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Formal Models for Predicting Behavioral Intentions in Dichotomous Choice Situations

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Abstract

In attitude-behavior-research behavioral intention is applied as an intervening variable between attitude and behavior. This article is concerned with formal models for predicting behavioral intentions. It refers to situations in which subjects must choose between two alternative behaviors. Consequently, two contraints for the behavioral intentions are presupposed:

1) behavioral intentions vary between the two boundaries 'completely decided against' and 'completely decided for',

2) the behavioral intentions for two alternative behaviors are mutually dependent.

Four different models for predicting behavioral intentions are presented, theoretically evaluated with respect to the two constraints, and empirically tested. The results of the empirical test accord with the results of the theoretical evaluation.

1. Introduction

In the field of attitude psychology, two of the most prominent approaches are certainly Fishbein and Ajzen's theory of reasoned action (TORA; Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) and its extension, Ajzen's theory of planned behavior (TOPB; Ajzen, 1985, 1991, 1993). Both approaches are conceived for predicting and explaining future behavior on the basis of variables which can be assessed by means of questionnaires. Consequently, both approaches have important characteristics in common; i.e. the future behavior is traced back to variables which can be assessed by questionnaires and the questionnaire variables in turn are traced back to each other. Moreover, in the TORA and in the later ver-

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sions of the TOPB (Ajzen, 1991, 1993) a variable called 'behavioral intention' constitutes the immediate predictor of the behavior. The behavioral intention, however, is predicted differently within both approaches. In the TORA, the two variables 'attitude towards the behavior' and 'subjective norm' are applied as predictors. In the TOPB a variable called 'perceived behavioral control' is added as a further predictor.

In the discussion about TORA and TOPB, several further additional predictors have been proposed. Examples are - among others - the frequency of past trying (Bagozzi & Warshaw, 1990), moral obligation (Gorsuch & Ortberg, 1983; Parker, Manstead, & Stradling, 1995; Pomazal & Jaccard, 1976; Raats, Sheperd & Sparks, 1995; Zuckerman & Reis, 1978), self-identity (Biddle, Bank, & Slavings, 1987; Charng, Piliavin, & Callero, 1988; Granberg & Holmberg, 1990), ethical intentions (Kurland, 1995), and emotions (Doll, Mentz & Orth, 1991). Up to now, the question as to which variables are required for predicting the behavioral intention is far from being answered and, consequently, extensively discussed (cf Jonas & Doll, 1996).

Most contributions to this discussion accord roughly with the same pattern. In the theoretical part, the hypothesis concerning possible predictors of the behavioral intention is presented by means of a diagram of arrows, and, in the empirical part, this hypothesis is tested by means of multiple regression techniques. More specifically, in the statistical analyses the common influence of all hypothesized predictors on the behavioral intention is assessed by means of a multiple linear correlation coefficient and the individual influence of a specific predictor variable by means of the corresponding standardized beta in a multiple linear regression equation. Statistically significant deviation of the standardized beta from zero is interpreted as indicating that the corresponding variable influences the behavioral intention over and above all other hypothesized predictor variables. Moreover, a relatively large standardized beta is usually understood as reflecting a relatively strong influence of the corresponding variable, whereas a relatively small standardized beta is interpreted as indicating a relatively weak influence.

By applying this statistical approach, the theoretical hypotheses are implicitly formalized as a particular specification of the Classical Multiple Linear Regression Model (cf Greene, 1997, Chap 6). In this specification, the behavioral intention is considered as the regressand and the hypothesized predictors as the regressors in a multiple linear regression equation. Although most statistical analyses concerned with predicting behavioral intentions rely upon this model, the model's adequacy for this purpose is hardly ever critically discussed. This, however, could have disadvantageous consequences, since, like any other model, this model defines a specific kind of relationship between the hypothesized predictors and the behavioral intention. If this relationship is wrong and if the common influence of a set of hypothesized predictors is investigated by means of this wrong model the corresponding statistic - as for example the multiple correlation coefficient - may indicate only a weak influence although, in fact, this influence is rather strong. Moreover, parameters which are defined by the model - as for example the standardized beta - will no longer have an interpretable empirical meaning if the basic model is inadequate.

Therefore, this contribution is mainly concerned with the formal properties of possible models for predicting behavioral intentions or - to put it briefly - with formal models for predicting behavioral intentions. In the first part, the formal characteristics of the concepts involved in the prediction of behavioral intentions are elaborated. In the second part, different formal models which could be applied for predicting behavioral intentions are presented and critically evaluated with respect to these formal characteristics. In the third and last part, the application of the different models is demonstrated with the same set of data.

2. Conceptual Presuppositions

The kind of relation which may hold between the behavioral intention and possible determinant variables is - at least partially - determined by the formal characteristics of all these variables and of the objects to which these variables refer. The objects are mainly the subjects and the behavior in question. The variables are the behavioral intention as criterion and the various variables which are applied as possible predictors of the behavioral intention.

2.1. The objects under consideration

2.1.1. The subjects

Quite obviously, the subjects who are questioned by means of the questionnaire belong to the objects under consideration. These subjects can be easily characterized formally as a set of well defined and well distinguished elements. In the following, this set will be denoted by the capital letter S. The small letter s will be used for an arbitrary element out of this set.

2.1.2. The behavior

Furthermore, the behavior to which the questionnaire refers belongs to the objects under investigation. Usually, this is not a behavior which must be performed unavoidably. If this were the case, considerations about predicting behavior and behavioral intentions would be superflous. Hence, the behavior in question can always be understood as an element of a set of behaviors from which subjects must choose one. The behavior within such a set may be the two alternatives to perform and not to perform a certain action or the different possible voting decisions in a political election. Minimally, there are always two alternative behaviors, which are mutually disjunctive and altogether exhaustive. Psychologically, this is the elementary and thereby the paradigmatical case. So the following considerations are restricted exactly to this case. The set of these two alternative behaviors will be denoted by the capital letter B with $B=\{b_0, b_1\}$. The first element of this set, i.e. b_0, will always be referred to as the target behavior and the second element, i.e. b_1, as the alternative behavior.

2.2. The variables under consideration

The behavioral intention and the variables proposed as predictors for the behavioral intention are the variables under consideration. At least most of these variables can be characterized formally as real-valued functions on the cartesian product of the set of behaviors and the set of subjects. The formal properties of these real-valued functions define which models can be applied reasonably for predicting behavioral intentions and they define the theoretical meaning of parameters within the models.

Partly, these presupposed formal properties are characteristics of the scale level. Unfortunately, in studies concerned with predicting behavioral intentions the various variables are hardly ever assessed in such a way that their scale level can be determined in the sense of representational theory of measurement (Krantz, Luce, Suppes & Tversky, 1971; Luce, Krantz, Suppes & Tversky, 1990; Suppes, Krantz, Luce, & Tversky, 1989). If only for practical reasons, this will usually not be possible. So, the scale level assumptions are mainly derived from the theoretical intended meaning of the variables. Consequently, they are somewhat hypothetical. However, starting with assumptions of such a hypothetical status may sufficiently be justified by the truism that there can be no empirical research which is completely based upon doubtlessly true presuppositions. Moreover, to a certain degree the presupposed hypothetical assumptions can be tested together with the models based upon these assumptions; i.e. if the variables are represented numerically in correspondence with the scale level assumptions and if the respective model is valid under this numerical representation then this result provides an empirical argument for both, the validity of the model and the validity of the scale level assumptions. The same argumentation holds for the formal properties which are assumed in addition to scale level assumptions.

2.2.1. The behavioral intention

The concept of behavioral intention has been used with varying interpretations. When presenting the TORA, Fishbein and Ajzen (1975; Ajzen & Fishbein, 1980) define behavioral intention as the agent's subjective probability that he or she will perform the behavior. Warshaw and Davis (1985) argue that this concept differs from the concept of intention as it is understood in every day language. They define behavioral intention as 'the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior' (Warshaw & Davis, 1985, p. 214). They characterize Fishbein and Ajzen's original concept of behavioral intention as behavioral expectation. In the first version of the TOPB, Ajzen (1985) applies both concepts distinguished by Warshaw and Davis, i.e. the concepts of behavioral intention and of behavioral expectation. Ajzen assumes that the behavioral expectation is proportional to the product of behavioral intention and subjective behavioral control. In later versions of the TOPB, Ajzen (1991, 1993) dispenses with the concept of behavioral expectation and interprets the concept of behavioral intention as an indicator of 'how hard people are willing to try' and 'how much of an effort they are planning to exert' (Ajzen, 1991, p. 181). In the main, this concept is identical to the concept of goal intention of Gollwitzer (1993).

Both more actual concepts of behavioral intention, i.e. the concept of Warshaw and Davis (1985) on the one hand and the concept of Ajzen (1991) and Gollwitzer (1993) on the other, differ in an important aspect. The concept of Warshaw and Davis reflects how near people have come to a decision. Extreme behavioral intentions mean that people are decided. An extremely low behavioral intention means a decision against and an extremely high behavioral intention a decision for the behavior. A medium behavioral intention reflects the state of being undecided whether to perform or not to perform the behavior. In contrast, the behavioral intention in the sense of Ajzen (1991) and even more the goal intention in the sense of Gollwitzer (1993) reflect the effort people are prepared to invest, presupposed they have decided for the behavior. A low intention in this sense means low effort, and a high intention high effort.

Accordingly, intentions in these different senses will be influenced in a different way by expected hindrances to the behavior. If people must fear that they will be confronted with severe difficulties when performing a certain behavior, then they will usually be reluctant to decide for this behavior; i.e. the behavioral intention in the sense of Warshaw and Davis will be influenced rather negatively by hindrances. If, however, people have already decided, then they will usually be willing to invest that amount of effort which is required to surmount the expected hindrances; i.e. the goal intention in the sense of Gollwitzer will be influenced rather positively by hindrances (Gollwitzer, 1993, p. 151). Consequently, a high behavioral intention in the sense of Warshaw and Davis means that people will try to perform the behavior with the necessary amount of effort. In contrast, the behavioral intention in the sense of Gollwitzer more directly reflects the amount of effort which people are prepared to invest. Because this amount will usually be adjusted to the expected hindrances, differences in the amount of effort will be neutralized by these hindrances when people try to realize the behavior. So, the behavioral intention in the sense of Warshaw and Davis will contain more relevant information for predicting behavior than the goal intention in the sense of Gollwitzer.

Additionally, there are two further arguments for applying the concept of Warshaw and Davis. 1) In most studies there is a time interval between the questioning and the behavior. No final decision can be expected at the time of questioning or - to put it in concepts of Heckhausen's Rubikon-Model (cf Gollwitzer, 1990) - people will be in the predecisional phase. In this phase people will presumably better understand a question concerning the degree to which they have already formulated a conscious plan to perform or not to perform the behavior - i.e. behavioral intention in the sense of Warshaw and Davis - than a question concerning the amount of effort they will invest in performing this behavior - i.e. goal intention in the sense of Gollwitzer. 2) The concept of Warshaw and Davis is explicitly conceived to discriminate those who want to perform the behavior from those who do not want to perform the behavior. In contrast, the concept of Gollwitzer only refers to people who have already formed a conscious plan to perform this behavior and consequently mainly discriminates among these people.

Of course, all these arguments do not imply that the behavioral intention in the sense of Warshaw and Davis is the absolutely best possible predictor of behavior. This is not true. Mainly, the behavioral intention reflects those influence factors of behavior which are under voluntary control. Yet, there are still different influence factors. So, usually, behavior can best be predicted by the behavioral expectation (Sheppard, Hartwick & Warshaw, 1988; Warshaw & Davis, 1985). However, for a better understanding of the causes of behavior, those factors which are under voluntary control should be separated from those which are not. So, for the purpose of predicting and explaining future behavior by means of questionnaire data, behavioral intentions and behavioral expectations in the sense of Warshaw and Davis should be applied together and, for a better understanding of the voluntary part, the causes of the behavioral intention should be investigated more thoroughly.

The concept of behavioral intention in the sense of Warshaw and Davis will be denoted below by the capital letter I and formally characterized as a real valued function on the cartesian product of the set of subjects and the set of alternative behaviors; i.e. $I : B * S \to R$. Consistently with the general methodological paradigm in attitude research, this real valued function is interpreted as an interval scale, and it is assumed that values of this scale can be assessed by appropriately constructed rating scales.

In addition to these metrical properties, the concept of behavioral intention in the sense of Warshaw and Davis implies two constraints concerning the occurrence of numerical values. The first constraint refers to the range of possible values, the second to the relation between behavioral intentions for both alternative behaviors.

The first constraint states that nobody can be more decided against a behavior than *completely* decided against it and that, likewise, nobody can be more decided for a behavior than *completely* decided for it. Let λ_L be the scale value for 'completely decided against' and λ_U the scale value for 'completely decided for' with $\lambda_L < \lambda_U$, then this constraint can be formulated as

$$\text{for all } (b,s) \in B*S: \lambda_L \leq I(b,s) \leq \lambda_U. \qquad (1)$$

In the following this constraint will be referred to as the *limited range constraint.*

Presupposing this constraint, the formal characterization of the concept of behavioral intention can be reformulated as $I: B*S \rightarrow [\lambda_L, \lambda_U]$. For numerical convenience λ_L should be set equal to zero and λ_U equal to one. A numerical representation of behavioral intentions which is normed in this way will be denoted as I' and the following holds for all possible numerical representations of behavioral intentions

$$I'(b,s) = [I(b,s)-\lambda_L] / [\lambda_U - \lambda_L]. \qquad (2)$$

Note that the limited range constraint is implied by the concept of behavioral intention in the sense of Warshaw and Davis but not by the concept of goal intention in the sense of Gollwitzer. In the case of the goal intention there is no distinctly defined upper boundary. Independently of how much effort a person is willing to invest it could always be possible that this effort can be increased.

The second constraint states that the behavioral intentions for two alternative behaviors are mutually determined. This constraint follows from the rather weak psychological assumption that people correctly process the behaviors within the respective set as mutually disjunctive and altogether exhaustive events. If, in this case, a person is completely decided for one alternative then he or she must be completely decided against the other alternative. Moreover, if a person is completely undecided with respect to one behavior he or she must also be completely undecided with respect to the other behavior. To put it more generally and more formally, a subject is assumed to have a constant sum of determination at his or her disposal which he or she distributes between the two alternative behaviors.

For behavioral intentions which are not normed with respect to the limits this constraint can be formulated as

$$I(b_0,s) + I(b_1,s) = \lambda_U - \lambda_L \qquad (3)$$

For normed behavioral intentions it reduces to

$$I'(b_0,s) + I'(b_1,s) = 1 \qquad (4)$$

This constraint will be referred to as the *constant sum constraint.*

The constant sum constraint is even more specific of the concept of behavioral intention proposed by Warshaw and Davis. This concept reflects a person's position drifting between two incompatible goals. The more a person approaches to one goal the more he or she must withdraw from the other. A more motivational concept of intention, as Gollwitzer's concept of goal intention, does not imply the constant sum constraint. Independently upon what alternative a person finally chooses he or she may be willing to invest a large amount of effort in both cases. Likewise, a person may be very unwilling to invest too much effort in any case.

At least implicitly, the idea of the constant sum constraint has already been applied for the assessment of behavioral intentions. It is a necessary presupposition for the technique employed by Van den Putte, Hoogstraten & Meertens (1996, S. 259). These authors request subjects to express their intentions by distributing a constant amount of points among the different behavioral possibilities. If the behavioral intentions are assessed by this technique the constant sum constraint is fulfilled trivially. If, however, the behavioral intentions for both alternative behaviors are assessed independently from each other this condition can be violated empirically. Violations can then be interpreted as hints that subjects do not understand the concept of behavioral intention in the sense presupposed here. In any case, the following considerations are restricted to data for which the constant sum constraint is fulfilled.

2.2.2. The predictor variables

Unfortunately, in the literature several different variables are discussed as possible determinants of the behavioral intention. Not all of these variables can reasonably be assumed to possess the same formal characteristics. So the following considerations restrict to the most typical case; i.e. all predictor variables are assumed to have the same formal characteristics as the attitude towards the behavior. The formal principles for different cases may be constructed by modifying the principles which are constructed for this prototypical case.

In the following, the predictor variables will be denoted by a capital G and the index k for the kth predictor variable. In part, these variables are assumed to possess the same formal characteristics as the behavioral intention, i.e. they are formally characterized as real valued functions on the cartesian product of the set of subjects and the set of alternative behaviors; i.e. $G_k : B*S \to R$, and - consistently with the prevailing methodological paradigm - they are assumed to be measured on interval scale level. In contrast to the behavioral intentions, however, no additional constraints for the occurrence of numerical values are assumed. There is no reason to assume a lower or an upper limit for attitudes. Even if a behavior is evaluated extremely negative, there may still be a behavior which is evaluated more negatively. The same may hold for the positive area. Likewise, there is no reason for assuming a special kind of dependency among the attitudes towards both alternative behaviors. Somebody who has the choice between watching a football game in TV or going to a party may have positive attitudes to both alternatives. On the other hand, somebody who has the choice between eating the food in his firm's canteen or eating nothing may have a negative attitude towards both.

3. Possible Formal Models

Under these conceptual propositions very different models for predicting behavioral intentions are possible. In this article, however, only models of a special kind are discussed: they all are specifications of the Classical Multiple Linear Regression Model (cf Greene, 1997, Chap 6). The general form of this model is

$$y = \left[\sum_{k=1}^{m} \beta_k x_k\right] + \alpha + \varepsilon \tag{5}$$

with y the regressand, x_k the kth regressor, m the number of regressors, β_k the multiplicative weight for the kth regressor, α an additive constant and ε an error term. β_k and α must be estimated from data under presupposition of certain assumptions concerning the error. In the stricter version of the model, the error is assumed to be distributed normally with a mean of zero and a constant variance for all possible combinations of predictor values (for an extensive discussion of the error assumptions presupposed in classical multiple linear regression statistics see Greene, 1997, chap. 6).

In most studies concerned with predicting behavioral intentions, only variables referring to the target behavior are taken as predictors. These predictors are treated as regressors and the behavioral intention as regressand in the multiple linear regression model. Moreover, when presenting the results, standardized beta are very often reported and interpreted. Standardized beta are those multiplicative weights which result when the regressand and all regressors are z-transformed; i.e. when the values are presented as differences from the sample specific means divided by the sample specific standard deviations. Thus the statistical model which is implicitly applied in these studies can be written as

$$I^{(z)}(b_0,s) = \left[\sum_{k=1}^{m} \beta_{0k} G^{(z)}k(b_0,s)\right] + \alpha_0 + \varepsilon(b_0,s), \tag{6}$$

with $I^{(z)}$ the z-transformed behavioral intention, $G^{(z)}k$ the z-transformed predictor variables, m the number of predictor variables, β_{0k} the standardized beta which result if only variables referring to the target behavior are considered, α_0 the corresponding additive constant and $\varepsilon(b_0,s)$ the error term. Because all involved variables are z-transformed, the additive constant is always equal to zero. In the following this model will be referred to as the traditional model.

In the present research concerned with predicting behavioral intentions, the traditional model is presupposed more or less implicitly. Perhaps the most implicit aspect consists in referring to z-transformed variables by way of interpreting standardized beta. These standardized beta are automatically calculated by each professional statistic program independently of how the variables are entered into the calculation. There are certainly at least two good reasons for this automatism. 1) There are a lot of well understood relations between the standardized beta and the intercorrelations between the regressand and the regressors. Accordingly, standardized beta are relatively easily to interpret. 2) In many cases, all involved variables are different interval scales. Accordingly, each scale is only determined up to multiplication by a positive and addition by an arbitrary constant and can be transformed in this way independently of every other scale. The multiplicative and additive parameters in a multiple regression equation, however, change if the original variables are transformed in this way. Consequently, they have only little empirical meaning. The z-transformation, however, is uniquely defined with respect to the given sample and the same holds for the parameters referring to the variables transformed in this way.

The second reason loses its conceptual basis if a variable like the behavioral intention is applied as criterion variable. Admittedly, the behavioral intentions are not assumed to possess more than interval scale level; but they are assumed to possess empirically meaningful lower and upper limits, - i.e. 'completely decided against' and 'completely decided for'. These boundaries have an empirical meaning which is independent from sample specific means and sample specific standard deviations. Consequently, a standardization with respect to these two boundaries - as it is proposed in equation 2 - represents more empirical meaning than a z-transformation. The same will hold for the corresponding parameters in a linear multiple regression equation. Moreover, the construct of behavioral intention - as it is introduced here - is defined, among others, by two constraints referring to these two boundaries. Consequently, models which predict behavioral intentions should render predictions which are consistent with these constraints. Whether this condition is fulfilled can best be investigated if the respective model refers to behavioral intentions which are directly standardized with respect to the boundaries. For these reasons, only models of this kind will be discussed in the following.

Just like the traditional model, all models discussed here are specifications of the Classical Multiple Linear Regression Model. This allows the application of all parameter estimation and testing procedures including the corresponding calculation programs developed in this context. All these models are investigated with respect to two aspects: 1) the empirical meaning of the parameters, and 2) the consistency of the model with the two constraints referring to the behavioral intentions. Two kinds of models are discussed: 1) models which only refer to information about single behaviors - for simplicity usually the target behaviors - and 2) models which refer to information about both alternative behaviors together.

3.1. Models for single behaviors

Two models which refer only to information about single behaviors are discussed. The first one is nearly identical to the traditional model. The only difference is that the behavioral intentions are standardized to the boundaries. This model will be referred to as the *ordinary linear model for single behaviors*. The second model is the one which the statistical literature would suggest as the nearest alternative. This model will be referred as the *logit model for single behaviors*.

3.1.1. The ordinary linear model for single behaviors

The ordinary linear model for single behaviors is

$$I'^{(z)}(b_0,s)=\left[\sum_{k=1}^{m}\beta_{0k}G_k(b_0,s)\right]+\alpha_0+\varepsilon(b_0,s) \tag{7}$$

Thereby, $I'(b_0,s)$ is the behavioral intention standardized with respect to both boundaries (see equation 2). For the predictor variables - for the present - no standardization is presupposed.

The precise meaning of the parameters β_{0k} and α_0 depends upon what formal aspects of the parameters stay invariant under all permissible transformations of the predictor variables. Let γ_k be an arbitrary positive constant which is multiplied with G_k and δ_k an arbitrary constant which is added to G_k. Furthermore, let β_{0k} and α_0 be the parameters which are estimated when the ordinary linear model for single behaviors is applied to the transformed variables. Then

$$\beta^*_{0k}=\beta_{0k}/\gamma_k \tag{8}$$

and

$$\alpha^*_0=\alpha_0-\sum_{k=1}^{m}(\beta_{0k}\delta_k)/\gamma_k \tag{9}$$

holds. Moreover, for the standard errors SE it holds

$$SE(\beta^*_k)=SE(\beta_k)/\gamma_k \tag{10}$$

and

$$SE(\alpha^*)=\left[\left(\alpha-\sum_{k=1}^{m}\delta_k\beta_k/\gamma_k\right)\Big/\alpha\right]SE(\alpha) \tag{11}$$

(see Appendix A).

Thus, the parameters β_{0k} and α_0 change in correspondence to the admissible transformations of the predictor variables. As the only invariant aspect, the β_{0k} will never change sign; they therefore express whether the corresponding predictor variable influences the behavioral intention detrimentally, beneficially or not at all. Because the standard errors for the β_{0k} change with the same factor as the corresponding parameters, the results of the statistical tests for deviation from zero also stay invariant under all admissible transformations. The β_{0k} acquire more empirical meaning if all predictor variables can be scaled on the same interval scale (i.e. $\gamma_k = \gamma_0$ for all k). Then the ratios between the β_{0k} are invariant under all admissible transformations of this scale. The β_{0k} then reflect the relative linear influence of the predictor variables in dependence of units of the same interval scale. Independently of whether the predictor variables are scaled on the same or on different interval scales, the additive constant α_0 and the corresponding standard error can vary arbitrarily and thus have no empirical meaning.

If the predictor variables are not scaled on the same interval scale, the β_{0k} can be made comparable by dividing the predictor variables by the sample specific standard deviation. By this procedure the β_{0k} are uniquely defined. They then reflect the relative linear influence of the predictor variables in dependence of standard deviations determined in the given sample. Note that the β_{0k} standardized in this way are not identical with the usual standardized beta. The latter would result if, additionally, the criterion variable was divided by its sample specific standard deviation. However, the ratios between the β_{0k} are the same for both kinds of standardization. The additive parameter α_0 also acquires a unique meaning if the predictor variables are completely z-transformed. It then represents the behavioral intention predicted for a person with average values on all predictor variables.

A theoretical interpretation of the parameters, however, only makes sense if the model is altogether theoretically adequate. Presupposing the concept of behavioral intention introduced here, this may be questioned, as this model can predict values which violate 1) the limited range constraint and/or 2) the constant sum contraint. The first violation is equivalent to predicting that a subject is even more decided than completely decided. This will happen especially for subjects who have extreme values on all predictor variables. The second violation can consist in predicting that a subject will, at the same time, decide to perform and not to perform the target behavior. A violation of this kind can happen if the model is applied separately to both alternatives and if a subject has high values on all predictor variables for both alternatives.

3.1.2. The logit model for single behaviors

A model which does not violate the limited range constraint can easily be constructed by linking the predicting variables with the criterion by means of a non-linear function which is restricted to both sides. This idea has already been successfully applied for predicting binary variables by means of quantitative variables (cf. Andreß, Hagenaars & Kühnel, 1997; Fahrmeir, Hamerle & Tutz, 1996; pp 247). The most common non-linear function applied in this context is the logistic function. Accordingly, the nearest alternative to the ordinary linear model for single behaviors is constructed by means of this function; i.e.

$$I'(b_0,s) = \frac{\exp\left\{\left[\sum_{k=1}^{m}\beta_{0k}G_k(b_0,s)\right]+\alpha_0+\varepsilon(b_0,s)\right\}}{1+\exp\left\{\left[\sum_{k=1}^{m}\beta_{0k}G_k(b_0,s)\right]+\alpha_0+\varepsilon(b_0,s)\right\}} \qquad (12)$$

Note that equation 12 differs in one important aspect from the equation which is usually applied for predicting binary by quantitative variables. The equation for predicting binary variables does not contain any error term, because this equation actually refers to probabilities. Equation 12, however, does contain an error term, because this equation refers to single realizations.

By some simple algebraic transformations equation 12 can be transformed to

$$\ln\{I'(b_0,s)/[1-I'(b_0,s)]\} = \left[\sum_{k=1}^{m}\beta_{0k}G_k(b_0,s)\right]+\alpha_0+\varepsilon(b_0,s). \qquad (13)$$

The latter formulation directly reveals the way in which this model is a specification of the Classical Multiple Linear Regression Model. The left hand term in this formulation is referred to as logit; therefore the whole model is called logit model for single behaviors.

The parameters β_{0k}, α_0, and $\varepsilon(b_0,s)$ of the logit model for single behaviors relate to the logits of the behavioral intentions in the same way as the corresponding parameters of the ordinary linear model for single behaviors relate to the behavioral intentions themselves. All results concerning the empirical meaning of the parameters can be transferred with the respective change in interpretation. With respect to the behavioral intentions themselves the logit model for single behaviors can only predict values between zero and one. Therefore, values predicted by this model cannot violate the limited range constraint. However, if the model is separately applied to both alternative behaviors, the predicted values can still violate the constant sum constraint.

3.2. Models for pairs of behaviors

Presumably, violations of the constant sum constraint can only be avoided by considering information about both alternative behaviors. In the relevant literature, there are already some approaches which rely upon this idea (Jaccard 1981; Jaccard & Becker, 1985;

Sperber, Fishbein & Ajzen, 1980). These approaches, however, do not exactly refer to the criterion variable which is considered here. Sperber, Fishbein and Ajzen are concerned with differences between behavioral intentions instead of behavioral intentions themselves. Jaccard is concerned with a forced choice behavioral intention instead of a behavioral intention which allows for several degrees of determination between 'completely decided against' and 'completely decided for' the respective behavior. Therefore, two different models are presented here. In these two models, differences between the predictor variables for both alternative behaviors form the regressors. Apart from this, these models are analogous to the models for single behaviors. Accordingly, they are referred to as the *ordinary linear model for pairs of behaviors* and the *logit model for pairs of behaviors*.

3.2.1. The ordinary linear model for pairs of behaviors

Let b_i be one of both alternative behaviors with $i \in \{0,1\}$, the ordinary linear model for pairs of behaviors is then

$$I'(b_i, s) = \left\{ \sum_{k=1}^{m} \beta_{ik} \left[G_k(b_i, s) - G_k(b_{i-1}, s) \right] \right\} + \alpha_i + \varepsilon(b_i, s) \qquad (14)$$

Of course, predictors which are of the same kind but refer to alternative behaviors can and should be assessed on the same interval scale. This condition fulfilled, the origins of the regressors are uniquely defined because they are constructed as differences of values from the same interval scale. Consequently, in contrast to the analogous model for single behaviors, additive transformations of the predictor variables do not change the regressors.

In comparison with the analogous model for single behaviors, this different formal property has no effect on the invariance characteristics of the multiplicative constants and the corresponding standard errors. They both change inversely proportionally with multiplicative transformations of the predictors and are unaffected by additive transformations (see Appendix A). Hence, all results concerning the empirical meaning of the multiplicative parameters in the analogous model for single behaviors can be transferred with the corresponding change in interpretation. Note, however, that in contrast to the model for single behaviors the regressors are not identical to the predictors. They are constructed as differences of the predictors. Therefore, for standardization the regressors must be divided by the sample specific standard deviations of the *differences* between the predictor values.

The fact that the origins of the regressors are uniquely determined has, however, severe consequences for the additive constant. In contrast to the additive constant in the analogous model for single behaviors, this constant and the corresponding standard errors stay invariant under all permissible transformations of the predictor variables (see Appendix A). Hence this constant has an interpretable empirical meaning. It is equal to the behavioral intentions predicted for persons who have zero differences for all predictor variables. If both alternative behaviors are equally salient for the subjects and if the predictor variables capture all factors influencing the behavioral intention then these persons should be completely undecided; i.e. in this case the additive constant should be equal to 0.5. A value smaller than 0.5 indicates that influence factors which disfavor the respective behavior have been neglected, and a value greater than 0.5 indicates that influence factors in favor of this behavior have been neglected.

Note, that this special empirical meaning of the additive constant results because differences of the predictors are applied as regressors. If the predictors for both alternative behaviors were entered as two different regressors and if, thereby, separate multiplicative parameters were estimated for each behavior then the additive constant would lose this meaning. The fact, that differences and not single variables are applied as regressors also influences the effects of variable transformations. The additive constant stays invariant under additive and multiplicative transformations of the predictors, but it changes under additive transformations of the regressors. Therefore, the latter transformation would destroy the empirical meaning of the additive constant. For this reason, the differences should not be z-transformed!

The ordinary linear model for pairs of behaviors has yet another important property. It results if the behavioral intentions to be predicted accord with the constant sum constraint. Substituting according to equation 4 into equation 14 and algebraic transforming render

$$I'(b_{i-1},s)=\left\{\sum_{k=1}^{m}\beta_{ik}\left[G_k(b_{i-1},s)-G_k(b_i,s)\right]\right\}+1-\alpha_i-\varepsilon(b_i,s) \tag{15}$$

Except for the parameters and the error term, equation 15 is identical to the formula which would result if the ordinary linear model for pairs of behaviors were applied to the other behavior. The parameters and the error term, however, still refer to the original behavior. This implies a strict relationship between the parameters and the error term in both possible applications of the model. It holds

$$\begin{array}{ccc} \beta_{ik} & = & \beta_{1-i;k} \\ \alpha_i & = & 1-\alpha_{1-i} \\ \text{and} & & \\ \varepsilon(b_i,s) & = & -\varepsilon(b_{1-i},s) \end{array} \tag{16}$$

The relation between both additive constants is completely consistent with the theoretical interpretation of the additive constant discussed above. If the additive constant is 0.5 for one of both behaviors, the same holds for the other - both consistent with the assumption that no important variables have been neglected. If, however, the additive constant is greater than 0.5 for the target behavior it must be smaller than 0.5 for the alternative behavior - both indicating that factors in favor of the target behavior have not been taken into consideration in the study. Moreover, the relations between the parameters in both applications imply that the sum of the behavioral intentions predicted in both applications is always equal to one; i.e. the model is consistent with the constant sum constraint. However, just like the ordinary linear model for single behaviors the corresponding model for pairs of behaviors can still predict values outside the limits for behavioral intentions; i.e. the model is still inconsistent with the limited range constraint.

3.2.2. The logit model for pairs of behaviors

The nearest way to guarantee that both constraints cannot be violated is combining differences with the logistic function. The resulting model is

$$I'(b_i, s) = \frac{\exp\left\{\left\{\sum_{k=1}^{m} \beta_{ik}\left[G_k(b_i, s) - G_k(b_{1-i}, s)\right]\right\} + \alpha_i + \varepsilon(b_i, s)\right\}}{1 + \exp\left\{\left\{\sum_{k=1}^{m} \beta_{ik}\left[G_k(b_i, s) - G_k(b_{1-i}, s)\right]\right\} + \alpha_i + \varepsilon(b_i, s)\right\}} \tag{17}$$

which is equivalent to

$$\ln \frac{I'(b_i, s)}{1 - I'(b_i, s)} = \left\{\sum_{k=1}^{m} \beta_{ik}\left[G_k(b_i, s) - G_k(b_{1-i}, s)\right]\right\} + \alpha_i + \varepsilon(b_i, s) \tag{18}$$

Just as in the case of the single behavior models the parameters of the logit model refer to the logits of the behavioral intentions in the same way as the parameters of the ordinary model refer to the behavioral intentions themselves. Consequently, the invariance characteristics for the parameters are the same in both models; i.e. the multiplicative parameters and the corresponding standard errors change inversely proportionally with multiplicative transformations of the predictor variables, whereas the additive parameter and the corresponding standard error stay invariant under all permissible transformations of the predictor variables. However, because the logit of 0.5 is equal to zero, the additive constant must be zero if both behaviors are equally salient and if all influence factors are captured.

If the model is applied separately to both alternative behaviors the relations between the multiplicative parameters and the error terms in both applications are the same as in the case of the ordinary model for pairs of behaviors. But, for the additive constant,

$$\alpha_i = -\alpha_{1-i} \tag{19}$$

holds. Just as in the case of the ordinary linear model for pairs of behaviors these relations guarantee that the predicted values correspond to the constant sum constraint. Moreover, the logistic function guarantees that the limited range constraint cannot be violated. Therefore, the logit model for pairs of behaviors is the most adequate model for predicting behavioral intentions - at least theoretically.

4. Example

In the following, all four models presented here will be applied to the same set of data. The two alternative behaviors to which these data refer are doing the military service versus doing the community service. In Germany, all healthy young men from the age of eighteen are obliged to do military service. For conscientious reasons, however, they are allowed to refuse to do this, in which case they must do community service instead. In the latter case they will, for example, work in a hospital or care for handicapped people. The conditions for choosing between both services and the periods of service change with time. At the time of the study presented here, i.e. Winter 1995/96, a person who wanted to refuse military service had to send a request with substantiation to the responsible authorities. The substantiation was checked and, if it was conclusive, the request was accepted. Standard substantiations which usually found acceptance were available as publications. So nearly every request was accepted. In the very few cases of rejection, the applicant had to substantiate his request in an oral hearing. The periods of service were thirteen months for the military and fifteen months for the community service.

In addition to community service there were and still are other services which can be absolved instead of military service. For example, the young men can engage for ten years at the voluntary fire-brigade. These different possibilities, however, are very seldom chosen. Therefore they could be and have been neglected in the study.

4.1. Method

4.1.1. Subjects

Subjects were 79 male high school students from three different schools in Aachen, Germany. All of them were attending the twelfth class. (In Germany, high school terminates with the thirteenth class and students are allowed to finish school before they have to do military or community service.) All subjects were German citizens. All subjects participated voluntarily in the study without being paid.

4.1.2. Material

The material was a questionnaire designed for testing some aspects of the TORA. Accordingly, the questionnaire contained questions pertaining to behavioral intentions, attitudes, subjective norms, belief strengths, evaluations, normative beliefs, and motivations to comply (see Table 1). Belief strengths and evaluations are judgments referring to possible salient consequences of the behavior; according to the TORA these judgments are the antecedents of the attitude towards the behavior. Subjective norms and normative beliefs are judgments referring to important reference persons; according to the TORA these judgments are the antecedents of the subjective norm. The questionnaire refers to fifteen different salient consequences and ten different reference persons determined in a prestudy. Behavioral intentions, attitudes, subjective norms, belief strengths, and normative beliefs were assessed separately for each of the two alternative behaviors. In contrast, evaluations and motivations to comply were assessed independently of the behavior. Consistently with the research tradition for all variables, seven category rating scales were applied. In all cases only the extreme categories of the rating scales were semantically labeled (see Table 1). To make attitudes and subjective norms directly comparable, in contrast to the usual approach both variables were assessed by the same question format.

Table 1: Variables, Questionnaire Items and Extreme Categories

Variable	Questionnaire Item and Extreme Categories
Behavioral Intention	I intend to do x certainly no ... certainly yes
Attitude	If I only consider my own interests I think that doing x is extremely bad ... extremely good
Subjective Norm	If I only consider the interests of those people who are important to me I think that doing x is extremely bad ... extremely good
Belief Strength	If I do x I shall experience y certainly no ... certainly yes
Evaluation	For me experiencing y is extremely bad ... extremely good
Normative Belief	z thinks I should do x on no account ... absolutely
Motivation to Comply	For me complying with the wishes of z in general is extremely unimportant ... extremely important

4.1.3. Procedure

The questionnaires were handed out at the beginning of school lessons. They were filled in immediately.

4.2. Results

Two of the 79 subjects filled in only parts of the questionnaire. These subjects were excluded from all further analyses. For the remaining 77 subjects the consistency of the behavioral intention judgments with the constant sum constraint was checked. The two judgments of a subject were classified as consistent with this constraint either when in both cases the middle category was chosen or when the chosen categories deviated from the middle category in opposite directions but to the same extent (measured in numbers of categories). Given these criteria, the answers of 60 subjects correspond to the constant sum constraint; i.e. these subjects seem to have understood and answered the questions exactly in the intended sense. Therefore, the data of these 60 subjects are applied for comparing the four models for predicting behavioral intentions.

The attitudes and the subjective norms are investigated as possible predictors. Two different measures of these variables are applied alternatively: 1) the values which are directly assessed by means of the corresponding rating scales and 2) the values which are calculated from the belief strengths, evaluations, normative beliefs and motivations to comply by means of the corresponding prediction equations of the TORA (for a discussion of the prediction equations see Appendix B). Both kinds of measures are applied alternatively because the second measure is assumed to differentiate better between different extreme latent values than the first one[1]. As both logit models are specially designed for the relation between a criterion variable which is restricted to both sides and predictor variables which are not restricted, the relative advantage of the logit models is assumed to become more evident with the second measure.

All predictor variables correlate significantly with each other (see Table 2). Not surprisingly, variables referring to different behaviors correlate negatively. All correlations, however, are distinctly different from minus one. This implies that predictions based upon differences can differ from predictions based only upon single variables. Calculated and directly assessed variables correlate at about the same level as is usually found in studies of this kind. The same holds for the correlations between attitudes and subjective norms towards the same behavior. As a slight flaw from the viewpoint of the TORA, however, the latter correlations are about as high as the former. This may result from the fact that directly assessed and calculated measures differentiate differently between extreme latent values. In any case, the relatively high intercorrelations between different predictors will make the multiplicative parameters difficult to interpret.

Table 2: Intercorrelations Between the Predictor Variables

Military					Community			
	Attitude		Subj. Norm		Attitude		Subj. Norm	
	Dir.[a]	Cal.[b]	Dir.[a]	Cal.[b]	Dir.[a]	Cal.[b]	Dir.[a]	Cal.[b]
	v1	v2	v3	v4	v5	v6	v7	v8
v1	1.00	.62	.62	.61	-.45	-.46	-.55	-.75
v2	.62	1.00	.85	.60	-.53	-.54	-.78	-.65
v3	.62	.85	1.00	.58	-.51	-.59	-.85	-.63
v4	.61	.60	.58	1.00	-.65	-.49	-.56	-.81
v5	-.45	-.53	-.51	-.65	1.00	.41	.50	.59
v6	-.46	-.54	-.59	-.49	.41	1.00	.60	.51
v7	-.55	-.78	-.85	-.56	.50	.60	1.00	.64
v8	-.75	-.65	-.63	-.81	.59	.51	.64	1.00

Note: n=60 and $p<0.01$ (two-tailed testing) for all correlations. [a]Directly assessed by rating. [b]Calculated according to the prediction equations (see Appendix B).

To apply the four models, the judgments for the behavioral intentions have to be - in a conceptually adequate way - numerically coded as numbers between zero and one. Thereby, the conceptual adequateness depends upon how the subjects are assumed to understand the judgment categories. Five assumptions are presupposed here. 1) Each category represents an interval of the continuum of possible behavioral intentions. 2) All these intervals have the same width. 3) For each pair of neighboring categories the upper interval boundary of the lower category is identical to the lower interval boundary of the upper category; i.e. all intervals are directly adjacent. 4) The lower interval boundary of the lowest category is identical to the lower limit of the range of all possible behavioral intentions; i.e. it is equal to zero. 5) The upper interval boundary of the uppest category is identical to the upper limit of the range of all possible behavioral intentions; i.e. it is equal to one.

If subjects understand the categories in this way then choosing a specific category can be induced by any degree of behavioral intention which lies within the interval belonging to this category. For this reason each category is numerically coded by the mean of the two corresponding interval boundaries. Let $u(b_i, s) \in \{1,2,3,4,5,6,7\}$ be the index of the category chosen by subject s for behavioral alternative b_i then the resulting coding rule is

$$I'(b_i, s) = [u(b_i, s) - 0.5]/7 \qquad (20)$$

Because the categories are coded as means of interval boundaries the value for the lowest category is higher than zero (exactly 1/14) and the value for the uppest category is smaller than one (exactly 13/14).

This numerical coding procedure has also an important technical advantage. Because the values of the behavioral intentions can neither be equal to zero nor equal to one all values can be transformed into logits. This allows to estimate the parameters of both logit models by way of the equations 13 and 18 respectively. So the parameters of all four prediction models can be and have been estimated according to the principle of ordinary least squares.

To evaluate the empirical validity of the four models three different measures are applied: 1) percentage of individual predictions violating the limited range constraint, 2) percentage of individual predictions violating the constant sum constraint with a tolerance interval of +/-0.1, and 3) a statistic reflecting the percentage of explained variance. Following a proposal of Greene (1997, p. 256) an analog of the usual squared multiple correlation is applied. It is

$$R^2 = 1 - SS_D / SS_Y \,, \tag{21}$$

whereby SS_D is the sum of squared deviations between predicted and directly assessed behavioral intentions and SS_Y is the sum of squared deviations of the directly assessed behavioral intentions from their mean. For the ordinary linear models this statistic is equivalent to the usual squared multiple correlation.

The first measure will trivially be zero for both logit models and the second measure will be zero for both difference models. These two measures only reflect whether violations of both constraints happen if a theoretically inadequate model is applied. Only the third measure can provide critical results against each of the four models and thereby allow a non-trivial comparison among these models. The results of these tests also provide some cautious empirical hints concerning the empirical validity of the diverse theoretical assumptions incorporated in the models and the numerical coding of the rating scale answers. Note that the third measure is slightly unfair against the logit models: the parameters of the ordinary linear models are estimated by maximizing exactly this statistic; the parameters of the logit models, however, are not. Unfortunately, a completely fair measure can principally not be constructed (see Greene, 1997, p. 256).

The results of the model tests (see Table 3) are consistent with the theoretical expectations. Both constraints referring to the predicted values are violated unless the respective model does not allow for these violations. Also the R^2 show the expected pattern. They increase with each theoretical improvement of the model; i.e. each model for pairs of behaviors produces a higher R^2 than the corresponding model for single behaviors, and each logit model produces a higher R^2 than the corresponding ordinary linear model. As expected, the improvement produced by the logit transformation is distinctly higher for predicted than for directly assessed predictor variables. For the directly assessed predictor variables for single behaviors there is no appreciable improvement. Altogether, these result can be interpreted as an empirical support for the theoretical assumptions from which these models have been derived and which are incorporated in the measurements.

Table 3: Empirical Validity of the Four Models

	Military			Community		
Model	PV1[a]	PV2[b]	R^2	PV1[a]	PV2[b]	R^2
	Directly Assessed Predictors					
Single Behaviors						
Ordinary Linear	1.7	35.0	.83	6.7	35.0	.75
Logit	0	28.3	.83	0	28.3	.75
Pairs of Behaviors						
Ordinary Linear	11.7	0	.85	11.7	0	.85
Logit	0	0	.87	0	0	.87
	Calculated Predictors					
Single Behaviors						
Ordinary Linear	8.3	58.3	.66	8.3	58.3	.46
Logit	0	58.3	.73	0	58.3	.53
Pairs of Behaviors						
Ordinary Linear	11.7	0	.67	11.7	0	.67
Logit	0	0	.76	0	0	.76

Note: n=60. [a]Percentage of individual predictions violating the limited range constraint. [b]Percentage of individual predictions violating the constant sum constraint with a tolerance interval of +/-0.1.

All four models are meant as devices for investigating the relative influence of different predictor variables. Hence, it is interesting to know whether these models provide different patterns. Thereby, in the case of the directly assessed predictors two kinds of relative influence can be considered. These variables rely upon the same questioning format and can thus be interpreted as realizations of the same interval scale variable. Consequently, the multiplicative parameters for the variables in original scaling and for the variables divided by the sample specific standard deviations can be interpreted. In contrast, the calculated predictors cannot be interpreted as values of the same interval scale and, therefore, only the relative influence of the variables divided by their standard deviations is empirically meaningful.

For the directly assessed predictors, all four models render the same results concerning the relative influence of both predictor variables; i.e. only the subjective norm proves to be a significant predictor, but not the attitude. Consequently, the multiplicative parameters for the attitude are always near zero, the ratios between the parameters for both variables are rather unstable and a more detailed consideration of the different kinds of relative influence makes no sense. For the calculated predictors, different models render different results concerning the relative influence of the predictor variables. When the intentions to do community service are analysed by means of the models for single behaviors both, the attitude and the subjective norm, have a significant influence on the behavioral intention. When, however, the intentions to do military service are analysed, only the attitude has a significant influence. Analyses by means of both models for pairs of behaviors also produce a significant contribution only for the attitude. Given that the models for pairs of behaviors are theoretically and empirically more adequate, this indicates that for the calculated predictors, in fact, only the attitude significantly influences the behavioral intention (see Table 4).

Table 4: Multiplicative Parameters for the Attitude and the Subjective Norm

	Original[a]			Standardized[b]		
Model	Att[c]	SN[d]	Ratio[e]	Att[c]	SN[d]	Ratio[e]
	Directly Assessed Predictors					
Single Behaviors Ordinary Linear						
Military	-0.01	0.14*	-0.06	-0.02	0.34*	-0.05
Community	0.02	0.13*	0.19	0.04	0.29*	0.15
Logit						
Military	-0.01	0.80*	-0.02	-0.02	1.90*	-0.01
Community	0.15	0.73*	0.21	0.26	1.66*	0.15
Pairs of Behaviors						
Ordinary Linear	0.00	0.07*	0.02	0.00	0.33*	0.01
Logit	0.03	0.42*	0.07	0.08	1.86*	0.04
	Calculated Predictors					
Single Behaviors Ordinary Linear						
Military	-	-	-	0.28*	0.02	13.61
Community	-	-	-	0.13*	0.15*	0.86
Logit						
Military	-	-	-	1.63*	0.14	11.83
Community	-	-	-	0.75*	0.89*	0.84
Pairs of Behaviors						
Ordinary Linear	-	-	-	0.28*	0.02	13.79
Logit	-	-	-	1.62*	0.14	11.34

Note: n=60. [a]Both predictors in original scaling (from -3 = 'extremely negative' to 3 = 'extremely positive'). [b]Both predictors divided by their sample specific standard deviation. [c]Attitude. [d]Subjective Norm. [e]Ratio between the multiplicative parameters for the attitude and the subjective norm. *p<0.01 two-tailed.

Thus, analyses for both kinds of predictors lead to contradictory results. Mathematically this can be reduced to the fact that in one of two cases the directly assessed attitude can be better predicted by the calculated subjective norm than by the calculated attitude and that, vice versa, in one of two cases the directly assessed subjective norm can better be predicted by the calculated attitude than by the calculated subjective norm (see Table 2). This, in turn, may indicate that the questions which are applied here for assessing the attitude and the subjective norm have not been exactly understood in the way they were intended.

As a special feature of the models for pairs of behaviors, the additive constant also has an empirical meaning. If all relevant influence factors are considered in the questionnaire and if both behaviors are equally salient then the additive constant should be 0.5 in the ordinary linear model and zero in the logit model. For the data at hand this is not true - neither for the directly assessed nor for the calculated predictors (see Table 5). For both models and both kinds of predictors the constant deviates in the same direction. With the intention to do military service as criterion the constant in the ordinary linear model is significantly higher than 0.5 and the constant in the logit model is higher than zero.

Table 5: Additive Parameters for the Models for Pairs of Behavior

Model	Parameter	Standard Error	Significance[a]
	Directly Assessed Predictors		
Ordinary Linear	0.5543	0.0192	$p<0.01$[b]
Logit	0.3495	0.1125	$p<0.01$[c]
	Calculated Predictors		
Ordinary Linear	0.6428	0.0286	$p<0.001$[b]
Logit	0.8534	0.1626	$p<0.001$[c]

Note: n=60. In each case the intention to do military service constitutes the criterion. [a]Two-tailed. [b]Deviation from 0.5. [c]Deviation from zero.

These results indicate that factors which are in favor of doing military service are not considered in the questionnaire. The conditions for choosing between both behaviors give rise to a hypothesis concerning the missing influence factors. Getting permission to do community instead of military service requires a certain amount of effort. A person who wants to do community service has to write a substantiated request and to sent it to the responsible authorities. In some cases he even has to defend his request in an oral hearing. In contrast, a person who wants to do military service can simply wait until he is called up. No effort at all is required, and this lack of required effort could be the missing factor in favor of military service.

5. Discussion

Four different formal models for predicting behavioral intentions have been presented and comparatively evaluated - theoretically and empirically. The results of both kinds of evaluation speak for the fourth model; i.e. for the logit model for pairs of behaviors. Theoretically, this model is superior to the other models because the model predictions are automatically consistent with the two constraints which define among others the construct of behavioral intention. Empirically, this model is superior because it fits best to the data. Moreover, together with the ordinary linear model for pairs of behaviors but in contrast to both models for single behaviors, the logit model for pairs of behaviors contains an empirically meaningful additive constant. This constant can help to detect whether important influence factors have been omitted in the respective study. All these aspects argue for the application of the logit model for pairs of behavior to investigate possible predictors of the behavioral intention.

There are, of course, also limitations. Applying this model requires that there are exactly two distinctly predefined alternative behaviors. Natural settings, however, may deviate from this in at least two aspects: 1) there may be more than two distinctly predefined competing behaviors, or 2) only the target behavior may be predefined, but not the - possibly infinitely many - competing behaviors. The first kind of deviation could and should be handled by developing reasonable generalizations of the logit model for pairs of behaviors. The second kind of deviation, however, requires some additional effort. The best solution for this case would be to develop questioning strategies which reveal in a parsimonious and well structured way the competing behaviors which subjects have in mind. Subsequently, mathematical models referring to the results of these strategies should be developed. For the time being, the second kind of deviation could best be handled by applying the logit model for single behaviors to the target behavior.

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Appendix A

Influence of positively linear transformations on the parameters of the regression equation and on their standard errors

Influence on the parameters

Let *y* be the vector of the regressand variable values, x_k with $1 \le k \le m$ the vector of the kth regressor values, and let β_k and α be the parameters of the corresponding regression equation; i.e.

$$y = \left[\sum_{k=1}^{m} \beta_k x_k\right] + \alpha \tag{A1}$$

Let y^* and x^*_k be positively linear transformations of y and x_k; i.e.

$$y^* = \gamma_y y + \delta_y \text{ and } x_k^* = \gamma_k x_k + \delta_k \tag{A2}$$

with γ_y and γ_k positive. Let further β_k^* and α^* be the parameters of the corresponding regression equation; i.e.

$$y^* = \left[\sum_{k=1}^{m} \beta_k^* x_k^*\right] + \alpha^* \tag{A3}$$

Substitution into A3 according to A2 and algebraical transformation render

$$y = \left[\sum_{k=1}^{m} \left(\beta_k^* \gamma_k / \gamma_y\right) x_k\right] + \left(\alpha^* - \delta_y + \sum_{k=1}^{m} \beta_k^* \delta_k\right) \Big/ \gamma_y \tag{A4}$$

Because of A1 this implies that

$$\beta_k^* = \beta_k \gamma_y / \gamma_k \text{ and } \alpha^* = \alpha\gamma_y + \delta_y - \sum_{k=1}^{m} \delta_k \beta_k \gamma_y \Big/ \gamma_k \tag{A5}$$

If now the regressand variable is uniquely determined (i.e. $\gamma_y = 1;\ \delta_y = 0$) both equations reduce to

$$\beta_k^* = \beta_k / \gamma_k \text{ and } \alpha^* = \alpha - \sum_{k=1}^{m} \delta_k \beta_k / \gamma_k \tag{A6}$$

If, additionally, the origins of the regressor variables are determined (i.e. $\delta_y = 0$, which for example holds if the predictors are constructed as differences between values of the same interval scale) then the following holds

$$\beta_k^* = \beta_k / \gamma_k \text{ and } \alpha^* = \alpha \tag{A7}$$

Influence on the standard errors

The additive constant in a multiple linear regression equation can also be conceptualized as a parameter multiplied with a constant vector; i.e.

$$y = \sum_{k=1}^{m+1} \beta_k x_k \tag{A8}$$

with $\beta_{m+1} = \alpha$ and x_{m+1} a unity vector. Let now x_k^{**} be $\lambda_k x_k$, β_k^{**} the corresponding multiplicative parameter in the regression equation, $SE(\beta_k)$ the standard error for β_k, and $SE(\beta_k^{**})$ the standard error for β_k^{**}. Then some algebraical transformations applied to the definition of the standard error imply that the following holds for all k with $1 \le k \le m+1$

$$SE(\beta_k^{**}) = SE(\beta_k)/\lambda_k \tag{A9}$$

Note now that the additive term in A4 is equal to α and that, therefore, because of A5 A4 can be reformulated to

$$y = \left[\sum_{k=1}^{m} \beta_k^* (\gamma_k / \gamma_y) x_k \right] + \alpha^* \left[\alpha \Big/ \left(\alpha\gamma_y + \delta_y - \sum_{k=1}^{m} \delta_k \beta_k \gamma_k / \gamma_k \right) \right] \tag{A10}$$

i.e. the multiplicative and additive transformations applied to the m vectors in equation A1 are identical to only multiplicative transformations applied to the m+1 vectors in equation A8. Because of A9 this implies for the standard errors

$$SE(\beta_k^*) = (\gamma_y / \gamma_k) SE(\beta_k) \text{ and}$$

$$SE(\alpha^*) = \left[\left(\alpha\gamma_y + \delta_y - \sum_{k=1}^{m} \delta_k \beta_k \gamma_y / \gamma_k \right) \Big/ \alpha \right] SE(\alpha) \tag{A11}$$

If the regressand variable is uniquely defined (i.e. $\gamma_y = 1$; $\delta_y = 0$), the relations reduce to

$$SE(\beta_k^*) = SE(\beta_k)/\gamma_k \text{ and}$$

$$SE\left(\alpha^*\right)=\left[\left(\alpha-\sum_{k=1}^{m}\delta_k\beta_k/\gamma_k\right)\Big/\alpha\right]SE(\alpha) \tag{A12}$$

If the origins of all regressor variables are also uniquely determined (i.e. $\gamma_y = 1$; $\delta_y = 0$; $\beta_k = 0$), the following holds

$$SE\left(\beta_k^*\right)=SE(\beta_k)/\gamma_k \text{ and}$$

$$SE\left(\alpha^*\right)=SE(\alpha). \tag{A13}$$

Appendix B

Prediction Equations of the TORA

The prediction equation for the attitude is

$$att(b_i,s)\propto\sum_{j=1}^{n_c}bel\left(b_i,s,c_j\right)\cdot eval\left(s,c_j\right) \tag{B1}$$

with att(b_i,s) subject s's attitude towards behavior b_i, bel(b_i,s,c_j) subject s's belief that consequence c_j will happen after behavior b_i, eval(s,c_j) subject s's evaluation of consequence c_j, and n_c the number of salient consequences. Beliefs and evaluations are both numerically coded with zero for the middle category.

The prediction equation for the subjective norm is

$$sn(b_i,s)\propto\sum_{k=1}^{n_r}nb\left(b_i,s,r_k\right)\cdot mc\left(s,r_k\right) \tag{B2}$$

with sn(b_i,s) subject s's subjective norm for behavior b_i, nb(b_i,s,r_k) subject s's normative belief about reference person r_k's wishes concerning behavior b_i, mc(s,r_j) subject s's motivation to comply with the wishes of reference person r_k, and n_r the number of salient reference persons. The normative beliefs are coded with zero for the middle and the motivations to comply with zero for the lowest category.

The numerical coding applied here is identical to the coding proposed by Ajzen and Fishbein (1980). Some authors, especially Orth (1985, 1987), have criticized this approach from a measurement theoretical perspective. They argue that the variables in question are at best measured on interval scale level and that, therefore, the location of zero is the result of a completely arbitrary setting. Under this presupposition both prediction equations of Fishbein and Ajzen are empirically meaningless. Orth (1985, 1988) proposes a modification of these equations which is also empirically meaningful for variables which are only measured on interval scale level. This modification, however, requires estimating additional parameters from data. According to the point of view assumed here, it can be reasonable to formulate hypotheses about the metrical characteristics of the variables, before these characteristics are substantiated in an exact measurement theoretical way, and to incorporate these hypotheses by way of the corresponding numerical coding into the model. Here, the prediction equations of Fishbein and Ajzen together with the original coding are understood in exactly this sense.

Footnotes

1) When the values are directly assessed, the measure for each variable relies upon exactly one rating scale. These rating scales are restricted on both sides, whereas the latent variables which are meant to be assessed are not restricted in this way. Therefore, extreme latent values of very different degrees will most probably be projected on the same extreme category. In contrast, when the values are calculated, the measure for each variable relies upon a lot of different rating scales. These rating scales refer to qualitatively different aspects for judging the behavior. Even subjects with very extreme attitudes or subjective norms will usually not judge all of these aspects extremely. At most, this will hold for the subjects with the most extreme attitudes or subjective norms. Therefore, extreme latent values of different degrees will most probably be projected onto different calculated measures; and more extreme calculated measures will usually correspond to more extreme latent values. For these reasons, the calculated measure is expected to differentiate better between different extreme latent values than the directly assessed measure.