

Theory and Methods for Analyzing Relations Between Behavioral Intentions, Behavioral Expectations, and Behavioral Probabilities

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Abstract

The conceptual presuppositions for empirical research concerning the relations between behavioral expectations, behavioral intentions and behavior are discussed. The frame of a theory referring to this topic is developed. Methods for analyzing data are discussed with respect to this theory. The coefficient of correlation which dominates present main-stream research is criticized as being incompatible with the characteristics of the object under investigation. Two models which are compatible with these characteristics - the Simple Logit Model (SLM) and the Double Logit Model (DLM) - are presented and compared. Statistics referring to these models are discussed. All methods are demonstrated using empirical data.

Keywords: Behavioral intention, behavioral expectation, behavioral probability, method, prediction.

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1. Introduction

Empirical research is always essentially based upon conceptions which are selected a-priori to empirical research (cf. Balzer, Moulines & Sneed, 1987; Kuhn, 1976; Lakatos, 1970; Sneed, 1979). These conceptions can be either theoretical, i.e. belonging to the theory presupposed in formulating research questions, or methodological, i.e. belonging to the methodology applied for answering these questions. Infinitely many theoretical and methodological conceptions can be conceived of. Hence, a small subset must be selected a-priori to empirical research in order to make empirical research possible. However, selecting theoretical and methodological conceptions a-priori to empirical research bears dangers: as soon as these conceptions have been selected, they determine what can be found and what cannot be found empirically. Therefore, time and again, the conceptions chosen a-priori should be critically discussed.

A reasonable critical discussion requires that there are criteria to which this discussion refers. One criterion which the a-priori conceptions certainly should fulfil is correspondence between theoretical and methodological conceptions. There are, however, at least two different approaches for providing this correspondence: 1) one can start with methodology and define theoretical conceptions by means of the methodological tools at hand; or 2) one can start with theory and select or even newly construct methodological tools so that they accord optimally to theoretical conceptions.

Both approaches can be very useful. Their usefulness, however, will vary with the extent to which the object under investigation has already been explored. At the beginning, relevant theoretical conceptions are necessarily still vague, if they exist at all. Therefore, they can best be developed on the basis of methodological tools which have been successfully applied elsewhere. Different objects of investigation, however, might have different specific characteristics. Hence, methodological conceptions which have been successfully applied to one object are not necessarily the best for a different one. Therefore, with growing understanding it might be better to characterize the essence of theoretical conceptions independently of methodology and to look for research methods which accord optimally to these theoretical conceptions.

Because psychology is still a rather young discipline, in many specific areas of psychological research the first approach prevails. A prototypical example is the research concerned with the relation between questionnaire variables and actual behavior. This research discipline has emerged within attitude behavior research. It is concerned with the

questions as to what questionnaire variables relate best to behavior and as to what conditions moderate this relation. Previous results suggest that two types of variables are especially promising in this context: 1) behavioral expectations and 2) behavioral intentions. Correspondingly, an essential part of present research is concerned with these two variables as possible predictors (Ajzen, 1985; Eckes & Six, 1994; Jonas & Doll, 1996; Sheeran & Orbell, 1998; Sheppard, Hartwick, & Warshaw, 1988; Warshaw & Davis, 1985).

The empirical research in this context is mainly based upon one specific method: the coefficient of correlation. Data representing behavioral intentions or behavioral expectations on the one side and behavior on the other are usually analyzed by computing this statistic. A high correlation is interpreted as indicating a strong relation between the two variables. A low correlation is interpreted as indicating a weak relation. Moreover, if the correlation covaries with a third variable this is interpreted as indicating a moderating influence of the third variable on the relation. By way of this approach, theoretical conceptions like 'relation', 'strength of a relation', and 'moderating influence on a relation' are specified, if not created, by means of a methodological tool which has been adapted from other research contexts; i.e. by means of the coefficient of correlation.

Meanwhile, several theoretical ideas and empirical results which are more specific for the research context in question are at hand. Hence it might be questioned whether further research should be based upon the present conceptual system. Instead, one could attempt to formulate more specific theoretical conceptions independently of methodology and to design methodology to fit these theoretical conceptions. This is the major aim of the following argumentation. This argumentation divides into three parts. In the first part, basic theoretical conceptions are elaborated independently of methodology. In the second part, possible methods are discussed with respect to these basic theoretical conceptions. In the third part, all methods discussed in the second part are demonstrated using empirical data.

2. Theory

The enterprise of developing basic theoretical conceptions a-priori to methodological conceptions and a-priori to empirical research is unavoidably connected with one serious problem: there is not much left to provide criteria for substantiating the basic theoretical conceptions. There are only criteria for judging the final result of the research which is based upon these basic theoretical conceptions. According to the epistemological ide-

als presupposed here, this result should be an elaborated conceptual construction which optimizes two criteria at the same time: 1) it should correspond as much as possible to empirical findings; and 2) it should be as simple and as well-structured as possible.

Whether a set of basic theoretical conceptions will finally lead to such a result cannot be judged at the beginning. At best, it can be judged after a long series of empirical, methodological and more specific theoretical work, if at all (cf. Lakatos, 1970, pp. 132). There are, however, two necessary criteria which basic theoretical conceptions should fulfill: 1) they should seem plausible with respect to what is known at the time of their formulation; and 2) they should substantiate research which seems promising with respect to the finally intended result. Apart from this, basic theoretical conceptions can constitute no more (and no less) than one of many possible views on the object under investigation. The basic theoretical conceptions developed here are understood in exactly this sense.

Present research already provides a vast amount of empirical findings which constitute a critical instance for the plausibility of possible new basic theoretical conceptions. It also provides a vast amount of theoretical ideas referring to these findings. These ideas are more or less explicitly formulated, more or less widely accepted and more or less scattered over a lot of different contributions. Up to now, however, they have not been condensed within a comprehensive explicit formulation which might be appropriate for explicitly substantiating more specific research concerning the object under investigation. The basic theoretical conceptions presented here are mainly produced by such a condensation. This implies that these conceptions have two essential features. 1) They are not entirely new. All of them - or at least parts of all of them - have already emerged in the relevant theoretical discussion. 2) They are not identical with the whole of the ideas presented up to now. To provide the basis for developing a conceptual construction which is as simple and well-structured as possible, some ideas must be abandoned, others modified.

The meaning of a theoretical conception within a theory of empirical science is given by its reference to empirical phenomena. This implies a further difficulty if one tries to formulate a set of basic theoretical conceptions a-priori to empirical research. On the one hand, a set of basic theoretical conceptions with completely determined empirical meaning can hardly substantiate empirical research which provides new insights. On the other hand, a set of basic theoretical conceptions without any determined empirical meaning can not substantiate any empirical research at all. Hence, some intermediate

approach is required. Within this argumentation this intermediate approach is realized by segmenting the basic theoretical conceptions into two parts: 1) those conceptions for which the empirical meaning is determined a-priori to the development of the theory and 2) those conceptions for which the empirical meaning is intended to be developed together with the theory. The first part will be referred to as the outer, the second part as the inner part of the theory.²

2.1. The Outer Part of the Theory

The outer part of the theory is given by the variables which constitute the object under investigation. These variables are the behavioral intention, the behavioral expectation and the actual behavior. In the given research context the first two variables are discussed as possible predictor variables for the third variable and, accordingly, the third variable is treated as a criterion. Therefore, in the following, first the two predictor variables will be discussed together and then, separately, the criterion variable.

2.1.1. The Predictor Variables

Behavioral intentions and behavioral expectations are assessed by means of questionnaires. Hence, they can be discussed from - at least - two different perspectives: 1) the respondents' perspective and 2) the questionnaire designers' perspective as is revealed in the formulation of the question and the shaping of the answer modality. Here, strictly the second perspective is chosen. Accordingly, there is no need to substantiate the quantitative characteristics of the variables upon qualitative judgments of the respondents in the sense of representational theory of measurement (Krantz, Luce, Suppes & Tversky, 1971; Luce, Krantz, Suppes & Tversky, 1990; Suppes, Krantz, Luce & Tversky, 1989). In contrast, assumptions concerning the respondents' understanding of the variables, like for example assumptions concerning the metric properties of the respondents' mental representations, are made part of the assumptions to be tested by the methods discussed below.

² The meta-conceptions 'outer part of a theory' and 'inner part of a theory' have essential similarities with the meta-conceptions 'partial potential model of a theory' and 'model of a theory' as they have been introduced by Sneed (1979). However, both pairs of meta-conceptions are not identical. Applying the original meta-conceptions of Sneed would have produced some difficulties which are avoided with the meta-conceptions applied here.

The understanding of the two variables which is presupposed here is essentially influenced by the contribution of Warshaw and Davis (1985). According to these authors a behavioral expectation is "the individual's estimation of the likelihood that he or she actually will perform some specified future behavior" and a behavioral intention is "the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior". Moreover, both variables are understood to have a different relation to the volitional control which people believe to have over the behavior; i.e. to their behavioral control (cf. Ajzen, 1985; Liska, 1984; Warshaw & Davis, 1985). In line with these ideas, in the theory developed here, both behavioral expectations and behavioral intentions are understood as two different kinds of subjective probabilities. The behavioral expectation is understood as the subjective behavioral probability presupposing the behavioral control which the questioned person actually perceives; the behavioral intention, in contrast, is understood as the subjective behavioral probability which would result if there were perfect perceived behavioral control.

If both variables are subjective probabilities then they must possess two essential formal characteristics.

- 1) They are bounded to both sides. These bounds are the states 'completely decided for' and 'completely decided against' for the behavioral intentions and 'completely certain yes' and 'completely certain no' for the behavioral expectations.
- 2) There are several states between both bounds: These states are rank ordered and, moreover, there are meaningful distances between these states.

To express these ideas, both predictor variables are characterized as functions from the Cartesian product of the set of behaviors B and the set of subjects S into the real-valued interval between zero and one, i.e. $x:B*S \rightarrow [0,1] \subset \mathfrak{R}$. In the numerical representation, zero symbolizes the lower bound of the variable and one the upper bound. The numbers between zero and one are meant to represent the intermediate states according to their rank order and their distances from each other. Altogether, this is the same characterization as presented by Warshaw and Davis (1985).

2.1.2. The Criterion Variable

The variable which is meant to be predicted by the expectations and intentions is the behavior. Formally, this behavior can be understood as a binary variable with the two graduations "performed" and "not performed". However, because both predictor variables are understood as subjective probabilities it would be unwise to apply the binary behav-

ior as the immediate criterion variable of this prediction. This would result in attempting a deterministic prediction on the basis of probabilistic predictor variables. Thus, the probabilities of performing the behavior, i.e. the behavioral probabilities, are applied as an immediate criterion variable. Formally, these probabilities can also be characterized as a function from the Cartesian product of the set of behaviors and the set of subjects into the real-valued interval between zero and one, i.e. $p: B * S \rightarrow [0,1] \subset \mathfrak{R}$.

2.2. The Inner Part of the Theory

Presupposing the outer part of the theory, some very general research questions can be formulated:

- * What relations exist between behavioral intentions and behavioral expectations on the one hand and behavioral probabilities on the other?
- * What additional variables affect these relations?
- * How do they affect these relations?

These research questions may seem reasonable. However, a more thorough analysis reveals that they are actually much too general to initiate reasonable empirical research. The term which makes all these questions so general is the term 'relation'. This results from the fact that infinitely many relations and even infinitely many types of relations can be conceived of as holding between variables with the formal characteristics just described. Hence, further specification is needed of how the conception of a relation is understood in this context.

The inner part of the theory which is presented in the following mainly aims at delimiting the type of relation which should be taken into consideration within this context. This part mainly consists of two general psychological principles which are assumed to determine the relations between the variables in question. Firstly, these two principles will be presented and, secondly, the type of relation which should be taken into consideration will be delimited on the basis of these two principles.

2.2.1. The two basic principles

The two basic principles are:

- P1) Most people at least try to understand and to answer questions in questionnaires correctly.

- P2) There can always be motivational and/or cognitive factors which hinder people from understanding and/or answering questions correctly.

As mentioned above, the ideas incorporated in these principles are not new. Actually, principle P1 is at least implicitly assumed in almost every research concerned with and based upon questionnaires. Without assuming the first principle or something similar to this principle most questionnaire research would lack justification. A more specific example of presupposing the first principle is the argumentation with which Warshaw and Davis substantiate different predictive properties for expectations and intentions (Warshaw & Davis, 1985). Warshaw and Davis start with the general meaning of the terms 'expectation' and 'intention' and derive from this meaning that questionnaire answers referring to the term 'expectation' should be better predictors of behavior than questionnaire answers referring to the term 'intention'. Principle P2 is more or less implicitly accepted in most interpretations of questionnaire studies. Moreover, the general idea that human information processing is often impaired by motivational and/or cognitive limitations is explicitly stated in Simon's approach of bounded rationality (Simon, 1956, 1982, 1992) and likewise in most dual-process-theories (e.g. Fazio, 1990; Fiske & Neuberg, 1990; Petty & Cacioppo, 1986).

2.2.2. Constraints for the Presupposed Type of Relation

Altogether, the ideas expressed by the two principles presented above are not new. However, explicitly formulated in direct reference to questionnaire research they suggest some constraints for specifying what relation or - better - what type of relation should be taken into consideration in empirical research. Formally, a type of relation can be conceived of as a class of relations with similar mathematical properties. In this context, this class of relations should meet two conditions:

- 1) It should comprise that relation which would result if people succeeded in understanding and answering the questions correctly. This relation will further be referred to as the '*normatively correct relation*'.
- 2) It should comprise those relations which would result if people somehow failed to understand and answer the questions correctly. For interpretational reasons these relation should best be characterized by the manner in which they deviate from the normatively correct relation.

Altogether, the normatively correct relation constitutes something like a frame of references for all further conceptual developments. Hence, in the following, this relation

will be specified. As there are two different questionnaire variables under consideration, i.e. behavioral expectations and behavioral intentions, two different approaches for specifying the normatively correct relation are possible: a bivariate and a multivariate approach. The first approach consists in considering the relation between behavioral expectations and behavioral probabilities on the one hand and the relation between behavioral intentions and behavioral probabilities on the other hand separately. The second approach consists in integrating behavioral expectations and behavioral intentions in a common model for predicting behavioral probabilities. The bivariate approach is, necessarily, simpler than the multivariate approach. Moreover, in most cases, multivariate models can be developed by generalizing bivariate models. Hence, in the following argumentation, the bivariate approach is chosen. Thereby, firstly the relation between behavioral expectations and behavioral probabilities and, secondly the relation between behavioral intentions and behavioral probabilities is discussed.

In the case of the behavioral expectations the normatively correct relation can easily be determined. As described above, behavioral expectations are theoretically understood as subjective behavioral probabilities presupposing the given extent of subjective volitional control. Consequently, if people understand the question concerning their behavioral expectations correctly, behavioral expectations should equal behavioral probabilities. In other words, the normatively correct relation would be the identity function; i.e.

$$p(b,s) = x(b,s) \tag{1}$$

with b the behavior and s the subject under consideration. If behavioral expectations and behavioral probabilities correspond to this equation this means that subjects behave in correspondence with the expectations expressed in the questionnaire.

With the behavioral intention as predictor variable the normatively correct relation cannot be determined that easily. For this variable, correctly understanding and answering the questions does not imply a specific relation to behavioral probabilities. This is due to the fact that behavior can only be completely determined by intentions if this behavior is completely under volitional control (see above). Thus, only for the case of complete volitional control can a specific relation be specified. In this case, once more the identity function constitutes the normatively correct relation. If data for behavioral intentions and behavioral probabilities correspond to this equation this means that sub-

ject actually behave in correspondence with the intentions expressed in the questionnaire.

3. Methods

The theoretical conceptions just introduced define constraints to which methods for data analysis should correspond. This holds for both, the outer and the inner part of the theory. However, both parts of the theory have a different epistemological status. The outer part of the theory defines the essential characteristics of the object under investigation. Accordingly, constraints implied by this part are essentially independent of specific theoretical preferences. They simply define those conditions which each method should fulfill which is applied to an object with the given characteristics. In contrast, the inner part defines a voluntarily chosen point of view on an object with these characteristics. Accordingly, the constraints implied by the inner part essentially depend upon a specific theoretical preference. Different theoretical preferences are possible. Changing the theoretical preference by changing the inner part of the theory can produce different constraints for the methods although these methods still refer to the same object under consideration.

Although the theoretical conceptions introduced above provide certain constraints for selecting methods of data analysis, they do not completely determine which methods can and should be applied. Consequently, developing an appropriate methodology cannot consist of merely translating theoretical conceptions into methodological conceptions. It must also consist of further specifying theoretical conceptions, - especially those of the inner part the theory. In this respect, the further methodological discussion is also an extension of the theoretical discussion presented above.

Each method for analyzing the relationship between two variables is based upon two parts: 1) a specific type of relation and 2) a specific type of statistic. In the case of the squared coefficient of correlation, the specific type of relation is the class of all linear functions and the specific type of statistic is the proportion of criterion variance explained by a regression equation for which the parameters have been determined by ordinary least-square-estimation. Selecting a specific method for analyzing data always means selecting both: a specific type of relation and a specific type of statistic. Both selections are a-priori to empirical research and determine what can be found in empirical research. Therefore, in the following both selections, firstly the type of relations and

secondly the type of statistics, are discussed with respect to the theoretical conceptions just introduced.

3.1. Possible Types of Relations

As stated above, present main-stream research concerned with the relation between behavioral expectations, behavioral intentions and behavior is essentially based upon the coefficient of correlation. Therefore, one should first investigate whether the type of relation presupposed in this statistic is a reasonable model³ for the data at hand. This type of relation can be described by

$$p(b,s) = \beta * x(b,s) + \alpha. \quad (2)$$

This equation has one very important property: for certain values of α and β it predicts probabilities outside the range between zero and one, even if the predictor variable values lie within this range. More specifically, predictions outside the range of possible probabilities happen for $\beta < -1$, $\beta > 1$, $\alpha < \max\{0, -\beta\}$ and $\alpha > \min\{1, 1-\beta\}$. This means that the class of relations defined by equation 2 comprises relations which are inconsistent with the outer part of the theory. These relations are known a-priori not to exist for the object under investigation. Hence, this type of relations should not be applied in this research context.⁴ Therefore, in the following, two alternative types of relations are discussed as possible candidates.

3.1.1. The Simple Logit Model

If a variable with a restricted range - especially a probability - is to be predicted, then usually the logistic function is applied for modeling the relation between predictor and criterion (see e.g., Andreß, Haagenars & Kühnel, 1997, Chap. 5; Fahrmeir, Hamerle & Tutz, 1996, Chap. 6). With the variables at hand the resulting model is

³ In accordance with the usual interpretation in psychological literature, a model is understood as a description of a set of entities and not - as in great parts of the philosophical literature (e.g., Balzer, Moulines & Sneed, 1987; Sneed, 1979) - as an entity which corresponds to a given description.

⁴ Note that the argumentation against applying the class of simple linear function in this context is essentially the same as the argumentation against applying Classical Test Theory as a model for single test items (cf. Rost, 1999).

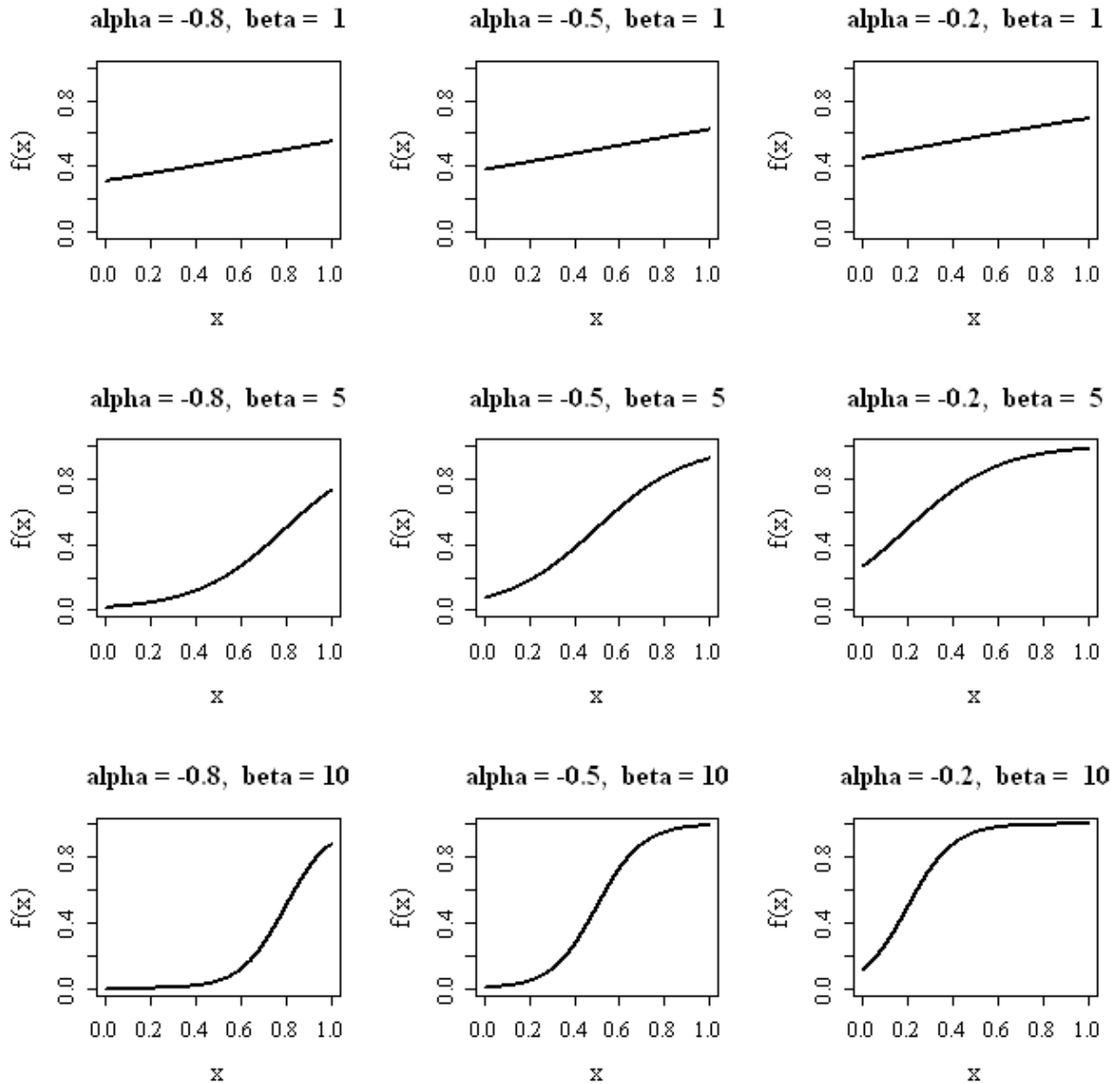
$$p(b, s) = \frac{\exp[\beta * x(b, s) + \alpha]}{1 + \exp[\beta * x(b, s) + \alpha]} \quad (3)$$

This is the model which is presupposed in logistic regression. A mathematically equivalent but better interpretable reformulation of this model is

$$p(b, s) = \frac{\exp\{\beta * [x(b, s) + \alpha']\}}{1 + \exp\{\beta * [x(b, s) + \alpha']\}} \quad (4)$$

with $\alpha' = \alpha/\beta$. In the following this model will be referred to as the *Simple Logit Model* (SLM).

For real-valued $x(b, s)$ and for real-valued parameters α' and β this model always predicts values between zero and one. For positive β the prediction function increases strictly monotonically. If β is positive and $x(b, s)$ tends to minus infinity, the predicted value tends to zero. If β is positive and $x(b, s)$ tends to infinity, the predicted value also tends to one. For negative β the opposite holds. For $x(b, s) = -\alpha'$ the predicted value always equals 0.5. For positive β the function accelerates (concave) left of $x(b, s) = -\alpha'$ and decelerates (convex) right of this point. The predicted values increase strictly monotonically with α' . Increasing β steepens the slope in the area around $x(b, s) = -\alpha'$ and flattens the slope in the extremes (see Figure 1). Moreover, the SLM also includes a deterministic relation between the predictor variables and the behavior as a special case. This case results if the multiplicative parameter tends to infinity.

Figure 1: Different specifications of the Simple Logit Model

The SLM is obviously consistent with the constraints imposed by the outer part of the theory. It can only predict probabilities within the range between zero and one. It suffers, however, from a different deficiency: the identity function which constitutes the normatively correct relation is no special case of the model. Therefore, the SLM does not correspond to the inner part of the theory. The SLM cannot reflect to which extent data actually correspond to the normatively correct relation and, thereby, to which extent expectations or intentions actually correspond to future behavior. Even if data fit perfectly to the normatively correct relation, this cannot be detected if data are analyzed

by means of the SLM. Moreover, because the normatively correct relation is no special case of the SLM, the parameters of the SLM cannot directly reflect deviations from this relation. Hence, they bear only limited meaning with respect to the theory presupposed here.

Nevertheless, one might try to interpret the parameters of the SLM with respect to this theory. In the case of the additive parameter this will be partially successful. This parameter reflects something like the general bias in the predictor variables. A relatively high additive parameter indicates that the actual behavioral performance is relatively high in comparison with the expectations or the intentions. A relatively low additive parameter indicates the opposite. There is, however, no value for which the SLM generally predicts that the behavioral performance corresponds to behavioral expectations or behavioral intentions. The most promising candidate for this value is certainly -0.5. With an additive parameter equal to -0.5 the SLM predicts behavioral probabilities of 0.5 if expectations or intentions are also equal to 0.5. However, for all other predictor values with the exception of two special cases, any specification of the SLM with an additive parameter of -0.5 will predict behavioral probabilities which are either too high or too low in comparison with the corresponding predictor values. Hence, the additive parameter of the SLM can only very cautiously be interpreted as an indicator of general bias.

The multiplicative parameter's theoretical meaning with respect to the theory is even more vague than the theoretical meaning of the additive parameter. Therefore, this parameter is not discussed further in this context.

3.1.2. The Double Logit Model

To overcome the problems connected with the SLM, an alternative model is introduced here. This model results through applying the linear function to the logits of both, the predictor and the criterion variable. Written in logits the model equation is

$$\ln \left[\frac{p(b,s)}{1-p(b,s)} \right] = \beta * \ln \left[\frac{x(b,s)}{1-x(b,s)} \right] + \alpha. \quad (5)$$

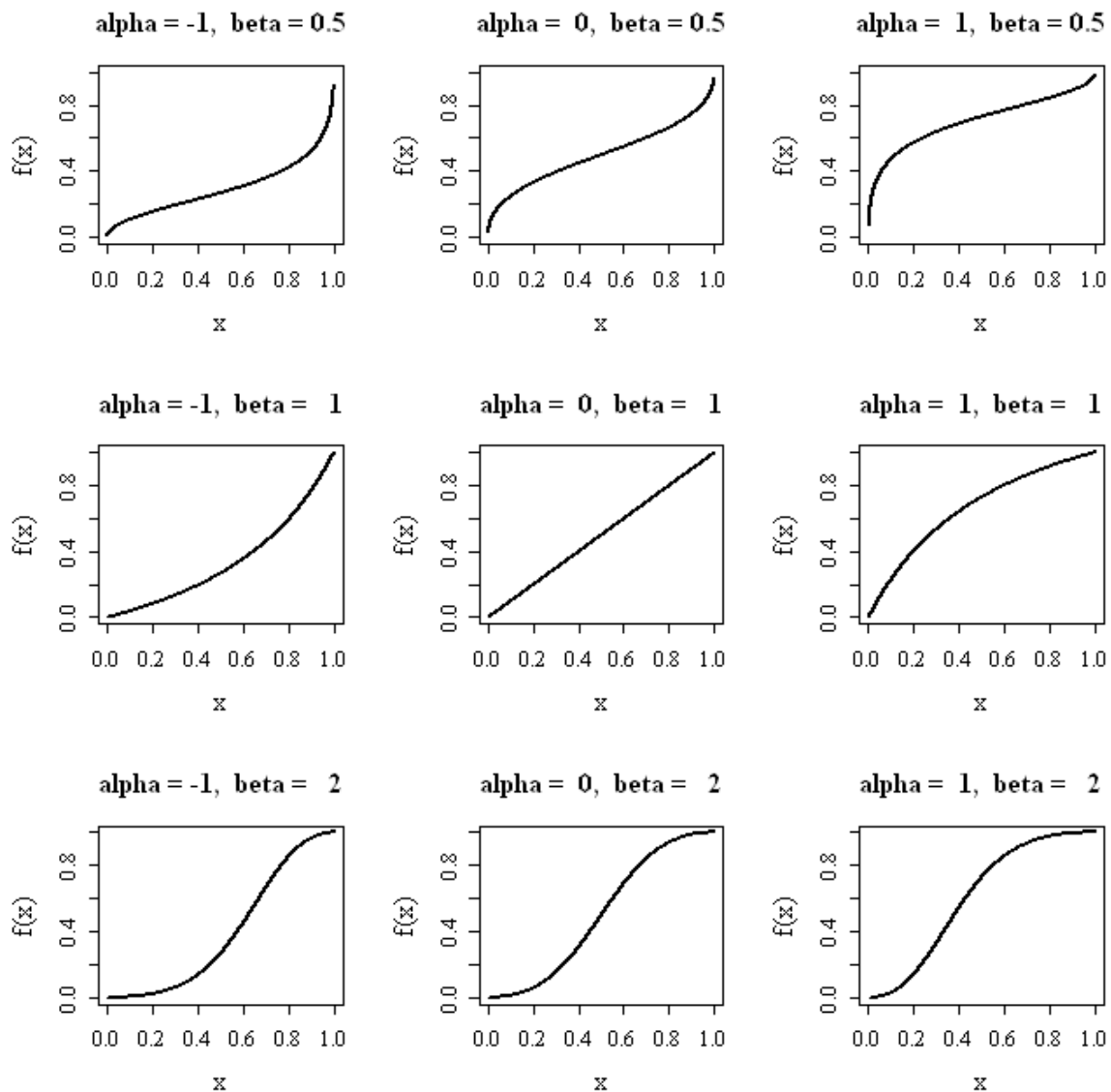
Solving for $p(b,s)$ renders

$$p(b,s) = \frac{\exp(\alpha)}{\exp(\alpha) + \left[1/x(b,s) - 1 \right]^\beta} \quad (6)$$

(see Appendix A). In the following, this model will be referred to as the *Double Logit Model* (DLM).

Like the SLM, the DLM can only predict values between zero and one, independently of the values of α and β . For $0 < x(b,s) < 1$ all predictions lie between zero and one. If $x(b,s)$ tends to zero, the predicted value also tends to zero. If $x(b,s)$ tends to one, the predicted value also tends to one. A positive α elevates the function and a negative α lowers it. A β greater than one steepens the function in the middle of the area of definition and flattens it near the bounds. A β smaller than one but greater than zero has the opposite effect (see Figure 2). Just like the SLM, the DLM also includes a deterministic relation between the predictor variables and the behavior as a special case. Again, this case results if the multiplicative parameter tends to infinity.

Figure 2: Different specifications of the Double Logit Model



Just like the SLM, the DLM is consistent with the constraints imposed by the outer part of the theory. For predictor values within the range between zero and one it can only predict values within exactly the same range. However, in contrast to the SLM, the DLM is also consistent with the constraints imposed by the inner part of the theory. The identity function is a special case of the model: it results for $\alpha=0$ and $\beta=1$. Therefore, the DLM can reasonably be applied for analyzing data with respect to the theory presupposed here. The parameters of the DLM reflect to which extent data correspond to the normatively correct relation and, thereby, to which extent behavioral probabilities correspond to behavioral expectations or behavioral intentions.

Both parameters have a distinct and important theoretical meaning. The additive parameter reflects the general bias in the predictor values. An additive parameter lower than zero indicates that the behavioral probabilities are lower than the corresponding expectation or intentions. An additive parameter higher than one indicates the opposite. An additive parameter equal to zero indicates that there is no general bias. If, additionally, the multiplicative parameter is equal to one, all predicted probabilities exactly correspond to the expectations or intentions upon which the prediction is based. The multiplicative parameter reflects the differential bias with respect to a special reference value. This reference value is $1/\{1+\exp[\alpha/(\beta-1)]\}$ (see Appendix B). If the multiplicative parameter is lower than one, then the behavioral probabilities of subjects with predictor values lower than the reference value are higher than the corresponding expectations or intentions, whereas the opposite holds for subjects with predictor values higher than the reference value. If the multiplicative parameter is greater than one the tendencies for both subject groups are the other way round. A multiplicative parameter equal to one reflects that there is no differential bias at all.

3.2. Possible Types of Statistics

Models as they have just been discussed provide the conceptual basis for deriving statistics which can be applied for analyzing data. There are different types of statistics which can be derived from a given model. On the one hand there are statistics referring to single parameters of the model; on the other hand there are statistics referring to the model's overall fit. In both cases, descriptive statistics and the corresponding statistical tests can be distinguished. Moreover, there are different approaches for deriving these statistics. In statistical literature, mainly two approaches based upon different procedures of parameter estimation are discussed. One approach is based upon ordinary least-square-estimation (OLS), the other upon maximum-likelihood-estimation (MLE).

All these different statistics reveal different aspects of data. In this way they have a different theoretical meaning. The following argumentation is concerned with discussing this meaning with respect to the theory presupposed here. Firstly, the different aspects of the OLS- and the MLE-approach are discussed and, secondly, the different characteristics of statistics referring to single parameters and statistics referring to the model's overall fit.

3.2.1. OLS versus MLE

Within the OLS-approach parameters are estimated by minimizing the sum of squared deviations of the criterion values from the model predictions. Statistical tests referring to these parameters are based upon the parameter estimates' variances (i.e. the squared standard errors) and covariances which, in turn, are determined on the basis of the squared deviations (cf. Greene, 1997, Chap. 6.6.4 and 10.2.2). The overall fit of the model is assessed by the generalized multiple squared correlation R^2 . It is defined as

$$R^2 = 1 - \frac{SS(\text{model})}{SS(\text{constant})} \quad (7)$$

with $SS(\text{model})$ the sum of squared deviations of criterion values from model predictions and $SS(\text{constant})$ the sum of squared deviations of criterion values from the criterion mean (cf. Greene, 1997, p. 256). If the class of simple linear functions is applied as model, R^2 is identical with the squared coefficient of correlation.

Deviation of R^2 from zero can be tested by

$$F(r-1, N-r) = \frac{R^2/(r-1)}{(1-R^2)/(N-r)} \quad (8)$$

with r the number of estimated parameters and N the number of subjects (cf. Greene, 1997, Chap. 10.5). For a linear prediction model and a normally distributed prediction error, the resulting test statistic is F-distributed with $r-1$ and $N-r$ degrees of freedom.

Within the MLE-approach the parameters are estimated by maximizing the likelihood of the criterion values under presupposition of the model. Just like in the OLS-approach, parameter tests are based upon the parameter estimates' variances and co-

variances. However, within the MLE-approach, these statistics are determined by means of the second derivatives of the logarithmized likelihood function (cf. Fahrmeir, Hamerle & Tutz, 1996, Chap. 2.3; especially equations 2.28, 2.29, 2.30). The overall fit is assessed by the likelihood ratio index L^2 , which was originally proposed by McFadden (1974, p. 121; cf. Greene, 1997, Chap. 19.4.2). It is defined as

$$L^2 = 1 - \frac{\ln[L(\text{model})]}{\ln[L(\text{constant})]} \quad (9)$$

with $L(\text{model})$ the likelihood of data presupposing the model and $L(\text{constant})$ the likelihood of data presupposing the criterion mean.⁵

Deviation of L^2 from zero can be tested by the likelihood ratio

$$LR = -2 \ln \left[\frac{L(\text{constant})}{L(\text{model})} \right]. \quad (10)$$

If N is sufficiently large ($N \geq 50$) and if data are determined by a constant probability then LR is approximately chi-square distributed with $r-1$ degrees of freedom (cf. Fahrmeir, Hamerle & Tutz, 1996, Chap. 2.2.). Again, r is the number of estimated parameters. Just like in the OLS-approach, rejection of the statistical zero-hypothesis means that the tested model explains significantly more variance than the constant. It does not mean that the tested model is verified.

Both approaches, OLS and MLE, differ with respect to presuppositions concerning the error distributions, i.e. the distributions of the deviations of the observed criterion values from the model values. OLS-statistics can be computed without presupposing specific error distributions. For computing MLE-statistics, these distributions must be specified. For normal error distributions, MLE renders the same parameter estimates as OLS. However, with respect to the characteristics of the resulting statistics MLE is su-

⁵ The likelihood ratio index is denoted with L^2 in order to emphasize the analogy to R^2 . Unfortunately, this implies a deviation from other relevant systems of denotation. Andreß, Hagenars, and Kühnel (1997, p. 38), for example, apply the denotation L^2 for a goodness-of-fit statistic which reflects the deviation of data from the model.

rior to OLS. MLE-parameters are consistent and asymptotically efficient for all regular error distributions and thereby for all distributions which are usually at hand (cf. Greene, 1997, Chap. 4.5.1). For OLS-parameters these properties can only be taken for granted in the case of normal error distributions. Otherwise the characteristics of OLS-parameters are obscure. Moreover, in the MLE-approach, the principles for statistical testing refer to all regular error distributions. In contrast, the statistical tests in the OLS-approach are based upon presupposing normal error distributions.

Within the theory presupposed here, the observed criterion variable is a relative frequency and the directly predicted variable a probability. Relative frequencies belonging to the same probability are known to be distributed binomially. Hence, the conditions upon which the OLS-approach is based are not fulfilled. Thus the MLE-approach should be applied. This constitutes a second argument against applying the coefficient of correlation in this research context. Not only is this statistic derived from an inappropriate type of relations but also by means of an inappropriate statistical approach. Among other things this implies that statistical decisions in previous research are based upon wrong assumptions.

Note that MLE, in contrast to OLS, can only be reasonably performed if the statistical model to which it is applied fulfills certain requirements. For all possible parameter values this model should always predict probabilities within the admissible range between zero and one. Otherwise, in some cases, the likelihood function will no longer have a proper maximum and, consequently, the numerical procedure for determining MLE-parameters will break down. Thus, the arguments for MLE and against OLS are, indirectly, further arguments against applying the class of simple linear functions as the presupposed model in this context of research.

3.2.2. Single Parameter versus Overall Fit Statistics

Statistics referring to single parameters and statistics referring to the overall fit address different topics. Hence, there is some justification for expecting them to have a different theoretical meaning. However, before elaborating these differences it might be worthwhile to investigate the extent to which these statistics can provide theoretically useful information. For this purpose they should be - as far as possible - independent of theoretically irrelevant aspects of data. Therefore, these statistics are now discussed with respect to this ideal. More specifically, the effects of two specific theoretically irrelevant aspects of data are analyzed: 1) the effects of range and 2) the effects of grouping.

The first aspect, i.e. range, refers to the predictor variable. In some studies only a small range of the predictor variable can be investigated whereas in other studies a wide range is available. Ideally, statistics describing the relation between a predictor and a criterion variable should provide the same result independently of the range which can be investigated. Single parameter estimates and overall measures of fit differ with respect to this criterion. Both alternative measures for overall fit, R^2 and L^2 , depend upon the range considered in the study. They decrease with range. If only a very small range is considered, both statistics approximate to zero even if data are perfectly generated by the model in question. Parameter estimates, in contrast, are mostly independent of range (cf. Bortz, 1993, p. 198; Cohen & Cohen, 1975, Chap. 2.11.3; Dawes & Smith, 1985, p. 559; see also Appendix C).

The second aspect, i.e. grouping, refers to the criterion variable. In the models discussed here the immediate criterion variable is a vector of probabilities. These probabilities, however, cannot be directly assessed empirically. Instead, the data which are directly at hand are a binary variable with zero and one as possible values. This opens different possibilities for handling this variable when statistics are computed: 1) the binary variable can be treated directly as criterion variable and 2) subjects with the same predictor variable value can be grouped together and the relative frequencies for these groups of equivalent subjects can be treated as criterion variable.

There is no problem if a statistic renders the same result for both possible modes of the criterion variable. Otherwise, however, the question arises as to which mode renders the theoretically more important information. There is one rather obvious essential argument for the second mode. Relative frequencies based upon more than one observation are better estimations of probabilities than relative frequencies based upon only one observation. Therefore, the second mode of defining the criterion variable corresponds more to the variable addressed by the model than the first mode. There is, however, at the same time, also an essential argument against the second mode. Because the predictor variable is continuous, each grouping of subjects according to their predictor variable values relies upon arbitrarily segmenting the range of the predictor variable. At best, this arbitrary segmentation results from choosing a specific graduation of the answer modality. If the same statistic is computed for different segmentations this will usually produce different results. Thus a statistic based upon such an arbitrary segmentation has no clear-cut meaning.

Both arguments are true. The resulting dilemma cannot be resolved. Therefore, those statistics are at an advantage which are invariant under grouping. Both measures referring to overall fit, i.e. the generalized multiple squared correlation R^2 and the likelihood ratio L^2 , depend upon grouping. They both increase with grouping. In contrast, parameter estimates, whether determined by OLS or MLE, are independent of grouping (see Appendix D). This provides a further argument against overall measures of fit and for single parameter estimates. With respect to inferential statistics, the OLS- and the MLE-approach differ. Inferential statistics in the OLS-approach depend upon grouping; statistical decisions become less conservative with grouping. In contrast, inferential statistics in the MLE-approach are independent of grouping (see Appendix D).

Altogether, the considerations concerning the effects of both, range and grouping, produce the same result: the here considered statistics referring to the overall fit of the model are highly dependent upon irrelevant aspects of data, whereas the statistics referring to single parameters are not - at least not upon the aspects investigated here. Consequently, theoretical concepts would be better specified by statistics referring to single parameters than by statistics referring to overall fit. This is a further argument against applying the coefficient of correlation as it is applied in present main-stream research.

4. Example

The methods discussed above will now be demonstrated with data from an empirical study. The subjects of this study were 107 students (26 male, 81 female, mean age 23.9, (std=4.9)) with psychology as a subsidiary subject. The behaviors were 16 weekend activities (see Table 1). These behaviors were selected on the basis of a pilot study in which 20 subjects were asked to list typical weekend activities. The weekend was defined as the interval from Friday 6 p.m. to Sunday 12 p.m.. The main study consisted of two surveys. In the first survey behavioral expectations, behavioral intentions and judgments of perceived behavioral control were assessed. To ensure the metric properties of the answer modality, subjects were asked to express their judgments as integer numbers between zero and one hundred. In the second survey subjects were asked to tell for each behavior whether they had performed it. The first survey was performed in the context of three different university lectures on the Tuesday and the Wednesday before the weekend in question. The second survey was performed in the context of the same three university lectures in the week directly after the weekend.

Table 1: Behaviors investigated in the study

1)	going jogging
2)	sleeping until at least 10 a.m.
3)	studying for at least 2 hours
4)	going to a party
5)	going swimming
6)	playing lotto ^a
7)	going to the theatre
8)	going to a cafe
9)	pasting photographs into an album
10)	having friends round to visit
11)	ordering a pizza
12)	doing nothing for at least 2 hours without interruption
13)	going shopping
14)	phoning grandmother
15)	watching sports on TV
16)	doing the laundry
^a Lotto is a lottery game played weekly in Germany.	

Data from all subjects are available for 56 out of 64 variables. For the remaining eight variables maximally three data are missing per variable (see Table 2). Descriptive analysis shows that the 16 behaviors cover a large range from very seldom to very frequent behaviors (see Table 2). The responses from the first questionnaire, which originally range from zero to one hundred, were numerically coded as numbers between zero and one. The specific coding rule relies upon the idea that the discrete questionnaire responses represent segments of the continuous interval between zero and one. Questionnaire responses between 1 and 99 are assumed to represent the surrounding one-percent segments. Accordingly, these responses were coded by dividing the original value by one hundred. In contrast, both extreme questionnaire responses are assumed to represent the corresponding extreme half-percent segment. Accordingly, responses of 0 were coded as 0.0025 and responses of 100 as 0.9975. (For a coding principle referring to the usually applied seven-category rating scales, see Konerding, 1999, p. 20)

Table 2: Descriptive statistics

Behavior	Expectation ^a			Intention ^a			Perc. B. Control ^a			Performance		
	M	SD	N	M	SD	N	M	SD	N	M	SD	N
1)	0.14	0.29	107	0.23	0.33	106	0.58	0.39	107	0.08	0.28	107
2)	0.62	0.38	107	0.76	0.32	106	0.76	0.33	107	0.69	0.46	107
3)	0.44	0.36	107	0.53	0.37	107	0.73	0.30	107	0.46	0.50	107
4)	0.42	0.39	107	0.61	0.33	107	0.64	0.36	107	0.44	0.50	107
5)	0.14	0.25	107	0.33	0.36	107	0.56	0.39	107	0.09	0.29	107
6)	0.06	0.18	107	0.06	0.19	107	0.59	0.44	107	0.04	0.19	107
7)	0.12	0.24	107	0.38	0.33	107	0.43	0.38	107	0.07	0.26	107
8)	0.47	0.35	107	0.59	0.34	107	0.73	0.33	107	0.50	0.50	107
9)	0.08	0.19	107	0.17	0.28	107	0.43	0.42	107	0.04	0.19	107
10)	0.61	0.35	106	0.80	0.21	107	0.76	0.29	107	0.61	0.49	107
11)	0.20	0.27	107	0.32	0.32	106	0.64	0.39	107	0.17	0.38	107
12)	0.47	0.40	107	0.62	0.37	107	0.61	0.39	107	0.61	0.49	106
13)	0.49	0.34	107	0.55	0.34	107	0.68	0.33	107	0.72	0.45	107
14)	0.15	0.29	106	0.24	0.33	104	0.43	0.46	107	0.15	0.36	105
15)	0.15	0.28	107	0.15	0.30	107	0.58	0.43	107	0.21	0.41	107
16)	0.33	0.37	107	0.29	0.35	107	0.59	0.40	107	0.31	0.46	107

^aNumerically coded as values between zero and one.

To demonstrate the application of different measures for overall fit, the squared coefficient of correlation, the likelihood ratio index for the SLM, and the likelihood ratio index for the DLM were computed with the behavior as the criterion and with, alternatively, the expectation and the intention as the predictor (see Table 3; for hints concerning computation see Appendix E).⁶ In several respects all three statistics provide the

⁶ One of the reviewers suggested performing also goodness-of-fit tests with the models as statistical zero-hypotheses. This has not been done for two reasons. The first reason is a statistical reason. The statistics usually applied for this purpose are Pearson's chi-square, the log-likelihood-ratio chi-square, and Neymann's modified chi-square (cf. Andreß, Hagenaaars, and Kühnel, 1997, p. 38). These statistics vary with grouping. Moreover, for ungrouped data, i.e. for groups with size one, the statistics' distributions under presupposition of the model are not known. In any case they cannot be approximated by chi-square distributions (cf. Fahrmeir, Hamerle & Tutz, 1996, p. 260). The second reason for not performing a goodness-of-fit test is epistemological. According to the epistemological position of the author, no model made by a human being will ever be true. Moreover, according to this position, closeness to truth is not the most important criterion a model should fulfil. Instead, an optimal compromise between closeness to truth and conceptual simplicity is desired. Presupposing this position the information which can be provided by

same results. According to all three statistics both predictor variables have a statistically significant relationship with behavior except for behavior 9. In the latter case there is only a significant relation for the DLM with the intention as predictor. Moreover, with the exception of behavior 11, all three statistics provide the same result concerning the comparison between expectations and intentions. Except for behaviors 9 and 11 all three statistics indicate that the behavioral expectation is the better predictor. For behavior 9 both likelihood ratio indices show a very slight tendency in the opposite direction. For behavior 11 the squared coefficient of correlation favors the behavioral expectation, whereas the likelihood ratio indices for both, the SLM and the DLM, favor the behavioral intention.

Table 3: Measures of overall fit^a

Behavior	Expectation			Intention		
	R ²	L ² (SLM)	L ² (DLM)	R ²	L ² (SLM)	L ² (DLM)
1)	0.55**	0.64**	0.65**	0.36**	0.52**	0.45**
2)	0.34**	0.29**	0.25**	0.24**	0.19**	0.18**
3)	0.27**	0.21**	0.22**	0.19**	0.15**	0.13**
4)	0.39**	0.32**	0.32**	0.27**	0.22**	0.25**
5)	0.40**	0.41**	0.37**	0.12**	0.19**	0.16**
6)	0.73**	0.84**	0.85**	0.45**	0.57**	0.47**
7)	0.50**	0.54**	0.49**	0.06*	0.10**	0.08**
8)	0.05*	0.04**	0.03*	0.04*	0.03**	0.02*
9)	0.00	0.00	0.01	0.00	0.01	0.06*
10)	0.15**	0.12**	0.10**	0.06*	0.04**	0.04**
11)	0.47**	0.10**	0.06**	0.18**	0.19**	0.13**
12)	0.48**	0.44**	0.44**	0.21**	0.17**	0.17**
13)	0.10**	0.09**	0.12**	0.05*	0.04**	0.04**
14)	0.40**	0.36**	0.34**	0.34**	0.35**	0.29**
15)	0.47**	0.41**	0.42**	0.31**	0.25**	0.25**
16)	0.46**	0.39**	0.38**	0.25**	0.20**	0.24**

** p < 0.01, one-tailed. * p < 0.05, one-tailed. ^aR² is the squared coefficient of correlation, L₂(SLM) the likelihood ratio index for the Simple Logit Model, and L²(DLM) the likelihood ratio index for the Double Logit Model.

a goodness-of-fit test with the model as statistical zero-hypothesis has only limited value.

However, as argued above, the theoretical meaning of measures of overall fit is rather restricted. Statistics referring to single parameters will convey deeper insights - presupposed that the statistical model is wisely chosen. To compare the explorative value of the parameters of the different models discussed above, the parameters for the linear regression equation, the SLM and the DLM were computed (see Tables 4, 5, and 6). In accordance with mainstream research, parameters for the linear regression equation were determined by means of OLS. In contrast, in accordance with the argumentation above, parameters for the SLM and the DLM were determined by means of MLE.

As argued above, the main deficiency of the linear regression equation is that it may predict probabilities outside the range between zero and one. With the behavioral expectations as predictors this actually happens for 6 of the 16 behaviors. With the behavioral intentions as predictors this happens for 3 behaviors (see Table 4). In addition to the theoretical arguments presented above this may be taken as an empirical argument against applying the linear regression equation as a statistical model for this kind of data. For this reason no interpretation of these parameters is attempted.

Table 4: Prediction with linear equations and OLS-parameters

Behavior	Expectation				Intention			
	α	β	%<0 ^a	%>1 ^b	α	β	%<0 ^a	%>1 ^b
1)	-0.02	0.73	71.0	0	-0.03	0.50	56.6	0
2)	0.24	0.72	0	0	0.14	0.72	0	0
3)	0.14	0.72	0	0	0.15	0.58	0	0
4)	0.10	0.80	0	0	-0.04	0.79	10.3	0
5)	-0.01	0.72	56.1	0	0.00	0.28	0	0
6)	-0.01	0.92	84.1	0	-0.01	0.68	85.0	0
7)	-0.02	0.79	59.8	0	0.00	0.19	0	0
8)	0.34	0.33	0	0	0.32	0.31	0	0
9)	0.04	0.03	0	0	0.03	0.04	0	0
10)	0.27	0.55	0	0	0.16	0.55	0	0
11)	0.08	0.45	0	0	-0.01	0.49	0	0
12)	0.21	0.85	0	22.4	0.24	0.60	0	0
13)	0.51	0.42	0	0	0.56	0.29	0	0
14)	0.03	0.78	0	0	0.00	0.65	0	0
15)	0.05	0.98	0	5.6	0.09	0.75	0	0
16)	0.03	0.84	0	0	0.12	0.66	0	0

^aPercentage of predictions smaller than zero. ^bPercentage of predictions greater than one.

The SLM-parameters presented here (see Table 5) refer to the reformulated version of the SLM (see equation 4). As argued above, for this version of the SLM at least the additive parameter can - with some caution - be interpreted with respect to the theory presupposed here. Values lower than -0.5 might be interpreted as indicating that behavioral probabilities tend to be lower than the corresponding expectations or intentions. Values higher than -0.5 might be given the opposite meaning. Presupposing this interpretational rule, the additive parameter indicates that subjects overestimate their behavioral performance for behaviors 9 and 11 and underestimate performance for behaviors 12 and 13. Moreover, in the same sense the additive parameter indicates that subjects intend more than they actually realize for the behaviors 5, 7 and 9 whereas the opposite holds for behavior 13. As argued above, the multiplicative parameter of the SLM bears no theoretically relevant meaning with respect to the theory presupposed here. Therefore, these parameters are not further interpreted.

Table 5: Prediction with the SLM and MLE-parameters

Behavior	Expectation				Intention			
	α^a	SE(α') ^b	β	SE(β) ^c	α^a	SE(α') ^b	β	SE(β) ^c
1)	-0.75	0.18	7.32	1.84	-0.90	0.23	6.78	1.86
2)	-0.33	0.11	3.90	0.74	-0.49	0.17	3.51	0.78
3)	-0.50	0.11	3.47	0.70	-0.61	0.16	2.65	0.63
4)	-0.49	0.10	4.12	0.73	-0.71	0.15	4.24	0.89
5)	-0.71	0.12	5.50	1.26	-1.21**	0.25	3.23	1.04
6)	-0.51	0.22	14.29	7.62	-0.71	0.17	7.40	2.24
7)	-0.68	0.13	6.74	1.58	-1.41**	0.31	2.77	1.24
8)	-0.48	0.25	1.34	0.58	-0.60	0.33	1.26	0.60
9)	-5.34**	0.91	0.62	2.31	-3.93**	0.72	0.87	1.52
10)	-0.40	0.17	2.51	0.65	-0.61	0.34	2.37	1.00
11)	-0.85*	0.14	2.70	0.88	-0.89*	0.16	3.51	0.91
12)	-0.29**	0.07	5.67	1.04	-0.43	0.15	2.76	0.62
13)	-0.03**	0.15	2.34	0.73	0.12*	0.27	1.47	0.67
14)	-0.63	0.10	4.82	1.01	-0.76	0.14	4.73	1.03
15)	-0.42	0.07	6.47	1.37	-0.56	0.09	3.91	0.87
16)	-0.58	0.10	4.80	0.83	-0.59	0.11	3.23	0.69

**p < 0.01, two-tailed. *p < 0.05, two-tailed. ^aThe additive parameter of the reformulated SLM (see equation 4) with statistical test for deviation from 0.5. ^bStandard error for the additive parameter of the reformulated SLM. ^cStandard error for the multiplicative parameter.

To overcome the interpretational difficulties connected with the SLM, the DLM was presented as an alternative. With the DLM both parameters, the additive and the multiplicative parameter, can be interpreted with respect to the theory presupposed here. Inspection of these parameters shows that data do not correspond to the normatively correct relation, neither for behavioral expectations, nor for behavioral intentions (see Table 6). The additive parameters deviate significantly from zero more often than would be expected if the normatively correct relation held; however, the pattern of deviation is different for both variables. The additive parameters for the behavioral expectations vary around zero, whereas the additive parameters for the behavioral intentions are mostly lower than zero. The multiplicative parameters seem to be generally lower than one for both variables. Moreover, for most behaviors, they are closer to one for expectations than for intentions.

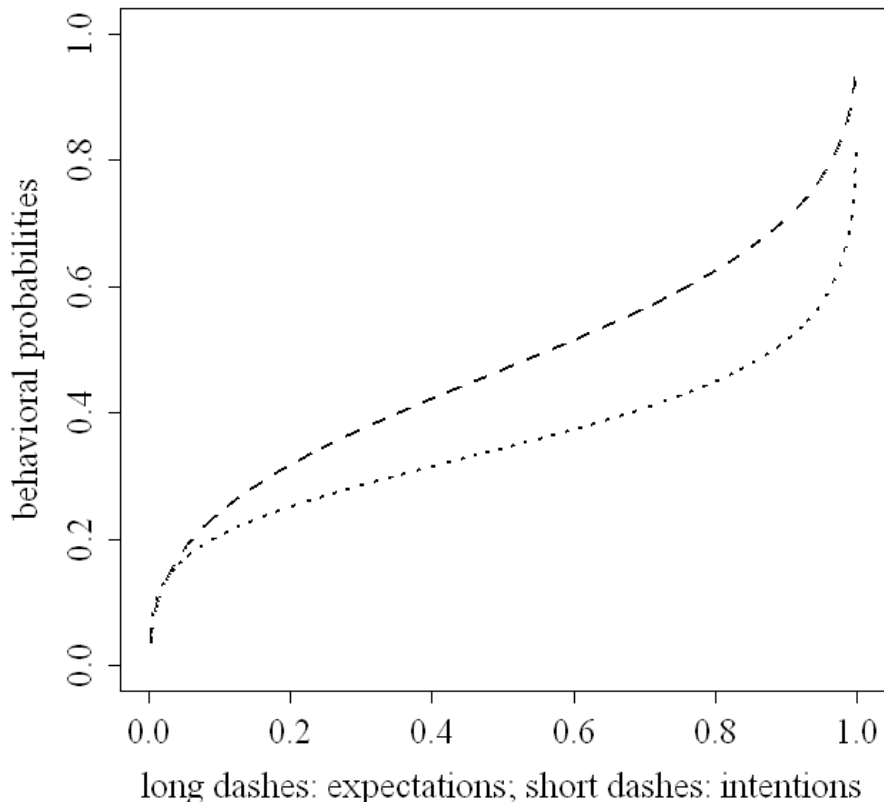
Table 6: Prediction with the DLM and MLE-parameters

Behavior	Expectation				Intention			
	α^a	SE(α) ^b	β	SE(β) ^c	α^a	SE(α) ^b	β	SE(β) ^c
1)	-1.61**	0.58	0.81	0.24	-2.41**	0.54	0.51**	0.13
2)	0.64**	0.24	0.36**	0.08	0.08	0.28	0.29**	0.07
3)	0.02	0.23	0.39**	0.09	-0.23	0.21	0.25**	0.06
4)	-0.04	0.25	0.45**	0.09	-0.81**	0.26	0.48**	0.10
5)	-1.32**	0.43	0.53**	0.14	-2.28**	0.38	0.28**	0.09
6)	-0.42	1.45	2.36	2.10	-1.40*	0.68	0.66	0.23
7)	-1.24*	0.52	0.74	0.23	-2.45**	0.39	0.23**	0.11
8)	0.01	0.20	0.13**	0.06	-0.07	0.20	0.09**	0.06
9)	-2.76**	0.80	0.11**	0.16	-2.75**	0.54	0.19**	0.13
10)	0.20	0.22	0.25**	0.07	-0.01	0.28	0.18**	0.08
11)	-1.16**	0.31	0.19**	0.08	-1.32**	0.28	0.30**	0.10
12)	1.06**	0.32	0.59**	0.12	0.23	0.23	0.28**	0.06
13)	1.12**	0.25	0.28**	0.08	0.93**	0.22	0.14**	0.07
14)	-0.67	0.37	0.43**	0.10	-1.12**	0.32	0.41**	0.10
15)	0.21	0.41	0.59**	0.13	-0.26	0.36	0.35**	0.08
16)	-0.26	0.28	0.53**	0.11	-0.21	0.27	0.34**	0.07

**p < 0.01, two-tailed. *p < 0.05, two-tailed. ^aWith statistical test for deviation from zero. ^bStandard error for the additive parameter. ^cWith statistical test for deviation from one. ^dStandard error for the multiplicative parameter.

For an overall comparison between both variables the DLM-parameters were estimated over all behaviors but separately for both variables. For the behavioral expectations the additive parameter is -0.12 ($SE = 0.07$) and the multiplicative parameter is 0.46 ($SE = 0.02$); for the behavioral intentions the corresponding parameters are -0.64 ($SE = 0.06$) and 0.32 ($SE = 0.02$). Both functions differ from the identity function. For both functions the multiplicative parameters are significantly smaller than one ($p < 0.01$). For the behavioral intentions, additionally, the additive parameter is significantly smaller than zero ($p < 0.01$). Altogether, the function for the behavioral expectations seems to be closer to the identity function (see Figure 3). An exact test for comparing the corresponding parameters of both functions is difficult to construct because nothing can be said about the covariances between the parameter estimates. Therefore, the statistical test is based upon the worst case; i.e. complete dependency. In this case, the covariance between the parameter estimates equals the product of their standard errors. Under this presupposition the function for behavioral expectations is significantly higher ($z = 3.94$, $p < 0.01$, two-tailed) and steeper ($z = 3.28$, $p < 0.01$, two-tailed) than the function for the behavioral intentions.

Figure 3: Prediction functions for behavioral intentions and behavioral expectations

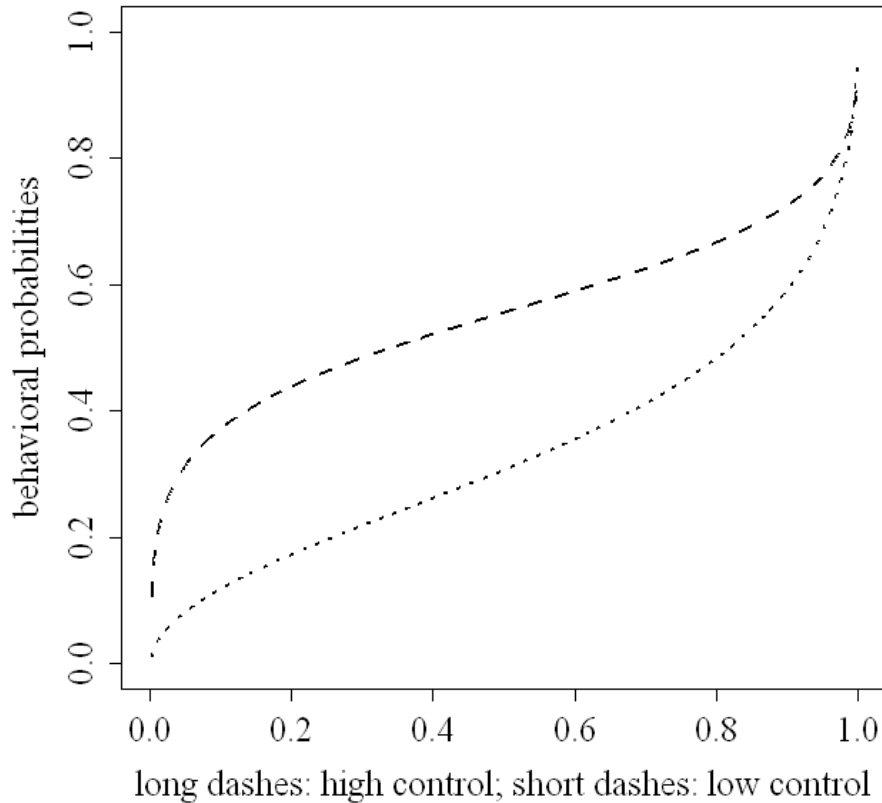


Altogether these results are in line with the presupposed understanding of both predictor variables. According to this understanding, behavioral expectations should be based upon the perceived behavioral control whereas behavioral intentions should rather be independent of perceived behavioral control. Presupposing that perceived behavioral control covaries with actual behavioral control this implies that the prediction function for behavioral expectations should be steeper and higher and closer to the identity function than the prediction function for the behavioral intentions. This is also in line with the theoretical considerations and empirical findings of Warshaw and Davis (1985). However, the analysis with the DLM reveals in a more detailed manner how the predictions by means of intentions and expectations differ.

Although the prediction functions for the behavioral expectations are comparatively closer to the normatively correct prediction function they are not identical with this function. Subjects seem to generally overdiscriminate their future behavior. Moreover, both parameters of the DLM seem to vary with behavior. This gives rise to the question concerning the reasons of this variation.

One hypothesis might be that the differences between the parameters are produced by differences in actual behavioral control which should show in a covariance between the parameters and perceived behavioral control. To test this hypothesis the sample of the 16 behaviors was median-split according to the perceived behavioral control means (assignment of behaviors: low control: 1,5,6,7,9,14,15,16; high control: 2,3,4,8,10,11,12,13; cf. Table 2). The data for the behaviors within one group were merged and the DLM-parameters were estimated separately for each group. For the lower control behaviors the additive parameter is -0.81 (SE = 0.14) and the multiplicative parameter is 0.54 (SE = 0.05); for the higher control behaviors the corresponding parameters are 0.23 (SE = 0.08) and 0.34 (SE = 0.03). Under presupposition of independence between the corresponding estimates of both groups the function for the lower control behaviors is significantly lower ($z = -6.307$, $p < 0.01$, two-tailed) and steeper ($z = 3.880$, $p < 0.01$, two-tailed) than the function for the higher control behaviors (see Figure 4).

Figure 4: Prediction functions for behavioral expectations under different conditions of behavioral control



Obviously, behavioral control affects the relation between behavioral expectations and behavioral probabilities, - however, for both DLM-parameters in a different way. With decreasing behavioral control the additive parameter moves away from zero, which is additive parameter of the identity function. In contrast, with decreasing behavioral control, the multiplicative parameter approaches one, which is the multiplicative parameter of the identity function. It seems that subjects try to cope with decreasing behavioral control by forming less extreme behavioral expectations. By this strategy they successfully counteract differential bias. However, they fail to adjust their expectations to the additive influence of behavioral control.

5. Summative Discussion

The central concern of this contribution has been the conceptual framework which must be presupposed in empirical research referring to behavioral expectations, behavioral intentions and behavior. A theory referring to this topic has been presented and possible methods have been discussed with respect to this theory. The theory can be divided into two parts: 1) the outer part, which describes the actually given characteristics of the object under investigation and 2) the inner part, which describes a specific, voluntarily chosen point of view on the object under investigation. Two conceptual parts of possible methods for analyzing data, i.e. the type of relation and the type of statistic incorporated in this method, have been discussed with respects to both parts of the theory.

The coefficient of correlation which dominates present main-stream research in this context has been discarded because both, the incorporated type of relation and the incorporated type of statistic, do not fit to the outer part of the theory. Two different models, the SLM and the DLM, both describing a specific type of relation, have been discussed. They both fit to the outer part of the theory; however, with respect to the inner part of the theory the DLM is superior. The theoretical properties of OLS in comparison with MLE and of statistics for overall fit in comparison with statistics for single parameters have been discussed. It has been argued that MLE-statistics referring to single parameters provide the theoretically most useful information.

All methods discussed above have been demonstrated using empirical data. MLE-parameter statistics provide, on the one hand, results which are in line with previous findings. On the other hand they provide additional insights which could not have been obtained easily by previous methods. This suggest that the DLM might be a very helpful tool in detecting the effects of possible moderator variables. Moreover, the DLM might serve as a conceptual basis for mathematically modeling more differentiated psychological hypotheses concerning the prediction of behavior. Among other things, multivariate generalizations of the DLM could be developed. Perhaps it will also be possible to estimate the parameters of the DLM on the basis of the characteristics of the behavior and/or of the subjects. In this case, the DLM could be applied for predicting behavior which is actually in the future at the time of prediction.

References

- [1] Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckmann (Eds.), *Action-control: From cognition to behavior* (pp. 11-39). Heidelberg: Springer.
- [2] Andreß, H.J., Hagenaaars, J.A. & Kühnel, S. (1997). *Analyse von Tabellen und kategorialen Daten*. Berlin: Springer.
- [3] Balzer, W., Moulines, C. U. & Sneed, J. D. (1987). *An architectonic for science*. Dordrecht: D. Reidel Publishing Company.
- [4] Bortz, J. (1993). *Statistik für Sozialwissenschaftler*. Berlin Heidelberg: Springer.
- [5] Cohen, J. & Cohen, P. (1975). *Applied multiple regression/correlation analysis for the behavioral sciences*. Hillsdale, New Jersey: Lawrence Erlbaum Associates Publishers.
- [6] Dawes, R.M. & Smith, T.L. (1985). Attitude and opinion measurement. In G. Lindzey & E. Aronson (Eds.), *Handbook of Social Psychology* (Vol. 1, pp. 509-566). New York: Random House.
- [7] Eckes, T. & Six, B. (1994). Fakten und Fiktionen in der Einstellungs-Verhaltens-Forschung. *Zeitschrift für Sozialpsychologie*, 25, 253-271.
- [8] Fahrmeir, L., Hamerle, A., & Tutz, G. (1996). *Multivariate statistische Verfahren. (2. überarbeitete Auflage)*. Berlin: Walter de Gruyter.
- [9] Fazio, R.H. (1990). Multiple processes by which attitudes guide behavior: The MODE model as an integrative framework. In M.P. Zanna (Ed.), *Advances in Experimental Social Psychology* (Vol. 23, pp. 75-110). San Diego, Cal.: Academic Press.
- [10] Fiske, S. T. & Neuberg, S. L. (1990). A continuum of impression formation, from category-based to individuating processes: influences of information and motivation on attention and interpretation. In M. P. Zanna (Ed.), *Advances in Experimental Social Psychology* (Bd. 23, pp. 1-74). San Diego: Academic Press, Inc.
- [11] Greene, W.H. (1997). *Econometric analysis, 3rd edition*. Upper Saddle River, NJ: Prentice-Hall, Inc.

-
- [12] Jonas, K. & Doll, J. (1996). Eine kritische Bewertung der Theorie überlegten Handelns und der Theorie geplanten Verhaltens. *Zeitschrift für Sozialpsychologie*, 27, 18-31.
- [13] Konerding, U. (1999). Formal models for predicting behavioral intentions in dichotomous choice situations. *Methods of Psychological Research*, 4(2), 1-32. <http://www.mpr-online.de/>.
- [14] Krantz, D.H., Luce, R.D., Suppes, P., & Tversky, A. (1971). *Foundations of Measurement: Additive and Polynomial Representations* (Vol. 1). New York: Academic Press.
- [15] Kuhn, T.S. (1976). *Die Struktur wissenschaftlicher Revolutionen*. Frankfurt am Main: Suhrkamp.
- [16] Lakatos, I. (1970). Falsification and the Methodology of Scientific Research Programmes. In I. Lakatos & A. Musgrave (Eds.) *Criticism and the growth of knowledge* (pp. 91-196). Cambridge: Cambridge University Press.
- [17] Liska, A. E. (1984). A critical examination of the causal structure of the Fishbein/Ajzen attitude-behavior model. *Social Psychology Quarterly*, 47, 61-74.
- [18] Luce, R. D., Krantz, D. H., Suppes, P., & Tversky, A. (1990). *Foundations of measurement: Representation, axiomatization, and invariance* (Vol. 3). New York: Academic Press.
- [19] McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 105-142). New York: Academic Press.
- [20] Petty, R. E. & Cacioppo, J. T. (1986). *Communication and persuasion*. Hillsdale, NJ: Erlbaum.
- [21] Rost, J. (1999). Was ist aus dem Rasch-Modell geworden? *Psychologische Rundschau*, 50(3), 140-156.
- [22] Sheeran, P. & Orbell, S. (1998). Do intentions predict condom use? Meta-analysis and examination of six moderator variables. *British Journal of Social Psychology*, 37, 231-250.
- [23] Sheppard, B.H., Hartwick, J. & Warshaw, P.R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modification and future research. *Journal of Consumer Research*, 15, 325-343.

-
- [24] Simon, H.A. (1956). Rational choice and the structure of the environment. *Psychological Review*, 63, 129-138.
- [25] Simon, H.A. (1982). *Models of bounded rationality*. Cambridge, MA: MIT Press.
- [26] Simon, H.A. (1992). *Economics, bounded rationality, and the cognitive revolution*. Aldershot Hants, England: Elgar.
- [27] Sneed, J.D. (1979). *The logical structure of mathematical physics, 2nd edition*. Dordrecht: Holland: D. Reidel Publishing Company.
- [28] Suppes, P., Krantz, D. H., Luce, R. D., & Tversky, A. (1989). *Foundations of measurement: Geometrical, threshold, and probabilistic representations*. (Vol. 2). New York: Academic Press.
- [29] Warshaw, P.R. & Davis, F.D. (1985). Disentangling behavioral intention and behavioral expectation. *Journal of Experimental Social Psychology*, 21, 213-228.

Appendix A: Transformation from equation 5 into equation 6

To shorten notation let $p(b,s)$ be p and $x(b,s)$ be x . Equation 5 then is

$$\ln\left[\frac{p}{1-p}\right] = \beta * \ln\left[\frac{x}{1-x}\right] + \alpha \quad (A1)$$

Delogarithmizing renders

$$\frac{p}{1-p} = \left[\frac{x}{1-x}\right]^\beta * \exp(\alpha). \quad (A2)$$

Multiplying by $1-p$ renders

$$p = \left[\frac{x}{1-x}\right]^\beta * \exp(\alpha) - p * \left[\frac{x}{1-x}\right]^\beta * \exp(\alpha). \quad (A3)$$

Adding the term which is subtracted on the right side of the equation renders

$$p * \{1 + \left[\frac{x}{1-x}\right]^\beta * \exp(\alpha)\} = \left[\frac{x}{1-x}\right]^\beta * \exp(\alpha). \quad (A4)$$

Dividing by the term which is multiplied with p on the left side renders

$$p = \frac{\left[\frac{x}{1-x}\right]^\beta * \exp(\alpha)}{1 + \left[\frac{x}{1-x}\right]^\beta * \exp(\alpha)}. \quad (A5)$$

Reducing the ratio on the right side by $[x/(1-x)]^\beta$ renders

$$p = \frac{\exp(\alpha)}{[x/(1-x)]^\beta + \exp(\alpha)}. \quad (A6)$$

Because $[x/(1-x)]^\beta = [(1-x)/x]^\beta = (1/x-1)^\beta$ equation A6 is equivalent to

$$p = \frac{\exp(\alpha)}{(1/x-1)^\beta + \exp(\alpha)}. \quad (A7)$$

Resubstituting p and x renders equation 6.

Appendix B: Bias and differential bias in the DLM

In this context bias means that the predicted values are not equal to the predictor values. According to equation 6 the predicted values are higher than the predictor values if and only if

$$\frac{\exp(\alpha)}{\exp(\alpha) + [1/x - 1]^\beta} > x. \quad (B1)$$

Independently of the model parameters, the DLM predicts zero if the predictor value is also zero and it predicts one if the predictor value is also one. Therefore, the following considerations are restricted to predictor values between zero and one. In this interval,

transforming an inequality corresponding to equation 6 into an inequality corresponding to equation 5 does not change the direction of the inequality sign. Hence, for $0 < x < 1$ B1 is equivalent to

$$\beta * \ln\left[\frac{x}{1-x}\right] + \alpha > \ln\left[\frac{x}{1-x}\right]. \quad (B2)$$

Subtracting $\beta * \ln\left[\frac{x}{1-x}\right]$ renders

$$\alpha > \ln\left[\frac{x}{1-x}\right] - \beta * \ln\left[\frac{x}{1-x}\right]. \quad (B3)$$

For further consideration, three cases must be distinguished: $\beta < 1$, $\beta = 1$, and $\beta > 1$.

For $\beta < 1$ dividing inequality B3 by $1 - \beta$ renders

$$\frac{\alpha}{1-\beta} > \ln\left[\frac{x}{1-x}\right]. \quad (B4)$$

Delogarithmizing renders

$$\exp\left[\frac{\alpha}{1-\beta}\right] > \frac{x}{1-x}. \quad (B5)$$

Because of $0 < x < 1$ multiplying with $1-x$ renders

$$(1-x) * \exp\left[\frac{\alpha}{1-\beta}\right] > x. \quad (B6)$$

Adding $x \cdot \exp[\alpha/(1-\beta)]$ renders

$$\exp[\alpha/(1-\beta)] > x * \{1 + \exp[\alpha/(1-\beta)]\}. \quad (B7)$$

Because $1 + \exp[\alpha/(1-\beta)]$ is always positive dividing by this term renders

$$\frac{\exp[\alpha/(1-\beta)]}{1 + \exp[\alpha/(1-\beta)]} > x. \quad (B8)$$

Reducing the ratio on the left side of the inequality by $\exp[\alpha/(1-\beta)]$ renders

$$\frac{1}{\exp[\alpha/(\beta-1)] + 1} > x. \quad (B9)$$

Hence, for $\beta < 1$ predicted values are higher than predictor values if x is smaller than $1/\{\exp[\alpha/(\beta-1)] + 1\}$. If x is greater than this value the opposite holds.

For $\beta = 1$ inequality B3 reduces to

$$\alpha > 0; \quad (B10)$$

i.e. in this case there is no differential bias but only a general bias which solely depends upon α .

For $\beta > 1$ dividing inequality B3 by $1 - \beta$ renders

$$\alpha / (1 - \beta) < \ln [x / (1 - x)]. \quad (B11)$$

Consequently, all further considerations are analogous to the case $\beta < 1$, only with the inequality sign reversed. Hence, for $\beta > 1$ predicted values are lower than predictor values if x is smaller than $1 / \{\exp[\alpha / (\beta - 1)] + 1\}$. If x is greater than this value the opposite holds.

Appendix C: Dependency upon Range

To investigate the effects of different ranges on parameter estimates and measures of overall fit a Monte-Carlo-Study was performed. In order to get an impression of the generalizability of results, OLS- and MLE-statistics for two different types of relations were considered. The first type of relation is the class of simple linear functions. For this type of relation the OLS-parameters and R^2 , i.e. in this case the squared coefficient of correlation, were investigated. The second type of relation is the class of relations defined by the DLM. For this type of relation the MLE-parameters and L^2 were investigated. To make L^2 as analogous as possible to the squared coefficient of correlation as it is usually determined in this research context, L^2 was computed without grouping individual data pairs into classes of pairs with equal predictor values.

To enable that the characteristics of all the statistics just mentioned could be investigated with the same data, data were generated by the identity function. This function is a special case of both types of relations under investigation. Three different ranges were realized: 1) large range: minimal predictor value: 0.05, maximal predictor value: 0.95; 2) small range left: minimal predictor value: 0.02625, maximal predictor value: 0.47625; 3) small range right: minimal predictor value: 0.52375, maximal predictor value: 0.97375. In all three range conditions ten different predictors values were applied. They were all separated by equal intervals. In the first condition the interval was 0.1, in the other two conditions 0.05. The distributions of predictor values were chosen such that the sum of

the standard errors for the predicted values was equal for all three conditions. For this reason no small range condition in the middle of the interval could be realized. For each condition 1000 different sets of data were generated. Each set of data consisted of 100 pairs of data with ten pairs of data for each different predictor value.

As expected, R^2 and L^2 vary dramatically with range whereas the parameter estimates stay invariant (see Tables C1 and C2). Moreover, R^2 and L^2 are not very large although they were computed for data generated by the optimal model. Inspection of these statistics would possibly produce the conclusion that there is no strong relation between predictor and criterion. The parameter estimates, in contrast, vary rather narrowly around the true parameters. Hence, they will usually reveal the true relation between both variables.

Table C1: Linear equations with OLS-statistics: results of the Monte-Carlo-Study

Range	α^a		β^b		R^2	
	M	SD	M	SD	M	SD
large	0.00	0.07	1.00	0.11	0.34	0.07
small left	0.00	0.06	1.01	0.27	0.12	0.06
small right	0.00	0.22	1.00	0.27	0.12	0.06

Note. For each condition 1000 data sets were analyzed. ^aAdditive parameter of a linear equation. ^bMultiplicative parameter of a linear equation.

Table C2: DLM with MLE-approach: results of the Monte-Carlo-Study

Range	α^a		β^b		L^2	
	M	SD	M	SD	M	SD
large	0.01	0.25	1.04	0.23	0.28	0.07
small left	0.04	0.41	1.08	0.39	0.12	0.06
small right	-0.03	0.40	1.07	0.38	0.12	0.06

Note. For each condition 1000 data sets were analyzed. ^aAdditive parameter of the DLM. ^bMultiplicative parameter of the DLM.

Appendix D: Dependency upon Grouping

The OLS-Approach

Let f be the model under investigation, N the number of subjects, and q_i the binary variable describing behavioral performance with q_i equal to one if subject i performs the behavior and with q_i equal to zero otherwise. Then, the sum of squared deviations for the values of individual subjects is

$$SS(\text{model})_I = \sum_{i=1}^N \left\{ f[x(b, s_i)] - q_i \right\}^2. \quad (D1)$$

Let M be the number of equivalence groups defined by subjects with equal predictor values and $G = \{g_1, \dots, g_M\}$ the set of different equivalence groups. Further, let $x(b, g_i)$ be the predictor variable value common to all members of equivalence group g_i , n_i the number of subjects in equivalence group g_i , and k_i the corresponding number of subjects who actually performed the behavior. Then the sum of squared deviations for the values of equivalence groups is

$$SS(\text{model})_G = \sum_{i=1}^M n_i * \left\{ f\left[x(b, g_i)\right] - k_i/n_i \right\}^2. \quad (D2)$$

Rearranging the formula for the individual subjects renders

$$SS(\text{model})_I = \sum_{i=1}^M \sum_{j=1}^{n_i} \left\{ f\left[x(b, s_{ij})\right] - q_{ij} \right\}^2. \quad (D3)$$

Because

$$k_i = \sum_{j=1}^{n_i} q_{ij} \quad (D4)$$

and

$$x(b, g_i) = x(b, s_{ij}) \quad \text{for all } s_{ij} \in g_i \quad (D5)$$

the following relation holds

$$SS(\text{model})_G = SS(\text{model})_I - \sum_{i=1}^M \left[k_i - k_i * k_i/n_i \right], \quad (D6)$$

i.e. both sums differ only by an additive term which is independent of the parameters to be estimated. Consequently, minimizing both sums with respect to the parameters renders exactly the same results. Thus, parameter estimation according to OLS is independent of grouping subjects with equal predictor values.

Within the OLS-approach the corresponding standard errors are determined by multiplying a term which is independent of grouping with the sum of squared residuals, i.e.

with $SS(\text{model})_I$ or $SS(\text{model})_G$ respectively (cf. Greene, 1997, Chap.6.6.4 and 10.2.2). Because $k_i * k_i / n_i$ cannot be greater than k_i , $SS(\text{model})_G$ cannot be greater than $SS(\text{model})_I$ (see equation D6). Consequently, the standard errors become smaller with grouping. This in turn implies that statistical tests referring to parameter estimates become less conservative with grouping.

Let \bar{y} be the overall relative frequency of behavior then

$$SS(\text{const } t)_I = \sum_{i=1}^N (\bar{y} - q_i)^2 \quad (D7)$$

is the sum of squared deviation of the criterion values from the criterion mean for individual data and

$$SS(\text{const } t)_G = \sum_{i=1}^M n_i * (\bar{y} - k_i / n_i)^2 \quad (D8)$$

the corresponding expression for grouped data. Both expressions are related by

$$SS(\text{const } t)_G = SS(\text{const } t)_I - \sum_{i=1}^M [k_i - k_i * k_i / n_i]. \quad (D9)$$

Consequently, the generalized squared correlation for individual data, R^2_I , and the corresponding statistic for grouped data, R^2_G , are related by

$$R^2_G - \frac{\sum_{i=1}^M [k_i - k_i * k_i / n_i]}{SS(\text{const } t)_I} = R^2_I. \quad (D10)$$

Because the term which is subtracted from R^2_G cannot be negative, R^2 increases with grouping. The statistic for testing deviation from zero is affected correspondingly.

The MLE-Approach

Using the notation introduced above, the likelihood function for individual subjects is

$$L(\text{model})_I = \prod_{i=1}^N f[x(b, s_i)]^{q_i} * \{1 - f[x(b, s_i)]\}^{1-q_i} \quad (D11)$$

and the likelihood function for equivalence groups is

$$L(\text{model})_G = \prod_{i=1}^M \binom{n_i}{k_i} * f[x(b, g_i)]^{k_i} * \{1 - f[x(b, g_i)]\}^{n_i - k_i}. \quad (D12)$$

Both formulas are related by

$$\ln[L(\text{model})_G] = \ln[L(\text{model})_I] + \sum_{i=1}^M \ln \binom{n_i}{k_i}; \quad (D13)$$

i.e. the logarithms of both functions are equal up to an additive constant which is independent of the parameters to be estimated. Therefore, just like for OLS, estimation of parameters is invariant under grouping of data with equal predictor values.

In contrast to OLS, the standard errors estimated according to MLE do not change with grouping! This holds because in MLE standard errors are determined exclusively on the basis of the second derivatives of the logarithmized likelihood function (cf. Greene, 1997, Chap. 19.4). Because the first derivatives are the same for individual and for grouped data the second derivatives are also identical.

Analogously to D13, likelihoods of data given the criterion mean are related by

$$\ln[L(\text{constant})_G] = \ln[L(\text{constant})_I] + \sum_{i=1}^M \ln \binom{n_i}{k_i}. \quad (D14)$$

Consequently, the likelihood ratio index for individual data, L^2_I , and the corresponding statistic for grouped data, L^2_G , are related by

$$L^2_G + \frac{\sum_{i=1}^M \ln \binom{n_i}{k_i}}{\ln[L(\text{constant})_I]} = L^2_I. \quad (D15)$$

Because the term added to L^2_G is negative, L^2 increases with grouping. However, on the other hand D13 and D14 imply also that the statistic which tests the deviation of L^2 from zero, i.e. $LR = -2 \ln[L(\text{constant})/L(\text{model})]$, stays invariant under grouping.

Appendix E: Hints for Computation

OLS-statistics for linear equations can easily be computed with each program module for linear regression which is contained in each professional statistical program package. MLE-statistics for the SLM and the DLM can be computed by means of program modules for logistic regression. In SPSS 9.0 for Windows the program module for logistic regression is contained in the more general module 'Regression' and is titled 'Binary Logistic...!.

As usual in logistic regression the computations of the corresponding SPSS-module refer directly to the SLM in its untransformed version (equation 3). The additive parameter of the transformed version of the SLM (equation 4) can be computed by dividing the original additive parameter by the original multiplicative parameter. Unfortunately, the variances and the covariances of the transformed version's parameters cannot that easily be determined on the basis of the corresponding statistics of the original ver-

sion. If the additive and the multiplicative parameters are estimated at the same time, the relationship between the estimates' variances and covariances is rather complicated. Hence, the relationship between the corresponding statistics for the original and the transformed version is also rather complicated. However, if one estimates the additive parameter for the transformed version under presupposition of the original version's multiplicative parameter, then the standard error for the additive parameter of the transformed version results by dividing the corresponding statistic of the original version by the multiplicative parameter. This could be taken as a rough approximation. Following the same rough approach, the standard error of the original version's multiplicative parameter can be taken as an estimation for the corresponding statistic of the transformed version.

The statistics for the DLM can be determined by means of standard software for logistic regression after appropriately transforming the predictor variable. Let $z(b,s)=\ln[x(b,s)/(1-x(b,s))]$ then a further reformulation of the DLM is

$$p(b,s) = \frac{\exp[\beta * z(b,s) + \alpha]}{1 + \exp[\beta * z(b,s) + \alpha]}; \quad (E1)$$

i.e. the DLM is equivalent to the untransformed SLM with the logits of the behavioral expectations or behavioral intentions as the predictor variable. Hence, if one enters $z(b,s)$ as predictor variable in a standard module of logistic regression all resulting statistics are directly statistics referring to the DLM.

Note, that the standard output of the SPSS-module discussed here does not directly provide the likelihood ratio index nor the corresponding tests. However, this module provides the basis for computing these statistics. The output twice contains a statistic which is referred to as '-2 Log Likelihood'. In the first instance, under the heading 'Initial Log Likelihood Function', it is identical with $-2*\ln[L(\text{constant})]$. In the second instance it is identical with $-2*\ln[L(\text{model})]$.