). The calibrated results for the habit update interval are shown

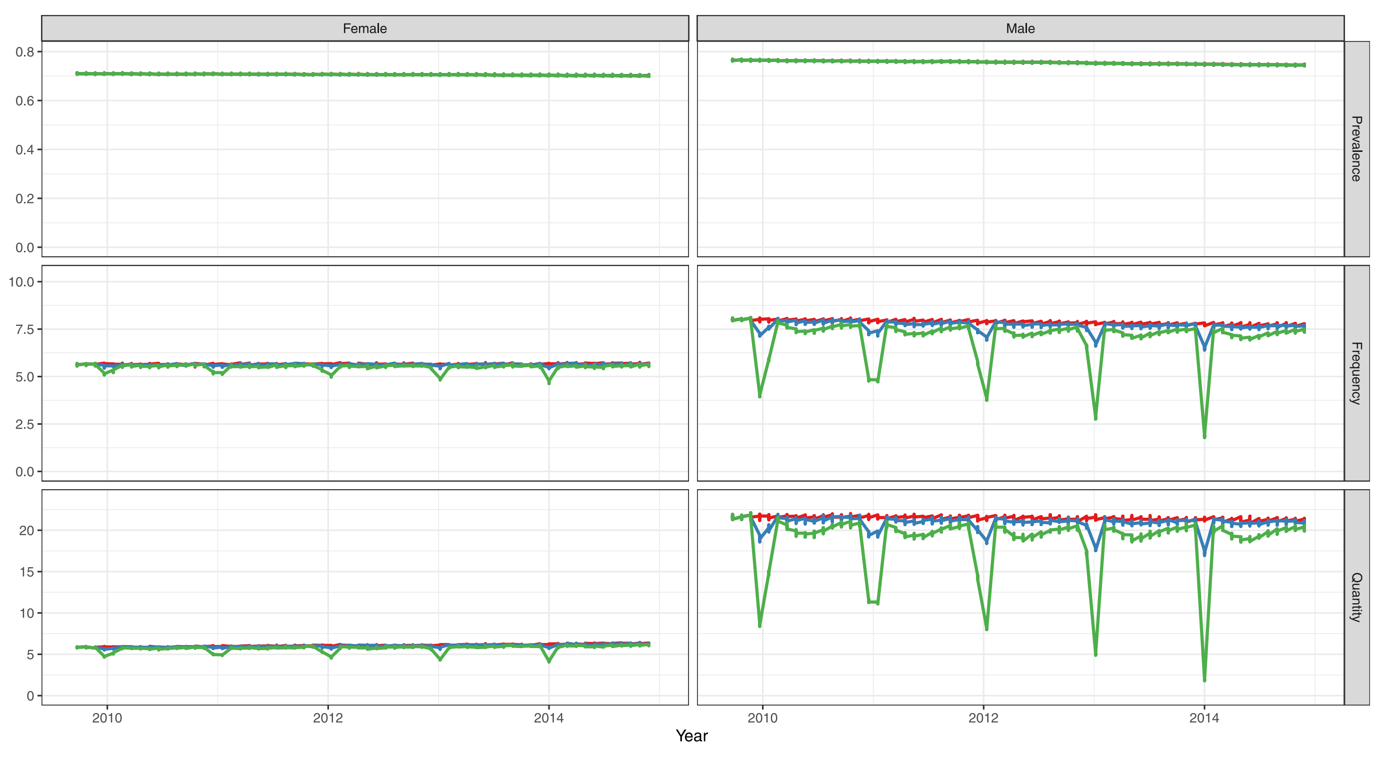

Fig. 4. Mean monthly prevalence, frequency, and quantity of alcohol use following a simulation of Dry January starting in January 2010 and simulated every January up to 2015.

in Fig. 3B. Habit update interval refers to the number of days considered when updating each individual's habit. The model that best fits historical data has a mean habit update interval of 99.5, meaning that on average, it takes individuals in the model 3 months to form new habits. βAttitude and βNorms describe the relative strength of attitudes and norms when calculating intentions. Attitudes (βAttitude = 0.89) are given a lower weighting compared to norms (βNorms = 0.98).

3.3. Simulating Dry January

Fig. 4 shows mean monthly prevalence, quantity, and frequency of alcohol use following a simulation of Dry January. We tested two scenarios: (1) 20% of eligible individuals take part in temporary abstinence; and (2) 100% of eligible individuals take part. 20% of individuals taking part induces a moderate annual change in monthly quantity and frequency for males with a smaller change seen for females. In both cases, we see a large difference in drinking initially caused by a percentage of individuals in the model stopping drinking for the entire month of January. This recovers throughout the remainder of the year but still remains below the baseline model (in which no eligible individuals took part in "Dry January") This effect is more marked in males, with a smaller difference observed among females following the intervention. The effect on annual population level drinking in males is much larger when 100% of the eligible population take part, compared to 20%.

4. Discussion

Previous work examining the TPB and DPT in relation to alcohol use has tended to focus on studying the theoretical constructs in specific subgroups of the population. Here we have presented a conceptual model for decision making about drinking based on TPB and DPT and implemented this in an individual-level simulation model of a whole population. The model provides evidence that suggests these theories may be generalisable to broader alcohol use behaviours in the general population of the US. We demonstrated that, using equations derived from these theories, we can represent historical trends in the prevalence and frequency of alcohol consumption in the US between 1984 and 2012, but the model is not simultaneously able to represent drinking quantity. The parameters from the best calibrated model can elucidate how these constructs may be operational for determining alcohol use in the population. Our model suggests that the percentage of drinking driven by past behaviour is likely to be higher in very heavy drinkers compared to medium to heavy and lighter drinkers and abstainers. The length of time taken to form and change habits in our model is approximately 99.5 days. This model is useful for appraising the impact of hypothetical scenarios on population level drinking. A temporary abstinence intervention "Dry January" in a proportion of the population affects the whole population's drinking in the short-term. This has a small effect if 20% and a moderate effect when 100% of the eligible population take part. The effect of Dry January is more pronounced in males, which may be due to the higher number of eligible individuals (currently consuming 3+ drinks per day) in the male population.

The relationship between increased automatic behaviour and heavy drinking is supported by previous research that suggests that the more frequently a behaviour is performed the more decoupled it becomes from intentional control (Hamilton et al., 2020). In our model, the heaviest drinkers exhibit the highest proportion of non-intentional behaviour suggesting that this particularly affects habitual heavy drinking. The length of time taken to update habits in the model was approximately 100 days. This is longer than suggested by previous research that finds a median of 66 days for a behaviour to become habitual (Lally et al., 2010), but does fall within the interquartile range (39–102) reported. Our modelling suggests that norms have a larger influence on intentions than attitudes, whereas *meta*-analyses of primary research have suggested that the converse is true (Cooke et al., 2016; Hagger et al., 2016). It is important to note that of the studies included in these *meta*-analyses, only two collected data in populations other than university students. One study estimated that subjective norms make a larger contribution than attitudes to intentions to consume alcohol (Kim & Hong, 2013), whereas the other estimates the opposite relationship (Hagger et al., 2012). These studies were conducted in Korean and European populations and no studies to date have been conducted to explore the TPB constructs for alcohol consumption in the general US population. These studies highlight that the weighting of TPB variables can vary depending on the population studied and suggests that further US general population studies are required to inform models and intervention design.

This model is a first iteration of the combined TPB and DPT model that can be built upon using our software architecture (Vu et al., 2020) that is robust and adaptable, allowing for the addition of new mechanisms. We are able to explicitly model two fundamental components of alcohol use, individual-level determinants (e.g. personal attitudes) and social-level influences (changing societal norms). Additionally, we can account for an individual's day-to-day variability in alcohol consumption in a data-driven way. This provides a more nuanced understanding of population alcohol use and can permit the investigation of how interventions might affect specific types of drinking. Further, our simulated population contains detailed sociodemographic properties including age, race/ethnicity and educational attainment. Therefore, our model can be extended in future investigations to examine the impact of targeted interventions on the alcohol use of specific population subgroups.

Our model is a good, but not perfect fit to historical data and struggles to adequately model changes in male quantity of consumption over time. Currently, we only have mechanisms that represent some of the attitudes and norms about drinking, as well as the habitual pathway. These do not fully explain all aspects of alcohol use and we would expect models containing a richer set of mechanisms to be a better fit to the target data. In particular, the model does not appear to have passed the test of generative sufficiency for trends in male drinking quantity. In order to better explain these trends, we would need to integrate further explanatory mechanisms into the dynamical model. One candidate for inclusion is PBC, and future agent-based modelling work should attempt to include this.

Having a limited number of mechanisms constrains the type of analysis and experiments we can do; however, it does demonstrate the types of behaviour changes we can model using this approach. When expressing components of a theory as an equation in a simulation model, it is not possible or desirable to model every nuance of the theories; it is necessary to reduce complexity. Therefore, some aspects of theory were omitted from this first model (e.g. the context-dependent nature of automatic behavioural responses). Additionally, the TPB is thought to be most predictively useful when behaviours are most proximal to the intentions. To be able to predict individual drinking episodes we would need individuals to have a more detailed physical context (Kairouz & Greenfield, 2007). We plan to develop a social network model to enable interactions between individuals and their environments. This will aid the modelling of cue- and context-dependent alcohol consumption and the modelling of choice-architecture environmental interventions.

These findings from the modelling can be useful for population health policy design because they enable theories largely developed and tested in limited demographics to be scaled and scrutinised at the whole population level. By incorporating policy logic models (formal descriptions of the anticipated pathways to the effect of an intervention) into calibrated, theory-led models, whole population outcomes can be estimated. For example, a prospective programme of screening and brief intervention could be appraised by incorporating the mechanisms expected to alter alcohol use following a brief intervention (e.g. changes of perceptions of norms, changes in attitudes and habits) into the simulation model (Purshouse et al., 2013). The transparent nature of ABMs can also help guide intervention design, e.g. if the calibrated model suggests habits are more important than intentions in certain groups then the intervention design would want to focus on changing habits more than intentions. Theory-led simulation models can also be used for evaluation, post implementation, by calibrating the theory parameters to subsequent trends in population alcohol use.

Our simulation model is a fundamental enabling component for future alcohol policy modelling: it can be easily adapted, is built according to a standard architecture that allows for the integration of other theories, and permits the representation of a wide variety of alcohol use determinants. Empirically, the model is a good fit to data (especially for frequency, and quantity for females), suggesting that these theoretical models are relevant at a population level. Our model suggests that a combination of habits and intentions are important determinants of alcohol use behaviours, and that alcohol reduction interventions should aim to target both types of behaviour. We anticipate that the model will be particularly useful as a core component in future policy simulations for assessing the potential impact of public health interventions designed to reduce population-level alcohol use.

5. Author statement

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CRediT authorship contribution statement

Charlotte Buckley: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Matt Field:** Conceptualization, Writing - review & editing. **Tuong M. Vu:** Methodology, Software, Formal analysis, Writing - review & editing. **Alan Brennan:** Conceptualization, Methodology, Project administration, Funding acquisition. **Thomas K. Greenfield:** Conceptualization, Writing - review & editing. **Petra S. Meier:** Conceptualization, Writing - review & editing. **Alexandra Nielsen:** Conceptualization, Methodology, Formal analysis, Writing - review & editing. **Charlotte Probst:** Conceptualization, Methodology, Formal analysis, Writing - review & editing. **Paul A. Shuper:** Conceptualization, Writing - review & editing. **Robin C. Purshouse:** Conceptualization, Methodology, Project administration, Funding acquisition, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.addbeh.2021.107094.

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