Supplemental Material

CBE—Life Sciences Education

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Āwhina Revolution: Supplementary Material

Te Rōpū Āwhina

Te Rōpū Āwhina (Āwhina) was established at Victoria University of Wellington in 1999 by the Deputy Dean (Equity) who, as a member of the Science, Technology, Engineering and Mathematics (STEM) faculty senior management team, was responsible for Āwhina's day to day and strategic work. Āwhina was built around the Māori concept of whānau (literal meaning = 'extended family') and resourced by the STEM Faculties. Āwhina embodied many ideas suggested for reducing tertiary ethnic inequalities (Leggon & Pearson Jr, 2009; Linn, Palmer, Baranger, Gerard, & Stone, 2015), in particular, a leader dedicated to the long-term improvement of Māori and Pacific success in STEM disciplines, and having a position of influence in the STEM faculties (Leggon, 2015; US Committee on Underrepresented Groups and the Expansion of the Science and Engineering Workforce Pipeline, 2011). Key Āwhina characteristics included an on-campus whānau environment with a strong kaupapa (values base) of contributing to Māori and Pacific community development and leadership, high expectations around grades and degree completions, aspiration for postgraduate study, collective success and reciprocity; community connectedness; peer support and mentoring (as a mentee or mentor); extensive interactions with and strong "buy-in" from academic staff; outreach; academic tutoring; committed and high-calibre senior Āwhina staff, and a robust evidence-base to evaluate success. Importantly Āwhina had its own distinct and independent "life", and in this regard it was critical that Āwhina's leader was a senior STEM faculty member and directly involved in Āwhina's everyday work. Furthermore the whānau had the autonomy to decide its kaupapa, and the implementation of that kaupapa in strategic and day-to-day work. Whānau members often summarised this aspect of Āwhina as "doing it for ourselves".

In Āwhina all whānau members accepted and treated one another respectfully, and worked collectively and individually for success. From their first year all whānau members were expected to strive for high grades, complete their degrees within the allocated time, and aspire to postgraduate studies. They were encouraged and assisted to develop leadership skills and to understand their role as culture changers within the university, workplace, and community. In each year between 1999 and 2015 a majority of MP students in the STEM faculties were Āwhina whānau members and contributed to its work.

Mentors and mentees were central to Āwhina's work and the concept of manaakitanga (nurturing that is beneficial and reciprocal) was central to the Āwhina kaupapa. Mentors were nurtured formally and informally by senior students and staff mentors, and career and community mentors. In turn, mentors focused on building academic momentum in first and second year mentees and ensuring the continuation of Āwhina by training mentees to become mentors. Mentors were high achievers in their subject area, often final year undergraduates or postgraduates, and performed their roles voluntarily. Their primary role was to provide on-call academic help in their specialty subjects, build the capability of high school pupils and first year mentees to transition successfully from high school to university, and academically strengthen first- and second-year mentees to become senior mentors and leaders in their communities. Āwhina mentors were likely to have come from a similar background to their mentees and could usually relate to pressures unique to Māori and Pacific students. Senior mentors had designated responsibilities for the day-to-day running of various aspects of Āwhina such as whānau room (see later) compliance, outreach, mentor support, special events, the Āwhina library, monitoring Āwhina progress, or scholarships. When these responsibilities were particularly significant to the functioning of Āwhina they received a modest stipend. All mentors were expected to be positive role models at all times, support one another, and provide leadership. Their Āwhina experience was accepted as preparation for future leadership roles in the workplace and in Māori and Pacific communities and organisations.

At the beginning of each trimester a report containing Māori-Pacific student details was extracted from the university central student database. Mentees were identified and allocated by degree major to mentors who then contacted their mentees and set up a time to meet kanohi ki te kanohi (face to face). Mentees were encouraged to use the Āwhina whānau rooms (see later) during the day when not in lectures, laboratories or tutorials so they could easily access help. Following that first meeting mentors maintained regular contact with mentees through weekly study sessions in the whānau rooms and by phone or email. As well as providing subject-specific academic help and information, mentors also assisted mentees to develop good study habits and skills, and ran regular weekly sessions for other courses where they had expertise. Mentors were the first point of contact for their mentees and acted as an 'early alert system'. Mentees were expected to focus on their academic work while on campus, keep in contact with their mentors, work together in the whānau rooms, ask for help when they needed it, and support other Āwhina whānau members. This made whānau rooms busy workplaces where at any one time there could be individual or group study, tutorials run by mentors or staff, mentors working with their mentees or mentees working together. Exam preparation sessions for all first and second-year mentees were held in the two weeks preceding exams.

Between 2003 and 2014 Āwhina funded and coordinated Equity Help sessions aimed at inadequately prepared students in core 1st year STEM courses. Equity Help facilitators were high achievers with good social skills who had recently completed the papers they facilitated, with some having previously sought assistance in Equity Help sessions themselves. Multiple sessions were run weekly, along with exam preparation sessions during study breaks, attracting up to half the students taking the course. Pass rates for those who attended were always higher than those of students who did not.

Āwhina also had a secondary school and community-based outreach component. Āwhina mentors assisted Māori-Pacific pupils in local low- to mid-decile secondary schools[1] to raise aspirations and achievements in science, technology and mathematics. Participating schools had high Māori and Pacific enrolments, were supportive of their pupils, involved whānau in pupil education, and had designated staff to liaise with the on-campus component of Āwhina. Mentors met with teachers, pupils, and their whānau and made regular visits to the school to work in class with school pupils. Conversely, pupils and whānau visited the STEM faculties for 'hands-on' science sessions in the laboratories to experience first-hand the excitement of scientific discovery and the relevance of science to their everyday lives.

Āwhina was active in a wide range of rangatahi (young person) or whole whānau (all age) community-based outreach activities in venues such as community halls, rugby clubrooms, art galleries, event centres, Parliament, urban and rural Marae (traditional Māori meeting place), and outside on beaches. These activities were one to four days in duration with tens to thousands of participants of all ages. The rationale for these events was to promote science and technology as areas in which Māori-Pacific already participated successfully, to encourage rangatahi to undertake STEM degrees, and to provide an opportunity for mentors to strengthen connections with, and contribute to, their communities.

Āwhina brought the whole whānau together for significant events including an annual birthday celebration where summer research results were presented, and whānau successes acknowledged. Mentors organised and ran these occasions which were attended by mentors, mentees, their off-campus whānau (e.g., grandparents, parents, partners, children, and friends), staff, community and institutional supporters. These events strengthened commitment to the goals of Āwhina and reaffirmed the kaupapa that underpinned the progress that had been made.

The Āwhina budget covered wages and operational costs of between 2 and 3 full time staff and several whānau rooms, together with Āwhina Awards, casual staff, travel, and Āwhina functions. Each School (discipline-specific clusters within Faculties) had a contact staff member for Māori-Pacific students, but most staff were easily accessible and worked with mentors and mentees in their offices or in whānau rooms. Staff provided references for employment, assisted with applications for scholarships, funded and/or supervised Āwhina summer researchers, attended Āwhina celebrations, participated in outreach activities, assisted students experiencing personal, financial or academic difficulties, and often donated text books to the Āwhina library. Āwhina resources included a well-stocked library of prescribed textbooks and relevant theses, Āwhina summer researcher reports, past exam papers, and quiet individual and group study spaces within whānau rooms.

Much of the formal on-campus mentoring took place in Āwhina whānau rooms. Whānau rooms were secure dedicated spaces with continuous 24-hour, 7-day access where students could use resources such as computers and printers (with free printing) not available to them off-campus. Whānau rooms were a key part of the campus experience for Āwhina members because they brought students together with their peers to create support networks. Whānau rooms were physically located within faculty Schools to enhance the relationship between Āwhina whānau members, staff, and other students.

Scholarships played an important role in strengthening Āwhina at undergraduate level and increasing postgraduate numbers. The Deputy Dean (Equity) worked closely with a number of sponsors on targeted scholarships to increase the postgraduate pool. Summer Research Awards for second and third year Āwhina undergraduates, awarded by a committee comprising the Deputy Dean (Equity) and the awardee's academic supervisor, also helped transition students to postgraduate study. Āwhina students were encouraged and assisted to apply for Māori/Pacific-specific scholarships such as Iwi Trust Board Awards, Māori Education Trust Awards, Government-funded internships and Government-funded awards such as Te Tipu Pūtaiao Māori Fellowships for postgraduate research, and prestigious international graduate programmes.

Āwhina postgraduate students were encouraged to support one another and work more closely with STEM staff. They launched and co-ordinated the fortnightly Āwhina Postgraduate Seminar Series which provided a whānau forum where research was critiqued and cross-disciplinary synergies explored prior to presentation at seminars and conferences. Research experiences were shared and problems associated with poster production, and data collection and analysis were jointly resolved.

Āwhina Incubators were small whānau groups of students in the same degree programme but at different levels who worked together to improve whānau outcomes. Incubators were led by senior Āwhina mentors or STEM academic staff, and would meet for 1-2 hour sessions each week as well as for revision sessions during the exam study breaks. In 2015 incubators existed for biology, biomedical science, biotechnology, chemistry, computer science, engineering, environmental studies, geology, geography, marine science, mathematics and statistics, psychology, and physics.

Leading up to the retirement of the Deputy Dean (Equity) in December 2015, Āwhina whānau and supporters fought tenaciously to ensure Āwhina's continuation. Āwhina had the support of the communities it represented, and Āwhina researchers were busy strengthening evidence for its success. Nevertheless, with the retirement of the Deputy Dean, Āwhina was replaced by an institutional “support” programme based on those in the non-STEM faculties which had no evidence of success.

Hierarchical Bayesian Modeling

This section presents a brief introduction to the components of Bayesian hierarchical modelling relevant to this article. For a more general introduction, see Gelman and Hill (2007) and the references therein.

The key feature distinguishing Bayesian from traditional frequentist analysis is the probabilistic description of unknown parameters. The frequentist views probability as a long-run frequency whereas the Bayesian view expresses belief in a statement about the statistical properties of unknown quantities. Bayesian analysis is a statistical procedure that updates the probability distribution of a parameter as more evidence becomes available. More formally, the prior distribution of a parameter is combined with data to produce a posterior distribution using Bayes law.

A typical Bayesian analysis proceeds in four steps(Glickman & Van Dyk, 2007). The first step formulates a probability model that describes the distribution of the data for given parameter values. An advantage of Bayesian methodology is that it facilitates the fitting of models that are designed to capture the complexity of any given data generating process. This article uses a *hierarchical* (also known as multi-level or mixed-effect) probability model, which combines a series of simple models into a single more appropriate model by incorporating parameters that vary at multiple levels. In this article the model is hierarchical to allow covariates defined across several strata (e.g., ethnicity, time) to help predict completion rates within individual strata, and to model inter-stratum variability. Similarly hierarchical models are particularly suited for modelling data that have a hierarchical structure because they allow for the possibility that one stratum might provide information about another. For example, an analysis of STEM completion rate data from several universities might use university-level information such as the existence of a credible STEM equity programme and/or the proportion of STEM academic staff that are Māori-Pacific.

The hierarchical structure of the model in this article is expressed in Equations 1 - 5. Equations 1 and 2 represent the first level of the hierarchy and describe the within-stratum distributions. More specifically, the number of completions within a given stratum is assumed to follow a Poisson distribution with the rate drawn from a stratum-specific gamma distribution. This is a formal way of expressing the fact that the completion rate for Māori-Pacific students in 1998, for example, might have a mean and variability that is different for non-Māori-Pacific students in 1998, or for Māori-Pacific students in 1999 for that matter. The parameter ζ in equation 2 models such inter-stratum variability. The second level of the hierarchy, expressed in Equations 3 and 4, predicts the mean stratum-specific completion rate using information defined at a broader level. Crucially, this allows the parameters from one stratum to be partially determined by data from other strata. The autoregressive term in Equation 4 ensures a relationship between the same stratum in successive years as would be expected. Equation 5 makes explicit the fact all parameters identified are drawn from prior sampling distributions – see the *jags* code in Figure S2 for some of the choices made in this paper. Equations 1 – 5 combine to fully describe the data generating process as a function of the parameters. In the most general sense, the probability model can be expressed by $p(\boldsymbol{y}|\boldsymbol{\theta})$ which describes the distribution of the data $\boldsymbol{y}$ conditional on the set of parameters $\boldsymbol{\theta}$.

The second step of a Bayesian analysis is to decide on prior distributions $p(\boldsymbol{\theta})$ which formally quantify the prior knowledge or belief about the model parameters before the data are observed. There are two general approaches to choosing a prior distribution. An *informative prior* expresses a researcher's knowledge about the substantive problem, which could be based on expert opinion or other data. This article instead uses non-*informative* *priors*, which assumes no prior knowledge about the parameters. This is implemented in the analysis by sampling potential parameter values from very broad probability distributions and is described by the third level of the hierarchical model presented in Equation 5 (see Gelman, Carlin, Stern, & Rubin, 2004 for a more detailed description on choosing non-informative priors). Together Equations 1 – 5 describe the three-level hierarchical model, which illustrates how standard probability distributions can be combined to form more appropriate models to describe the complexity of the data generating process. It is worth noting that the joint probability model for parameters is often constructed using assumptions of exchangeability. There are many articles that discuss this important concept and its applications e.g., Gelman et al. (2004). In brief model parameters are exchangeable if their joint distribution is invariant to permutations of indices. One consequence of this assumption is that the exchangeable parameters can be sampled independently from a prior distribution, perhaps governed by an unknown parameter vector. Consider the prior model parameter vector $\boldsymbol{\beta}$ of Equation 3 and suppose there are $i = 1 \cdots \mathrm{I}$ strata. We have no information to distinguish any $\boldsymbol{\beta}_i$ apart from sample size, and we do not want to do so: these parameters are intended to pool information across strata. All are therefore sampled independently from a vague (broad) normal distribution as can be seen in the *jags* code shown in Figure S2. In contrast, completion rates λ are modelled non-exchangeably since they are drawn from gamma distributions with stratum-dependent parameters.

The third step in a Bayesian analysis is to observe the data and update the beliefs about model parameters by constructing the posterior distribution of the parameters of interest using Bayes law. More specifically, the posterior distribution of the parameters $p(\boldsymbol{\theta}|\boldsymbol{y})$ is constructed using the following relationship

$$p(\boldsymbol{\theta}|\boldsymbol{y}) \propto p(\boldsymbol{\theta})L(\boldsymbol{\theta}|\boldsymbol{y})$$

where $L(\boldsymbol{y}|\boldsymbol{\theta})$, the likelihood function, uses the data model $p(\boldsymbol{y}|\boldsymbol{\theta})$ to derive the joint probability of the observed data as a function of the parameters. The posterior distribution is obtained by multiplying the prior distribution $p(\boldsymbol{\theta})$ by the likelihood and then normalizing the resulting expression to integrate or sum to one (since it is a probability distribution). The final step is to summarize the posterior distribution in a meaningful way. In this article, point estimates were computed as the median of the posterior distribution while the degree of uncertainty was expressed as the end points of the interval corresponding with the 5^{th} and 95^{th} percentiles of the posterior distribution (often referred to as credible intervals).

In simple cases the parametric form of the posterior distribution can be explicitly derived, and summaries (e.g., means and uncertainties) can be computed from it. For example if it is reasonable to assume that the prior and likelihood distributions have the same functional form (conjugacy: see Gelman et al. (2004)) the parametric form of the posterior distribution can be inferred. Usually such assumptions are not possible and some form of posterior simulation such as Markov chain Monte Carlo (MCMC) is necessary. One particular Markov chain algorithm, the Gibbs sampler (see e.g., Gelman et al., 2004) as implemented in the *jags* software package, is used in this article.

Gelman et al. (2004) note that for Bayesian models in general "the posterior distribution is centred at a point that represents a compromise between the prior information and the data, and the compromise is controlled to a greater extent by the data as the sample size increases". For hierarchical Bayesian models in particular the posterior distributions of parameters can be viewed as a compromise between two extreme approaches to estimation: "no pooling", and "partial or complete pooling" of strata (see chapter 12 in Gelman & Hill, 2007 for a discussion of this point). This feature is known as *shrinkage* and is demonstrated in Equation (6), which shows that for the models used in this article the completion rate mean within a given stratum is a weighted average of the observed empirical completion rate within that stratum (no pooling) and the mean completion rates estimated by pooling information across more than one stratum (partial pooling).

As an example consider undergraduate completion rates in the non-STEM faculty group. The component of **β** representing (linear) temporal effects is estimated using information pooled across all non-temporal and non-ethnic stratum combinations (gender x pDoS). Put another way, the prior model is a smoother representation of temporal effects than is provided by empirical stratum-specific completion rates. Posterior completion rates for each analysis stratum are a "blend" of the empirical rate from that stratum and the predictions of the prior model with expectation defined by equation (6).

Figures S1a and S1b show posterior estimates of the shrinkage parameter B_{tj} defined by equation (7) for undergraduate degrees. In all cases, estimated shrinkage parameters are usually greater than 0.5, suggesting that the prior model has a dominant influence on expected posterior completion rates (via equation (7)). Consequently there is significant smoothing of posterior completion rates. Within that general observation, the shrinkage parameters for MP students are typically greater than for non-MP students. Similarly shrinkages for STEM students are usually greater than for non-STEM students as one would expect given the smaller number of MP than non-MP students, and STEM than non-STEM students. Generally speaking, in strata with small numbers of students we find the estimated variance parameter ζ to be large compared with the number of students predicted by the prior model ($\mu_{tj}S_{tj}$) and B_{tj} to be close to 1. While shrinkage is not specifically a Bayesian concept (Greenland, 2008), in the model presented here the influence of data and prior model on the posterior distribution is particularly simple, at least in terms of expectations.

Unlike frequentist inference Bayesian inference does not rest on assumptions of repeated sampling and the asymptotic properties of the statistical procedures. Instead, it provides inferences that are exact, conditional on the data and model, without reliance on asymptotic approximations or large sample sizes. Estimates and uncertainties are therefore more reliable than their frequentist counterparts, particularly for small sample sizes. This property further strengthens the applicability of Bayesian modelling to minority populations. Hierarchical Bayesian estimation has also been shown to have greater out-of-sample predictive accuracy (Gelman, 2006). That is, hierarchical estimates are expected to be less affected by random variation and to more accurately predict completion rates and rate ratios in the future (say). Furthermore, hierarchical Bayesian methods have good variance reduction properties (Best, Richardson, & Thomson, 2005; Greenland, 2008) and credible intervals derived from them would be expected to be reliable measures of uncertainty.

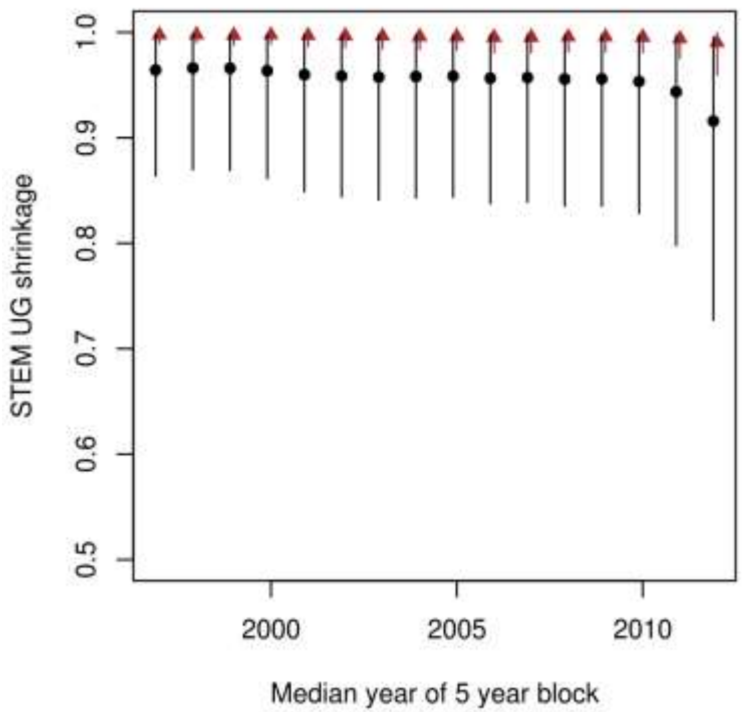

Figure S1a: Māori-Pacific (MP: triangles) and non-MP (circles) shrinkage parameters in the STEM faculties.

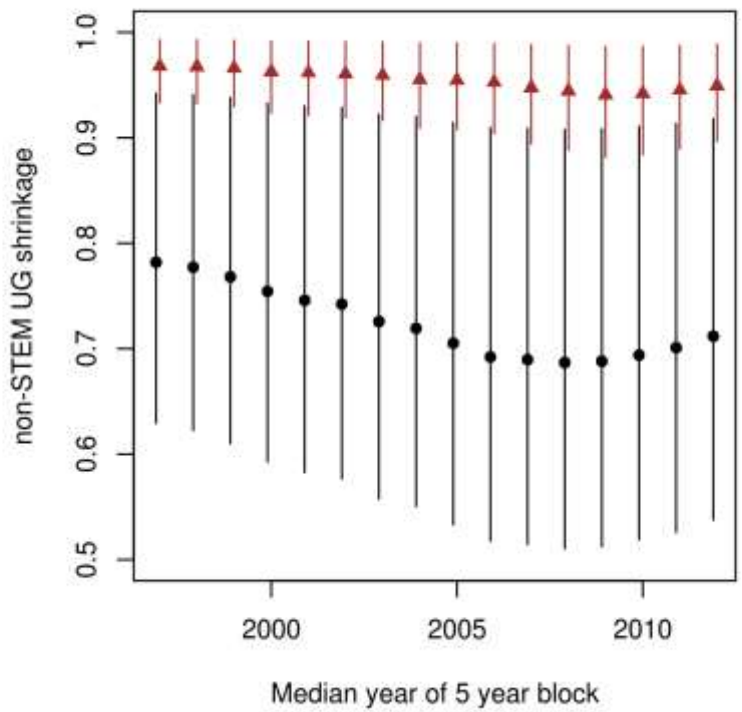

Figure S1b: Māori-Pacific (MP: triangles) and non-MP (circles) shrinkage parameters in the non-STEM faculties.

```
var nQuals[I], StudyTime[I], theta[I], lambda[I], a[I], b[I], mu[I], shrink[I], beta[9], zeta, shrink0,
sigbeta, e[16],   mu.e[16], p, p1, rho;
model {
 for (i in i:I) {
  nQuals[i] ~ dpois(theta[i])
  lambda[i]  ~ dgamma(a[i],b[i])
  theta[i] <- lambda[i]*StudyTime[i]
  a[i] <- zeta
  b[i] <-  zeta/mu[i]
#Prior model linear predictors
  mu[i] <- exp(beta[1] +  beta[2]*DoSstartf1[i] + beta[3] *DoSstartf2[i] + beta[4]*DoSstartf3[i] +
        beta[5]*DoSstartf4[i] + beta[6]*TotMPTRUE[i] + beta[7]*GenderfM[i] + beta[8]*Yr[i] +
        beta[9]*TotMPTRUEXYr[i] + e[YrNdx[i]])
  shrink[i] <- zeta/(zeta + mu[i]*StudyTime[i])
 }
#Specify the common uniform shrinkage prior for zeta via a uniform  prior for shrink0 and then use
#the relationship between shrink0 and zeta to obtain zeta from z0 (eqn 4, Christiansen & Morris)
#with zeta0 set to 500
 shrink0 ~ dunif(0, 1)
 zeta <- 500*shrink0 / (1-shrink0)
#Specify uninformative priors for the beta hyper-parameters using
#Normal distributions with large variance (small precision).
 for (k in 1:9) {
        beta[k] ~ dnorm(0.0, 1.0e-6)
 }
#Allow for AR(1) errors in yr
 e[1]  ~  dnorm(mu.e[1], p1)
 mu.e[1] <- 0
 for (t in 2:16) {
        e[t] ~ dnorm(mu.e[t], p)
        mu.e[t] <- rho*e[t-1]
 }
 rho ~ dunif(-1,1)
 p1 ~ dgamma(1, 0.001)
 p ~ dgamma(1, 0.001)
}
```

Figure S2: *jags* implementation of the HB model for undergraduate completion rates in the non-STEM faculties. I is the total number of strata (=320 for Yr (16) x TotMP (2) x Gender (2) x DosStart (5)); nQuals = total number of completions in each stratum. Data read from an external file are represented by variables in capitals/lower case. These are: I, nQuals, StudyTime, Yr; DosStartf are the 4 non-zero levels of an R factor variable with 5 levels; TotMPTRUE is the TRUE component of an R logical variable; GenderfM is the male level ('M') of an R factor with levels 'F' and 'M'; the interaction between ethnicity and Yr is represented by the variable TotMPTRUEXYr; YrNdx[i] generates the correct Yr value for stratum i.

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