Experiments with crossed effects in marketing-communication research: What do the experimental settings tell us?

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Abstract
Experimental designs often are analyzed using a Repeated Measures ANOVA. Yet, this method does not suffice to describe all variance in a crossed effects experiment. Responses are generated from the same subjects and simultaneously those responses will be collected for the same stimuli, exposing the independence of the observations and the generalizability of the results. The current study contributes to this methodological concern by reanalyzing data from previous research with a mixed-effects model with 'subject' and 'stimulus' as random effects. That model realizes a significantly improved descriptive and predictive power, unveiling a substantial effect of stimuli on the experimental outcome.

Key words: *crossed effects experimental design, mixed-effects model, marketing-communication research*

Track: *Modeling and Marketing Analytics*

1 Introduction

There is a burgeoning interest in marketing-communication research for experimental designs (Alhabash & Wise, 2012; Janssens et al., 2011; Krakowiak & Oliver; 2012; Mazodier, Quester, and Chandon, 2012). Because of their strictly controlled settings, experiments enable the inference of causal relations between variables, which are more conclusive than the correlational findings of inquiries and observational studies. In the present contribution, a methodological issue related to experimental designs will be raised. We will argue that Repeated Measures ANOVA (RM ANOVA) is not suited to simultaneously model all sources of variance in a crossed effects experiment, jeopardizing the generalizability of the results. We will reanalyze an existing experiment in marketing-communication research (Janssens et al., 2011) to demonstrate that mixed-effects models are more suited to accurately model the distinct sources of variance in an experimental crossed effects design.

2 Problem statement: variance in experimental designs

In experimental research, the most commonly used statistical technique is RM ANOVA to include the variance between the subjects in the model (Alhabash & Wise, 2012; Janssens et al., 2011; Krakowiak & Oliver; 2012; Mazodier, Quester, and Chandon, 2012). Since subjects generally respond to multiple stimuli, the assumption of independence of observations is violated in experiments. To put it differently, the responses generated by the same subject will tend to show a certain degree of internal homogeneity and will tend to differ from the responses generated by the other subjects. However, RM ANOVA models overlook one important source of variance that has to be represented to further structure the error, namely the stimuli. Responses to the same stimulus can be expected to show a certain degree of internal consistency over the subjects and differ from the responses to the other stimuli.

In a crossed effects design, all subjects participating in the experiment respond to the same set of stimuli. Consequently, the observations display a twofold dependency since they are grouped under the subjects, each subject responding to the same set of stimuli, as well as under the stimuli, each stimulus being responded to by the subjects participating in the experiment. Therefore a statistical model is required that includes both sources of variance simultaneously in order to generalize the results beyond the sample of subjects as well as beyond the sample of stimuli used in the experiment. This is impossible in a RM ANOVA where only one source of variance is modeled, generally the subjects. In psychological research, different solutions have been proposed to overcome this problem, such as the F1 and F2 statistics and the F'_{min} statistic. However, all these solutions face different problems that can be overcome by using mixed-effects models (see Baayen et al. (2008), Quené & Van den Bergh (2008) and Richter (2006) for a discussion). Finally, the sphericity and homoscedasticity assumptions of RM ANOVA, which appear not always to be tested, do not apply to mixed-effects models.

Mixed-effects models are characterized by the combination of fixed and random effect terms (Gelman & Hill, 2007; Pinheiro & Bates, 2000). Fixed effect terms exhaust all levels of a parameter. Hence, their values cover all values in the population, such as gender which is male or female. Random effect terms are sampled from a larger population and therefore only represent a sample of the actual population. Fixed effect terms are modeled by means of contrasts and random effect terms are modeled as random variables with 0 as mean and an unknown variance ($N(0,\sigma^2)$). Mixed-effects models allow to account for the non-independence of observations by inclusion of random effects corresponding to the grouping variables, viz. the subjects and the stimuli in the experiment, so that correlations between observations are directly modeled.

In this contribution, we will fit a random intercept model, where a separate intercept is estimated for every value of the grouping variables, viz. the subjects and the stimuli in the experimental design. This boils down to a correction for each subject and each stimulus according to the deviation of their variance to the overall mean variance (represented by the overall intercept in the fixed part of the model).

3 Case study

3.1 Original experiment

The main purpose of the original experiment was to investigate whether exposure to a mating cue induces perceptual readiness (Janssens et al., 2011). To this end, subjects were briefly exposed to 10 visual stimuli. Each stimulus was a display consisting of six products. Subsequently the subjects were instructed to list as many products as they could recall (Roskos-Ewoldsen & Fazio, 1992). Of the six products within a given display, one product was associated with a high status. The hypothesis predicts that exposure to a mating cue will automatically divert attention towards that object in the visual display that evokes a high social status and that this will be especially the case for single men as opposed to men involved in a committed relationship. Male subjects were exposed to either a sexily dressed female experimenter or a plainly dressed female experimenter before engaging in a visual status display task.

Fournier & Richins (1991) found that materialists often prefer consumption of high status associated goods. In a similar vein, Richins (1994) showed that people high in materialism are more likely to place greater importance to expensive goods and goods that communicate prestige than people low in materialism. Thus, it seems very reasonable that attention to high status goods, often expensive luxury items (Richins & Dawson, 1992; Wang & Wallendorf, 2006), may be a suitable indicator of materialism. Therefore, a computerized visual display task was used to measure participants' attention to status (Roskos-Ewoldsen & Fazio, 1992). This task measures the attention people have for certain displayed objects. This visual attention task was used to measure people's attention to and interest in status goods. Participants were instructed that they would be exposed to six products displayed on a computer screen for a short period of time and were asked to recall as many products as possible. They were exposed to ten different displays, each consisting of six different product pictures. Each display remained on the screen for one second and comprised one picture of a status product (e.g. Breitling watch, Porsche, exclusive mansion) and five pictures of functional products (e.g. stapler, towel), randomly arranged in a circle on the computer screen. After exposure to each display, participants had 25 seconds to write down as many products as possible after which they were exposed to the next display.

The experimental condition, viz. the presence or absence of a mating cue, was manipulated through the clothing of the female who led the experiment. Two conditions were created, to which subjects were randomly assigned: the experimenter was either plainly (control condition) or sexily dressed (mating cue condition).

To check to what extent the subjects were involved in a (serious) relationship their relationship status was asked. Responses were made using a 7-point Likert scale, ranging from 1 (*I am single*) to 7 (*I am married*). Each participant received a dichotomous relationship status score: single (n = 72) (responses < 3) or in a committed relationship (n = 61) (responses > 3).

One hundred and thirty-three male heterosexual students participated, varying in age from 17 to 32 years (*M* = 20, *SD* = 1.79). Of these participants 70 (52.6%) were assigned to the control condition (exposed to plainly dressed young woman), and 63 (47.4%) to the mating cue condition (exposed to sexily dressed young woman).

3.2 Data matrix

The original data matrix has to be adapted since both the subjects and the stimuli have to be simultaneously included as parameters in the model equation in order to appropriately structure the crossed effects design of the experiment. In the RM ANOVA with an error term for subjects, an aggregate stimulus score is computed per subject over the 10 stimuli by adding the successful recalls of the status product. This procedure suggests that every subject was presented only one stimulus rather than that the same 10 stimuli were presented to every subject, as it was actually the case.

To fit a mixed-effects model, every combination of subjects and stimuli has to be made explicit in the data matrix to reflect the variance due to both the subjects and the stimuli. This results in an expanded data matrix: instead of *i* rows, viz. one per subject (*n* = 133), the matrix contains *i* x *j* rows, viz. one for every subject x stimulus combination (*n* = 1,330). When generating a contingency table for subjects (row variable) and stimuli (column variable), the crossed effects design of the experiment – every subject responding once to every stimulus – now clearly shows up, as illustrated in table 1:

	s01	s02	s03	s04	s05	s06	s07	s08	s09	s10
p1097	1	1	1	1	1	1	1	1	1	1
p4420	1	1	1	1	1	1	1	1	1	1
p5626	1	1	1	1	1	1	1	1	1	1
p6001	1	1	1	1	1	1	1	1	1	1
p6313	1	1	1	1	1	1	1	1	1	1
…	…	…	…	…	…	…	…	…	…	…

Table 1: Contingency table summarizing the crossed effects design in adapted data matrix

Moreover, the level of measurement of the response variable is changed from numerical (sum of successful recalls of the 10 high status products per subject) into binomial (success vs. failure for the recall of the high status product for each stimulus by each subject). Consequently, we need the mixed-effects variant of a logistic regression, a generalized linear mixed-effects model (GLMM) (Gelman & Hill, 2007), with the odds $^{\text{success}}/_{\text{failure}}$ for the recall of the high status product as response variable.

3.3 Case study revisited

The original study using the RM ANOVA with subjects as random effect term will be reanalyzed by means of a GLMM with relationship status (`relation`) and mating cue (`condition`) as fixed effect terms and subject and stimulus as random effect terms. The GLMMs will be fitted by means of the `lme4` library (Bates, 2005; Bates et al., 2013) in R. To be more precise, two GLMM models will be estimated. First, a model with only subject as random effect (`glmm1`) will be fitted as non-numerical pendant of the RM ANOVA in Janssens et al. (2011). Next, the full GLMM model will be fitted with both subject and stimulus as random effects (`glmm2`). Both models are random intercept models, where only the intercept can vary over the values of the random effect terms.

We start by inspecting the coefficients of the fixed effect terms. The data in table 2 show that the major split is caused by the removal of the aggregation over the stimuli, since the main effect of relation is significant in both GMLLs as opposed to the RM ANOVA. Furthermore, the differences between both GLMMs are limited to slight modifications of the regression coefficients.

Parameter	**`rm.anova`**	**`glmm1`**	**`glmm2`**
`condition`	`NS`	`NS (0.13)`	`NS (0.17)`
`relation`	`NS`	`** (0.43)`	`** (0.56)`
`condition*relation`	`*`	`* (-0.51)`	`* (-0.66)`

Table 2: Significance (coefficients) of fixed effect terms in RM ANOVA and GLMMs

Although the data in table 2 seem to suggest a minor impact of the inclusion of a random effect term for stimulus in the model, the model statistics yield a different image. First of all, the inclusion of the random effect term for stimulus realizes a highly significant reduction of the variance, as shown in table 3:[1]

```
Models:
glmm1: hs.recall ~ relation * condition + (1 | subject)
glmm2: hs.recall ~ relation * condition + (1 | stimulus) + (1 |
subject)
      Df    AIC    BIC  logLik  Chisq Chi Df Pr(>Chisq)
glmm1  5 1742.0 1767.9 -865.97
glmm2  6 1492.4 1523.6 -740.21 251.53      1  < 2.2e-16 ***
```

Table 3: Model comparison between both GLMMs: descriptive power

These findings are corroborated by the comparison of the index of concordance (*c* index) of both models: whereas the model with only subject as random effect term has a rather unsatisfactory *c* index of 0.5933 (95% CI = [0.5915;0.5951]), the model with two random effect terms displays a highly satisfactory *c* index of 0.8078 (95% CI = [0.8065;0.8091]).[2]

The model statistics clearly support the model with both random effects (`glmm2`). Let us now have a closer look at the random part of this model.

```
Random effects:
 Groups      Name        Variance Std.Dev.
 subject     (Intercept)  0.18367  0.42857
 stimulus    (Intercept)  1.13734  1.06646
Number of obs: 1330, groups: subject, 133; stimulus, 10
```

Table 4: Random effects in `glmm2`

In order to gage the proportion of the total variance explained by the random effects, we will compute the intra-class correlation coefficient (ρ) for both random effects. Again, the figures show that the impact of the subjects ($\rho = 0.0793$) is outreached by the impact of the stimuli ($\rho = 0.4914$), which are responsible for almost half of the variance in the model. It is common in experimental research that random effects account for substantial proportions of the overall variance, but generally it are the subjects rather than the stimuli who account for the major part of the variance.

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[1] An ANOVA with χ^2 as test statistic was performed on the difference between the log likelihood (`logLik`) of both GLMMs multiplied by -2, which follows a chi-squared distribution.

[2] The *c* index computes the area under the Receiver Operating Characteristic curve, that plots the true positive rate against the true negative rate. When interpreting the *c* index ($c \in [0.5;1.0]$), $c \geq 0.8$ is considered to be indicative of a very good model.

The effect of both random parameters is shown in figure 1, were the random intercepts of the subjects (plot above) and the stimuli (plot below) are visualized with their 95% CI in grey. The dotted black horizontal line represents the overall intercept which is the mean of all random intercepts. Please notify that the random effects rather than the coefficients of the intercepts are plotted, which implies that they identify the deviations from the overall intercept (dotted line in both plots) which is the mean of all the random intercepts and equals 0 (cf. section 2). In the plot above, we can observe that the subjects display moderate variance and that all CIs cross the overall intercept. As suggested by the above-mentioned results, more clear-cut differences emerge from the plot for the stimuli. On the one hand, the intercept of 6 out of 10 stimuli significantly differs from the overall intercept (stimuli s01, s03, s06, s07, s08, s09). On the other hand, two distinct clusters of stimuli with significantly different random intercepts arise ({s01, s03, s08} vs. {s02, s04, s05, s06, s07, s09, s10}).

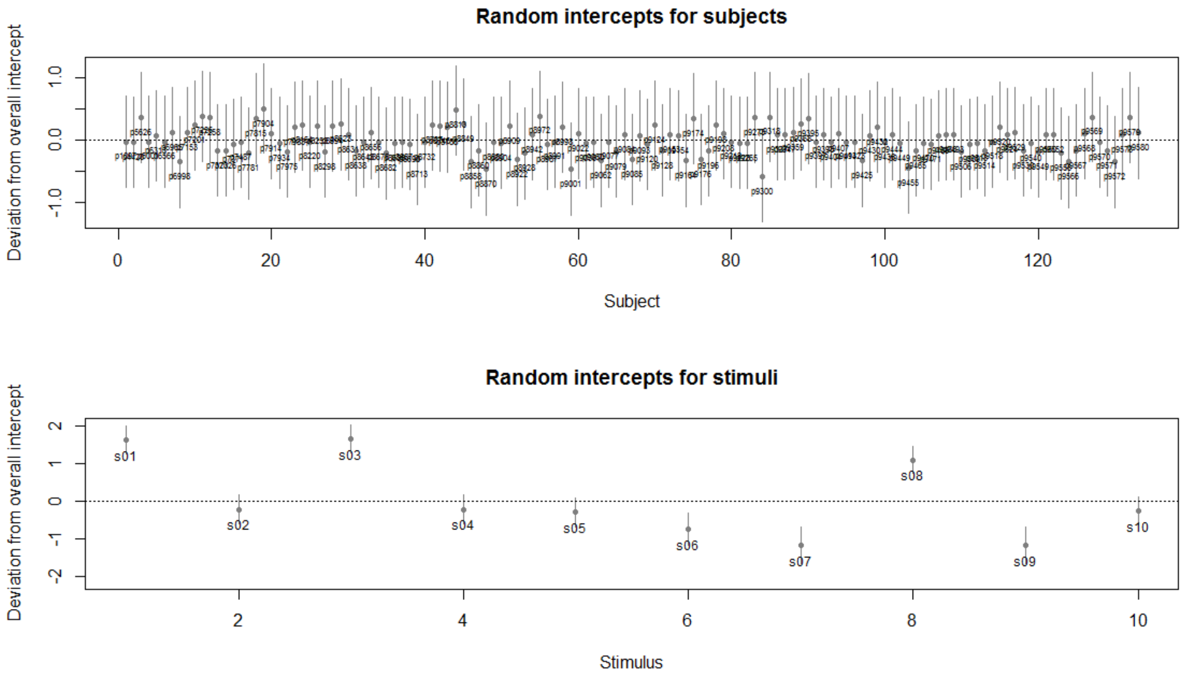

Figure 1: Plots of deviations of random intercepts for subjects and stimuli from overall intercept

4 Discussion

The present research hypothesized that RM ANOVA is not the technique best suited to model variance in an experiment with crossed effects. Although coefficients and their p-values hardly differ, the inclusion of the second random effect term for the stimuli significantly improved the descriptive and predictive power of the model due to the further structuring of the error term. Results show that the baseline values for the stimuli display significant differences from the overall baseline value of the model and that baseline values of the stimuli mutually differ significantly. These findings are overlooked in a RM ANOVA with random effect for subjects only. Moreover, the high intra-class correlation for stimulus clearly proves that the subjects' responses show a high degree of intra-group closeness: observations for the same stimulus are similar on different subjects and simultaneously different from the observations for other stimuli.

The GLMM has unveiled a significant effect of the stimulus on the successful recall of high status goods, suggesting an impact of the screen position of the goods.

Further research will proceed along the following two lines. Firstly, it will be tested whether the present GLMM model can be improved by including random slopes allowing the fixed effect terms to vary across subjects and stimuli. Secondly, to fully understand the role of the stimuli, the impact of the screen position on the successful recall rate will be investigated.

In short, the results argue for a well-considered selection of the statistical technique in experimental research in order to represent the characteristics, especially the non-independence of the observations, of the research design to obtain the best fitting model and to maximize the generalizability of the results.

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