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Dissertação de Mestrado

EXCUSE GIVING, SOCIAL DECISION MAKING, AND BAYESIAN STATISTICS: THE MATHEMATICAL PSYCHOLOGY OF AN ATTRIBUTIONAL PROCESS

Víthor Rosa Franco

Brasília, 23 fevereiro de 2017

Excuse giving, social decision making, and Bayesian statistics:
The mathematical psychology of an attributional process

Desculpas, tomada de decisão social e estatística Bayesiana:
A psicologia matemática de um processo atribucional

Víthor Rosa Franco

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Orientador: Prof. Dr. Fabio Iglesias

Comissão Examinadora:

Prof. Dr. Fabio Iglesias
Programa de Pós-Graduação em Psicologia Social, do Trabalho e das Organizações
Universidade de Brasília - UnB
Presidente

Prof. Dr. André Luiz Marques Serrano
Programa de Pós-Graduação em Ciências Contábeis
Universidade de Brasília - UnB
Membro externo

Prof. Dr. Ronaldo Pilati
Programa de Pós-Graduação em Psicologia Social, do Trabalho e das Organizações
Universidade de Brasília - UnB
Membro interno

Prof. Dr. Jacob Arie Laros
Programa de Pós-Graduação em Psicologia Social, do Trabalho e das Organizações
Universidade de Brasília - UnB
Membro suplente

Brasília, 23 fevereiro de 2017

DEDICATÓRIA

Dedico esta dissertação a todos aqueles que abrem mão de suas verdades pessoais em busca do conhecimento verdadeiro.

Oh honey I'm searching for love that is true,

But driving through fog is so dang hard to do.

Please paint me a line on the road to your heart,

I'll rev up my pick up and get a clean start.

John Kruschke (about Bayesian data analysis)

It's frightening to think that you might not know something, but more frightening to think that, by and large, the world is run by people who have faith that they know exactly what is going on.

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CONTENTS

INDEX OF TABLES

INDEX OF FIGURES

ABSTRACT

In line with an emerging paradigm, theorization in psychology should not be restricted to verbal descriptions of thought and behavior. If phenomena can be somehow expressed by numbers, theory must adopt mathematical and probabilistic reasoning, in a way that traditional data analysis cannot accomplish. While often implemented in theories of decision making, signal detection and item response, mathematical and probabilistic reasoning are rarely identified in important socio-psychological processes. Excuse giving occurs when someone tries to disengage one's self from the cause of a social fault. It is an impression management strategy mostly explained by attributional theory, not yet subjected to a mathematical psychological approach. The main objective of this thesis was to formalize and test part of Weiner's attributional theory as a social decision making process. By using dichotomous judgment tasks of usability and distance evaluation of adequacy, consequences and assumptions of excuse giving were assessed in two studies. Study 1 (n = 63) was aimed at explaining why people prefer external over internal excuses. Bayesian multidimensional scaling identified that external and internal excuses occupy different psychological spaces. Also, a quantum model of order effects fitted the data well, which means that the preference of excuse types could be predicted by the quantum principle of interference. Study 2 (n = 92) was conducted to formally characterize excuse giving as an impression management process. It is congruent with attributional theory, where motivational latent variables predict which excuse type people would rather use. A Bayesian latent mixture model showed that people indeed preferred external excuses, but only when highly motivated to be excused. The findings of this thesis make it possible to make better inferences about how people excuse themselves. As measured in a psychological space, people differentiate excuses given their level of adequacy, being the consequences of this differentiation moderated by the motivation one has to manage a relationship. Furthermore, using an excuse can be affected by taking into account its consequences and in which order they are evaluated. Further investigation should study if these inferences are generally valid. Some aspects of attributional theory remain unexplored from a mathematical psychology perspective, which could help clarify the often puzzling evidence in the literature. Applications of excuse giving and social decision making are discussed.

Keywords: excuse giving; attribution theory; formal theorizing; cognitive modeling; Bayesian analysis.

RESUMO

De acordo com um paradigma emergente, a teorização em psicologia não deve ser restrita a meras descrições verbais de como nos comportamos e pensamos. Se os fenômenos podem ser de alguma forma expressos por números, a teoria precisa também adotar um raciocínio matemático e probabilístico, algo que a análise tradicional de dados não pode realizar. Embora natural no avanço das teorias de tomada de decisão, de detecção de sinal e de resposta ao item, entre outras áreas, isso raramente é identificado em importantes processos sociopsicológicos. Desculpar-se é o processo de desvencilhar a si mesmo da causa de uma falha social. É uma estratégia de gerenciamento de impressões, em grande parte explicada pela teoria atribucional, a qual ainda não foi submetida a uma abordagem de psicologia matemática. O objetivo principal desta dissertação é formalizar e testar parte da teoria atribucional de Weiner como um processo de tomada de decisão social. Isso foi feito ao se avaliar as hipóteses sobre as consequências e pressupostos no contexto de desculpas em dois estudos, usando tarefas de julgamento dicotômico sobre usabilidade e tarefas de julgamento de distâncias de adequação. O Estudo 1 foi conduzido para explicar por que as pessoas preferem desculpas externas ao invés de internas. Utilizando o escalonamento multidimensional Bayesiano, 63 participantes permitiram identificar que as desculpas externas e internas ocupam diferentes espaços psicológicos. Além disso, um modelo quântico de efeitos de ordem teve um bom ajuste aos dados, o que significa que a preferência de tipos de desculpas pode ser predita pelo princípio quântico da interferência. O Estudo 2 foi conduzido para caracterizar formalmente o processo de se desculpar como um processo de gerenciamento de impressões. Isto significa, e é congruente com a teoria atribucional, que a variável latente motivacional deve prever qual tipo de desculpa as pessoas preferem usar. As respostas de 92 estudantes de graduação foram modeladas através de um modelo Bayesiano de mistura latente. Os resultados mostraram que as pessoas realmente preferem desculpas externas, mas somente quando altamente motivadas para serem desculpadas. Os achados desta dissertação mostram que as pessoas diferenciam as desculpas de acordo com seu nível de adequação, medido em um espaço psicológico. Esta diferenciação é moderada pela motivação que se tem de gerenciar um relacionamento. Finalmente, o uso de uma desculpa pode ser afetado pelas possíveis consequências que são levadas em conta, e em que ordem elas são avaliadas. Pesquisas futuras precisam avaliar a possibilidade de generalização dessas inferências. Além disso, aspectos da teoria atribucional permanecem inexplorados a partir de uma perspectiva de psicologia matemática, os quais poderiam ajudar a esclarecer evidências ambíguas na literatura. Aplicações do uso de desculpas e tomada de decisão social são discutidos.

Palavras-chave: desculpas; teoria de atribuição; teorização formal; modelagem cognitiva; análise Bayesiana.

EXCUSE GIVING, SOCIAL DECISION MAKING, AND BAYESIAN STATISTICS: THE MATHEMATICAL PSYCHOLOGY OF AN ATTRIBUTIONAL PROCESS

"I am sorry, but I am just very lazy". According to empirical findings by Weiner (2006), many people would hardly accept an excuse like that from someone who refused to help in a difficult time. These empirical findings also show that excuses with external causes, based on situational justifications, are usually, and by large, preferred over excuses with internal causes, based on dispositional justifications. Despite the large use of Weiner's attribution theory (1995) to explain those findings, recent evidence shows moderating effects that affect the overall logic for the attribution theory (e.g., Pilati et al., 2015).

The psychological mechanism of attribution theory applied to excuses is theorized mainly by verbalizing. This means, in plain English, that it is based largely in a "good idea" and indirect inferences of implied relations between variables are verbally reported. Therefore, the study of excuses, and the attribution theory itself, could be invigorated with the practice of formal theorization—the use of logic and mathematics to describe theories (Devlin, 2012).

Mathematics is the language of quantities and patterns (Pasquali, 2001). Traditionally, in psychology as a whole, mathematics and statistics are mostly used to analyze data. The theorizing is mostly verbal, which means that phenomena are explained without formalization (Adner, Polos, Ryall, & Sorenson, 2009). Nevertheless, as empirical sciences mature, theoretical and empirical progress often leads to the development of formal models—in psychology, they can be called cognitive models. This happens as a consequence of the need to describe quantities and patterns, which are hard to describe with natural language. To a data scientist, as a mathematician or a statistician, cognitive models remain naturally interpretable as statistical (or mathematical) models, and in this sense modeling can be considered an elaborate form of data analysis. The main difference is that models will formalize processes and parameters that have stronger claims to psychological interpretability (Lee, in press). As a consequence, statistical, mathematical and cognitive models are very alike. It is often possible for a statistical model to have valid interpretations as a method of data analysis and as a psychological model. Similarly, psychological models developed in a specific context can be extended to other applications. This means that different psychological processes may function alike. Therefore, despite the duality, the distinction between data analysis and psychological modeling is a useful one.

Lewandowsky and Farrell (2010) describe three different classes of quantitative models. The first is data description. As the name suggests, they only describe relations of variables. They are explicitly devoid of psychological content, although the modeled function constrains possible psychological mechanism to the phenomena. The second is process characterization. These models postulate and measure distinct cognitive components. Yet, they are neutral about how specific instantiations underpinning the cognitive components work. Finally, we have process explanation. Like characterization models, their advantage stands on hypothetical cognitive constructs. However, they provide detailed explanation about those constructs. Summing up, descriptive models tell us that variables are somehow related. Characterization models tell us what processes originate the variables relations. Explicative models tell us how exactly variables are related. Each model has its advantages and drawbacks. It is up to the research problem, and the researcher, to define which will suit better the data available.

Here we investigate psychological aspects of excuse giving by applying formal theorization. The present dissertation is organized in two independent manuscripts, following the American Psychological Association guidelines for submission to scientific journals. Manuscript 1 describes a survey, aimed to testing two explicative models for excuse giving: distances in psychological spaces for control loci differentiation and quantum cognition of preferences for excuse type. Manuscript 2 describes another survey, aimed to test a Bayesian latent-mixture model, so there is a reported formal characterization of excuse giving as an impression management process.

It should finally be pointed out that these papers are a first attempt to initiate a research program of social decision making, focused mainly on the use of quantitative analysis and, even more, formal theorizing, which is sparse in the psychological literature as a whole (Coleman, 1964; Doignon & Falmagne, 1991; Falmagne, 2005; Lewandowsky & Farrell, 2010). Results from this type of research may have many potential applications to benefit psychology as a science, lowering questionable research practices and also lowering unending debates that cannot be solved with simple discussion of ideas (e.g., Heathcote, Brown, & Mewhort, 2000).

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Representational space and quantum cognition:

Why do people prefer external excuses?

Abstract

Excuses can have external or internal causes. Literature shows that external are usually more acceptable than internal ones. Does this preference stands albeit the use of more precise analysis of preference? This study has two main objectives. First, to test the hypothesis that good and bad excuses are constrained in different psychological spaces by a Bayesian Multidimensional Scaling (BMDS) model. Second, to estimate the preference people should have about two different types of excuses based on a quantum model of order effect. Sixty-three undergraduate students judged the use of external and internal excuses presented in different orders, and eight excuses, evaluated in an adequacy scale. Results showed that external and internal excuses are constrained in different psychological spaces and that preference in excuse-giving context follows a quantum principle of interference. Consequences of those findings make essential that individual differences and their relation with excuses types be further investigated.

Key-words: Excuse-giving; attribution theory; Bayesian Multidimensional Scaling; quantum model of order effect.

Representational space and quantum cognition: Why do people prefer external excuses

Excusing oneself involves two meaningful processes: first, self-evaluations of one's ability and will to act well (Snyder & Higgins, 1988); and second, a perception about one's need to be excused by others (Schlenker, 1980). Although different, both have a convergent purpose - impression management. According to decision making theory, one way of people distinguishing themselves is through their preferences (Dake & Wildavsky, 1991; Levin & Hart, 2003). In an excuse-receiving context, excuses with external causes are generally more accepted than excuses with internal causes (Weiner, 2006). Nevertheless, there are neither direct evidences about excuse-givers preferences nor estimates for the magnitude of this inferred preference.

The study of preferences has been guided mostly by theories that value maximization and assume that each person possesses stable preferences for all possible options—an internal global preference set (i.e., utility theory; Kami, Maccheroni, & Marinacci, 2015; prospect theory; Glöckner & Pachur, 2012). This has a meaningful consequence: despite prescribing a utterly simple set of decision rules, if one does not have a global preference, the application of the principles of value maximization is idle (Tversky & Simonson, 1993).

Moore (1999) argues that actual behavior deviates from predicted behavior by models of value maximization because people do not possess established global preference orderings. The author proposes that, instead of global preferences, people have mental schemas that allow them to generate preferences when called for. Therefore, it is important to know if apparently different alternatives are perceived as such. Also, even if not perceived as different, it is relevant to know whether elements of the same category present different preference orders, one over another.

One method vastly used in psychology to identify the differences between a set of stimuli (or categories of options) is multidimensional scaling (MDS, Young, 2013). It has been used, for example, to study animacy categorization (Sha et al., 2015), organizational values (Smith, Dugan, & Trompenaars, 1996) and stereotyping (Koch, Imhoff, Dotsch, Unkelbach, & Alves, 2016). In summary, MDS can be said to be a method for estimating the distance between objects in a psychological space. In this psychological space, however, positive or negative poles have no meaning–they only represent relative spatial locations (Young, 2013). This makes possible to know if stimuli are differently evaluated, but impossible to infer the valence of the evaluation.

To evaluate the valence of judgments, one can use an order effect paradigm (Moore, 1999). Order effects occur when preferences change given different orders of exposition of the possible alternatives. Thus, formal models of order effects can be used to make inferences about the preferences one has. The task to mathematically model order effects, however, is no easy to classical probability theory apparatus (Aerts & Sozzo, 2011). A growing framework of modeling techniques, called quantum cognition, on the other hand, has been successful to model different types of order effects (Bruza, Wang, & Busemeyer, 2015).

Both modeling techniques, MDS and quantum model for order effects, can show, respectively, how people tell excuse types apart and test the possible preference for one type over another. Therefore, the objective of this study is twofold: testing whether excuses with external and internal causes occupy different psychological spaces; and modeling the relative valence and magnitude of these differences using a parameter-free quantum model of order effects.

Excuse giving and attribution theory

To commit a social fault demands that one uses an impression management strategy known as excuse giving: ideally, you want your relevant ones to know that you did not want to cause harm (Mehlman & Snyder, 1985). When one has to manage his or her impression in an excuse-giving context, deciding between strategies involves, at least, two basic beforehand paths (Weiner, 2006): the cause of your fault was dispositional (internal); or situational (external). This means that the fault can be a consequence of a characteristic that you present (e.g., “Sorry, but I’m lazy”) or an event independent of who you are (e.g., “Sorry, but there was a traffic accident”). Saraiva and Iglesias (2013) have shown, using Weiner’s attribution theory in a Brazilian context, that people tend to accept external excuses more than internal ones. Weiner et al. (1987) have originally identified this same trend, so they labelled external excuses as “good” and internal excuses as “bad”.

From a value maximization point of view, it would be expected that, since external excuses are more likely to be accepted, they should also be more likely to be used. Nevertheless, when excuse-givers use convenient causes, they risk being seen as deceptive, self-absorbed, and ineffectual (Schlenker, Pontari, & Christopher, 2001). This means that, influenced by the context, excuse-givers would have to worry not only with being absorbed, but also with not being perceived as deceivers. Empirically, without a specific relational context, this may have two main consequences: internal and external excuses are differentially evaluated; and excuse-givers will have the same preferences as excuse-receivers.

Difference evaluation and preferences are difficult to be analytically tested (Hunt, 2006). Lewandowsky and Farrell (2010) argued that classical statistical analysis does not allow to making explanatory conclusions about psychological processes. To make inferences about why people differentiate excuse-types and the mechanism the predict preferences estimates, more elaborate models should be used. Respectively, a multidimensional scaling and a quantum model for order effects provide explanations for the psychological processes involved.

Spatial analysis of human mental representations

The study of the how humans distinguish between stimulus domains starts with the concept of human mental representation, or the internal cognitive abstraction that represents external reality (Perner, 1991). Mental representation theory, in turn, is the basis for the MDS model (Shepard, 1974), which has provided psychologically meaningful representations of many stimuli domains (Young, 2013). MDS is a statistical method for finding a spatial representation of a set of objects, based on the (dis)similarities between them, represented in low-dimensional spaces. The distance between each pair of objects is the estimative of similarity between them, so more similar objects are nearer each other than dissimilar ones.

The initial development of the formal theory behind MDS was done by Shepard (1987). His theory centered on how stimulus generalization occurs. Nowadays, not only it is used to study the relation between categorization, identification and learning (Nosofsky, 1992) of stimulus classes, but is also a tool to understand how psychological constructs, such as personality traces (Papazoglou & Mylonas, 2016), are represented in the human mind. Facet theory (Canter, 2012), a systematic approach to facilitating theory construction, is also heavily based on the use of the MDS. However, the present paper is oriented to its original use, estimation of distance between psychological representations, given by Shepard (1987).

Despite all of its successful use, the application of MDS has its limitations, such as restricted capacity to estimate the real distance between representations. Such limitation can be surpassed by Bayesian multidimensional scaling (BMDS, Appendix A), a method developed by Oh and Raftery (2001). The authors propose a series of modifications in the classical MDS and show that BMDS has, at least, three main gains. First, it provides a better fit than classical MDS. Second, it provides a probability distribution of the estimated distances, an exclusive characteristic of Bayesian methods (see Gelman & Shalizi, 2013). Third, the Bayesian criterion for size selection, MDSIC, is a direct method to estimate the optimal dimensionality of the measurements.

The estimation of preferences: Modeling order effects

As a general consensus, preferences are revealed when an option is picked over other ones, dominating it, even when the others are normatively irrelevant (Moore, 1999). In other words, options that are accompanied by a downward comparison to an inferior option are thereby seen as more attractive. The converse of this pattern is the tendency for options to be less popular when they are dominated by other alternatives than when they are not, even if those other alternatives are normatively irrelevant. This is what the paradigm of order effects tries to measure (Xu & Wang, 2008). The modeling of order effects, however, is not a simple task.

Recent research has shown that human decision making is biased by inferences in similar ways to incompatible quantum observables (Busemeyer, Wang & Lambert-Mogiliansky, 2009). Also, judgments about individual preferences are dependent, acting as entangled quantum states (Aerts & Sozzo, 2011). Both series of evidences characterizes the quantum cognition framework. Quantum cognition (QC) is a paradigm stemming from the field of physics for constructing cognitive models based on the mathematical basis of quantum probability theory. This theory, just like the classical probability theory, is also a framework for assigning probabilities to events, based on different assumptions about random events underlying process (see Gudder, 2014).

One important feature of QC models is the complementarity of the measurements (Aerts, 2009). This means, for instance, that the order of a pair of questions presented in a questionnaire may bias the participant response. The mechanism for this consequence is the fact that classical probability necessarily obeys the commutative rule, which states that conditioned probabilities affect each other equally, independent of the order of their computation. Quantum probability, on the other hand, follows the complementarity rule: the measure of a first event produces a context that changes the value of the next event.

Therefore, order effects are a natural consequence of a QC probabilistic model, but not a trivial task for models based on classical probability theory (Busemeyer & Wang, 2015).

Trying to account for order effects, Wang, Solloway, Shiffrin and Busemeyer (2014) introduced a QC model known as quantum model of order effect (QMOE, Appendix B). QMOE is a parameter-free model, which means it has not to estimate any of its parameters from data. Nevertheless, it can be tested using a chi-squared test of the observed order effect and of the a priori forecast assumption, called quantum question equality (QQ). For the former, the test should be significant, but for the latter, the test should be not.

To calculate the effect of order of the answer probability, one only need to subtract the probability of using the internal excuse, as it is presented after the external excuse, from the probability to use the internal excuse when it is presented before the external excuse. If the probability remains the same, no order effect is observed. If the probability increases, there is an additive effect of order. If the probability decreases, there is a subtractive effect of the order (for details on the computation of the QQ, see Wang et al., 2014).

Summating, external excuses are preferred over internal excuses for those who receive than. The same trend may be expected when in the perspective of those who give them. Also, it is necessary to have a more robust analytical method to test this inference. BMDS can be used to show that, in a psychological space, people differentiate those excuse types. QMOE can be used to show what the magnitude of the difference between those excuse types. It is hypothesized that BMDS will show different clusters for internal and external excuses and that QMOE will show a preference for excuses with external causes.

Method

Participants

To test the hypothesis of this study, 63 undergraduate psychology students from a federal institution, with mean age of 20 years (*SD* = 2.17), answered the final questionnaire.

Following Barnett’s (1972) orientation on sample size for MDS, a sample of at least 61 people was sought. Despite this orientation being made for classical MDS, BMDS has better performance with smaller samples sizes (Oh & Raftery, 2001).

Measures

Initially, four judges evaluated 16 written excuses created for this study. There were four contexts, also used by Saraiva and Iglesias (2013), each with four initial excuses, two external and two internal, modified from Weiner (2006). The contexts were related to: being late for an appointment; missing an appointment; having a poor performance on a task; and harming someone. Specific relationship types, as a friendship, were avoided, given that they could bias participants’ responses (Franco, Iglesias, & Melo, 2015). Aiming to keep only the more recognizable excuses—within external and internal categories—any excuse statements that were discordantly judged were excluded. Finally, there were four excuses reflecting a tardy individual and two excuse statements for two other contexts, half external and half internal. The final items used in this study are presented in Table 1.

Table 1

Final excuses according to theoretical locus of control and specific context.

Context	**Internal Excuses**	**External Excuses**
Late for an appointment (Imagine that you arrived late for an appointment and have to apologize)	**Sorry I'm late, but I forgot that we had scheduled that appointment.**	**Sorry I'm late, but I had to call a plumber to fix a leak that appeared today at home.**
	Sorry I'm late, but I wanted to arrive a little later.	**Sorry I'm late, but I came by bus and it broke on the way.**
Missing an appointment (Imagine that you did not attend an event and need to apologize)	**Sorry I did not appear, but this event was not relevant to me so I stood at home.**	**Sorry I did not appear, but I had to take my mother, who got sick, to the hospital.**
Poor performance (Imagine that you had a poor performance in any group task and have to apologize)	**I'm sorry not to have given the best of me, but I did not wanted to worry myself with it.**	**I'm sorry not to have given the best of me, but I was very sick.**
Harming others (Imagine that you caused harm to someone and needs to apologize)	**Excuse me the harm that I caused, even though I knew that it would happen.**	**Excuse me the harm that I caused, but I was trying to fulfill a commitment.**

Procedures

Participants were invited from an email list. They were instructed to answer an online questionnaire with three main parts. First, the late/tardy for an appointment context statements were shown and two of the excuses, internal or external, in random order. In this case, participants should only indicate if they would or would not use the presented alternatives. Second, participants were shown all other contexts and excuses, also in a random order. In this case, they should judge on a scale ranging from 0 to 10, the adequacy of the excuse in the given context. Finally, participants answered questions about their sexes and age, followed by a short debrief.

Results

The hypothesis that people differentiate between external and internal excuses because of their position in a psychological space was tested first. This was done by the application of Bayesian multidimensional scaling (BMDS) model to the data. Gower dissimilarities for ordinal measures (Gower, 1985) were estimated for the distances between excuses, given the nature of the measurement. To perform any Bayesian model, one needs to employ an algorithm that creates a quantity of simulated cases (named as “runs”). The initial cases are discarded (“burned in”) to avoid biased walks based on some initial random value (Gelman, Carlin, Stern, & Rubin, 2014). As the actual calculation of posterior distributions is computationally demanding, algorithms are used to sample–estimate the parameters of the model (see Gelman et al., 2014).

For the present analysis, 35000 runs were set, with a 5000 initial burn in simulations. Those settings assured the convergence of all parameters estimations, according with Heidelberger and Welch (1983) and Geweke (1991) criteria. As for the optimal number of dimensions, MDSIC reached its lowest value at two dimensions, with a value equals to -

38.31 and a Stress equals to .22. For a graphical inspection of the fit, Figure 1 presents clusters of the excuses using BMDS. Internal excuses (I#) are closer from each other and the same trend is observed for external excuses (E#).

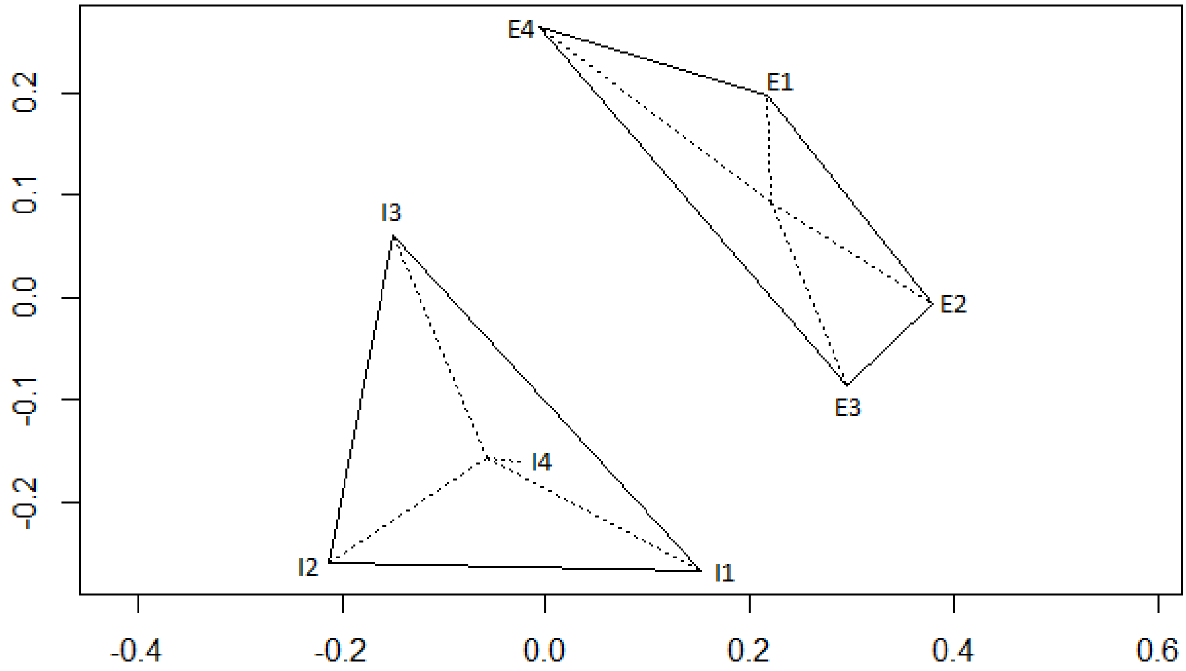

Figure 1. *Clusters of the excuses using BMDS. Internal excuses (I#) are closer from each other and the same trend is observed for external excuses (E#).*

Table 2, on the other hand, shows the estimates for the mean distance for pair of excuses of the same type (Internal-Internal and External-External) and of different types (External-Internal or Internal-External). Finally, it is also shown the estimates for the lower bound and the higher bound of the 95% Bayesian confidence interval, or more commonly, the high density interval (HDI; Kruschke, 2010).

Table 2

Average estimated distance to each type of pair of excuses and their lower (LB) and higher (HB) bounds of High Density Intervals (HDI).

	LB (2.5%)	Mean	HB (97.5%)
I - I	.07	.32	.57

E - E	.06	.31	.56
I - E	.15	.40	.65

The difference of those distributions can be seen in Figure 2. It is possible to see that there is more overlapping between average same excuse type distances (Internal-Internal and External-External) than average different excuse type distances (External-Internal or Internal-External). Bootstrapped paired t-tests were used to test the difference of those distributions (given that all participants judged all the excuses). A 1,000 random samples were performed with size equal to 63 (the sample size of this study). No significant difference was found between Internal-Internal and External-External distances, $t(62) = .41$, $p = .48$, $d = .07$, 95% CIs [-1.65,2.45], [.01,.97], and [-.28,.44], respectively. Nonetheless, the difference between Internal-External and Internal-Internal/External-External distances was significant, $t(62) = 4.03$, $p < .01$, $d = .71$, 95% CIs [2.03,6.35], [3E-8,.04], and [.37,1.09], respectively.

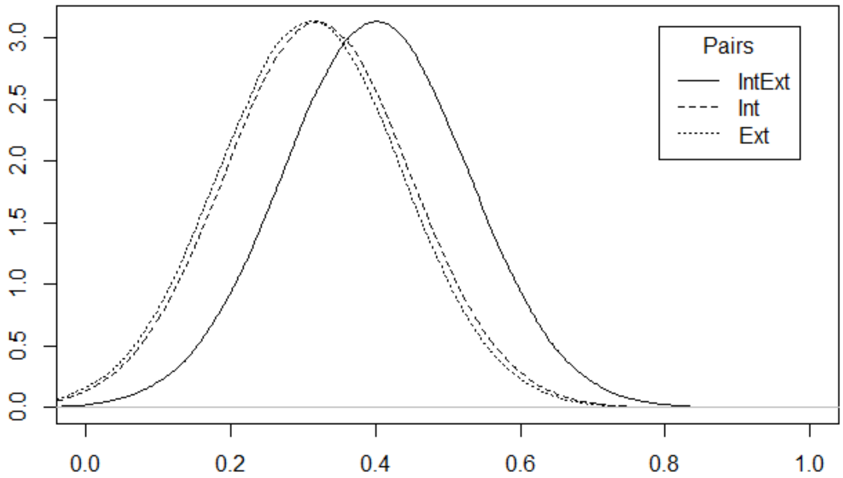

Figure 2. *Density estimations for the average distances between excuses pairs of same excuse type distances (Int and Ext) and of different excuse type distances (IntExt).*

To test the second hypothesis, that excuse–givers have preference for a given excuse type, the quantum model of order effect was applied to data. Contingency tables were constructed to measure the order effect and assure independence of the questions. The order effect was of a magnitude of .015, or 1.5%. Then, discrepancy tests were conducted.

Discrepancy testing follows a chi-squared distribution, but distinguishes itself from Pearson's chi-squared test and traditional chi-square goodness of fit test (see Wang et al., 2014). The order effect was significant, $\chi^2(3) = 7.60$, $p = .05$, and the QQ equality was respected, $\chi^2(1) = .013$, $p = .90$. These findings, and the contingency tables, are shown in Table 3.

Table 3

Contingency tables for estimation of the order effect and the discrepancy tests.

Observed proportions of the two question orders

External-Internal

	Iy	In
Ey	.030	.454
En	.030	.485

Internal-External

	Ey	En
Iy	.000	.033
In	.468	.500

Order effect

	Ey	En
Iy	.030	-.003
In	-.012	-.015

Discrepancy tests

Order effects	$\chi^2(3) = 7.60$, $p = .05$
QQ Equality	q = - .015 $\chi^2(1) = 0.01$, $p = .90$

Discussion

This study had two main objectives. First, to test whether a BMDS model can verify the hypothesis that external and internal excuses are constrained in different psychological spaces. The second was to use a model to estimate the preference people should present about two different types of excuses. To the first one, the BMDS model showed that external and internal excuses, or "good" and "bad" excuses, define different psychological-spatial clusters. This means that people assume different psychological representations, and therefore spaces, to this kind of excuses. To the second one, the quantum model of order effect (QMOE) showed that people have a slight preference for the external excuse.

One motivation to use MDS and BMDS is to have a formal basis for choosing the number of clusters, given a certain number of objects (Oh & Raftery, 2001). This cluster can show that people have a homogeneous process of judgement of excuses. In the present study, participants rated in which degree each excuse fits a given context. This is different from asking them to judge how acceptable each excuse is. Mussweiler (2003) argued that different basis for comparison—either similarities or dissimilarities—affects which final judgment people will make about a group of stimuli.

By focusing on identifying the most relevant features, the goodness-of-fit found in the present study could be sensible to the process of how one retrieves information about the alternatives. For instance, based on Smith and Zarate (1992) exemplar–based model of social judgment, an excuse-giver self-schemata, a social context, and an in-group/out-group dynamics could change which dimension it focus in order to evaluate a given excuse in a more naturalistic set. Therefore, in future studies, it would be relevant not only to try to control which dimension is being evaluated, but also to estimate relevant dispositional variables.

As found by Weiner et al (1987), people present preference for external over internal excuses. Using an order effect paradigm, in the present study, the internal excuse presented a negative order effect (Moore, 2002), which was significant according to the QMOE. This has an important implication. While traditional theory of measurement assumes that psychological measurement is just retrieval of latent information, this study corroborates that context and procedure of measurement may affect measurement itself (Khrennikov, Basieva, Dzhafarov, & Busemeyer, 2014). Again, this a conundrum for classical probability theory, but an easy task for quantum probability models of cognition.

If preferences in an excuse-giving context can be better described within a QC framework, three relevant aspects of how the mind works should be taken into account (Busemeyer & Bruza, 2012). First, judgments and decisions are not simply read out from memory, but rather, they are constructed from the cognitive state for the question at hand. Second, as a consequence, making a judgment or decision changes the context and disturbs (or interferes with) the cognitive system. Thirdly, this change will then affect the next judgment or decision, thus producing order effects. This is the quantum principle of interference (Khrennikov, 2003).

Summing up, further investigation in the excuse-giving context should consider two important issues from the present study. First, excuses may be evaluated in more than one dimension. This evaluation may be sensitive to dispositional characteristics that predict by which dimension (or dimensions) one will react upon to. Second, the decision of which excuse to use follows a quantum principle of interference. Both issues make the case for defining which type of excuse may interact with subpopulations of individuals and how this affects their impression management strategies.

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Who wants to be excused? A Bayesian latent-mixture model of an impression management process

Abstract

People typically feel a need to be excused when they commit social faults. Given that external excuses are usually more acceptable than internal ones, and considering excuse giving as an impression management process, it is plausible to assume that people with different dispositional motivations to be excused will have different patterns of excuse giving. Therefore, the present study has the objective of testing the fit of a Bayesian latent mixture model to a context of excuse giving. Ninety-two undergraduate psychology students judged the usability of four external and four internal excuses presented in random order. Results showed that the model is adequate to explain the pattern of responses in data. Also, that there is more people willing to be excused than people not willing to. Consequences of these findings make essential to identify exactly what motivational content affects decision making, and what is the process behind the choice of the excuse to use.

Key-words: Excuse-giving; attribution theory; Bayesian modeling; latent variable.

Who wants to be excused? A Bayesian latent-mixture model of an impression management process

Solving conflicts in social relationships is an inevitable part of everyday life. A common strategy used in this context is excuse giving, as explanations used for self-serving purposes aiming to reduce personal responsibility for some fault by disengaging core components of the self from an incident (Schlenker, 1980). Weiner (1985) proposed that the excuse process involves how people manage causal attributional perceptions, thus, meaning that the excuse giving can be understood as an impression management process. Weiner, Amirkhan, Folkes and Verette (1987) have also shown that excuses are more efficient if they have properties that make people perceive them as more excusable. Therefore, excuses that imply external, unstable causes are largely more accepted, while excuses that imply internal causes are largely less accepted. However, the literature shows that people not always prefer to use external excuses over internal ones (e.g. Weiner, 2006; Franco, Iglesias & Melo, 2014). A model designed to explain the best variables to predict which excuses will be used is still necessary, so the aim of the present study is to present and test such a model.

Managing your impression with excuses

People evaluate which emotions are elicited on others by their behavior, before taking a course of action. At least that is what is expected from Weiner’s attribution theory (1986). This theory has been successful to explain individual's willingness to engage in information seeking (Savolainen, 2013), reasons for the disruption of commercial relations (Kalamas, Laroche, & Makdessian, 2008), and how perceptions of responsibility are linked to ideology and political attitudes (Sahar, 2014). According to Weiner (2010), the process of causal attribution has seven distinct steps. The most prominent ones are the outcome, the causal ascriptions and the behavioral consequences. The first involves the evaluation of consequences of behaving in a particular way—which emotions one, or others, will feel. The second is about the evaluation of what causes are related to what kind of emotion. At last, there is the decision of what course of action to take. In an excuse giving context, this process can be exemplified as: when one commits a social fault, he/she may consider the real reason (e.g., "I did not want to go"), analyze this explanation for causal properties (internal, controllable, and intentional), anticipate the consequences of communicating that cause (e.g., high anger), and then make an action decision (withhold revealing the real cause) (Weiner et al., 1987). The property of choosing what to do, based on what others will think of you, characterizes excuse giving as an impression management process.

A temptative framework by Leary and Kowalski (1990) on impression management can be matched with the previous attribution process proposal. It actually enables the parallelization of both theories. The authors specified two major components: impression motivation (whether and how much one is motivated to manage one's own impressions); and impression construction (strategies to manage impressions in a given direction). The impression motivation component can be simply defined, in the excuse giving context, as people wanting (or needing) more or less to be excused by to whom they have committed a fault. The logic is: if a person has stronger needs to maintain a relationship, she will optimize the strategies to manage her own impression, while a person with low needs in maintaining a relationship will tend to use worse strategies (Pessoa, 2009). In the excuse giving context, if one has committed a fault and the maintenance of the relationship is something desired, one will tend to use external over internal excuses (Weiner, 2006).

The impression construction component involves a more elaborated procedure, for two main reasons: what could be the strategies used to select the elements that composes the excuse; and what motivational processes could interact with these strategies. This level of the model can be thought as a decision making process, as it involves the conscious selection of some possible choices (Morçöl, 2007). Based on Weiner's attributional theory (1986), the strategies used to select the elements that composes the excuse can involve how people perceive which causes are attributed to their actions, based on the locus of control (external, internal), stability (stable, unstable) and controllability (controllable, incontrollable) implied by the meaning of the construction of the excuse. Motivational processes that might interact with these strategies are the uncertainty, when the outcome is not certainly known, and the risk involved, the possibility of the outcome being harmful, all common characteristics of the excuse contexts (Dow & da Costa Werlang, 1992). A “utilized” signal detection theory based model can be used to describe this component, as it is particularly useful in predicting responses in situations of uncertainty and risk (Lynn & Barrett, 2014).

At least two models can be proposed for the excuse giving process given those components: one that predicts the excuse people use only by the motivation they have to do it; and one that calibrates the elaboration of the excuse by the motivation people have to be excused (minimizing uncertainty and risks). To test the first one, a Bayesian hierarchical latent-mixture model is proposed to express the relationship between motivation and type of excuse, and it is inspired by Lee and Wagenmaker (2013) “two-country quiz” model. In statistics, a mixture model is a technique of modeling that is used to predict if categorical latent variables that represent subpopulations, where population membership is not known, can be inferred from the data. This process is usually called as finite mixture modeling (McLachlan & Peel, 2004). A special case of this family of analysis is latent class analysis (LCA). In the present scenario, the latent classes explain the relationships among the observed dependent variables, as in a data reduction procedure, but it provides classification of individuals, in contrast to factor analysis. The model about minimizing uncertainty and risks is beyond the scope of this study.

Bayesian cognitive modeling

Modeling can be thought as the process of formalizing—expressing in mathematical or logical terms—scientific theories. Cognitive modeling is what modelers in psychology do (Busemeyer & Diederich, 2010). Albeit there is a whole world of techniques to cognitive modeling, one of the most prominent approaches is the Bayesian cognitive modeling (Lee & Wagenmakers, 2014). This approach is based on Bayesian statistics; a framework where knowledge and uncertainty about variables is represented by probability distributions, and this knowledge can be processed, updated, summarized, and otherwise manipulated using the laws of probability theory (Lee, in press). Therefore, Bayesian statistics provides a formal proceeding for making inferences different to the frequentist framework of using p-value based analysis (for details see Barnett, 1999; Kruschke, 2014; Samaniego, 2010).

Bayesian statistics are known for its flexibility; there is no unique way for doing things right (Gelman, Carlin, Stern, & Rubin, 2014). The analysis of data depends on the argument you use to construct an analytical model, based on your knowledge on probability theory or on previous work. There are, at least, three different ways it can be applied in cognitive modeling (Lee, 2011). The first is to use Bayesian methods as standard analyses of data. The second one is to apply Bayesian statistics as a working assumption about how the mind makes inferences. Finally, Bayesian methods can be used in cognitive science to relate models of psychological processes to data. Each of these modeling perspectives has a singular goal in making sense of data.

When using Bayesian statistics as a method for conducting standard analyses of data, one is following the lead of some authors that proposes the abandon of statistical inference that is based on sampling distributions and null hypothesis significance testing (e.g., Edwards, Lindman, & Savage, 1963; Kruschke, 2010; Wagenmakers, 2007). They argue that inference based on frequentist framework—therefore, on the use of p-values, confidence

Intervals and error sampling—does not provide coherent conclusions about data. Some of the ideas that gave strength to this rationale were formally backed up by a statement made by the American Statistical Association (Wasserstein & Lazar, 2016). This statement is built on six principles concerning p-values and their use. For the present study, the sixth is the more relevant one: by itself, a p-value does not provide a good measure of evidence regarding a model or hypothesis. When testing models, you are obviously concerned with this principle, making Bayesian statistics the right choice for such end.

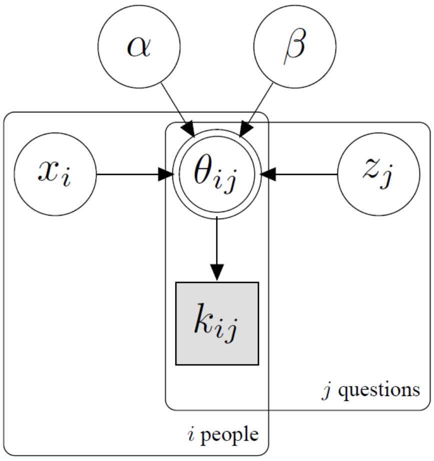
There is also the Bayesian statistics as a working assumption about how the mind makes inferences. This approach is generally known as the Bayesian mind (Griffiths, 2006). In this case, Bayesian inference is used as an account of why people behave the way they do, without trying to account for the mechanisms, processes or algorithms that produce the behavior, nor how those processes are implemented in neural hardware. This has been an influential theoretical position in the cognitive sciences (e.g., Chater, Tenenbaum, & Yuille, 2006) and is worth noting that it does not require the application of Bayesian data analysis. What it simply does is to say people receive inputs about the world, apply Bayes' theorem, and then generate outputs (broadly, any cognition or behavior). Therefore, it simply says that people's mind is Bayesian when doing rational analysis.

Finally, for a full accounting of models on how mind works, there is the use of Bayesian statistics to relate models of psychological processes to data (e.g., Lee & Wagenmakers, 2014). It has some fundamental differences as compared to data analysis and the Bayesian mind approaches (Lee, in press). First, it has the goal to specialize the analytical model and to relate some aspect of cognition to behavioral or any observed data. For example, instead of using a generic generalized linear model to test data about decision-making, you could test if the take-the-best model (Gigerenzer & Goldstein, 1996) makes accurate predictions about what is observed in data. Second, there is no requirement that the cognitive models being related to data make Bayesian assumptions. Instead, they are free to make any sort of processing claims about how cognition works (Kruschke, 2010). The goal is simply to use Bayesian statistical methods to evaluate the proposed model against available data. Therefore, this third approach is the one which will be used to model how latent motivations (cognition) predict judgements about the usability of excuses (behavior).

Who wants to be excused: Bayesian latent-mixture model

The model can be exemplified as: in a given context (e.g. a friend's birthday), you have to give an excuse for having committed a fault (e.g. you forgot her birthday). But you have at least a couple of things to consider before giving the excuse: how much you desire to maintain a good relationship with that person, and, depending on the strength of your desire, which excuse is more appropriate for that purpose. Figure 1 describes this situation in a graphical representation of a hierarchical Bayesian model (Appendix C). Thus, it expresses the causal relationship between latent motivations to be excused (categorically defined as high or low) predicting what kind of excuse (external or internal) people will tend to use.

The notation used is the same as in Lee (2008). The observed variables are represented by shaded nodes and the unobserved variables are represented by unshaded nodes. Discrete variables are represented by square nodes, while continuous variables are represented by circular nodes. Stochastic variables are represented by single-bordered nodes, and deterministic variables are represented by double-bordered nodes. Finally, encompassing plates are used to denote independent replications of the graph structure within the model.



$$\begin{aligned}
&\alpha \sim \text{Uniform } (0,1)\\
&\beta \sim \text{Uniform } (0,\alpha)\\
&x_i \sim \text{Bernoulli } (0.5)\\
&z_j \sim \text{Bernoulli } (0.5)\\
&\theta_{ij} \leftarrow \begin{cases} \alpha \text{ if } x = z \\ \beta \text{ if } x \neq z \end{cases}\\
&k_{ij} \sim \text{Bernoulli } (\theta_{ij})
\end{aligned}$$

Figure 1. *Graphical model representing the response being predicted by the match of the level of motivation to be excused and the quality of the given excuse*.

In this case, α is the probability of a person to use the excuse correctly associated with one's latent group (e.g. use external excuse while belonging to the high motivation for impression management subpopulation). On the other hand, β is the probability of a person to use the excuse correctly associated with the other latent group (e.g. use internal excuse while not belonging to the low motivation for impression management subpopulation). Accordingly, α is expected to be high and β is expected to be low. To express this knowledge about the rates, the priors constrain $\alpha \geq \beta$, by defining α ~ dunif (0,1) and β ~ dunif (0,alpha) as a way to specify a joint prior over α and β in which $\alpha \geq \beta$, but it does not escapes criticism (for details, see Lee & Wagenmakers, 2014). The binary indicator variable x_i assigns the *i*th person to one or another management motivation subpopulation, and z_j assigns the *j*th item to one or other type of excuse (good or bad). Both are expressed by a Bernoulli distribution centered on .5. The probability the *i*th person will use the *j*th excuse is θ_{ij}, which is simply α if the motivation to manage match the type of excuse, and β if it does not. The actual data k_{ij} indicating whether or not the excuse was used follows a Bernoulli distribution with rate θ_{ij}. Finally, the model does not assume previous bias for subpopulation or excuse category belonging, configuring non-informative priors (Jeffreys, 1946).

Summing up, people might have different motivations to be excused after committing a social fault. According to attribution and impression management theories, this is what predicts the course of action in a given social interaction. In a latent variable analysis context, measuring the exact motivations may not be possible without further theoretical considerations. Therefore, it can be useful to distinguish people with intrinsic motivation classes: those who are highly motivated to be excused, and those who are not. In an excuse giving context, high or low motivation to be excused can predict the use of external and internal excuses, respectively. This happens because external excuses are, generally, more likely to be accepted than internal excuses. Finally, the Bayesian framework, through a latent-mixture model, makes it possible to test the described relations.

Method

Participants

To test the proposed model, an online selection task with 92 psychology undergraduate students, with mean age of 21 years (*SD* = 2.98), was conducted. This sample size was estimated with the goal to achieve a 95% high density interval (HDI) of maximal width of .2, given that the high and low motivation group have, at least, .55 bias towards using good and bad excuses, respectively. This procedure is based on Kruschke's (2014) suggestions to a Bayesian method of sample size estimation.

Measures

Initially, four judges evaluated the 16 written excuses created for this study. There were four contexts, also used by Saraiva and Iglesias (2013), each with four initial excuses, two external and two internal, that were modified from Weiner (2006). The contexts were related to: being late for an appointment; missing an appointment; having a poor performance on a task; and harming someone. Specific relationship types, as a friend relation, were avoided, given that they could bias the participants' responses (Franco, Iglesias & Melo, 2014). Aiming to keep only the more recognizable excuses—within external and internal categories—any excuse statements that were discordantly judged were excluded. Finally, there were four excuses reflecting a tardy individual and two excuse statements for two other contexts, half external and half internal. Nevertheless, for the first context, only two excuses were kept aiming to keep the same number of excuses for each context. The final items used in this study are presented in Table 1.

Table 1

Final excuses according to theoretical locus of control and specific context.

Context	**Internal Excuses**	**External Excuses**
Late for an appointment (Imagine that you arrived late for an appointment and have to apologize)	**Sorry I'm late, but I wanted to arrive a little later.**	**Sorry I'm late, but I came by bus and it broke on the way.**
Missing an appointment (Imagine that you did not attend an event and need to apologize)	**Sorry I did not appear, but this event was not relevant to me so I stood at home.**	**Sorry I did not appear, but I had to take my mother, who got sick, to the hospital.**
Poor performance (Imagine that you had a poor performance in any group task and have to apologize)	**I'm sorry not to have given the best of me, but I did not wanted to worry myself with it.**	**I'm sorry not to have given the best of me, but I was very sick.**
Harming others (Imagine that you caused harm to someone and needs to apologize)	**Excuse me the harm that I caused, even though I knew that it would happen.**	**Excuse me the harm that I caused, but I was trying to fulfill a commitment.**

Procedures

Participants were invited through several email lists. They were instructed to answer an online questionnaire with two main parts. First, the participants were shown all contexts and their respective excuses in a random order. In this case, participants should only indicate if they would or would not use the presented alternatives. Second, participants answered questions about their sexes and age, followed by a short debrief.

Results

The model estimates four parameters from data. The first one is the probability to use an excuse typical from their subpopulation. This parameter is called α (alpha). The second one is the probability to use an excuse typical from the other subpopulation. This parameter is called β (beta). Thirdly is the proportion of participants in each motivation subpopulation. Fourth, the empirical category of each of the excuses. Accordingly, α is expected to be at least .05 higher than β, to avoid a randomness pattern in answers. Also, it is expected that most participants will be labelled as highly motivated to excuse. This means that most participants will, dominantly, use external excuses. Finally, the empirical category of the excuses should be equal to the theoretical category of the excuses.

To test the model, 35000 runs, being 5000 for burn in and 30000 for the simulation, were initiated. These settings assured the convergence of all parameters estimations, according with autocorrelation (Kruschke, 2014) and Geweke (1991) criteria. The autocorrelation criterion involves correlating the simulated estimate with itself, but with shifts (lags) in the chain. The value should get close to 0 as the lag gets higher. But, if the values are greater than .1, there is no convergence in your estimates. Also, autocorrelation estimates the effective sample size (ESS), which is the number of usable runs in a chain. As a convergence diagnostic tool, as closer as the ESS gets from the kept simulations (in this case, 30000), the better is the chain. The Geweke criterion involves mimicking the simple two-sample test of means. If the mean of the first 10% runs of the chain is not significantly different from the last 50%, then it can be concluded that the target distribution converged somewhere in the first 10% of the chain.

Table 2 shows the mean and the 95% HDI of α and β parameters' estimates of the model. It is possible to see that the probability of using an excuse of your own subpopulation (M_α = .52) is considerably higher than the probability of using an excuse of other subpopulation (M_β = .10). Also, there is no over position of these estimates, given that the

95% HDI of each does not share any value. Nevertheless, it should be noted that most of the participants where categorized as being highly motivated to excuse themselves (close to 88%). This difference makes the values of α and β more sensitive for the high motivation group estimates. Anyway, the robustness of those estimates is assured by the convergence of the chain and the precision of the excuses type categorization.

Table 2

Mean and 95% HDI estimates for α and β parameters, and percentage of participants categorized in each subpopulation.

Parameters	**Mean**	**95% HDI**
α	0,5196	[0,4690; 0,5718]
β	0,1035	[0,0719; 0,1371]
	% of participants with high motivation	% of participants with low motivation
	88.04%	11.96%

The precision of the excuses type categorization by the model can be verified in Table 3. If there was no pattern in participants' response, the categorization of excuses and of subpopulations would be nonsensical. However, the categorization of excuses grouped each excuse as expected. This has two meanings. The first is that the excuses used as items in the present research were items with criterion validity. Secondly, given that the response and the categorization of the excuses affects the subpopulation estimation for each participant, it is possible to conclude that there is little bias in the subpopulation estimates.

Table 3

Excuses and their theoretical and estimated types.

Excuses	Theoretical Type	Estimated Type
Sorry I'm late, but I came by bus and it broke on the way.	External	1
Sorry I'm late, but I wanted to arrive a little later.	Internal	0
Sorry I did not appear, but I had to take my mother, who got sick, to the hospital.	External	1
Sorry I did not appear, but this event was not relevant to me so I stood at home.	Internal	0
I'm sorry not to have given the best of me, but I was very sick.	External	1
I'm sorry not to have given the best of me, but I did not wanted to worry myself with it.	Internal	0
Excuse me the harm that I caused, but I was trying to fulfill a commitment.	External	1
Excuse me the harm that I caused, even though I knew that it would happen.	Internal	0

Descriptive and inferential analysis can be used to further investigate the association between estimated subpopulation and excuse types. To begin with, before any modeling, internal excuses would be used only 11.14% of the time. External excuses, on the other hand, 51.08% of the time. This implies an overall preference for external excuses, what helps to explain why most participants where categorized as high motivated to be excused. Bayesian hierarchical binomial analysis can be used to compare the estimates of relative frequency of success for two or more groups (Kruschke, 2014, Appendix D). This analysis can be thought as the “Bayesian chi-squared test”. However, Pearson’s chi-squared tests the null hypothesis that row variable is completely independent of the column variable. The Bayesian hierarchical binomial analysis, on the other hand, is a statistical model to estimate differences of proportions in different groups, which is the present aim. Table 4 shows that the proportion of use of excuses is related to the subpopulation. But, beyond the aggregated α estimate of the Bayesian latent mixture model, it can be seen that each excuse has a different rate of use in each subpopulation. Accordingly, high motivated people will use excuses that are more accepted by others than worst excuses. The opposite is true for low motivation subgroup.

Table 4

Bayesian hierarchical binomial analysis of latent subpopulation and rate of use of excuses.

Excuse	**High motivation**	**Low motivation**	**Mean difference of proportions**	**Relative use larger for High Motivation**
Ex1	.41 [.26, .56]	.030 [.0009, .082]	.37 [.21, .53]	99.9%
Ex2	.28 [.17, .41]	.080 [.015, .16]	.20 [.054, .35]	99.6%
Ex3	.31 [.17, .45]	.10 [.038, .19]	.20 [.044, .37]	99.4%
Ex4	.24 [.14, .36]	.078 [.011, .18]	.16 [.02, .30]	98.5%
In1	.14 [.072, .22]	.55 [.26, .81]	-.41 [-.68, -.11]	2.0%
In2	.13 [.055, .20]	.42 [.22, .65]	-.29 [-.52, -.065]	4.0%
In3	.15 [.086, .23]	.58 [.24, .89]	-.42 [-.74, -.072]	9.0%
In4	.16 [.091, .25]	.32 [.94, .59]	-.16 [-.44, .085]	11.0%
		Mean high motivation	**Mean low motivation**	
	External	.31 [.16, .51]	.07 [.009, .18]	
	Internal	.14 [.07, .23]	.46 [.15, .81]	

Finally, Figure 2 shows the posterior distributions for the aggregated values at the bottom of Table 4. On the left is the probability of using the external excuses. It can be seen that the high motivation group has a higher mean than the low motivation group, but larger dispersion. On the right is the probability of using internal excuses. It shows that the high motivation group has a lower mean, but considerably less dispersion. Two conclusions can be made. First, high motivation group is more concise in their preferences. Second, low motivation group is more concise in not using external excuses, but doubtful about internal excuses.

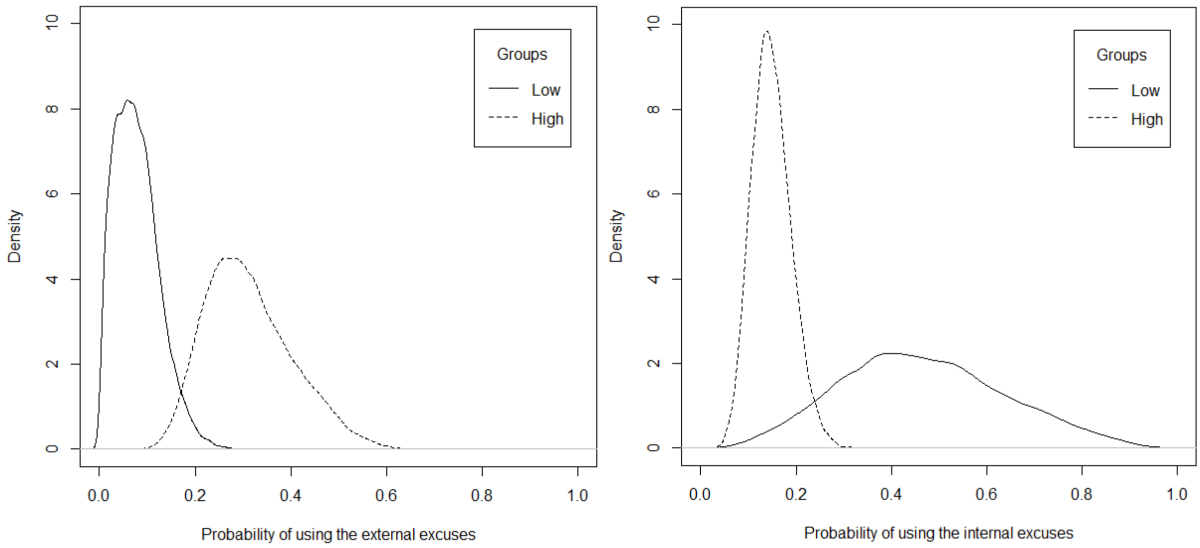


Figure 2. *Posterior density for the probability of using external (left) and internal (right) excuses for each group.*

Discussion

It was theorized that excuse giving shows properties of impression management and decision making processes. More specifically, that motivation, an impression management component, affects how a decision is made. Therefore, it should be expected that data about excuses could be readily explained by a model that accounts for both properties. A Bayesian latent-mixture model presents this characteristic. It explains the patterns of decision based on latent subpopulation and latent items' properties. This means that, given the adequacy of the model, we can conclude that there is evidence to say that the intensity of the motivation to be excused, despite of its content, can predict how people will excuse themselves.

Two main findings sustain this assertion. It was found that most participants were categorized as being highly motivated to be excused. This could be predicted by similar results found previously in the literature (e.g., Weiner et al., 1987; Weiner, 2006). Still, it could be also a sampling problem, albeit this is a less likely reason. Also, it was found that the excuses were correctly categorized. The model does not know, a priori, the theoretical categories of the excuses and how, accordingly to the theory, they should be categorized. It only knows the process that links the participants' latent subpopulation with the observed responses. Therefore, Weiner's attribution theory, and impression management theory, in an excuse giving context, can be formally described by a Bayesian latent-mixture model.

This statement has as prime consequence a claim that is supported by other authors: psychological theories can benefit from a broad use of modelling techniques (e.g., Lee, 2011; Lee & Wagenmakers, 2014; Lewandowsky & Farrell, 2010). The practice of general quantitative modeling is the approach of what is usually called mathematical psychology (Coombs, Dawes, & Tversky, 1970). According to Townsend (2008), mathematical psychology provides the means to work out the necessity of providing a rigorous and clear accounting of concepts and data. Through an approach driven by quantitative modeling, one can surpass the overly particular, and acts not only to accommodate an entire set of phenomena, but assays the ability of diverse theoretical notions and experimental operations—the assurance of the connectivity principle (Haack, 2007) in psychological science.

As far as attribution theory is concerned, there has been some temptative formalization of some of its core elements. For instance, Osborne and Weiner (2015) used latent profile analysis (LPA, a type of mixture model) to identify unique response patterns, demonstrating that three distinct response patterns underlie individual differences in peoples' poverty beliefs. As in the present study, it identifies that there is latent motivational component that predicts pattern of responses. Not as in the present study, the authors used a more general mixture model (LPA) and also related the groups with the content of the motivation, in the specific context of poverty beliefs. Therefore, more studies should be conducted to identify if these contents can be generalized to other contexts. Weiner's (2010) levels and specific motivational components—as others and one's elicited emotions—must also be properly quantitatively represented. Future studies might help to identify, for instance, if motivational motivators are task specific and to what extent they are dominated by dispositional variables.

As a final regard, it is important to note that evidence has shown that attributional processes may be moderated by cultural variables (e.g., Pilati et al., 2015). This aspect is one of the many reasons why you need to have a transcultural perspective when studying human behavior (Henrich, Heine, & Norenzayan, 2010). In attributional theory’s case, the original framework does not account for this kind of differences (Weiner, 2010). Therefore, a higher level of hierarchy in the model should be added, accounting for societal aspects. This should have as a consequence the changing of values, or of distributional aspects, of the parameters in the model. In an excuse giving context, if we think of it as a decision making process and if we think of culture as a group process, group decision making models (e.g., Khrennikov & Basieva, 2014) could be the starting point to a first solution of this problem.

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FINAL REMARKS

The main objective of this thesis was to formalize and test part of Weiner's attributional theory as a social decision making process. Specifically, it aimed at how excuse giving can be formalized, in a mathematical psychological sense, following previous empirical findings and models of classical and quantum probability theory. Two important findings in the literature on excuses were tested and modeled: people have preference for external excuses; and the cause of this preference involves the existence of some latent motivation for giving excuses in a particular way (Weiner, 2006).

To the best of our knowledge, this is one of the first attempts to provide a formal description of attributional theory (along with Osborne & Weiner, 2015). Now some aspects of excuse giving are known less tacitly. People attribute topologically distinguishable representations to internal and external excuses. The distinguishability of these representations are affected by which order they are evaluated, making internal excuses less usable when anteceded by external counterparts. In a more general perspective, motivation one has to manage a relationship stochastically explain his or her overall preference for using external or internal excuses. This is how people excuse themselves, according to the findings.

Finally, there are aspects yet to be formalized in attributional theory for excuse giving (Weiner, 2010). This task will prolong itself further, given that external aspects to the theory also need formalization (e.g., Pilati et al, 2015). As a research agenda, basics aspects of attribution must be first consistently formalized. For example, cultural variations must be investigated. Also, albeit the theoretical contribution, formalization also has practical value (Hunt, 2006). Excuse giving theory is often applied in relational, legal and consumer contexts (Kruglanski & Sleeth-Keppler, 2007) to solve many real problems. Formal theorization, with the explicit definition of parameters, gives us a kind of diagnosis of how to act upon a situation and generate a more desirable result.

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Appendix A: JAGS model for the Bayesian Multidimensional Scaling in Manuscript 1

```
# Bayesian Multidimensional Scaling
model{
 for(i in 2:n) {
      for(j in 1:i-1) {
        delta[i, j] ~ djl.dnorm.trunc(d[i, j], invphi2, 0, 999999999)
        sqd[i, j] <- pow((X[i, 1]-X[j, 1]), 2)
        d[i, j] <- sqrt(sqd[i, j])
        rawstressmat[i, j] <- pow(delta[i, j]-d[i, j],2)
      }
      rawstressvec[i] <- sum(rawstressmat[i, 1:i-1])
 }
 rawstress <- sum(rawstressvec[2:n])
 invphi2 ~ dgamma(a, b)
 for(k in 1:n) {
      X[k, 1] ~ dnorm(0, invlambda)
 }
 invlambda ~ dgamma(alpha, beta)
}
```

Appendix B: R script for the Quantum Model of Order Effects in Manuscript 1

```
# Quantum Model of Order Effects
rotate <- function(x) {t(apply(x, 2, rev))}
# A = External excuse
# B = Internal excuse
# A-B order
AB <- rotate(rotate(prop.table(table(df[,1],df[,2]))))
pAyBy <- AB[1,1]
pAnBy <- AB[2,1]
pAyBn <- AB[1,2]
pAnBn <- AB[2,2]
# B-A order
BA <- rotate(rotate(prop.table(table(df[,3],df[,4]))))
pByAy <- BA[1,1]
pBnAy <- BA[2,1]
pByAn <- BA[1,2]
pBnAn <- BA[2,2]
# Context (order) effects
CE <- BA - AB
CE
# Chi-squared tests
pab <- rotate(rotate(table(df[,1],df[,2])))
n = sum(pab)
pba <- rotate(rotate(table(df[,3],df[,4])))
m = sum(pba)
# Test for the order effect
# The log-likelihood for the unconstrained model
Gu <- pab[1,1]*log(pab[1,1]/n) +
      pab[1,2]*log(pab[1,2]/n) +
      pab[2,1]*log(pab[2,1]/n) +
      pab[2,2]*log(pab[2,2]/n) +
      pba[1,1]*log(pba[1,1]/n) +
      pba[1,2]*log(pba[1,2]/n) +
      pba[2,1]*log(pba[2,1]/n) +
      pba[2,2]*log(pba[2,2]/n)
```

```
# The log-likelihood for the constrained model
Gc <- (pab[1,1] + pba[1,1])*log((pab[1,1] + pba[1,1])/(n+m)) +
      (pab[1,2] + pba[2,1])*log((pab[1,2] + pba[2,1])/(n+m)) +
      (pab[2,1] + pba[1,2])*log((pab[2,1] + pba[1,2])/(n+m)) +
      (pab[2,2] + pba[2,2])*log((pab[2,2] + pba[2,2])/(n+m))
# The chi-quared statistic for order effect
Csqrdoe <- (-2) * (Gc - Gu)
Csqrdoe # with 3 dfs
# Test for the QQ equality
# The log-likelihood for the unconstrained model
Gu <- (pab[1,2] + pab[2,1])*log((pab[1,2] + pab[2,1])/n) +
      (pab[1,1] + pab[2,2])*log((pab[1,1] + pab[2,2])/n) +
      (pba[1,2] + pba[2,1])*log((pba[1,2] + pba[2,1])/m) +
      (pba[1,1] + pba[2,2])*log((pba[1,1] + pba[2,2])/m)
# The log-likelihood for the constrained model
Gu <- (pab[1,2] + pab[2,1] + pba[1,2] + pba[2,1]) *
       log((pab[1,2] + pab[2,1] + pba[1,2] + pba[2,1])/(n+m)) +
      (pab[1,1] + pab[2,2] + pba[1,1] + pba[2,2]) *
       log((pab[1,1] + pab[2,2] + pba[1,1] + pba[2,2])/(n+m))
# The chi-squared statistic for QQ equality
CsqrdQQ <- (-2) * (Gc - Gu)
CsqrdQQ # with 2 dfs
```

Appendix C: JAGS model for the Bayesian Latent Mixture Model in Manuscript 2

```
# Excuse Giving Model
model{
 # Probability of Choosing to Use the Excuse
 alpha ~ dunif(0,1)     # Match
 beta ~ dunif(0,alpha) # Mismatch
 # Group Membership For People and Excuses
 for (i in 1:nx){
      x[i] ~ dbern(0.5)
      x1[i] <- x[i]+1
 }
 for (j in 1:nz){
      z[j] ~ dbern(0.5)
      z1[j] <- z[j]+1
 }
 # Probability Used For Each Person-Excuse Combination By Groups
 for (i in 1:nx){
      for (j in 1:nz){
      theta[i,j,1,1] <- alpha
      theta[i,j,1,2] <- beta
      theta[i,j,2,1] <- beta
      theta[i,j,2,2] <- alpha
      }
 }
 # Data Are Bernoulli By Rate
 for (i in 1:nx){
   for (j in 1:nz){
      k[i,j] ~ dbern(theta[i,j,x1[i],z1[j]])
   }
 }
}
```

Appendix D: JAGS model for Bayesian analysis of group proportions in Manuscript 2

```
# Bayesian "chi-squared test"
model{
for(i in 1:length(x)) {
    x[i] ~ dbinom(theta[i], n[i])
    theta[i] ~ dbeta(1, 1)
    x_pred[i] ~ dbinom(theta[i], n[i])
  }
}
```