# ManDown - A Social Drinking Management App

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***Abstract*— Social drinking has become an accepted part of modern culture, and with that comes the possibility of intoxication due to overdrinking. In the US, alcohol consumption levels have increased across all age groups from 2001/02 to 2012/13 [1]. This project aims to develop an application to effectively manage social drinking by reducing the incidence of intoxication for a user. A look into existing mobile apps and an insight into the medical background behind intoxication is done. The overall system design, incorporating the data capture, management, machine learning and application design is proposed. Lastly, an experimental method for evaluating this app's success will be explained in this report.**

## I. Introduction

A report published by the UK Health and Social Care Information Centre estimates that in 2013/14, over a million people in the UK were admitted to hospital as a result of alcohol-related disease, injury or condition, which is 5% more than 2012/13 and 115% more than in 2003/04 [2]. The same report states that only 13% of respondents kept track of the units of alcohol they were consuming and that not everyone knew the amount of units in their drinks, which made the likelihood of accurate self-tracking low. The dangers of alcohol cannot be overstated, as a study shows that excessive consumption of alcohol accounts for 10% of deaths and 1 in 10 years of potential life lost in working-age adults in the US [3].

This makes it all the more critical that an effective method of promoting safe, responsible drinking is devised. ManDown aims to do that by targeting the average social drinker. It is designed to be a social and fun app with an emphasis on managing the alcohol intake of the user through active user input and passive data collection via sensors. The app will allow the users to have tipsy fun with games on the app but also use these games along with passive tracking from sensors to diagnose if the user is approaching the point of inebriation. The app will then advise the user to cut back on the alcohol intake. On the other hand, if the user is inebriated and in need of assistance, the app can help the user by notifying their friends or nearby app users that the user requires assistance.

## II. Related Mobile Apps

The idea of using everyday devices like a smartphone and a smartwatch to diagnose intoxication symptoms is a relatively novel idea. Most phone apps for alcohol management involve active inputs; the user constantly updates the app with information (units of alcohol drunk, time of consumption). *DrinkFree - Sobriety Counter*[4] is one such app that is marketed at drinkers, but has a limitation on the possible information that can be gathered from an inebriated user. By adding on diagnostics to our app, we hope to bypass this limitation to provide a greater level of convenience to the user.

A social app that is useful in providing a guide to our project is *GoodSam*[5]. The aim of this app is to provide first aid as quickly as possible to someone in danger. During an emergency, any app user in the vicinity of an affected person can react quickly through a notification from the app. This idea is something that we intend to implement through the social aspect of our app, to provide a level of safety to incapacitated users.

## III. Medical Background

Alcohol intoxication occurs when alcohol is consumed faster than the body is able to metabolise it. This causes effects throughout the body, the most noticeable of which are behaviour changes in the brain. Long term alcohol abuse is a widely researched field and shows that permanent damage can be caused; however, the consumption of alcohol is culturally acceptable in the UK, even encouraged. Therefore, the app will try to prevent the overconsumption of alcohol which may lead to long term damage, by diagnosing the short term effects discussed in this section.

### A. Effects on the Brain

The effects of alcohol on the brain are not well understood; there are various suggestions for how ethanol might depress brain function due to its ability to modulate ion channels, neurotransmitter receptors and transporters [6]. Ethanol is believed to affect blood vessels, the frontal lobe (affecting emotional response), the hippocampus (affecting memory), and the cerebellum (affecting motor control), among other locations.

A proposed mechanism by which alcohol affects the cerebellum is through an increase in the GABAergic inhibition of cerebellar granule cells resulting from increased output of the neurotransmitter GABA from the Golgi cells [7][8]. As the cerebellum controls movement, balance, and other complex motor functions, it provides an opportunity to diagnose intoxication levels. Alcohol depresses the cerebellum to cause a variety of effects [6], some of which are listed here:

1) Ataxia: Loss of coordination. This can involve an ataxic gait, which is a wide gait while walking
2) Nystagmus: Rapid involuntary movement of the eyes
3) Scanning Dysarthria: Slurred Speech

4) Slowed reaction time: Time to react to a stimulus is increased
5) Loss of motor control: Inability to properly control the body, causing crashes into walls or falling over

### B. Diagnosis of Symptoms

Standardized Field Sobriety Tests (SFST) [9] designed by the US police to detect intoxicated drivers provide an initial guideline into detecting the symptoms above. The three tests are:

1) Horizontal Gaze Nystagmus Test (HGN): The officer monitors whether the participant is able to follow a moving object with their eye gaze.
2) Walk and Turn Test (WAT) : Determines whether Ataxia and loss of motor control is observed in the participant. The participant is required to walk heel-to-toe along a line.
3) One Leg Stand Test (OLS): Also detects Ataxia and loss of motor control. The participant stands on one leg for 30 seconds, and the officer monitors their balance.

Several studies investigating the validity of the tests above have concluded that SFSTs are capable of 94% accuracy in correctly identifying a driver whose blood alcohol content is >0.08[10]. Hence, these tests are useful for providing an initial idea into previous methods for detecting intoxication symptoms. Our system design will attempt to incorporate the above tests into a smartphone application.

## IV. Research Hypothesis

The following hypotheses will be tested:

1) Data collected through a standard smartphone and wearables will provide good indicators for the level of intoxication of the user.
2) Users are more likely to regulate and reduce the amount drunk when using the app than without.
3) Gamification improves the accuracy of diagnostics compared to passive sensing alone.
4) Gamification improves user enjoyment and engagement compared to simple user inputs.

To further elaborate on the last hypothesis, games have been included in our app to enhance its appeal to the user and entice them into providing data. This is as opposed to non-game based user input, for example a drop-down menu to input what type of drinks user drank and how many.

## V. System Design

The proposed system consists of a smartphone, a wearable (e.g. smartwatch), and a mobile application to run on both. Additional sensors could be used to collect extra data, but this requires more effort on the part of the user to set up the system properly and is cumbersome. Therefore, the proposed system will use no extra sensors.

The system has been split into diagnostics and user management. The diagnostics will capture and process sensor data, then use machine learning to identify the state of intoxication of the user, including personalising the system to each particular user. User management focuses on tailoring the experience depending on their intoxication level through the user interface and allows gameplay to encourage app use.

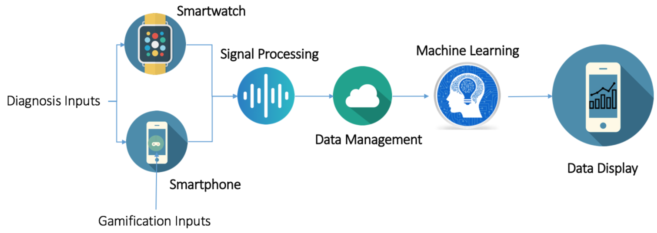


Fig. 1. System Diagram

### A. Data Capture

The system is constrained to sensors found in the smartphone and smartwatch. These include accelerometer, gyroscope, microphone, GPS, touch input, and camera. These sensors will be used to measure, detect and diagnose physiological symptoms that arise from alcohol intoxication.

Based on the symptoms of intoxication, the data can be broadly broken down into Body Motion Tracking and Active User Input.

*1) Body Motion Tracking:* Based on the WAT and OLS, walking and balance are key to detecting intoxication. This detection can be performed using a combination of accelerometer and gyroscope data from both the smartphone and the smartwatch, showing the presence of an ataxic gait and giving the differential for how jerky the arms are in motion. This assumes that the smartphone is attached or close to the body during the runtime of the app; use of the smartphone will cause noise in the data which will have to be filtered out.

*2) Active User Input:* Active user input is data collected from the user interacting with the application, which occurs during use of the app's available games. These games should provide touch, image, and speech input.

*3) Touch Input:* Touch input can be used inside a game to detect loss of motor control and reduced reaction times. These can easily be incorporated into a game to encourage users to provide this data. Users will also be able to log the quantity of alcohol consumed via the app's interface. Additionally, a query can be launched to incentivise users to 'check in' their consumption behaviour, triggered via a drinking gesture.

*4) Image Input:* Use of the phone camera and computer vision techniques allows an equivalent test to the HGN, detecting and quantifying movement in terms of speed and acceleration. Analysing these parameters will show the erratic eye movement of Nystagmus.

*5) Speech Input:* Slurred speech, correctly called Scanning Dysarthria, could be identified using the microphone on either the smartwatch or the smartphone and pattern recognition techniques.

| Diagnostic | Expected Utility | Ease | Score |
|---|---|---|---|
| Reaction Time | 5 | 5 | 25 |
| Walking Pattern | 4 | 4 | 16 |
| Loss of Motor Control | 4 | 3 | 12 |
| Nystagmus | 4 | 2 | 8 |
| Scanning Dysarthria | 4 | 1 | 4 |
| Quick Repetitive Actions | 2 | 2 | 4 |

TABLE I
DIAGNOSTIC SELECTION SUMMARY

### B. Selected Diagnoses

A summary of the suggested diagnoses can be found in Table I. Each diagnosis is given a score from 1-5, where 1 is least useful for diagnosis and simultaneously most difficult to implement. Multiplying these scores gives the most desirable diagnoses; as such, the top three diagnoses of Reaction Time, Walking Pattern, and Loss of Motor Control have been selected. The app will be written to attempt to identify these points and give an intoxication level based on them. The latter three will be kept as “nice-to-have” features which will be looked into should there be time to do so.

### C. Data Management

Data management is a crucial aspect of the application as it provides a base for the machine learning. Our database will be used to store historic sensor readings and gamification data from the user. Storing data on a Cloud service enables data sharing. It also adds robustness as data will not be stored solely on a smartphone which may be wiped or lost.

SQLite is used by default in Android devices; however, this database is local and is not ideal for our application. Therefore, remote server access with SQL databases could be used. The Android app would connect to the web service via HTTPS which enables access to the back-end web database. For our application, we are considering using MongoDB or MySQL databases.

Since the app collects personal information, data security plays an important role in our data management. The transfer protocol must be encrypted to prevent interception, and the database must be encrypted using Database Management Systems (DBMS), requiring user authentication to access data.

### D. Machine Learning

Due to the lack of similar work in classifying intoxication levels, machine learning must be used to create a general model of level. Furthermore, each user will have different reactions to intoxication, different tolerance levels and so on; as such, the general model should be personalised to each user. Furthermore, different users will have different body types or natural gaits, all of which will require machine learning to further refine the diagnostic. Ideally, the user would be prompted to enter their own intoxication level to improve the model. Finally, the model may be adapted to improve diagnostics for the individual user.

The search for concrete datasets has been unsuccessful. Therefore, the machine learning problem is narrowed to that of multiple classes with a small amount of data, which we will aggregate ourselves both through a testing phase, and through continued use of the app. The model used will be learned through use of labelled training data which we will obtain using a breathalyzer.

The results of the games and the data received from the sensors will be a set of discrete information, e.g. reaction time, score, velocity, etc. i.e. categorical dependent variables. There are many machine learning algorithms available; however, based on the fact that we are using supervised learning, that we may require multiple classes, and that we have a small dataset, the following algorithms are proposed as viable: Decision trees/random forest, Bayesian network, Support vector machine, Neural network, Logistic regression.

Cross-validation could then be used to determine the effectiveness of each, and the most suitable could be chosen. Cross-validation may also be useful for testing the model since the sample size is small.

### E. Application

The application will be composed of a user interface, games, and a management system for drinking.

*1) Interface:* The application interface will involve users inputting consumption quantities as well as viewing their intoxication statistics. For example, the “Drunkenness” indicator could be illustrated by a glass of beer, being more or less full depending on the estimated intoxication level. Pressing the beer glass directs users to a statistics page where current, max, and plot of intoxication over time is shown. Users will also have the ability to amend application settings such as sound options, history display period, and ideal intoxication threshold.

*2) Gamification:* Gamification is used to provide an engaging method to retrieve active user input. For example:

- Tap-A-Mole: A game which involves tapping moles on the head as they come out of their homes. This will allow ManDown to measure user reaction times.
- Tightrope: A game where players walk in a straight line while keeping the phone parallel to the ground. A marble will move from the centre of the screen using the gyroscope as input. Movement fluctuations can be used to measure loss of fine motor control and walking pattern.

A user progression system will be implemented, which awards badges to users based on how often they check-in when drinking alcohol. The badges rank users based on the frequency of check-ins and offer titles such as ‘Newbie’, progressing towards badges such as ‘Liquid Lunch’ and ‘Brew Master’. This system increases the amount of direct user input as it would incentivise users to compete with each other among their social group within the app [11]. The games also provide further data which can be incorporated in the machine learning algorithm.

*3) Drink Management:* Health risks of alcohol consumption are minimised by consuming a maximum of 14 units per week, preferably spread over three days or more (a unit being 10ml of ethanol) [12]. To manage consumption within these limits, ManDown provides intake recommendations to warn users if their consumption approaches either threshold, displaying how many more units they can consume safely. The recommendation system could be personalised by providing specific warnings to each user.

The consumption warning system can also use direct user input of alcohol intake, which users may or may not provide, in tandem with the machine learning. Consequently, a more robust management system will be employed to mitigate the risks of extreme intoxication. When high levels of intoxication are identified and users are found to be motionless, indicating they have been incapacitated, ManDown will autonomously inform the user's friends of their whereabouts and their need for help. An additional solution would be to contact emergency health services; however, this approach will be disregarded for the current evaluation and testing scope.

## VI. Experiment and Evaluation

Two separate experiments are required. The first is the gathering of training data necessary for the machine learning, while the second tests the four research hypotheses.

### A. Data Gathering Experiment

1) Obtain a baseline of participants with the app, by making them walk in a set path, the length of which will be determined as development continues. Participants will also be asked to play the games on the app, again to get a baseline.
2) Participants will consume a set amount of alcohol every 15 minutes for 45 minutes, with breathalyzer and app measurements every 5 minutes.

For the second experiment, split the participants into three groups: Full, No Game and Control. Testing for all 3 groups will happen simultaneously and it will be 1 hour long.

### B. Hypothesis Testing

1) Full and No Game participants will use the app every 10 minutes, except that No Games have no games installed with the app. Control participants will not use the app at all. Full and No Game users may freely use the app outside this time of their own volition, which checks for gamification appeal.
2) All participants will be allowed to regulate their own consumption, notifying supervisors of the drinks consumed. Comparing the Full and No Game users to the Control group shows regulation of alcohol intake.
3) All participants will be subject to breathalyzer checks every 10 minutes to obtain a quantitative assessment of the level of intoxication.
4) After the hour, allow all participants access to both versions of the app and survey the preferred version.

Participants will be asked to fill in a survey, which will include questions such as which version of the app was preferred, and if the participant would use the preferred version of the app outside of the experiment. It would also pose questions to the Full and No Game users such as whether they felt that they regulated their alcohol consumption as a result of the app.

## VII. Conclusion

Long-term consumption of alcohol has been identified to cause permanent brain damage as well as the second largest cause of cancer [13]. ManDown is an social application that alleviates problems associated with excessive drinking. The app relies on sensors embedded in smartphones and wearables to detect physiological effects of alcohol. Diagnostics are performed on the gathered data through a combination of machine learning and direct user input, to determine how inebriated the user is. Based on the level of inebriation, recommendations and aid can be provided to the user.

On the social aspect, the app will incorporate fun drinking games to attract users to keep using the app, therefore encouraging extended usage and the positive effects that go with it.

In the event that ManDown proves to be useful in providing a solution for these related issues, this could have significant benefits on the use of mobile healthcare applications on alcoholism.

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