

# **IMPACT OF A MOBILE E-HEALTH INTERVENTION ON BINGE DRINKING IN YOUNG PEOPLE**

The D-ARIANNA (Digital - Alcohol RiSk Alertness Notifying Network for Adolescents and young adults) project

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**Original research article resubmitted for publication to *Journal of Adolescent Health***

**Word count:** Abstract 195; Text 3493; Tables: 2; Figure: 1

**Running title:** eHealth App, binge drinking and young people

## **Funding**

This study was supported by a Grant from the Cariplo Foundation (DARIANNA, Digital-Alcohol RiSk Alertness Notifying Network for Adolescents – Project; Rif. 2011-1528).

## **Conflict of interest**

None.

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## **ABSTRACT**

**Purpose.** Binge drinking (BD) is common among young people. E-Health apps are attractive to them, and may be useful for enhancing awareness. We aimed to investigate the impact of a publicly available evidence-based e-Health app (D-ARIANNA), estimating current risk of BD by questions, matching identified risk factors, and providing in percent an overall risk score, accompanied by appropriate images showing mostly contributing factors in summary graphics.

**Methods.** A natural, quasi-experimental, pre-/post-test study was conducted. Subjects were recruited in pubs, clubs, discos, or live music events. They were requested to self-administer D-ARIANNA and were re-evaluated after two further weeks.

**Results.** Young (18-24 years) people (N=590) reported reduced BD at follow up (18% vs. 37% at baseline). To exclude systematic errors involving those lost at follow up (14%), the diminution in BD was confirmed in an appropriate GEE model with unweighted data on a last observation carried forward basis.

**Conclusions.** Our study provides evidence of population-level benefit at two weeks, attained with D-ARIANNA. This can be disseminated easily and economically among young people. However, additional components, including regular feedback and repeated administration by gamification, may be required in order to make this app suitable for longer-term impact.

**Keywords:** Binge Drinking; eHealth; Young adults

## **Implications and Contribution**

Binge drinking (BD) is common among young people and eHealth tools can be useful for BD. We tested impact of the eHealth app D-ARIANNA. After D-ARIANNA self-administration, young people reported a reduction in BD (37% vs. 18%). This approach can be disseminated easily and economically among young people.

Binge drinking (BD) is defined as  $\geq 4$  drinks for women,  $\geq 5$  drinks for men on a single occasion<sup>1</sup>. Although the use of the term may be not entirely appropriate, as compared for example with the term heavy episodic drinking, it is clearly recognizable not only to researchers in the field but also to the general public and young people in particular<sup>2</sup>. It is a significant public health concern in youth, with current rates of up to 27% both in the U.S. and in Europe<sup>3,4</sup>. Young adults who engage in BD are more likely to report other health risks such as riding with drink-drivers, smoking cigarettes, being a victim of violence, attempting suicide or using illicit drugs<sup>5</sup>. Young people's knowledge and perception of BD risks is often limited<sup>6</sup>, with impaired decision making playing a major role<sup>7</sup> in actions leading to immediate rewards, poor anticipation of the negative consequences and learning from previous mistakes<sup>8</sup>, probably ignoring or considering consequences not relevant to themselves<sup>9</sup>.

e-Health applications may encourage behavioral changes related to public-health priorities, with more than 90% of individuals worldwide<sup>10</sup> using mobile phones, including people with substance use disorders (SUDs)<sup>11</sup>. E-Health technology for SUDs enables interventions at a population level in a variety of formats, and interventions<sup>12</sup>. They have been used across various substances, for a range of populations and settings<sup>13</sup>. The advantages of e-Health for people with addiction problems include accessibility and availability, enhanced patient-clinician communication, the provision of information in an engaging manner, the individualization of the intervention, a greater sense of privacy, and reduced stigmatization or embarrassment about drug use<sup>14</sup>. In particular, e-Health tools have shown encouraging results in identifying BD, reducing alcohol use, and improving continuity of care among young people<sup>15,16</sup>. Given that the beneficial effects of standard preventive drug and alcohol interventions for young adults are modest<sup>17</sup>, e-Health tools might obviate some of the difficulties in implementing preventive strategies by taking advantage of young people's propensity to use electronic devices and their expertise with them (e.g., smartphones).

The current study aimed to evaluate the short-term impact, in terms of relapse in BD, of a recently developed evidence-based e-Health app (D-ARIANNA-Digital - Alcohol RiSk Alertness Notifying

Network for Adolescents and young adults) that incorporates a risk estimation model for BD in young people<sup>18</sup>.

## **Methods**

We used a natural experimental approach, i.e., providing an intervention and using the variation in exposure generated to analyze its impact<sup>19</sup>. This is appropriate for evaluating population level interventions, with repeated measures before and after the intervention<sup>20</sup>.

### *Settings and Procedures*

Recruitment took place outdoors in urban locations of Greater Milan, a region of about 3.3 million of inhabitants. We choose areas with a high density of pubs, clubs, discos, or live music events. Because the consequences of occasional BD are likely to be significantly different from those associated with more persistent bingeing, a single verbally asked screening question was used to identify a clinically severe population, comprising those with a history of bingeing on alcohol at least once in the last six months<sup>21</sup>. Young people (1) aged between 18 and 24 years, and (2) owning a smartphone running on Apple® iOS or Android™ (version 4.0 or later) operating systems, were consecutively recruited at pubs, clubs, discos and music events. People reporting current and previous treatments for alcohol use disorders, those with a current psychiatric condition, and those with vision problems were considered ineligible because of risk of treatment and other biases<sup>22</sup>. Participants received an information sheet and provided signed written informed consent. In order to facilitate sampling and to minimize embarrassment, the recruitment was conducted by young people similar to the target population, that is, students aged between 18 and 24 years, selected from different Schools of Milano Bicocca University. These twelve facilitators received 10 hrs. training on data collection procedures, including eligibility criteria, and were provided with a clear and unequivocal definition of BD. After a colloquial introduction, facilitators provided standard definitions of both drinks, though with plain language and examples, and binge drinking, explicitly using this term. As a result the question “Did you binge drink in

the past two weeks?” implied a closed-ended (yes/no) response. The facilitators provided information on the research project, obtained consent, and introduced and assisted with the e-Health app, helping participants to download it into their smartphones, checking that participants self-administered the e-Health app at least once. As an incentive, people who agreed to participate in the study received a t-shirt with the project logo. . In order to follow-up short-term outcome, facilitators arranged to phone all participants after 14 days, to establish whether they had engaged in BD in the intervening period. Those who answered the call received a €10.00 mobile phone top-up as an additional incentive. The facilitators repeated at follow-up the same exact wording, implying a closed-ended response, that was used at baseline. Follow-up occurred 14 days post baseline, regardless of when the app was further used in order to secure that the period of post-intervention assessment was clearly post intervention. Unfortunately, for privacy reasons, we were not able to assess how many times and when the app was further used.

### *Design*

Because of the chosen setting<sup>20</sup>, we consequently opted for a natural, quasi-experimental, pre-post test design without a control group<sup>23</sup>. The study was approved by the Ethics Committee of University of Milano Bicocca (The D-ARIANNA study, approval: 0009873/13).

### *Sample size*

For our power calculation, we used information from the Italian Institute of Statistics databases, assuming that in relevant age range the proportion of subjects who had recently binged on alcohol was 15%<sup>24</sup>. Given a 5% level of significance, 90% power, and attrition of 20%, 589 participants would be needed to detect a 5% difference in BD prevalence rates at follow-up.

### *The e-Health app (D-ARIANNA)*

D-ARIANNA (Digital - Alcohol Risk Alertness Notifying Network for Adolescents and young adults) provides an evidence-based current risk estimate for BD in young people<sup>18</sup>. First, we designed a

questionnaire, to be included in the e-Health app, investigating identified risk/protective factors. We took into account order and wording of the closed questions, to develop suitable response codes. We built short queries, banning negatives, based on phrases that young people can understand, avoiding formal lexicon, placing first simple and basic questions. For questions on impulsivity, we used the Substance Use Risk Profile Scale. Users' answers about risk and protective factors populate an algorithm and, based on the coefficients of a relevant estimation model, the e-Health app identifies low (0-43%), moderate (43.1-82%), and high (82.1-100%) risk levels for the single subject, with user-friendly screens and simplified graphical interfaces. D-ARIANNA is available free from the app-stores Google Play™ ([https://play.google.com/store/apps/details?id=com.saysoon.d\\_arianna.en](https://play.google.com/store/apps/details?id=com.saysoon.d_arianna.en)) and iTunes® (<https://itunes.apple.com/us/app/d-arianna-eng/id875252915?l=it&ls=1&mt=8>), and was included in the NHS health apps library (<http://apps.nhs.uk/apps/alcohol/>). Ten risk factors (five modifiable), and two protective factors were identified and included in the model. These comprise cannabis use (past 30 days), recent binge episodes (past two weeks), interest in discos and parties, smoking cigarettes, male gender, drinking onset at age 17 or younger, parental alcohol misuse, younger age, peer influence, impulsivity, as well as volunteering and school proficiency as protective factors. It uses a personalized risk communication to informed decision making by individuals taking test, based on the nature of the population involved<sup>25</sup>. Risk factors that contribute most to the overall score are shown in a closing summary message, though the app only predicts behavior and it does not offer information on why to change behavior. Details about risk estimation modeling (phase 1), design (phase 2), development and feasibility (phase 3) of the feedback-based e-Health app are fully described elsewhere<sup>18</sup>. In this paper we report on the impact of D-ARIANNA on BD relapse outcome (phase 4).

### *Outcome*

We chose a short term primary outcome, consistent with the expected impact of a one-shot self-administered e-Health app. We thus focused on detecting differences between the BD rates in the 2 weeks before and after the e-Health app self-administration.

## *Data Analyses*

We used Generalized Estimating Equation (GEE) analyses to investigate the longitudinal course over the study period of 2 weeks. GEE is a regression model that takes into account the correlation of repeated within-person measures<sup>26</sup>. Specifically, we used a logistic GEE model for the binary outcome BD in the past 2 weeks. However, risk and protective factors identified in the risk estimation model were also entered with a stepwise procedure in the GEE model, in order to take into account their effect on the outcome. Furthermore, we needed to exclude systematic errors involving those lost at follow up, verifying whether unobserved outcome data were missing: i) completely at random (MCAR, i.e., the probability of non-response depends neither on covariates nor on outcome); ii) simply at random (MAR, i.e., non-response is dependent on observed covariates and outcome values); or iii) not at random (MNAR, i.e., non-response depends on the value of the missing outcome itself, even when observed data are taken into account).

We therefore followed a structured approach<sup>27,28</sup>. We first assumed that missing data did not influence our outcome, implementing an unweighted GEE model under the MCAR assumption. Nevertheless missing outcome data might depend on observed covariates (the MAR condition). We consequently performed sensitivity analyses, via t-tests and cross tabulations, comparing those who dropped out versus those who did not, and implemented a weighted GEE model that accounted for data from those who dropped out. In addition, we used a multiple imputation (MI) procedure, based on replacing missing data by drawing from a distribution of likely values. If we detected differences from any of these estimations, there would be a reasonable chance of systematic error, and missing outcome data would hence be dependent on observed values. However, people who are binge drinkers might be reluctant to disclose their condition and to provide follow-up information about adverse drinking outcomes. This would imply that the probability of nonresponse depends on missing values, suggesting a MNAR condition. However, MAR and MNAR can never be proved or falsified<sup>27</sup>. We therefore analyzed our data further by systematically varying our assumptions about missing outcomes. We tested two extreme

models, i.e., a) all drop-outs would be bingers; b) all drop-outs would be abstinent, and a more conservative one, i.e., c) using last observation carried forward (LOCF) data for bingeing in the past 2 weeks. We evaluated how the estimates would change under each of these assumptions. Large deviations in regression parameters would indicate possible departures from MCAR<sup>29,30</sup>, implying the inadequacy of utilizing only complete data, while small deviations would justify a per-protocol analysis. We used Stata statistical software package (version 13.0; StataCorp, College Station, Texas).

## **Results**

### *Screening and Follow-up Assessment*

Participant flow, follow-up rates, and the numbers analyzed are presented in Figure 1. From potentially eligible consecutive subjects aged between 18 and 24 years (N=654) we selected those who reported BD at least once in the previous six months (N=590, 90%). No eligible individual refused to participate in the study. Of the 590, 224 (38%) had reported - at baseline recruitment - BD at least once in the past 2 weeks. Data on bingeing after D-ARIANNA self-administration were unavailable for 38 (17%) of the 224 subjects who reported bingeing in the past 2 weeks, and for 45 (12%) of the 366 who did not. Thus, we obtained follow-up data from 507 (86%) participants who had self-administered the e-Health app.

Figure 1 about here

### *Study Participants*

Table 1 presents baseline sociodemographic characteristics comparing those observed with those not observed at follow-up, together with several risk and protective factors included in the estimation model, for details see<sup>18</sup>. Persons dropping out were significantly more likely to have background of immigration and less likely to live with parents. However, they did not differ on any of the remaining attributes.

Table 1 about here

### *D-ARIANNA e-Health app impact*



Of subjects with complete follow-up data (N=507), 186 participants (37%) had at least one BD occasion in the two weeks before baseline, and 90 (18%) in the 2 weeks before follow-up assessment. However, we needed to exclude systematic errors affecting those lost at follow up. Thus, we used GEE and MI methods under the different assumptions about missing outcome data described above. Each GEE-model compared follow-up drinking data with baseline assessments. In addition, we took into account the effect of risk and protective covariates for binge drinking at multivariate level as reported in Table 2 that displays univariate and multivariate models under the different assumptions considered. Under the Missing Completely At Random assumption, analysis restricted to participants with complete data showed that the use of the e-Health app was associated with a statistically significant reduction in the proportion who had binged in the two weeks before assessment (OR 0.36, 95% CI 0.29-0.45,  $P < 0.001$ ). We then applied the MAR assumption. Weighted GEE analysis and a multiple imputation with 100 iterations both showed statistically significant estimates similar to those from the MCAR model, with ORs (95%CI) of 0.38 (0.29-0.51) and 0.40 (0.31-0.50), respectively. Next we applied the MNAR assumption in order to investigate three distinct scenarios. First, we evaluated two extreme conditions: 1) that *all* the participants lost to follow-up had binged (the worst case scenario, OR=0.68, 95%CI: 0.55-0.83); and 2) that *none* of those lost to follow-up had done so (the best case scenario, OR=0.30, 95%CI: 0.23-0.37).

It can be seen that the worst case scenario provides a rather different estimate from the unweighted model. While this supports the need to dealing with missing outcome data, it is based on a rather unrealistic condition. The last observation carried forward (LOCF) method provides a less extreme assumption which we think is more plausible, namely that the response remains constant at the last observed value (which is the baseline assessment). The relevant unweighted model gave an OR (95%CI) of 0.45 (0.37-0.55). Of all the models, this method provides the most appropriate and statistically meaningful estimate of the impact of the e-Health app, as it takes (reasonable) account of missing data. It allowed for the possibility that people who binge drink are more likely to drop out in order to avoid disclosing this condition: those lost to follow-up showed higher baseline rates, albeit not statistically

significantly so (see Table 1). Finally, multivariate models implemented under the different assumptions did not show clinically meaningful differences from their univariate counterparts, thus encouraging confidence in the estimates provided. In sum, at follow-up participants were significantly less likely to relapse than they were before D-ARIANNA self-administration, and missing data do not seem influence our findings.

Table 2 about here

## **Discussion**

### *Main findings*

We used a natural experimental approach to preliminarily study the beneficial impact, though needing a confirmatory trial<sup>31</sup>, of a novel, self-administered e-Health app on binge drinking in a large sample of subjects aged between 18 and 24 years. We had already reported that levels of acceptance of the app and participation were very satisfactory,<sup>18</sup>. In this study, we show that at follow up, after self-administration of D-ARIANNA, young people reported a reduction in BD in the preceding two-week period (37% at baseline vs. 18% at follow-up). In addition, the LOCF unweighted GEE model, appropriate in handling of missing data, confirmed a significant diminution in rates. Evidence for a positive impact of the e-Health app was corroborated by the role of risk and protective factors in multivariate analyses.

### *Limitations*

This proof-of-concept study has several limitations mainly due to the lack of a control group and to the extremely short duration of the follow-up, both making difficult to establish whether the use of this e-Health app can change the attitude to BD in the target population. The difficulty of mounting a controlled study in the chosen natural setting led us to opt for a quasi-experimental, pre/post- test design. This limitation is not unusual in e-Health interventions<sup>23</sup>. Indeed, we used a convenience sample, though identifying every subject belonging to the target population would help randomize recruiting. Although we are aware that the lack of a control group is a serious limitation, which cannot be overcome in any way, we chose a more pragmatic evaluation, that at least minimizes interference by research artifacts

stemming from intervention study participation. We maximized the external validity of the findings by using a large sample, more epidemiologically representative than special groups from specific settings such as school and college students. Our follow-up participation rates were good, and we addressed the potential for selection biases through our exhaustive methods of analyzing the impact of missing outcome data. However, it remains difficult to confirm an association between the change in outcome behavior and the intervention in this study, not to mention that recruiting at pubs and clubs perhaps implied a peak point of BD, making possible a regression to the mean phenomenon. We cannot even exclude that participants engaged in a particularly heavy drinking session on the day of recruitment might have been especially likely to not drink over the next two weeks due to BD consequences. In addition, we cannot rule out an Hawthorne observer effect, considering that participants knew their behavior was being tracked. We attempted to reduce this effect, involving peer facilitators instead of standard researchers and health professionals. Potential alternatives would include the creation of another cohort where researchers simply assess BD before and after without an e-Health app or comparing outcome from young people using the e-Health app to a drinking diary completed by participants.

We evaluated the persistence of binge drinking using a two-week follow-up, certainly a short term outcome, not to consider that, though using the same exact wording previously used, baseline and follow-up questions were asked in different settings using different modes. Though consistent, in terms of dose response relationship, with the impact of a one-shot e-Health app, this effect may decline over time, indicating a probable need for regular boosting.

Even if we have performed very complex statistical analyses, these cannot overcome main limitations described and the proof-of-concept nature of our study. There is thus a requirement for an adequately powered randomized clinical trial, preferably based not on self-report, but on urine testing, to confirm our results and to ascertain whether the use of this app is of any benefit in the prevention of BD. Such a trial will establish the efficacy of the app using regular feedback and repeated administrations, possibly with motivational components such as *gamification*<sup>32</sup>. There are grounds also for cross-cultural

replications, since southern European populations have relatively healthier drinking cultures as compared with the USA and Northern Europe<sup>3,4</sup>. Finally our study was open to the methodological weaknesses of e-health research, detecting subtle effects on behavior with problematic attrition of participants not engaged in clinical settings<sup>33</sup>.

### *Implications*

Certainly, our e-Health app shares the characteristics of usability, utility, and appeal typical of such applications<sup>34</sup>, and it should in principle be capable of wide dissemination, reaching large numbers of young people. Of course we need to consider the use of this e-Health app also in terms of ecological validity. This would imply different approaches according to chosen dissemination strategies. Clinicians could actually prescribe this app to high-risk youth, though the integration of this component in standard treatment programs needs to be considered. Alternatively, viral advertising also using existing social networking services could motivate youth, self-selecting to use this e-Health app. This could benefit from gamification previously described, in order to make the e-Health app more fun and motivational. Also existing features such as breathalyzer to be incorporated in the e-Health app would make this more appealing for young people rather than a simple screening approach. The D-ARIANNA model includes several risk factors for BD, as well as recognized protective factors. All are to some degree, modifiable, manageable conditions (see <sup>18</sup> for a full description of weighted risk factors). It could also be argued that provided information can improve decision making mechanisms in young people who binge drink, supporting behavioral changes <sup>8</sup>.

Our preliminary findings show that D-ARIANNA, encouraging awareness of the negative consequences of hazardous drinking, may help to deliver a preventive message about BD. Further developments might involve recalibration and refinement of the model, and additional risk factors excluded because the topics they covered were too sensitive (i.e., sexual orientation, history of sexual abuse, having a religion).

Behavioral (e.g.,<sup>17</sup>) and universal school-based prevention programs<sup>35</sup> have shown limited evidence in reducing BD, though its impact remains a cause for concern<sup>36</sup>. Smartphone- and computer-based applications are available for alcohol use disorders, and effectiveness in the continuing care of patients has been reported<sup>16, 37</sup>. Previous studies relied on web-based, feedback by email and text-messaging approaches<sup>38-40</sup>. D-ARIANNA is, to the best of our knowledge, the first evidence-based e-Health app for young people, specifically evaluating risk for BD, relying exclusively on personalized risk communication for informed decision-making rather than on common technological means such as GPS to identify high-risk locations (e.g.,<sup>16</sup>). Finally, whether smartphones will be practical platforms for preventive intervention in BD depends in part on cost. D-ARIANNA is freely available, whereas other apps are in the commercial market.

Thousands of health care applications for smartphones are available, but very few have been tested rigorously. The promising results of this trial point to the potential of a smartphone intervention for preventing relapse in binge drinking.

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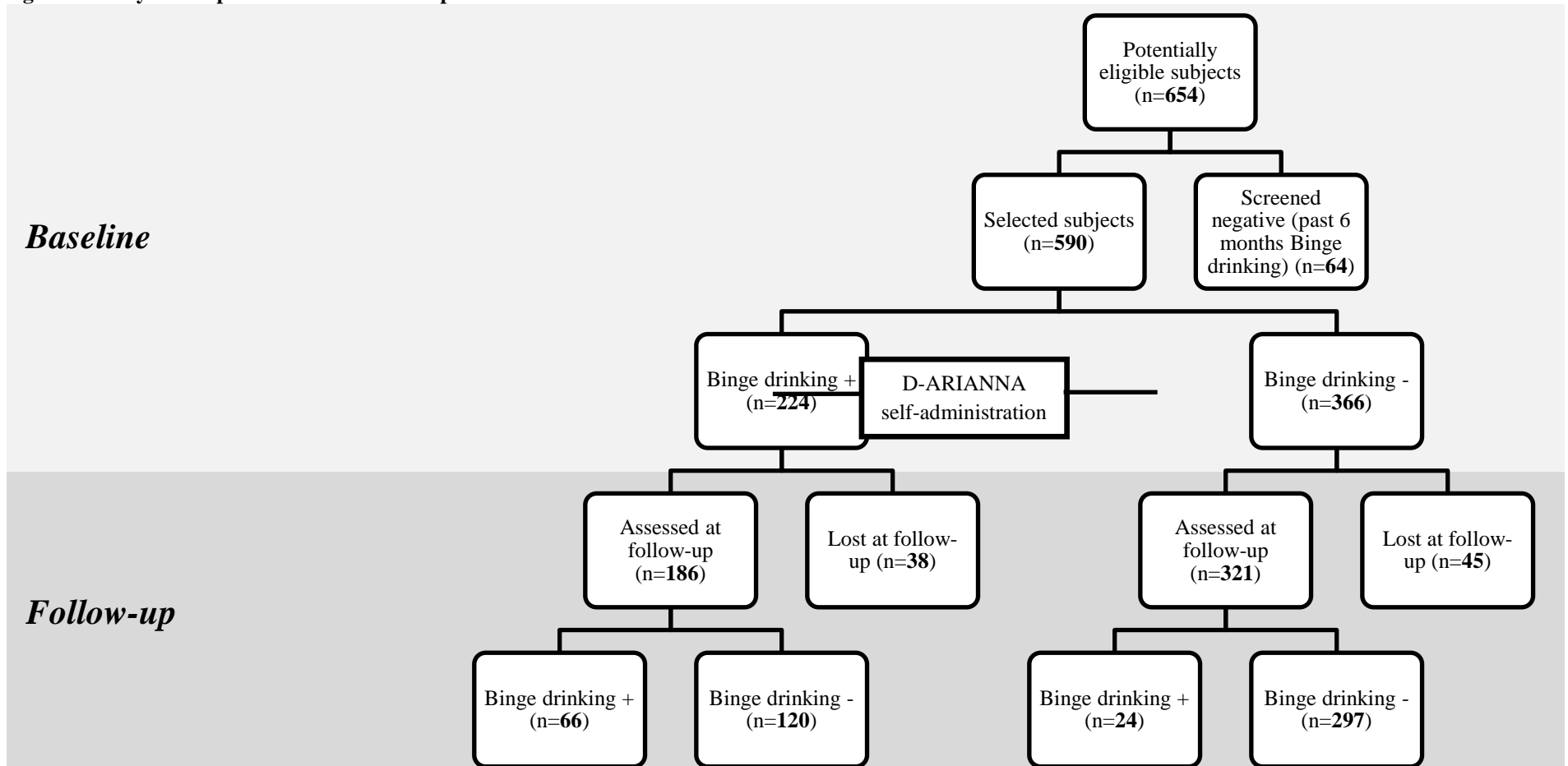
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Figure 1. Study Participant Flow and Follow-up Rates



**Table 1. Baseline characteristics of participants lost to follow-up relative to those followed up**

<b>Variable*</b>	<b>Follow-up N=507 (85.9)</b>	<b>Drop-out N=83 (14.1)</b>	<b>P</b>
<b>Female Gender</b>	264 (52.1)	40 (48.2)	0.512 <sup>a</sup>
<b>Age (years), mean (SD)</b>	20.6 (1.9)	20.9 (1.9)	0.137 <sup>b</sup>
<b>Immigration background</b>			0.010 <sup>a</sup>
No immigration background	451 (88.9)	64 (77.1)	
One parent born outside Italy	26 (5.1)	8 (9.6)	
Both parents born outside Italy	30 (5.9)	11 (13.2)	
<b>Living with parents</b>	392 (77.3)	54 (65.1)	0.023 <sup>a</sup>
<b>In a relationship</b>	205 (40.4)	32 (38.6)	0.893 <sup>a</sup>
<b>Educational attainment</b>			0.122 <sup>a</sup>
Not attending any course	57 (11.2)	14 (16.9)	
High school	151 (29.8)	17 (20.5)	
University	299 (59.0)	52 (62.6)	
<b>School proficiency, mean (SD)</b>			
High school (maximum 10)	7.1 (0.8)	6.9 (0.9)	0.377 <sup>b</sup>
University (maximum 30)	25.5 (2.5)	25.5 (2.4)	0.886 <sup>b</sup>
<b>Employed or in occasional jobs</b>	152 (30.0)	26 (31.3)	0.829 <sup>a</sup>
<b>Smoking cigarettes</b>	238 (46.9)	46 (55.4)	0.152 <sup>a</sup>
<b>E-cigarettes</b>	17 (3.4)	7 (8.4)	0.063 <sup>c</sup>
<b>Cannabis use</b>	159 (31.4)	39 (38.5)	0.194 <sup>a</sup>
<b>Early* onset of drinking</b>	383 (75.5)	62 (74.7)	0.869 <sup>a</sup>
<b>Past two weeks binge drinking</b>	186 (36.7)	38 (45.8)	0.113 <sup>a</sup>
<b>Peers binge drinking</b>			0.347 <sup>a</sup>
Only a few	50 (9.9)	11 (13.2)	
Most of them	457 (90.1)	72 (86.8)	
<b>Parental alcohol misuse</b>	61 (12.0)	10 (12.1)	0.997 <sup>a</sup>
<b>Positive alcohol expectancies<sup>†</sup> mean (SD)</b>	21.5 (3.6)	21.0 (4.7)	0.884
<b>Interest for discos and parties</b>	181 (35.7)	33 (39.8)	0.476 <sup>a</sup>
<b>Self-assessed religiosity<sup>‡</sup></b>	195 (38.5)	29 (34.9)	0.583 <sup>a</sup>
<b>Volunteering</b>	147 (29.0)	19 (22.9)	0.252 <sup>a</sup>
<b>Playing sports</b>	329 (65.3)	51 (62.2)	0.588 <sup>a</sup>
<b>Weekly pocket money</b>			0.408 <sup>a</sup>
0-20 Euros	177 (34.9)	25 (30.1)	
21-50 Euros	217 (42.8)	32 (38.6)	
51-100 Euros	84 (16.6)	18 (21.7)	
>100 Euros	28 (5.5)	7 (8.4)	
<b>Self-assessed Depression<sup>#</sup></b>	115 (22.7)	14 (16.9)	0.251 <sup>a</sup>
<b>Self-assessed Anxiety<sup>#</sup></b>	254 (50.1)	35 (42.2)	0.207 <sup>a</sup>
<b>Impulsivity<sup>§</sup> mean (SD)</b>	5.1 (2.1)	5.3 (2.1)	0.381 <sup>b</sup>
<b>Get on well with parents<sup>‡</sup></b>			0.876 <sup>a</sup>
Not at all	9 (1.8)	1 (1.2)	
Only a little	41 (8.1)	7 (8.4)	
Some	249 (49.1)	37 (44.6)	
A lot	207 (40.8)	37 (44.6)	
<b>Violent Video Game Use<sup>‡</sup></b>	59 (11.6)	4 (4.8)	0.081 <sup>c</sup>

Values are numbers (%), unless stated. \*drinking onset at age 17 or younger. †Assessed by AEQ-AB (Alcohol Expectancy Questionnaire-Adolescent, Brief). #Assessed by relevant single items at K-10. §Assessed by SURPS (Substance Use Risk Profile Scale) See <sup>14</sup> for References. <sup>a</sup>Pearson's Chi-square test; <sup>b</sup>Student's t test; <sup>c</sup>Fisher's exact test, <sup>d</sup>Mann-Whitney U test. \*There are missing values for some variables: the greatest number of missing values is for relationship status, where there are 490 ratings for follow-up participants and 78 for drop-outs; and for current employment, 498 and 82 ratings respectively. <sup>1</sup>Missing values for both follow-up participants and drop-outs=1

**Table 2. Binge drinking at two weeks follow-up**

<b>Assumption</b>	<b>GEE Method</b>	<b>OR (95% CI)</b>	<b>Robust SE</b>	<b>P</b>
<b>MCAR</b> (Complete data)	Unweighted	0.36 (0.29- 0.45)	0.04	<0.001
		0.30 (0.23-0.40)*	0.04	
<b>MAR</b>	Weighted	0.38 (0.29-0.51)	0.05	<0.001
	MI (N=100)	0.31 (0.22-0.44)*	0.05	
<b>MNAR</b>	Unweighted	0.40 (0.31-0.50)	0.05	<0.001
		0.33 (0.25-0.44)*	0.05	
Missing as bingers	Unweighted	0.68 (0.55-0.83)	0.07	<0.001
		0.64 (0.51-0.82)*	0.08	
Missing as abstinent	Unweighted	0.30 (0.23-0.37)	0.03	<0.001
		0.24 (0.18-0.32)*	0.03	
LOCF (Last observation carried forward)	Unweighted	0.45 (0.37-0.55)	0.04	<0.001
		0.39 (0.31-0.49)*	0.04	

\***Controlled for:** Age, gender, cannabis use, peers binge drinking, parental alcohol misuse, positive alcohol expectancies, self-assessed religiosity, volunteering, weekly pocket money, impulsivity, interest for discos and parties, smoking cigarettes

**Supplementary eFigure.** User-friendly screens for description of individual's risk level and factors that mostly contribute to the overall score

**DARIANNA**  
 Digital-Alcohol Risk Alertness  
 Notifying Network for Adolescents



**fondazione  
cariplo**



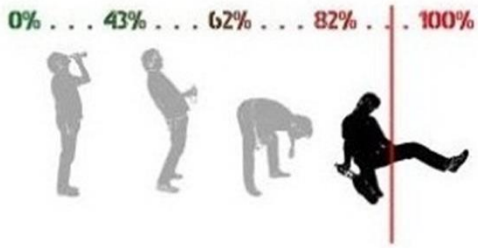
UNIVERSITA' DEGLI STUDI  
DI MILANO  
**BICOCCA**

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Credits      Next

**DARIANNA**

Estimated risk percentage is: **>90%**



0% . . . 43% . . . 62% . . . 82% . . . 100%

The risk percentage provided by D-ARIANNA is only an estimate of the probability of binge drinking. It does not imply the ability to predict that it will happen.

**DARIANNA**

Please remember that binge drinking is the consumption of five or more alcoholic drinks for men and four or more for women. Your risk for binge drinking is quite high. You must discuss it and its consequences with your family doctor. Your estimated risk percentage is

**>90%**

The risk percentage provided by D-ARIANNA is only an estimate of the probability of binge drinking. It does not imply the ability to predict that it will happen.

**DARIANNA**

The most important factors contributing to your risk are:

- . You hang out at clubs and parties.
- . Your academic performance is suboptimal
- . You are a smoker
- . You have many friends that drink too much
- . You have engaged in binge drinking at least once during the past 2 weeks.
- . You are fairly an impulsive person