

HELPING AND STIGMATIZATION OF PERSONS WITH MENTAL DISORDERS

by

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ERIC KUELKER

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Abstract

Beliefs about the controllability of the cause and of the cure of physical and mental problems have been hypothesized to determine affective reactions, which in turn determine helping intentions toward individuals with these problems (Weiner, Perry, & Magnusson, 1988), such as mental disorder. Other research has shown that knowledge/experience with mentally disordered persons, and perceptions of their dangerousness also influence rejection of persons with mental disorders. These varying beliefs and experiences were combined into a model of stigmatization and intentions to reject mentally disordered persons. The model hypothesized that perceptions of the controllability of mental disorder influences affective responses toward mentally disordered persons. Demographic characteristics of respondents, their prior contact with persons with a mental disorder and perceptions of their dangerousness were also hypothesized to influence affective reactions. In turn, affective reactions were postulated to predict behavioral intentions of assistance or rejection toward persons with a mental disorder. The model, and variants of it, were tested by structural equation modelling on data gathered from a random household sample interview study of 506 Winnipeg residents.

The model was a good fit to the data, with perceptions of the likelihood of harm by persons with a mental disorder being the strongest determinant of affective responses. Beliefs about dangerousness, controllability of mental disorder, respondent demographics and knowledge/experience with persons with a mental disorder also predicted affective responses. Affective responses incompletely predicted intentions to reject, as the previous variables directly predicted intentions to reject. The results present a difficulty to Weiner's (1980, 1993) theory of stigmatization, which states that controllability beliefs predict affective responses, which in turn predict intentions to neglect or help stigmatized persons. Other beliefs and characteristics of respondents and the social context of their interaction with mentally disordered persons may be more powerful determinants of intentions to reject or accept them.

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INTRODUCTION

Stigmatization Defined

Varying attributes between different groups of people are not well tolerated. Attributes that differ from those in the general population, and also are quite undesirable or discrediting, are called stigmas by Goffman (1963). He differentiates among three types of stigmas, the first being abominations of the body, or physical deformities. The second type "are blemishes of individual character perceived as weak will, domineering or unnatural passions, treacherous and rigid beliefs, and dishonesty, these being inferred from a known record of, for example, mental disorder, imprisonment, addiction, alcoholism, homosexuality, unemployment, suicidal attempts, and radical political behaviour" (p. 4). The third type of stigma are the tribal stigma of nation, or race and religion, transmitted through family lines.

Regardless of which type of stigma a person possesses, it intrudes on normal social interactions and may result in rejection, not merely of the stigma, but of the whole person. The person with a deeply discrediting stigma is seen as "quite thoroughly bad, or dangerous, or weak" (Goffman, 1963, p. 3) and open to public mockery, being refused service, etc. Goffman notes that the stigmatized person is seen by others as not fully human, and other imperfections may be attributed to the person in addition to the original stigma. Beliefs spring up to account for the original and the imputed stigmas, explaining their origin and rationalizing the animosity and discrimination against stigmatized people which so readily follow. The beliefs, emotions, and actions relating to stigmatized persons thus are significantly different from those relating to the normal or general population.

The three components of beliefs, affect, and intended behaviour have been connected within at least two theoretical frameworks. These theories of stigmatization will be explored first. After gaining a general theoretical understanding, specific attention will be turned to one of the stigmatized groups that Goffman explicitly mentions, namely, people with mental disorders. The

affects of pity and sympathy would be aroused. If the cause was controllable and internal (e.g., drunkenness), then emotions of disgust and anger would emerge. If the cause was external, then the person would be seen as a victim, with pity and sympathy aroused to them. The type of affect would then determine action, with sympathy and pity leading to help-giving, disgust and anger leading to neglect.

Weiner (1985) later argued that the causal dimension of stability was also important. He stated that, if the cause of the need was seen as both stable and uncontrollable, help would be more likely to be extended, because the needy person would be perceived as unable to help him or herself in the future as well as the present. This leads to the curious conclusion that stigmas with unstable causes (i.e., that are changeable) are less likely to evoke help in changing the cause of the stigma (Weiner, Perry, & Magnusson, 1988). Conversely, people who have stigmas with a stable cause, such as blindness, would be more likely to be helped.

Weiner et al. (1988) also theorized that the type of help would be dependent on, and congruent with, the controllability and stability of the stigma. For example, psychotherapy would be recommended for people with mental-behavioral stigmas such as addictions, which are generally seen to have controllable, unstable causes. Presumably, psychotherapy would help people control and reverse their addictions. Alternately, welfare or job training would be recommended for people with physical handicaps, which have uncontrollable, stable causes. Such interventions would help people cope with these permanent stigmas, rather than try to control or reverse the stigma.

In Weiner's (1993) analysis of reactions to people with stigmas, judgements of responsibility have been added to his theory. The exact sequence consists of an attribution of causal controllability, followed by judgements of responsibility, which lead to emotion and then behaviour in a linear fashion. However, the addition of judgements of responsibility does not add much explanatory power to the theory and may violate the quality of theoretical parsimony.

The attribution → emotion link appears to exist even in young children, although only partially. Children age five and older show increased dislike of obese, aggressive, or learning-disabled children when the targets are attributed increased responsibility for the cause of their problem (Sigelman & Begley, 1987). Dislike was lowest when the target child was described as low in responsibility for their problem, such as obesity due to a thyroid problem. Dislike was highest when the target child was described as highly responsible, such as obesity due to overeating. Wheelchair-bound children were liked equally, regardless of whether they had high or low responsibility for the cause of their condition, or whether no information was given. They were also liked more than children with other stigmas, especially aggressive children, who were liked least. The finding that the nature of the problem determined responses independent of responsibility for the problem is interesting. The authors hypothesized that children have limited exposure to wheelchair-bound children, who show only physical limitations. However, children have much more exposure to aggressive children, who violate moral norms and pose a danger to others. Thus, children have much more exposure to the negative social consequences of some stigmas, such as aggressiveness or obesity, and may be responding on the basis of this greater exposure. Additionally, children may react negatively when they are at risk from the direct harmful effects of a stigma, regardless of responsibility for its cause.

A follow-up experiment to the above study, however, demonstrated a problem with the attribution → emotion linkage (Sigelman, 1991). Explanations that a target child's physical disability was from uncontrollable factors failed to increase liking for the stigmatized child, even though the children understood the causal information and reduced the blame ascribed to the stigmatized child. The amount of liking was a function of the nature of the stigma, with a disabled child liked more than an obese child, regardless of the cause of the disorder. The result is that, if children are told another child's stigma is from controllable causes, disliking and social rejection increase. On the other hand, if the children are told the stigma is from uncontrollable causes, the

1978)⁴. Nunnally (1961) found that, compared to the normal population, persons with a mental disorder are more strongly associated with evaluations of being bad, worthless, dangerous, unpredictable, dirty, weak, etc. These negative evaluations, especially "unpredictable," were stronger toward psychotic than neurotic persons.

The concepts of "unpredictable" and "dangerous" merit special attention, since Nunnally (1961) concluded they are the cornerstones of public attitude to persons with a mental disorder. Members of the general public are very uncomfortable in the presence of former psychiatric patients because of fears that they will abruptly embarrass or endanger them. Research shows that perceptions of dangerousness result in greater social distance, or more distant social relationships, with former psychiatric patients (Link & Cullen, 1983; Trute, Tefft, & Segall, 1989). Perceptions of dangerousness are quite widespread. Rabkin (1980) reported that, in a 1975 community survey, only 17% of the participants agreed with the statement that "mental patients are not dangerous." This may change with time or location, as a 1991 community survey in Winnipeg, Manitoba found that roughly half the sample thought mentally disordered individuals were no more or less dangerous than the general population (Segall, Tefft, & Trute, 1991).

One should note that there is some truth to these public perceptions. Community mental health center clients (Harry & Steadman, 1988) and ex-mental patients are arrested at a rate greater than that of the general population, and the rate is rising (Steadman, 1981). Higher arrest rates are observed cross-culturally, as a birth cohort study in Stockholm found that individuals with a major mental disorder (schizophrenia, psychoses, affective psychoses, paranoid states) or with substance abuse were arrested at significantly higher rates than individuals with no mental disorders (Hodgins, 1993). Individuals with other mental disorders did not have higher arrest rates than people with no diagnoses (as measured by admission to a psychiatric hospital).

⁴More attention will be paid to studies published after these excellent reviews, since the most recent review (Bhugra, 1989) is spotty in coverage.

When offset controllability was allowed to predict emotions, instead of simply covarying with onset controllability in the above model, there was no change in any of the model fit indices. Consistent with this finding, the added paths from offset controllability to pity/fear and to liking were insignificant. In contrast, the path from offset controllability to blame/anger/fear was modestly significant and consistent with the expected effect that increased offset controllability was associated with more blame/anger/fear. All other paths were unchanged from the previous model.

Figure 2
Paths and fit indices of Weiner's (1986; 1993) model.

Goodness of fit of Brickman et al.'s model

When onset and offset controllability were combined to produce the pattern of controllability beliefs associated with Brickman et al.'s (1982) helping and coping models, there was no change in the fit of the overall model to the data, compared to the test of Weiner's (1993) model discussed above. Fit indices and significant path coefficients appear below in Figure 3. Only two of the four paths (Medical and Moral) from the helping and coping models were significant. Stronger belief in the Medical model predicted decreased blame/anger/fear and stronger belief in the Moral model modestly predicted more blame/anger/fear. The paths from emotions to rejection remained substantially unchanged from the paths reported above for Weiner's (1993) model discussed above.

Figure 3**Paths and fit indices of Brickman et al.'s (1982) model.**

Goodness of fit of the comprehensive model

The comprehensive model added to Brickman et al's. (1982) model the variables of age, education, knowledge/experience with mentally disordered persons, and perceptions of harm and dangerousness, as predictors of affect. This resulted in a notable improvement in fit of the model to the data relative to Brickman et al's. (1982) model alone. Significant path coefficients and fit values of the comprehensive model are in Figure 4 below.

Figure 4
Paths and fit indices of the comprehensive model of
stigmatization of persons with a mental disorder.

The improved fit of the model was clearly due to allowing more than controllability beliefs to determine affect. Increased age and education were modest negative predictors of blame/anger/fear. The negative relation between age and blame/anger/fear was contrary to the predicted positive relationship. Increased contact and the perceived likelihood of harm had stronger positive relations to blame/anger/fear, as predicted. Pity/sympathy/fear was positively predicted by increased perceptions of dangerousness and likelihood of harm, and especially by increased age. Only increased contact was a negative predictor of pity/sympathy/fear. Greater liking was strongly negatively predicted by perceived likelihood of harm and less so by perceived dangerousness. Increased contact was a rather modest positive predictor of liking. Finally, with the models of helping and coping, the only significant paths to emotions were modest positive paths from stronger belief in the Enlightenment and Moral models to blame/anger/fear. Stronger belief in the Medical model was a moderate negative predictor of this affect.

Affect continued to predict social rejection, with greater blame/anger/fear modestly predicting more rejection in social responsibility and social relations. Greater pity/sympathy/fear also predicted rejection in social responsibility and in social relations. The strongest link again was liking's path to rejection in social responsibility and in social relations, with greater liking predicting less rejection.

When Brickman et. al.'s (1982) models were replaced with beliefs about onset and offset controllability, the fit values were unchanged, as were all the paths in the model. The only significant path from either controllability variable to affect was that a stronger belief that individuals have control over the onset of their mental disorder positively predicted greater blame/anger/fear, consistent with prior theory and research.

The controllability variables were such modest predictors of affect that a decision was made to test a model with the paths from controllability variables to affect fixed to zero. In other words, affect would be predicted only by social demographics, contact, and perceptions of

dangerousness and harm. The χ^2 value increased by 38 on 12 degrees of freedom ($p < .001$), and the fit indices decreased by .005 to .01. These changes in the direction of poorer fit show that beliefs about controllability predict affect, but that other variables are much more important predictors of affect.

The fact that social demographics, contact, and perceptions of dangerousness and harm significantly predict affect accounts for the result that both the Weiner (1986; 1993) and Brickman et al. (1982) models have a poor fit to the data. Both models have beliefs about controllability as the only predictors of affect and do not include these other important predictors. Both models have fit indices in the range of .77 to .83, whereas fit indices of .9 or above are deemed to indicate an acceptable fit of the model to the data. Adding social demographics, contact, and perceptions of dangerousness and harm as predictors of affect to create the comprehensive model increased the range of fit indices from .84 to .93. This indicates that although the comprehensive model is a better fit to the data than the Weiner (1986; 1993) and Brickman et al. (1982) models, it is not an excellent fit to the data. New variables or modifications to existing variables (i.e. modelling interactions between two variables) are needed to achieve a better fit to the data for the model. Within the comprehensive model, the most important predictor (negative) of rejection in both social responsibility and social relations was liking, followed distantly by pity/sympathy/fear (positive). In turn, liking was most powerfully predicted (positive) by beliefs about the likelihood of harm from a mentally disordered person. Pity/sympathy/fear was most powerfully predicted (positive) by age.

Application of Models to Hypotheses

The seven hypotheses presented previously could be tested with different types of data analysis, only one of which was SEM. Simple correlations, partial correlations, and multiple regression were all used to corroborate and amplify the results from the structural equation

models. These multiple methods of testing hypotheses cross-validate findings from one approach, making conclusions from the data more certain. Cross-validation was not always possible, as certain hypotheses can be tested with only one approach. For example, interaction effects between variables can be analyzed easily with multiple regression, but are testable only with considerable difficulty in SEM (Saris & Stronkhorst, 1984). Fortunately, interaction effects were not hypothesized to occur in the present study.

Hypothesis 1

The first of the seven hypotheses presented previously was that positive affect would be the sole predictor of behavioral intentions to accept persons with a mental disorder, while negative affect would be the sole predictor of behavioral intentions of reject them. This hypothesis was tested with both multiple regression and structural equation modelling. Each type of analysis indicated that affect was not the only predictor of social rejection.

Stepwise multiple regression showed that affect variables were rather poor predictors of rejection in social relations when forced in as the initial block of independent variables ($R^2 = .078$). Forcing in onset and offset controllability marginally improved prediction (R^2 increased by .05). Adding demographics, knowledge/experience with mentally disordered persons, and perceptions of dangerousness and likelihood of harm in the final block of independent variables notably improved prediction of rejection in social relations (R^2 increased by .134). Detailed results are presented below in Table 2.

When rejection of mentally disordered persons in socially responsible roles was the dependent variable, affect variables again were rather modest predictors ($R^2 = .124$). Adding controllability beliefs in the next block of independent variables did not increase prediction of rejection (R^2 did not change). However, adding social demographics, knowledge/experience with persons with a mental disorder, and perceptions of dangerousness and likelihood of harm in the final block of independent variables markedly improved prediction of rejection in socially responsible roles (R^2 increased by .184). Detailed results are presented below in Table 3.

Table 4
Correlations from Demographics, Contact, and Beliefs about Dangerousness
and Harm to Rejection with Affect Controlled

<u>Variable Name</u>	<u>Rejection in Social Relations</u>	<u>Rejection in Social Responsibility</u>
Age	.19	n.s.
Education	-.12	-.17
Indirect Contact	n.s.	-.14
Social Contact	n.s.	-.13
Intimate Contact	-.16	n.s.
General Dangerousness	.18	.12
Known Dangerousness	.11	.10
Likelihood of Threat	.19	.38
Likelihood of Attack	.21	.39

It should be observed that affect did not relate to social rejection exactly as hypothesized. Pity/sympathy and liking were both conceptualized as positive emotions, and thus were expected to result in less rejection. However, in all models, the factor of pity/sympathy/fear was a stronger predictor of rejection than blame/anger/fear. Moreover, pity/sympathy and liking were not significantly correlated, and pity/sympathy was associated with negative emotion (e.g., fear). To illustrate, pity/sympathy and fear loaded on the same factor. Although pity/sympathy had a stronger loading on this factor than fear, the factor's relation to social rejection appears to be almost entirely due to the positive relationship between fear and rejection. Both partial correlations and multiple regression indicated that pity/sympathy had a non-significant relationship with social rejection once fear was controlled for as a covariate or entered first in regression.

Hypothesis 2

The second hypothesis was that a stronger belief that mental disorder is controllable in both onset and offset (i.e. the Moral model of Brickman et al. 1982) would predict stronger negative affect. The modest positive relationship between stronger beliefs in the Moral model and blame/anger/fear in both the Brickman et al. (1982) model and the comprehensive model (path coefficient = .14) was consistent with the hypothesis.

Hypothesis 3

The third hypothesis was that a stronger belief that mental disorder is uncontrollable in both onset and offset (the Medical model of Brickman et al., 1982) would predict stronger positive affect. The increased adherence to the Medical model being negatively related to blame/anger/fear in the two SEM models (path coefficient = -.33) mentioned above, did not invalidate the hypothesis. However, the hypothesis was not actually supported as stated, as the path from the Medical model to liking was non-significant, instead of being positive as predicted.

Hypothesis 4

Hypothesis four predicted slightly positive affect would be felt toward mentally disordered persons by individuals who considered mental disorder to be uncontrollable in onset and controllable in offset (the Compensatory model of Brickman et al., 1982). This hypothesis was not supported, as there were no significant paths from the Compensatory model to any of the latent constructs of emotion.

Hypothesis five

The fifth hypothesis, that the Enlightenment model (controllable in onset and uncontrollable in offset), would result in slightly negative affect was supported, although not strongly. There were no significant paths from the Enlightenment model to liking or to pity/sympathy/fear, but a modest positive path existed from this construct to blame/anger/fear in the comprehensive model, as expected.

Hypothesis six

Hypothesis six received mixed support in the comprehensive model. Increased perceptions of dangerousness and likelihood of harm, older age, lesser education, and less contact with persons with mental disorders were hypothesized to predict negative affect. Lesser education and increased beliefs about the likelihood of harm did predict increased blame/anger/fear. There was no significant relationship between beliefs about dangerousness and blame/anger/fear. However, there was a negative relationship between increased age and blame/anger/fear, and a positive relationship between increased knowledge/experience and blame/anger/fear, both findings which were contrary to the hypothesis.

Hypothesis 7

Hypothesis seven stated that decreased perceptions of dangerousness and likelihood of harm, younger age, greater education, and greater knowledge/experience with persons with a mental disorder will each independently predict positive affect. The clearest factor of positive emotion was defined largely by liking, with a secondary loading of pity/sympathy. As hypothesized, increased knowledge/experience with mentally disordered individuals, and decreased perceptions of possible danger and harm from them, predicted liking. On the other hand, age and education had no significant relationship to liking.

Pity/sympathy was originally conceived as measuring positive emotion, but fear loaded on this factor with a slightly smaller loading than pity/sympathy did. Interpretation of this seemingly mixed factor is quite problematic, as it positively predicted social rejection. Contrary to the hypothesis, decreased knowledge/experience, and increased age, perceptions of dangerousness, and likelihood of harm, positively predicted pity/sympathy/fear.

DISCUSSION

Models of Stigmatization

Weiner's Model of Stigmatization

Overall, the current results indicate that Weiner's (1986; 1993) model of stigmatization and helping explained less of the variance than the other models explored in the data analyses. Variables other than those incorporated by Weiner into his theory had significant effects, whether analyzed with partial correlations, multiple regression, or SEM. His model is not a sufficient statement of the determinants of social rejection of mentally disordered persons by the public in the current study. It is noteworthy that this study is cross-sectional, and thus could not control extraneous factors that may contaminate the statistical analysis. A controlled experiment or longitudinal study would eliminate some extraneous factors, and thus provide a more methodologically pure test of Weiner's (1986; 1993) model, or the other models, than the current study does. Unfortunately, this was not possible, given the time constraints for this study.

Difficulties emerged with Weiner's (1986; 1993) model of stigmatization other than its lack of explanatory power compared to other models. Although there was some support for the general framework, in which attributions of controllability predicted affect, and affect in turn predicted behavioral intentions, close examination revealed mixed support for each link.

The link from attributions to emotion was supported by the predicted result that perceived increased controllability over the origin of mental disorder resulted in increased blame/anger/fear. However, construing the origin of mental disorder as uncontrollable did not elicit affects linked with altruism, such as sympathy, pity, or liking, as hypothesized by Weiner (1993). Instead, there were no significant relationships between beliefs that mental disorder was uncontrollable in origin and affects of sympathy, pity, or liking.

The link from affect to behavioral intention was somewhat problematic also. Greater blame/anger/fear weakly predicted increased social rejection, whereas greater liking strongly predicted decreased rejection, as hypothesized. Further, the fear component of pity/sympathy/fear predicted increased rejection, congruent with Weiner's (1986; 1993) model. What is rather surprising is that, once fear had been controlled as a covariate, pity had no significant relationship with rejection. This did not occur in previous research, where pity was strongly associated with liking and help-giving (Weiner et al., 1988). The connection of pity to fear and subsequent social rejection in the present research is not easily explained.

One possibility of how fear is linked to both pity and blame/anger is that fear may be the basic emotional reaction of most individuals to persons with mental disorders (Tefft, 1995). This fear arises from their perceived dangerousness and likelihood of harm, which are very important predictors of affect in the comprehensive model. If fear is indeed the primary emotional response to mentally disordered persons, then individuals may respond secondarily in two ways. The first is a fearful response with compassion intermingled, such as being confronted with someone with a dangerous infectious disease, in which one may wish to help the needy person, but be simultaneously frightened of becoming ill or harmed oneself. The second type of response may be fear and hostility intermingled, as if meeting a violent criminal.

Another problem with the link in Weiner's (1986; 1993) model from affect to behavioral intention is that affect was not the sole predictor of behavioral intention, as he hypothesized. Age and education, knowledge/experience with persons with a mental disorder, perceptions of their dangerousness, and likelihood of harm all predicted intended social rejection independent of affect. The impact of these variables independent of affect is not entirely surprising. Other models of intended behaviour, such as the theory of planned behaviour (Ajzen & Madden, 1986), do not include affect as a predictor of behaviour. Even though affect is excluded from the theory of planned behaviour, considerable support has accumulated for its predictive validity (for a

review, see Kuelker, 1994). The success of general models of intended behaviour that do not include affect shows that affect is not the sole proximal cause of behaviour, as Weiner (1986; 1993) implies.

To be fair, the theory of planned behaviour is quite general and was not formulated to explain helping behaviour, as was Weiner's theory. However, other models of helping behaviour exist and theorists argue that, in most instances where the person must decide to act prosocially, a strong affective response is not forthcoming because the other's need is not compelling, or because immediate action is not necessary (Eisenberg, 1986). In these cases, help-giving or neglect is largely motivated by cognitive factors (e.g., analysis of costs versus benefits of helping) or personality factors (e.g., self-esteem and self-focus), not affective factors. Thus, it is not surprising that factors other than affect, such as beliefs, age and education, and contact partially determine whether mentally disordered persons would be helped or neglected by the public.

Brickman et al.'s Model of Helping and Coping

Although it has been noted previously that the models of helping and coping derived by Brickman et al. (1982) were theoretically more sophisticated than Weiner's (1986; 1993) model because they added offset controllability to onset controllability, this theoretical change did not enhance prediction of social rejection. This lack of empirical improvement of prediction may be due to various statistical and theoretical factors.

Several statistical and methodological reasons exist for the lack of increase in explanatory power of Brickman et al's. (1982) models over Weiner's (1986; 1993) model. First, the variables which measured Brickman et al's. (1982) models were highly kurtotic and skewed, even after logarithmic transformations to reduce kurtosis. This kurtosis may have attenuated the magnitude of the relationships of the constructs with the affect factors. Second, nearly a quarter of the respondents did not endorse, even in a minimal fashion, any of the four models. These individuals stated that they did not know how much control a person with a mental disorder had over either

the cause or the cure of their illness. Functionally, their responses acted as missing data and error variance, and would have weakened relationships to other variables. This may account for the fact that the only significant relationships observed involved the models which the most people endorsed (i.e., the Medical and Moral models.) Third, combining just two variables to represent Brickman et al's. (1982) models is not a comprehensive assessment of them. Better measurement of the latent constructs by using more variables may reveal stronger relationships with other variables.

An important methodological issue also exists as to the measurement of offset controllability, which is part of Brickman et al.'s (1982) models. When onset controllability is assessed, the respondent has observed a real outcome or event (i.e., another person has a stigma). Presumably, the respondent searches for attributions as to why the other person has the stigma (e.g., they are the victim of uncontrollable forces, or they brought the problem on themselves by their own stupidity, laziness, etc.). Based on these attributions, the respondent experiences affective reactions, which determine helping behaviour (c.f. Weiner, 1980; 1986).

However, when offset controllability is assessed, it is not clear that the respondent is reacting to an actual outcome or event. The stigmatized person's actual choices or attempts at offset control are not presented (e.g., Perry, 1991). The respondent has not observed the events surrounding offset control, or their outcome. He or she cannot engage in a clear attributional search as to why the events around the offset of the stigma occurred (e.g., the cure is beyond the stigmatized person's control, or the cure is in their control but they do not want to bother to help themselves). As a clear attributional search is not possible, affect will not be generated as a result of the attributions, and helping behaviors also will not follow.

If it appears that a problem such as mental disorder is controllable, and continuing through time, an observer may assume that the stigmatized person does not care to solve his or her own problem because of laziness, pride, etc. The observer would then respond with blame and anger,

and neglect to help. However, an alternate explanation exists as to why a controllable problem is continuing. It may be that the stigmatized person is working valiantly to bring about his or her cure, but the process is lengthy and the problems is not yet resolved. In this case, others would possibly react with considerable pity and liking to someone struggling to cure a difficult problem.

This attributional ambiguity around offset controllability would result in confused or inconsistent affective responses. As affect is a major determinant of helping intentions, these also would be ambiguous or inconsistent. In summary, because of the conceptual and methodological issues in the measurement of offset controllability, it would appear to have weak relationships with affect and helping intentions. Onset controllability does not have these difficulties and could have stronger relationships with affect and behavioral intentions than offset controllability.

The above difficulties could also explain why entering onset and offset controllability, which both predicted affect, in a model as covarying variables did not result in offset controllability predicting affect. In fact, there was no change in the fit or parameters of the model relative to when the Brickman et al. (1982) models were used, showing that offset controllability did not have predictive power.

In addition to the above issues, there is a theoretical reason why Brickman et al's. (1982) models did not provide more explanatory power than Weiner's (1986; 1993) model. Essentially, the multitude of potential causes and cures for mental disorder may be bewildering to the public, as they are to researchers and clinicians. A layperson may not hold to any one of these constructs with particular clarity because of the controversy over differing causes and cures. Alternately, that person simply may not have thought much about the issues. The constructs may only be represented in purer and, hence, more measurable form in institutions or groups which are involved in helping individuals with mental disorders and, thus, must formulate a model of cause and cure of mental disorder.

Although offset controllability did not predict affect, either as a covariate of onset controllability or when combined with it as in Brickman et al. (1982), other variables were significant predictors of affect and social rejection. When added, they make a comprehensive model of stigmatization of mentally disordered persons.

Comprehensive Model of Stigmatization

The considerable increase in percentage of variance explained in regression and in model fit when age and education, knowledge/experience, and beliefs about dangerousness and likelihood of harm were added shows that these are important predictors of affect and social rejection, independent of beliefs about controllability. Their importance as predictors was seen when a variant of the comprehensive model was analyzed without controllability beliefs as predictors of affect. There was only a modest worsening of fit (and decrease of R^2 in multiple regression) when controllability beliefs were not predictors, relative to when they were included in the comprehensive model.

Controllability beliefs in the comprehensive model

Several observations can be made about controllability beliefs as predictors of affect, which in turn predicts helping intentions. To begin, controllability beliefs are indeed significant predictors of affect and social rejection. This is in accordance with research by Weiner (1980) and others, reviewed above. However, the better fit of the comprehensive model shows that controllability is not the sole predictor of affect. The predictive power of other variables presents a challenge to Weiner's (1986;1993) theory of stigmatization and helping intentions as currently stated.

Another important observation is that, in the present study, variables other than controllability beliefs were far more powerful predictors of affect and social rejection. Several possibilities may explain this phenomenon. To begin, previous research generally had undergraduates respond only to questions about controllability, affect, and behavioral intentions.

The present study interviewed community dwelling adults on a wider variety of issues and beliefs about persons with a mental disorder. Differential responses may be given by undergraduates who, because of their education, may be more attuned to a cognitively-oriented causal analysis than the general public. Furthermore, responses may be influenced by the limited scope of the questions asked of undergraduates (e.g., which affect would you feel, would you help or not). A wider assortment of questions such as those asked in the 1990 WAS but not included in the present study (e.g., questions about authoritarianism, beliefs about mental health, etc) may evoke more diverse responses and weaker correlations. Finally, undergraduates are less diverse in terms of age, education, and experience than community dwelling adults, which may produce a different pattern of results between the two samples.

Another possible reason why other variables overshadow controllability as a predictor of affect is that stigma type predicts social rejection independent of affect (Reisenzein, 1986). Not all stigmas are responded to equally when controllability is held constant. These differential responses may be because various stigmas have attributes other than controllability associated with them. Researchers have listed several of these attributes, such as (a) visibility and obtrusiveness of a stigma (Goffman, 1963); (b) threat, whether of economic, societal, or physical harm (Katz, 1979); (c) ambiguity and disruption of social interaction; and (d) physical offensiveness (Albrecht et al., 1982). Depending on the stigma, these associated attributes may overshadow the controllability dimension as determinants of affect and social rejection.

The relative importance of controllability and other attributes of a stigma in determining helping intentions is a source of confusion and contradiction in the literature. Research by Weiner and others (Reisenzein, 1986; Weiner, 1980a; 1980b) consistently shows controllability to be a very important determinant of affect which, in turn, determines helping intentions. In contrast, Albrecht et al. (1982) found no correlation between controllability and social rejection. For example, alcoholics were held less responsible than those with heart disease for their condition,

yet had far more social rejection than the latter. Controllability was largely irrelevant as a determinant of rejection and other attributes of these stigmas determined helping intentions.

These contrary results may be resolved by examining the type and nature of helping intentions in the different studies. In studies by Weiner and his associates (Graham & Weiner, 1991; Reisenzein, 1986; Weiner, 1980a; 1980b), respondents read brief vignettes of people in need and were asked if they would provide short-term help to these people in the context of a very brief social interaction. Similarly, in a study of various stigmas requiring longer-term help, subjects were asked what types of government-administered help they would recommend and whether or not they would give personal assistance (the nature of the assistance was unspecified; Weiner et al., 1988). The hypothesized social interaction between the needy or stigmatized and the respondent was generally very brief and impersonal in this research programme. In marked contrast, the research by Albrecht et al. (1982) asked respondents how willing they would be to engage in long-term, close social knowledge/experience with stigmatized persons. The frequency and intimacy of social knowledge/experience was much greater in this latter study than in the studies by Weiner and his associates.

As frequency and intimacy of social interaction with stigmatized people is a major discriminating factor between the two research programs, it is plausible that these variables make attributes of stigmas other than onset controllability more salient as determinants of rejection. Variables which would negatively affect long-term social interaction, such as the possibility of embarrassing social scenes, or excessive dependency, or even violence from the stigmatized group, could be more salient and powerful determinants of social rejection than onset controllability.

This hypothesis is supported by other results from Albrecht et al. (1982). They asked open-ended questions of their respondents as to why they thought people would reject stigmatized individuals. Content analyses of these responses revealed that ambiguity and discomfort in social

interaction was the most frequently given reason for rejecting stigmatized people. This was especially true for physically disabled persons (83% of responses). Additional reasons were given for rejecting individuals with social disabilities, such as ex-convicts or persons with a mental disorder. In the latter case, threats to social well-being or physical well-being were frequently cited as reasons for rejection (44%), as well as perceptions of moral or characteriological weakness (24%). Individuals with social disabilities consistently evoked more social rejection than physically disabled persons.

What is noteworthy is that most of the reasons for rejecting stigmatized people would be salient only in long-term, close social interaction with them. Ambiguity of social interaction, and threats to physical and social well-being, would not be major concerns in impersonal and/or very brief social encounters and, thus, would not influence rejection. Since these variables are minimized, other attributes of stigmas, such as onset controllability or moral weakness, would emerge as more powerful determinants of social rejection.

It is possible that it is not only the number of stigma attributes involved that determines rejection, but also their potency. If a stigmatized person is considered a threat to one's physical well-being, that person will be rejected much more than if the stigmatized person presents a problem in terms of ambiguity of social interaction. This may explain why socially disabled persons are rejected more intensely than physically disabled people, since socially disabled persons are more often considered to be threats to physical well-being.

Relative potency of attributes would make attributes appear trivial at some times and important at other times. To illustrate, if controllability is paired with two different attributes in two different stigmas, one attribute (e.g., ambiguity in social interaction) may be weak in potency relative to controllability, making controllability the major determinant in rejection. In the second stigma, the other attribute (e.g., threat to physical well-being), may be more potent than controllability, relegating controllability to be a minor determinant of rejection.

The weakness of controllability as a determinant of affect relative to other variables in the present study may now be understood as resulting from different factors. To begin, the context of behavioral intentions was how willing the respondent would be to engage in long-term, close social interaction with persons with a mental disorder. As noted above, this context is very different from behavioral intentions in very brief and/or impersonal social contact, which is characteristic of Weiner's (1980b) approach. Because the present study used long-term, close social interaction as the context of intentions, attributes of persons with a mental disorder (e.g., perceived likelihood of harm) other than their controllability over the onset of their mental disorder would become relatively more salient.

Not only were these other attributes and causes of affect salient, they were far more potent than controllability beliefs in terms of how much they predicted affect. One latent construct by itself (likelihood of harm) had larger path coefficients to affect than did controllability beliefs. This indicates that, at least in some contexts, the public is more responsive to attributes other than onset controllability when responding to mentally disordered persons. As these attributes and determinants of affect can be more important than onset controllability in the current context, our discussion will turn to these attributes and determinants.

Other attributes and causes in the comprehensive model

The single most important attribute of mentally disordered persons in determining affective reactions was perceived likelihood of being personally harmed by them. This appears consonant with research reviewed previously that perceptions of dangerousness results in greater rejection (Trute et al., 1989). However, an important distinction exists. The distinction is that perceptions of the dangerousness of mentally disordered persons in general, and those the respondent knew personally, was also directly assessed in this study. However, dangerousness was not a powerful predictor of affect, which is surprising, as the correlated factor of likelihood of harm was such a strong predictor. The explanation may be that inquiring about the general dangerousness of

persons with a mental disorder is more abstract and impersonal than asking about the likelihood of these persons, living in one's neighborhood and meeting the respondent, harming him or her personally. Stronger affective reactions may be generated when personal outcomes are involved, which would be reflected in the larger path coefficients of likelihood of harm to affect.

Age and education also predicted affect, although not as hypothesized. Increasing age was a modest negative predictor of blame/anger/fear and a strong positive predictor of pity/sympathy/fear. Partial correlations revealed that age was more related to pity/sympathy, not fear. These results are contrary to what was hypothesized, that increasing age would predict more negative affect. Curiously, even though individuals of greater age felt more pity toward persons with a mental disorder, this did not translate into less rejection. When pity was controlled, or all five emotions were controlled, there was no significant change in the correlation of age to social rejection (both r 's = .19), compared to when age correlated directly with social rejection (r = .21). Increasing age was associated with greater rejection in social relations, regardless of pity or any other affect that was felt.

These results are difficult to reconcile with Graham and Weiner (1991), who concluded that pity and anger determine helping intentions, more so than beliefs about controllability, and that this pathway was consistent across groups that ranged in age from 5 to 95. A possible solution to these contradictory findings is that in Graham and Weiner's (1991) study, the help-giving was in the context of a minor emergency, and was very brief, impersonal, and did not expose the help-giver to any possible danger or harm. The current study assessed personal, longer-term help-giving, which some respondents believed could expose them to possible harm. This different context and higher perceived costs of help-giving may activate beliefs or other factors that are more salient to people of increased age.

Education was a modest negative predictor of blame/anger/fear, as predicted, but it was not a positive predictor of liking as hypothesized. Education may serve to inform and sensitize people

as to the plight of mentally disordered individuals, resulting in slightly less negative affect, but it may not make persons with a mental disorder more appealing and likeable. The small correlations of education to affect did not mean that education was insignificant, as it negatively correlated with both types of social rejection when affect was controlled in partial correlations.

Consistent with prior research, more education and younger age predicted less social rejection in this study. The puzzling finding is that more education and younger age did not produce affects that were consistent with helping intentions. It even produced affects contrary to the respondent's stated helping intentions, in the case of increasing age producing more pity/sympathy, but also more social rejection. The context and possible costs of help-giving, the nature of the recipient's problem, and other salient beliefs related to education and age, may all account for affect being unrelated, or even contrary, to helping intentions. Clearly, more research is necessary to explore these findings and hypotheses further.

The final determinant of affect and social rejection in the current study was knowledge of, and experience with, mentally disordered persons. Correlations revealed that overall, increased knowledge/experience or contact of any type led to less rejection. At a more specific level, individuals with contact at a social level with persons with a mental disorder reported mixed emotions to them. They reported increased liking, decreased pity/sympathy/fear, and increased blame/anger/fear, each at about the same magnitude of correlation ($r \approx .13$). Two hypotheses may account for these mixed emotions resulting from social contact.

The first possibility is that an individual who has had rather brief social contact with a mentally disordered person would have only a partial view of mental disorder and would be unaware of all its facets. However, with a complex phenomenon such as mental disorder, a partial view may lead to inconsistent or confused responses. People who have just had indirect contact with persons with a mental disorder have no direct experience and would not necessarily be aware of the complexity of the issues. They would have only a stereotyped view and their

responses would be more one-dimensional and, thus, more consistent. Those who have had intimate contact with mental disorder would have wrestled with the complexity of the issue, and possibly come to a consistent position.

A second hypothesis as to why mixed emotions result from social contact is that some respondents would have had negative experiences with persons with a mental disorder, resulting in blame and anger. Others would have had more positive experiences, leading to liking and less fear. Grouping those with positive and negative experiences together would allow correlations with both blame/anger/fear and liking to emerge, as the two groups of emotions are orthogonal. If the two types of emotions were strongly correlated, these differential responses would not be observed. The data support the hypothesis that some individuals have positive experiences with persons with a mental disorder, leading to liking, and others have negative experiences, leading to blame/anger. Correlations between social contact and one type of affect were unchanged when the other type of affect was controlled for, as opposed to when it was not.

Testing Models of Stigmatization

Many of the relationships among beliefs, affect, and social rejection discussed above were evaluated with SEM and other multivariate techniques. An important issue in this study is whether SEM helped clarify or obscure these relationships, relative to the use of more conventional statistical approaches.

SEM helped clarify relationships in the various models tested in several important and unique ways. One of the most important ways in which it helped to add clarity was to hold the influence of other variables constant to observe one variable's relation to others. Multiple regression cannot hold the influence of an independent variable constant, as regression coefficients change with each independent variable added to the equation. Partial and semi-partial correlations could hold the influence of one measured variable on another constant, but the number of correlations would have become very confusing in this study, as there were so many variables.

Additionally, one would be unable to measure the influence of one latent construct on another, holding other latent constructs constant, with partial correlations. This is only possible in SEM.

A second clarification unique to SEM is that two or more dependent variables can be predicted, and serve as predictors, simultaneously. In this study, the three emotion factors were predicted by various respondent characteristics and beliefs, which in turn predicted two social rejection factors. One cannot predict two or more dependent variables simultaneously with other multivariate approaches. In this study, the relationships of respondent characteristics and beliefs to affect would have been obscured. The prediction of social rejection would also be problematic, because this is a two factor scale. Multiple regression would predict only one factor at a time, and would inflate the influence of independent variables in each equation, because they would be predicting variance shared between the two social rejection factors. Furthermore, one cannot test a three step theory, such as the belief → affect → intention theory in this study, with conventional multivariate approaches and obtain clear and precise results. One would have to predict affect from belief, intention from affect, and then intention from belief while controlling for affect. Only one (measured or linear composite) variable could be used for affect or intention, instead of two or more (measured or latent) variables, as in the present study. The last area where SEM added clarity was in separating error variance from variance shared among the latent constructs, which again is not possible with conventional multivariate approaches.

Confusion and difficulty does arise with SEM because of its novelty and complexity. Using a confirmatory approach to data analysis is fairly novel. Evaluating the goodness of fit of the different models using different fit indices is confusing to the reader. There is also ambiguity as to the degree to which the lack of fit in the model is due to problems in the measurement model, or due to problems in the structural model in how the measured variables and latent constructs are theorized to relate to each other.

Despite the problems in understanding and applying SEM, the various models of the stigmatization of persons with a mental disorder evaluated in this study could not have been evaluated clearly with conventional multivariate methods. Conventional methods would also have sacrificed important information, such as the separation of error variance from true variance. For these reasons, the usage of SEM in this study was appropriate and worthwhile.

Future Directions

Future Research

A considerable number of hypotheses have been advanced in the preceding pages to account for various findings. These hypotheses and the empirical findings on which they are based need to be cross-validated with future research. Several areas stand out as needing further exploration.

The first area of cross-validation is the need for replication with experimental or longitudinal studies. The data in the present research is cross-sectional, and one cannot consider that the causal processes in stigmatizing mentally disordered persons have been discovered, only that a plausible model of these causal processes has been tested, and other models may exist. It may be that the direction of effects is different, or actually reversed in some paths. However, this is not the case with age and education as they clearly cannot be caused by beliefs or affect. On the other hand, certain beliefs about mentally disordered persons may cause other beliefs, which then result in affective responses, instead of beliefs causing only affective responses, as in the models tested in the present study. It even may be that negative affective reactions are rationalized by adopting various beliefs, and that causal paths are reversed to what is modelled in the present study. As noted, these possibilities can only be tested by experimental or longitudinal research, which could not be conducted in the present instance due to time constraints. Time constraints also prevented testing with Monte Carlo methods under what conditions and with what likelihood Weiner's (1986; 1993) and Brickman et. al's (1982) models would achieve good fit.

The second area involves the relationship of affect to behavioral intentions. To begin, affect was an incomplete predictor of intentions, which is a difficulty for Weiner's (1986; 1993) theory. Furthermore, pity did not conform to any of its hypotheses. It was uncorrelated with liking, when it theoretically should have been highly correlated. Instead, pity was directly correlated with fear. Pity also did not predict helping intentions as hypothesized, and the curious phenomenon was observed of people of increasing age feeling more pity and simultaneously rejecting mentally disordered persons. For these reasons, in this context pity cannot be considered simply as a positive emotion that elicits positive intentions. Instead, it acted more as a negative emotion in the present study, correlating with fear and rejection.

Future research should not only replicate, but explore the correlation of pity with fear and rejection. One possibility to research is that pity correlates with fear when people are confronted with stigmatized individuals who may be a physical threat to them. When stigmatized individuals are not a threat, then pity may correlate with liking because fear is non-existent.

One of the most important areas for future research is whether the social context of helping intentions is a major factor. Substantially different beliefs and affects would be relevant in brief, impersonal contact with the stigmatized, relative to lengthy, close social contact. In the first scenario, likelihood of harm would not be a very salient belief, while in the second, it may well be the most important factor in determining rejection. This could be explored in parallel with the relations of pity, fear, liking and other affects to each other. Individuals could respond to vignettes where they believe there is no likelihood of harm versus where they believe there is some likelihood of harm from interacting with a stigmatized person, with length of interaction varied (brief versus long-term) as well. Affective responses and behavioral intentions would reveal the structuring and relative importance of affect, length of interaction, personal distance, and likelihood of harm in responding to stigmatized people.

The fourth issue that should be examined is the relative importance of controllability versus other determinants of affect and helping intentions. Offset controllability may be as important as onset controllability, if it is measured after an outcome is known, or if it is measured more validly. Controllability in general may be less powerful than other beliefs, regarding mentally disordered persons, such as the likelihood of harm. Conversely, controllability may be more powerful than education, or social discomfort in interacting with the stigmatized, in determining social rejection. This ranking of causes of rejection would be an important prerequisite to developing a comprehensive theory of social rejection to all individuals with stigmas. If a comprehensive theory is possible, then it would point out what the most important beliefs and affects are and how to change them in order to reduce the rejection of stigmatized individuals.

Application of Research

If future research confirms the findings and hypotheses presented here, then important steps can be made to reduce the social rejection of the mentally disordered by the general community. The first step would be to address educational campaigns to the most potent determinants of social rejection of persons with a mental disorder. Focusing on the most important factors would be the most effective way of decreasing rejection. It would also be cost-effective, as the total effort required would be less than if one tried to change every possible belief that may result in rejection. Finally, it would be less overwhelming for the public, as they would be exposed to messages regarding two or three beliefs, rather than a half-dozen or more.

A second application is that interventions to increase positive behaviour can be tailored according to the type of behaviour required. If impersonal, brief helping behaviors are important, such as soliciting donations, then the factors which increase helping in such conditions can be addressed in the intervention. For example, if the hypothesis advanced above is correct, onset controllability may be the most important factor in determining helping in brief impersonal

conditions. However, if one is attempting to smooth the placement of a mentally disordered person in a work setting, then beliefs pertinent to long-term, close social interaction should be discussed with potential co-workers. These may very well include questions about the likelihood of harm from the mentally disordered person, the workers' affective responses to persons with a mental disorder in general and/or the individual to be placed in particular.

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Appendix A.
Measure of education

What is the highest level of education that you (and your spouse/partner) have completed?

	You	Spouse/Partner
No Schooling.....	01	01
Elementary School		
Incomplete.....	02	02
Complete.....	03	03
Junior High School		
Incomplete.....	04	04
Complete.....	05	05
High School		
Incomplete.....	06	06
Complete (GED).....	07	07
Non-University (Voc/Tech, Nursing Schools)		
Incomplete.....	08	08
Complete.....	09	09
University		
Incomplete.....	10	10
Diploma/Certificate (Hygienists).....	11	11
Bachelor's Degree.....	12	12
Medical Degree (Vets, Drs., Dentists).....	13	13
Master's Degree.....	14	14
Doctorate.....	15	15
NO SPOUSE.....	--	97
Don't Know.....	--	98
No Response.....	99	99

Appendix B.
Measures of affective responses toward mentally disordered persons

Introduction

Now we'd like to focus on a completely different aspect of mental illness. We know that people with a disability of some kind can arouse strong feelings in other people who don't have that particular disability. Therefore, we're interested in how mentally ill people as a group make you feel. Please understand that there are no good or bad feelings here, and no value judgements of any kind are implied by our questions. We mostly want to know how you respond emotionally to mentally ill people.

1. How much fear do you feel toward mentally ill people?
2. How much liking or attraction do you feel toward mentally ill people?
3. How much pity or sympathy do you feel toward mentally ill people?
4. How much blame do you feel toward mentally ill people? In other words, how much do you feel that the mentally ill are to blame for their condition?
5. How much anger do you feel toward mentally ill people?

Appendix C.

Social Rejection Scale

Social Relations Factor.

1. You would strongly discourage your children from marrying someone who had been a patient in a psychiatric hospital.
2. You would not resent the presence of a residence for discharged psychiatric hospital patients in your area.
3. You would agree to providing board and room for a discharged psychiatric patients in your home if you had room.
4. You would not object to a member of your family dating someone who had been a patient in a psychiatric hospital.
5. You would not object to a group of discharged psychiatric patients renting or buying an apartment or house on your street.
6. You can imagine yourself falling in love with someone who had been a patient in a psychiatric hospital.
7. If the house next door was for sale, you would object to someone with a history of psychiatric problems buying it.

Social Responsibility Factor.

1. If you were a manager and were responsible for hiring people to work for you, you would be willing to hire a discharged psychiatric patient.
2. You would welcome someone who had spent time in a psychiatric hospital to take part in your community functions.
3. You would be willing to work on the same job with someone who had been a patient in a psychiatric hospital.
4. If you were responsible for renting apartments in your building, you would not hesitate to rent living quarters to someone known to have been in a psychiatric hospital.

Appendix D.**Knowledge of and Experience with Mentally Disordered Persons Scale****Impersonal contact factor**

- 1. I have lived or worked close to a mental health facility.**
- 2. I have been to a mental health facility but not as a client or patient.**
- 3. I have received some formal education regarding mental health.**
- 4. I have read factual information or seen factual TV programs concerning mental health.**

Social contact factor

- 1. A friend of mine currently has or in the past has had mental problems.**
- 2. I am currently working with or in the past have worked with a coworker having mental health problems.**
- 3. In my job, I sometimes interact with or in the past have interacted with members of the public who appear to have mental problems.**

Intimate contact factor

- 1. I currently have or in the past have had professional help for mental problems.**
- 2. A member of my family currently has or in the past has had mental problems.**

caused from a latent variable and error variance, but as being causal indicators of a latent variable (Bollen & Lennox, 1991). For example, socio-economic status (SES) may be determined by a person's income, education, neighborhood, and occupational prestige. An increase in a person's occupational prestige would increase their SES, even if the other variables remained constant. The reverse is not true, that an increase in the latent construct of SES would also increase the causal indicators of income, education, etc. Bollen and Lennox also show that if income, education, etc are combined into a linear composite, instead of being viewed as causal indicators, then the linear composite is an inconsistent estimator of the latent construct of SES. One implication of this is that multiple regression produces incorrect results when it uses linear composites, as it very frequently does.

Whether multiple indicators are seen as effects of latent constructs or as causal indicators of them, SEM provides the most powerful use of them by separating error variance from true variance among the latent constructs. Furthermore, since the true variance among the latent constructs is being estimated by SEM, it provides more powerful and accurate tests of a theory than do other statistical techniques (Martin, 1987).

Statistical Assumptions of SEM

The statistical power cited above is not achieved easily, as SEM requires that certain assumptions be met. First, multivariate normality of variables is assumed for estimation by the most widely used and researched technique in SEM, maximum likelihood theory (Bentler & Bonett, 1980). However, there are other, less demanding techniques. Elliptical theory requires only symmetric data, not normally distributed data, while arbitrary distribution theory allows analysis of data with any type of distribution (Bentler, 1993). These last two methods, which are very technical to describe, are not well researched as to their performance.

A second assumption in SEM is that moderate to large sample sizes are used, as the statistical theory has been developed with the assumption of large sample properties (Bentler &

Bonett, 1980). When small samples are used, SEM has little power to detect a false model. Various studies suggest that sample sizes of 100 represent the lower bound of usefulness and larger samples should be used if the data is non-normal (Tanaka, 1987). Sample-size appropriateness is linked to the ratio of number of subjects to the number of parameters to be estimated. One guideline is that there may be as few as 5 participants per parameter to be estimated with normally and elliptically distributed data versus 10 participants per estimated parameter for arbitrarily distributed data (Bentler & Chou, 1987b). The estimation of parameters will be discussed below.

Concepts and Equations Used in SEM

Definition of Variables

The concepts in SEM are slightly different from those in multivariate techniques. To begin, the Bentler-Weeks theory (Bentler, 1993), which is the approach used here, defines a dependent variable as a variable that is expressed as a structural regression function of other variables. When latent variables are involved, the measured variables are viewed as being effects of (a) the latent variable with which they are associated and (b) the corresponding error term. Thus, both measured variables and latent variables which are caused by other latent variables are dependent variables. Any variable which is not a dependent variable is an independent variable, including error terms in the measured variables and disturbance terms in latent variables. A disturbance term is random variance in a latent variable which is not accounted for by the regression equations. As in multiple regression, the parameters to be estimated in a SEM model include the regression coefficients. Unlike multiple regression, the parameters in SEM also include the variances and covariances of the independent variables. In contrast, the variances and covariances of the dependent variables are not parameters to be estimated, but are to be explained by the other parameters.

Matrix Equations

The fundamental matrix equation for SEM in the Bentler-Weeks theory is:

$$\eta = \beta\eta + \gamma\xi$$

η is the matrix of dependent variables, which includes latent constructs which are caused by other latent constructs and measured variables associated with a latent construct. β is the matrix of regression coefficients of the dependent variables on each other. γ is the matrix of structural regression coefficients of the independent variables on the dependent variables. Finally, ξ is the matrix of independent variables. It includes causal latent variables, disturbance terms associated with latent variables, error terms associated with measured variables, and causal measured variables which are not associated with a latent variable, such as in path analysis. The variances and covariances among the independent variables are collected into the matrix Φ , which is defined as:

$$\Phi = E(\xi * \xi')$$

assuming that all variables are expressed as standard deviations from the mean. All parameters to be estimated are in the matrices β , γ , and Φ .

Solving for unknown parameters

Not all parameters in the matrices β , γ , and Φ need be estimated. Some parameters or coefficients can be fixed to certain classes of values based on theoretical considerations. These values can be (a) zero, indicating an absence of effects, or (b) a specific nonzero value indicating an effect of specifiable magnitude, or (c) equal or proportional values, indicating equal or proportional effects or variances (Hayduk, 1987). The number of parameters which must be estimated cannot exceed the number of data points. Data points are the variances and covariances of the measured variables. For p variables there are $\{p(p + 1)\}/2$ data points. If the number of parameters to be estimated exceeds the number of data points in a structural equation, then there is insufficient data to provide estimates of the parameters and the model is said to be under-

identified. It is important to note that if there are insufficient data points for just one structural equation, then the whole model with all of its structural equations is considered under-identified and, thus, cannot be evaluated correctly (Bentler, 1980).

If the number of parameters to be estimated equals the number of data points, so that there is only one possible solution to the structural equation, then the model is said to be just-identified. A just-identified or saturated model has zero degrees of freedom and can be fit to any set of data without error (Bentler & Bonett, 1980), since the parameters are simply transformations of the data (Bentler & Chou, 1987a). As a result, it is theoretically uninteresting because there are no degrees of freedom available with which to test hypotheses.

A model which has fewer parameters to be estimated than data points results in multiple ways to calculate the coefficients in a structural equation (Hayduk, 1987). This model is termed over-identified and, because of the excess of data points to parameters to be estimated, it has one or more degrees of freedom available with which hypotheses can be tested. This is the desired condition for a model since it is testable. Identification is more complex than presented here and Hayduk (1987) is recommended.

Evaluation of Model Adequacy

If a model is over-identified and, hence, estimates of parameters are possible with additional degrees of freedom available for testing hypotheses, estimates are computed according to various distribution theories. The choice of distribution theory depends on the nature of the distribution of the data, as discussed above. If the data are multivariate normal, then maximum likelihood or generalized least squares can be used to generate parameter estimates (Bentler & Bonett, 1980). Subsequently, the accuracy of these estimates needs to be evaluated. The estimated and fixed parameters are collected into the matrices $\hat{\beta}$, $\hat{\gamma}$, and $\hat{\Phi}$, which are multiplied together to generate the predicted covariance matrix $\hat{\Sigma}$ (Bentler, 1993). As noted above, the difference

between Σ^{\wedge} and the sample covariance matrix S is distributed as χ^2 , with a non-significant value indicating that the theoretical model is a good fit to the data.

Initial Model Evaluation

Although a non-significant χ^2 value indicates the model is a good fit to the data, two effects influence the χ^2 value, to the extent that even poor models can be accepted, or that valid models are rejected. These two effects must be examined and their influence minimized or controlled so that the most valid model is accepted despite these contaminating effects.

Sample size effect

As the χ^2 value is a direct function of sample size, the sample size has a notable effect on the decision to accept or reject a model. A non-significant χ^2 , which would indicate accepting the model as a possible explanation for the causal processes in the population, may simply be the result of a small sample size (e.g., 50 participants; Bentler & Bonett, 1980). Conversely, the probability of rejecting valid models increases with sample size. Minimal discrepancies between Σ^{\wedge} and S will be amplified by a very large n (e.g., 5,000 participants), resulting in a significant χ^2 and rejection of a model that is essentially valid.

Parsimony effect

A second difficulty in evaluating the goodness of fit of Σ^{\wedge} to S is that, generally speaking, models that are barely over-identified and have many parameters to be estimated have a better chance of being accepted than more parsimonious models with significantly fewer parameters to be estimated (James, Mulaik, & Brett, 1982). Moreover, the greater likelihood of acceptance of complex models increases with sample size (Cudeck & Henly, 1991). There are three reasons for this effect, the first being that capitalization on chance can occur with many parameters (Mulaik, James, Alstine, Bennett, Lind, & Stilwell, 1989). Random variations in the data may be accounted for by many parameters, but this is less likely to occur with few parameters. The

capitalization on chance is also known as overfitting, as the model is fit to the particular characteristics of the sample and may not fit another sample drawn from the same population.

Second, the model necessarily fits the data points used in estimating its parameters. The process of fitting a model ensures that it will exactly fit the data points that have been used to estimate parameters. If these data points were not used in estimation, the model would not necessarily fit them. Therefore, models with many parameters to estimate will fit the data better than models with few parameters to estimate. Third, data points used in model parameter estimation will be unavailable for model testing and, thus, fewer data points or degrees of freedom will be available to possibly disconfirm the model. The ideal situation would be to have the value of all parameters specified by theory, not by estimation, so that all data points would be available to test the model. Under these circumstances, each data point would act as a potential disconfirmation of the model and one could be most confident of a model that had survived all the potentially disconfirming tests.

Unparsimonious models are to be avoided not only because they are sometimes accepted inappropriately, but also because they yield parameter estimates that are less precise than more parsimonious models (Bentler & Mooijart, 1989). The more precise parameter estimates in parsimonious models will yield a more accurate picture of the causal processes that are hypothesized to be operating.

Hierarchical Model Testing

Evaluation of a model solely by the criteria of whether a non-significant χ^2 is obtained is misleading, due to the sample size and parsimony effects discussed above (Marsh, Balla, & McDonald, 1988). A number of strategies and statistics have been proposed to deal with these two effects in model evaluation, with varying degrees of success.

The first strategy in this controversial area is hierarchical model testing, in which two models are compared, one being a more restricted version of the other, or nested inside the other

(Bentler & Bonett, 1980). The restriction is that one or more free parameters in the first model (M_a) are fixed in the second (M_b). This restriction can be evaluated statistically because the difference between the χ^2 value of M_a and the χ^2 value of M_b is itself distributed as a χ^2 value, with degrees of freedom given by the number of free parameters that are fixed in going from M_a to M_b . If the χ^2 value of the difference between M_a and M_b is non-significant, it indicates that the free parameters in M_a that were fixed in M_b (usually to zero) were not statistically significant. A significant result of the χ^2 test indicates that the parameters are statistically significant and explain relations in the model. Comparisons between nested models is possible because sequential χ^2 difference tests are asymptotically independent (Steiger, Shapiro, & Browne, 1985), although multiple tests may yield significant results on chance alone. Sample size effects should be considered when a parameter is statistically significant, that a very large sample size may detect statistically significant, but theoretically or practically unimportant, parameters within the model.

This process can evaluate a hierarchically nested series of models and the significance of parameters that are fixed and free between models (Bentler & Bonett, 1980). The process has been refined by James et al. (1982) and Anderson and Gerbing (1988). James et al. (1982) recommend first creating a just-identified or saturated model (M_s), which has as many parameters as covariance data points in S . Since M_s is just-identified, it has zero degrees of freedom and fits the data perfectly. One then compares M_s to a measurement model (M_m) that evaluates how measured variables relate to the latent variables they are hypothesized to measure. The submodel that specifies how latent variables relate to each other in causal paths or covariances is known as the structural model.

The free parameters fixed from M_s to M_m are parameters going from measured variables to latent variables to which they are hypothesized to be unrelated. Fixing these paths results in the measurement model, since the free parameters in M_m are from the measured variables to the latent variables to which they are hypothesized to be related. All possible parameters among the

latent variables are free, leaving the structural model to be just-identified and fitting the data perfectly.

If the χ^2 difference between M_s and M_m is non-significant, one can conclude that the hypothesized measurement model fits the data. If the χ^2 difference is significant, the measurement model is faulty because the structural model is fitting the data perfectly rather than causing a lack of fit. If no theoretically sound changes to the measurement model result in good fit, then model testing should stop for two reasons. The latent constructs were not measured adequately and any model more restricted than M_m will also be rejected since M_m is rejected.

If M_m is accepted, then some free parameters in the structural model can be fixed to produce the theoretical model (M_t), which specifies the hypothesized causal structure. If the χ^2 difference is non-significant, then one can accept M_t as a possible model for the causal processes in the population. However, one should not accept M_t as the only model, because some free parameters can be fixed to produce a more constrained model (M_c) (Loehlin, 1987). A non-significant χ^2 between M_t and M_c would indicate M_c is a plausible model. M_c may fit better than M_t because the gain in degrees of freedom from fixing free parameters offsets the increase in χ^2 . Alternately, fixed parameters in M_t can be freed to produce a more unconstrained model M_u , which is also theoretically plausible and should be evaluated for goodness of fit (c.f. Anderson & Gerbing, 1988).

A more restricted model (M_r) than M_c may be tested, wherein all paths in the structural model are set to zero (James et al., 1982). M_r is the measurement model alone, with the structural model removed entirely. The χ^2 difference between M_c and M_r tests whether the structural model is statistically significant or not, having been eliminated in M_r . A significant result indicates that the structural model contains significant paths between latent variables which explain part of the data. A non-significant result indicates that there are no significant relationships among the latent variables.

Parsimonious fit index

James et. al. (1982) propose a fit index which measures the parsimony of the model by rewarding highly parsimonious models that have nearly as many degrees of freedom (d_f) as the null model (d_0). The Parsimonious Fit Index is defined as:

$$PFI = (d_f/d_0) [(\chi^2_0 - \chi^2_f)/(\chi^2_0)].$$

Values of the PFI which approach one indicate a parsimonious model with high goodness of fit to the data. In practice, PFI values close to one are unlikely because parsimony and goodness of fit are logically interdependent and opposed qualities, with goodness of fit increasing as parsimony decreases (Mulaik et al., 1989). No empirical research has been conducted on the PFI.

Bollen's DELTA2

Bollen (1989; 1990) proposes an index called DELTA2, which both controls for sample size effects, and rewards parsimonious models. DELTA2 is defined as:

$$DEL2 = (\chi^2_0 - \chi^2_f)/(\chi^2_0 - df_f).$$

It is not normed, but values very close to one are desirable, with values under one indicating poor fit and values over one indicating over-fitting of the model. DEL2 shows no sample size effect with both true and mis-specified models, and has low variability (Bentler, 1990; Bollen, 1989).

The three indices discussed so far are based on hierarchical model testing. Alternate fit indices exist, with different assumptions and methods of dealing with parsimony and sample size.

Goodness-of-fit index

A fit index developed using the discrepancy between the covariance matrix predicted by the model (Σ^{\wedge}) and the sample matrix S is the Goodness-of-Fit Index (Joreskog & Sorbom, 1984). It is purported to be independent of sample size and robust to violations of normality. The index functions by measuring the relative amount of variances and covariances accounted for by the model. It is defined as:

$$GFI = 1 - \{[\text{tr}(\Sigma^{\wedge-1}S - I)]^2/[\text{tr}(\Sigma^{\wedge-1}S)^2]\}$$

for maximum likelihood. A similar version exists for unweighted least squares (Joreskog & Sorbom, 1984). Sample size effects for the GFI have been repeatedly found (Anderson & Gerbing, 1984; Marsh et al., 1988; Wheaton, 1987) and the size of GFI depends on its estimation method (La Du & Tanaka, 1989). In its favor, the GFI appears to be unaffected by violations of normality (c.f. Gerbing & Anderson, 1992).

Adjusted goodness-of-fit index

Although the GFI is touted to be independent of sample size, it does not reward parsimonious models. The Adjusted GFI includes a penalty function for extra parameters in order to reward parsimonious models (Marsh et al., 1988). It is written as:

$$AGFI = 1 - [p \times (p + 1) / 2df] \times (1 - GFI).$$

For both the GFI and the AGFI, values close to the upper bound of one are desirable, indicating good fit (Joreskog & Sorbom, 1984). Values can go slightly negative for very badly fitting models. Like the GFI, the AGFI suffers from sample size effects (Anderson & Gerbing, 1984; Marsh et al., 1988) but not from violations of normality (Gerbing & Anderson, 1992).

Scaled Satorra-Bentler index

Another index designed to handle multivariate non-normality in data is the scaled statistic of Satorra and Bentler (SSB), which is part of the EQS program that analyses SEM models (Bentler, 1993). The reader is referred to Chou, Bentler, & Satorra (1991) for its very technical formula. When the data are severely non-normal, such as having high levels of skew and kurtosis, or dependency among latent factors and unique variates, the SSB performs very well (Hu, Bentler, & Kano, 1992; Chou et al., 1991), although it tends to over-reject models at small sample sizes (Hu et al., 1992). χ^2 statistics based on normal theory estimation are fairly robust when non-normality is not severe (Hu et al., 1992).

Non-central χ^2 indices

A new class of indices have been developed using the non-central χ^2 distribution (Bentler, 1990). This distribution differs from the central χ^2 distribution in that the means of the sum of squares may be different from zero and the size of that difference is defined by the non-centrality parameter δ (Saris & Stronkhorst, 1984). McDonald and Marsh (1990) show that the χ^2 value of a model is distributed as non-central χ^2 , with δ defined as:

$$n(\theta_s - \theta_t)J(\theta_s - \theta_t).$$

θ is the matrix of free parameters and J is Fisher's information matrix. If the fit of the model is perfect, as with a saturated model, the means of the sum of squares will be 0 and consequently δ will be 0. If model fit is imperfect, then $\delta > 0$, with larger values indicating greater model mis-specification (Bentler, 1990).

McDonald and Marsh (1990) rescaled δ by dividing it by n to yield δ^* . This Rescaled Non-centrality Parameter (RNP) is estimated without bias by:

$$RNP = d_t = (\chi^2_t - df)/n.$$

They propose that RNP be considered a fit index, with values approaching 0 indicating better fit. They also report a fit index by McDonald in which the RNP is transformed into a normed measure of centrality, which is estimated by:

$$MMC = \exp[-(1/2)RNP].$$

McDonald's Measure of Centrality (MMC) is normed to range from zero to one, with values approaching one indicating better fit.

Bentler (1990) proposed a non-central fit index based on nested models, in which the model of theoretical interest, M_t , is compared to the null model, M_0 . Bentler's Fit Index is defined as:

$$BFI = 1 - Q_t/Q_0 \text{ where } Q = \chi^2/n.$$

Values of the BFI which approach one indicate very good fit, but it can fall outside the 0-1 range. He proposed another index which must be in the range of 0-1. This Comparative Fit Index is defined by:

$$\text{CFI} = 1 - [\max(\delta_t, 0)] / [\max(\delta_o, \delta_t, 0)]$$

with values approaching one indicating good fit. The CFI and RNP are algebraically equivalent, except when $df > \chi^2$ (Goffin, 1993). The MMC and CFI behave very similarly to DEL2, showing no sample size effect with both true and mis-specified models and having low variability (Bentler, 1990).

Other fit indices

The 10 indices which were just described represent a subsample of the available fit indices. They are used and have been studied empirically in Monte Carlo simulations. Other indices are reformulations or scalings of these indices. For example, the incremental fit indices fall into two general forms (Marsh et al., 1988), given respectively as:

$$\text{Type 1 indices} = |t - o| / \text{Max}(t, o),$$

$$\text{Type 2 indices} = |t - o| / (e - o),$$

where t is the value of a fit index, o is the value for the null model, and e is the expected value of the fit index if the model is actually true. These forms, and others like the parsimony index (d_t/d_o) of James et al. (1982), can be used to reformulate the indices discussed above. Some reformulations based on Type 2 indices are independent of sample size and can be recommended for use (Marsh et al., 1988).

Recommendations for use

Despite its faults, the χ^2 and its p value should continue to be reported (Gerbing & Anderson, 1992), as the discrepancy between $\hat{\Sigma}$ and S is distributed as χ^2 . The fit indices that are useful for freedom from sample size effects are the TL, DEL2, MMC, and CFI. The PFI should be included when assessing fit in order to help identify the most parsimonious model with

the best fit. Under conditions of non-normality, the GFI and AGFI would be quite useful, even though statistics based on normal theory estimation are fairly robust when non-normality is not severe (Hu et al., 1992). When there is severe non-normality in the data, the SSB is the only defensible index. The GFI and AGFI were not reported in this study, as the computer program used in analysis (EQS) did not compute these values. The SSB was also not reported because it was not computed by the program, and because it was not necessary, as the data were not severely non-normal.

Model Modification

A common result upon fitting a model to data is to discover that it fits poorly according to various indices. This poor fit can be improved by freeing one or more fixed parameters in the model. In the extreme case, so many fixed parameters are freed that the model becomes saturated and fits perfectly. The alternate approach is to fix trivial free parameters so that the gain in degrees of freedom offsets the minimal increase in fit function (Chou & Bentler, 1990). The methods of detecting which parameter to free or fix will be surveyed before discussing the benefits and hazards of model modification.

Normalized residuals

The normalized residuals between the predicted covariance matrix Σ^{\wedge} and the sample matrix S can indicate which parameter to free. A residual significantly different from zero may indicate problems with model specification, since the value predicted by the parameter in Σ^{\wedge} differs from S .

Hierarchically nested models

The logic of hierarchical model nesting discussed previously can be applied to detect model specification errors. A parameter fixed in one model can be freed in another, and the difference between models (D Test) evaluated as to whether changing the parameter resulted in a significant improvement in fit for the less constrained model.

Estimated change

Several other techniques estimate the change in fit of the model if a given parameter is freed or fixed. The modification index (MI) in LISREL VI estimates the decrease in the fit function if a parameter is freed (Sorbom, 1989). The Wald (W) test and Lagrange Multiplier (LM) are available in EQS (Bentler, 1993) and are distributed as χ^2 variates, with r degrees of freedom when r parameters are being examined. The Wald test aids in model simplification by scrutinizing whether some free parameters can be fixed to zero. The LM test has the opposite function, examining whether some parameters fixed to be zero (or another value) can be freed. A Monte Carlo study showed the W and LM tests to be very similar to the D Test in hierarchical model testing, although the LM test returned incorrect results under some conditions (Chou & Bentler, 1990) and tends to overfit a model (Bentler & Chou, 1992). The W test can detect the erroneous results and identify the correct model (Chou & Bentler, 1990).

Model Modification Application

The techniques for choosing which parameter to alter should be used with considerable caution. These techniques have the benefit of improving model fit and thus increasing the possibility that the modified model reflects the causal processes which produced the data. However, model modification has several hazards.

The first hazard is that theoretically meaningless parameters may be included in the model solely because they improve model fit. Despite admonitions that only theoretically valid modifications be made (e.g., Saris & Stronkhorst, 1984), researchers may be tempted to contrive a theoretical justification for a modification (Steiger, 1990) or may even ignore making a theoretical justification (Bollen, 1990; MacCallum, Roznowski, & Necowitz, 1992). To illustrate, 37 modifications were made to one model (Newcomb, Huba, & Bentler, 1986), a number that destroys theoretical credibility.

A second problem is that modification indices are rather unreliable in detecting true mis-specification (Kaplan, 1988), an effect which increases as mis-specification becomes more severe (MacCallum, 1986). Thus, data-driven modifications will not necessarily correct for poor specification of the theoretical model.

A third difficulty is that capitalization on chance can easily occur with the large number of parameters in complex models (Cliff, 1983). Modifications may be due to the many parameters picking up on chance characteristics of the sample used in the analysis. This tendency is highly problematic in small samples, which show very unreliable and incorrect modifications (MacCallum, 1986). Capitalization on chance is also more likely after a sequence of modifications have been made. Since early modifications correct for large misfit and later modifications correct for small misfit, the later modifications may be due to chance characteristics of the sample (MacCallum et al., 1992; but see Bollen, 1990). Unfortunately, theoretically necessary modifications may be made late in the sequence, even when the model has a non-significant χ^2 value (MacCallum, 1986). One cannot have a short modification sequence to protect against capitalization on chance and still be confident that all necessary modifications have been made.

The final problem is that modifications are post-hoc analyses which are tested on a confirmatory basis (Cliff, 1983). The probability distributions and goodness-of-fit values do not apply, as they were derived for confirmatory testing. Mistakenly, the modified models are tested on these distributions. Post-hoc protective techniques (like the Scheffe test) would make post-hoc analysis defensible, but no such technique exists for SEM (Steiger, 1990).

The desirability of modifying a model to increase its fit is tempered by issues of theoretical meaningfulness, reliability of the modification indices, capitalization on chance, and statistical problems associated with post-hoc analysis. These issues caution against modifying a poorly fitting initial model (which is very frequently the case). However, if one does not modify a poorly

fitting initial model, one cannot know whether the model may reflect the causal processes. There are two methods for dealing with a poorly fitting initial model, cross-validating a model and specifying multiple initial models. Each method will be reviewed next.

Model Evaluation through Cross-Validation

Double sample cross-validation

Cliff (1983) recommends that a researcher split the data in half, fit and modify a model on sample *a* and then cross-validate the model on the unused half of the data, or validation sample *b*. The modified model can be legitimately applied to the validation sample, as the sample data did not influence the modification of the model. When a model developed on sample *a* (*Ma*) is applied to sample *b* (*Sb*), the resulting χ^2 value can indicate whether *Ma* has acceptable fit in *Sb* (Cudeck & Browne, 1983). A double cross-validation is suggested, where the free parameters of the model are estimated in sample *b* (*Mb*) and applied to sample *a* (*Sa*). When various models are tested, the model with the lowest cross-validation indices for both sets of data can be regarded as the one with the greatest predictive validity.

The preceding strategy is tight cross-validation, as all the parameter values from sample *a* are applied unchanged to sample *b* (MacCallum, Roznowski, Mar, & Reith, 1994). An alternative strategy is to fix all weights in linear equations and to re-estimate variances and covariances in the second sample (fixed weights strategy). Alternatively, one could fix all parameters reflecting structure among both measured and latent variables, and re-estimate the variances and covariances of error and disturbance terms (fixed structure). Another option is to fix the loadings of the measured variables onto their latent variables and to re-estimate all other parameters (fixed loadings). Finally, one could re-estimate all model parameters (loose cross-validation). All cross-validation strategies provide a method for evaluating the overall discrepancy resulting from the parameters which are fixed when applied to sample *b*.

When double sample cross-validation has been empirically studied, tight cross-validation shows clear sample size and parsimony effects. At small sample sizes, simple models are chosen as they have the lowest value of the discrepancy function. With increasing sample size, more complex models are chosen (Browne & Cudeck, 1989; Camstra & Boomsma, 1992; Cudeck & Browne, 1983; MacCallum et al., 1994). Fixed structure and fixed weights strategies show the same pattern, while fixed loadings and loose cross-validation strategies select the most complex model regardless of sample size (MacCallum et al., 1994).

Single sample cross-validation

The most serious drawback to double sample cross-validation is the need to split the sample, thereby losing valuable statistical power. The Akaike Information Criteria (AIC; 1974) and Schwartz Information Criteria (SIC; 1978) have been proposed as single sample indices which yield the same information as tight double sample cross-validation (Cudeck & Browne, 1983). A single sample cross-validation index (SSC) has been proposed which is mathematically equivalent to AIC when maximum likelihood is used in conditions of multivariate normality (Browne & Cudeck, 1989). Unfortunately, the AIC and SSC select less parsimonious models as sample size increases, until they select the saturated model in the largest sample (Browne & Cudeck, 1989; 1992). Therefore, they will not be discussed further.

A rather unhappy sense of *deja-vu* emerges at this point. Modifying a poorly fitting model was problematic for various reasons. Cliff (1983) suggested modifying a model until good fit was achieved and then using tight double sample cross-validation to test the model. However, empirical testing revealed both parsimony and sample size effects in both double and single sample cross-validation. These effects may be due to the use of χ^2 to evaluate double sample cross-validation. Since sample size and parsimony effects occur with χ^2 , it is unsurprising that these effects emerge when it is used in tight cross-validation. If an alternate fit index is used that

controls for one or both effects, such as the DEL2 or CFI, then tight cross-validation could be a viable test of a modified model.

Evaluation of Multiple Models

An alternative approach to data-driven modification of an initial model is to specify several theoretically plausible initial models and test each one (McDonald & Marsh, 1990). The model with the best fit to the data would be accepted as a possible explanation for the causal processes. Each model would be independently tested by the data, avoiding the problems of post-hoc modification. Although testing multiple models increases the risk of Type I error, such error is quite implausible in large samples because the high statistical power virtually ensures that models will be rejected.

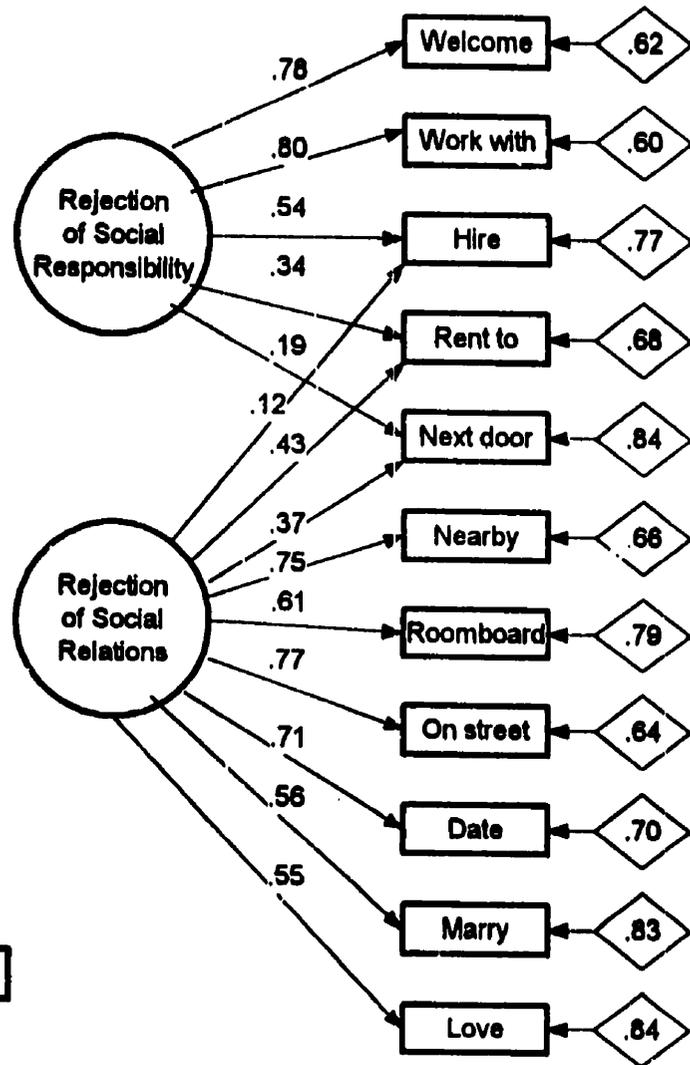
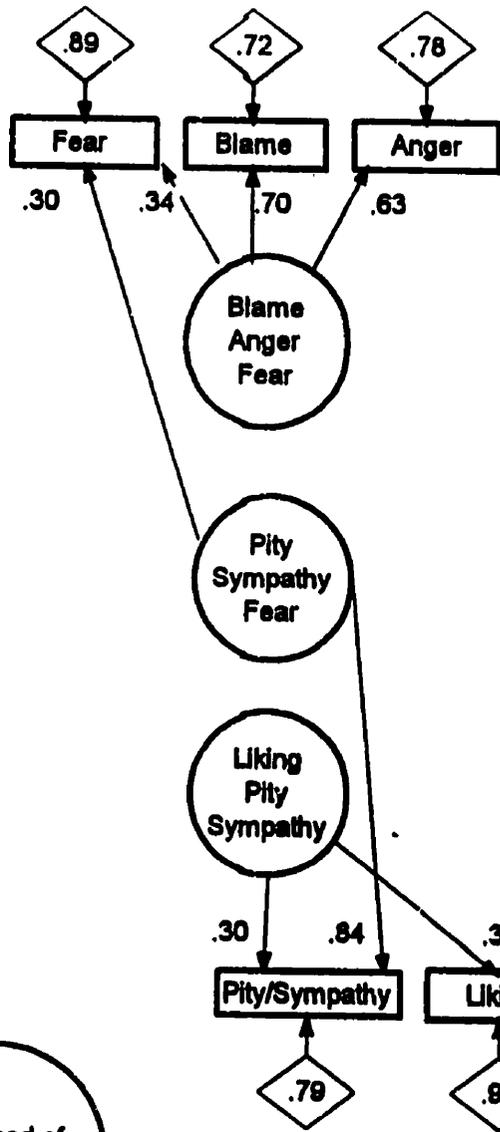
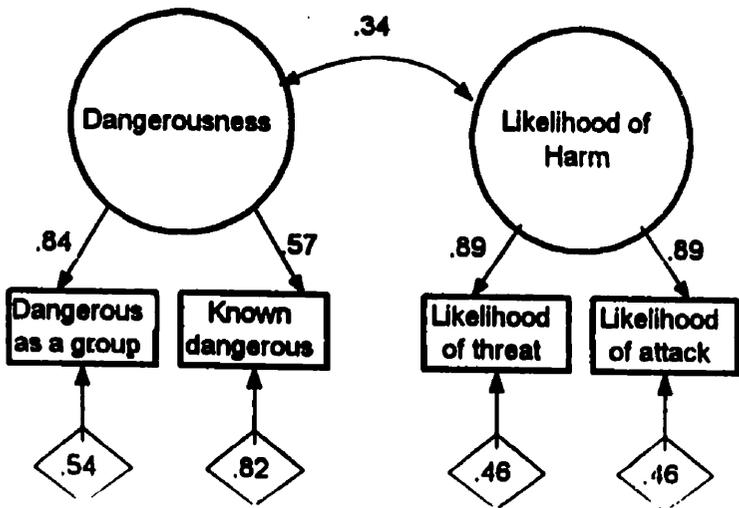
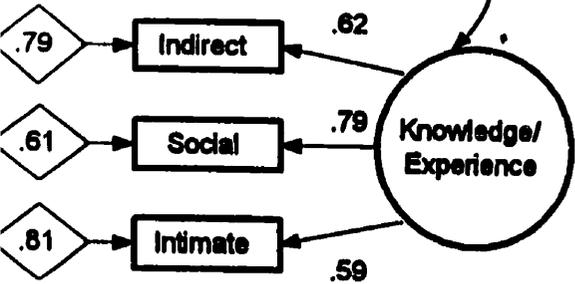
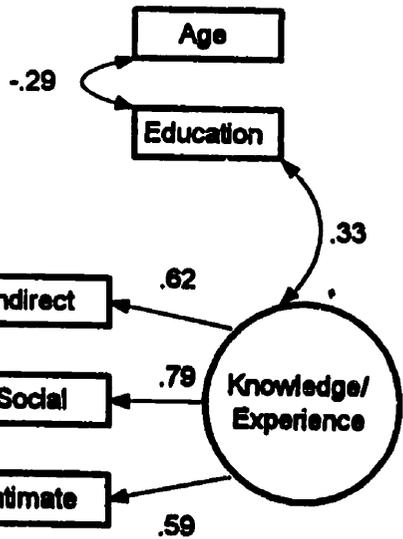
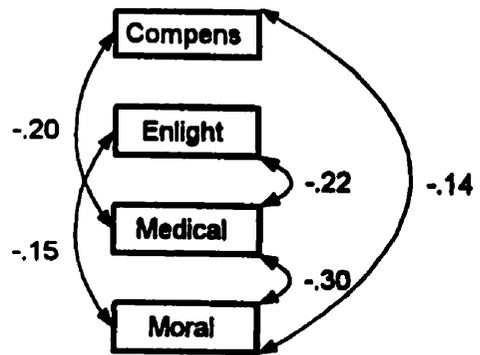
Model Acceptance

Once a theoretically plausible model has been selected by modification and cross-validation, or from a group of plausible initial models, then several cautions must still be observed in drawing conclusions from the model, especially if it was derived from cross-sectional data. The first caution is that SEM tests models which are hypothesized to reflect the causal processes which produced the data (Baumrind, 1983). If a model fits the data well, that does not prove that the causal processes have been irrefutably discovered. Rather, it only means that the hypothesis was not disconfirmed by the data. One cannot draw strong conclusions about causal processes unless well-controlled longitudinal or experimental research has been conducted. Second, several other as yet unspecified models may fit the data as well as or better than the selected model (Breckler, 1990).

The third caution is that, for any selected model, it is often possible to generate a number of models with different causal structures that all have identical fit to the data (Stelzl, 1986). These different models can be produced by inverting the causal order of variables or by replacing paths between variables by correlated residuals (Lee & Hershberger, 1990; Stelzl, 1986). The number

of equivalent models can be very large. In one study, there were shown to be 1.19×10^{18} equivalent models with exactly the same goodness of fit (MacCallum, Wegener, Uchino, & Fabrigar, 1993). However, the equivalent model issue is considered less serious in new areas of inquiry, as theoretical positions are emerging and a set of plausible models is an advance over what previously existed.

Appendix F
Measurement Model used in SEM Analysis



CompensL	-0.028	0.040	-0.023	-0.001	-0.048	-0.028
EnlightL	-0.013	-0.034	-0.086	-0.025	-0.047	-0.052
MedicalL	0.110	-0.011	0.066	0.032	0.033	0.033
MorallL	-0.052	0.009	-0.059	0.003	0.040	-0.019
Threat	0.409	0.304	0.318	0.459	0.334	0.289
Attack	0.439	0.324	0.293	0.470	0.355	0.282

	Iloving	Mtidcont	Mtsocont	Mtitcont	CompensL	EnlightL
Iloving	1.000					
Mtidcont	-0.183	1.000				
Mtsocont	-0.221	0.473	1.000			
Mtitcont	-0.213	0.365	0.487	1.000		
CompensL	-0.013	-0.027	-0.044	-0.041	1.000	
EnlightL	-0.013	0.021	0.012	0.060	-0.086	1.000
MedicalL	-0.035	0.066	0.027	0.046	-0.185	-0.205
MorallL	0.030	-0.075	-0.013	-0.003	-0.127	-0.141
Threat	0.229	-0.138	-0.171	-0.179	-0.020	0.013
Attack	0.248	-0.117	-0.137	-0.177	-0.033	0.027

	MedicalL	MorallL	Threat	Attack
MedicalL	1.000			
MorallL	-0.303	1.000		
Threat	-0.006	-0.076	1.000	
Attack	0.006	-0.049	0.785	1.000