Available online at www.sciencedirect.com

SCIENCE DIRECT®

Schizophrenia Research 78 (2005) 251–260

SCHIZOPHRENIA RESEARCH

www.elsevier.com/locate/schres

Visual processing in schizophrenia: Structural equation modeling of visual masking performance

Yuri Rassovsky[a,b,*], Michael F. Green[a,b], Keith H. Nuechterlein[a,c], Bruno G. Breitmeyer[d], Jim Mintz[a,b]

[a]*Department of Psychiatry and Biobehavioral Sciences, Geffen School of Medicine at UCLA, 760 Westwood Plaza (C8-747/NPI), Los Angeles, CA 90024-1759, USA*
[b]*VA Greater Los Angeles Healthcare System, USA*
[c]*Department of Psychology, University of California, Los Angeles, USA*
[d]*Department of Psychology, University of Houston, USA*

Received 26 November 2004; received in revised form 3 May 2005; accepted 9 May 2005
Available online 21 June 2005

Abstract

Schizophrenic patients consistently demonstrate performance deficits on visual masking procedures. In visual masking, the subject's ability to process a target stimulus is reduced by another stimulus (mask) presented either before (forward masking) or after (backward masking) the target. Masking procedures employed in schizophrenia research have used several experimental paradigms. Most early studies have used high-energy masks (i.e., the mask is stronger than the target) and spatially overlapping target and mask. More recently, studies have begun to employ relatively weak (i.e., low-energy) masks, as well as masks that surround, but do not spatially overlap, the target. Data for forward and backward masking components of four masking conditions (target location and identification with a high-energy mask, target identification with a low-energy mask, and target identification with equal energy paracontrast/metacontrast) were collected from 75 patients with schizophrenia. Based on theoretical distinctions among masking procedures, we compared four models of visual masking using structural equation modeling. Although high zero-order correlations were found among the masking parameters, a four-factor model, in which factors were separated on the type of response (target location and identification), the shape of the function (monotonic and non-monotonic), and the overlap of the stimuli (overlapping and non-overlapping), provided the best fit for the data. These findings suggest that the four masking procedures used in this study may tap unique aspects of visual processing and are not redundant. The results also support theories of the different mechanisms underlying performance on these measures.

Keywords: Visual masking; Paracontrast; Metacontrast; Schizophrenia; Neurocognition

---

[*] Corresponding author. Department of Psychiatry and Biobehavioral Sciences, Geffen School of Medicine at UCLA, 760 Westwood Plaza (C8-747/NPI), Los Angeles, CA 90024-1759, USA. Tel.: +1 310 478 3711x43197; fax: +1 310 268 4056.

E-mail address: yurir@ucla.edu (Y. Rassovsky).

doi:10.1016/j.schres.2005.05.011

1. Introduction

Schizophrenic patients consistently demonstrate performance deficits on visual masking procedures, as they require longer time intervals between target and mask to identify the target stimulus, compared with controls (Braff et al., 1991; Cadenhead et al., 1998; Rund, 1993; Saccuzzo et al., 1974; Saccuzzo and Schubert, 1981). Visual masking procedures are thought to assess the earliest components of visual information processing (Green et al., 1994a; Green et al., 1994b; Saccuzzo, 1974; Schuck and Lee, 1989). In these paradigms, the subject's ability to process a visual stimulus (target) is reduced by another visual stimulus (mask) presented shortly before (forward masking) or after (backward masking) the target. Visual masking is thought to occur through a combination of two processes, referred to as integration and interruption (Turvey, 1973). Integration refers to the fusion of the mask and target due to their close temporal and spatial proximity, whereas interruption reflects a disruption of slightly later-stage processing of the target by the mask.

A dual-channel masking model of visual processing (Breitmeyer, 1984; Breitmeyer and Ganz, 1976) has been proposed to explain these processes at a physiological level. According to this model, masking involves two types of visual channels, transient and sustained, which differ in their anatomical and psychophysiological characteristics. Transient channels, in this view, are activated first and convey information about onset, offset, and location of a stimulus. This activation is followed by activity in the sustained channels, enabling a more detailed analysis of the stimulus. This model thereby provides a physiological framework for the concepts of interruption and integration. Masking by interruption, in this view, occurs when transient-channel activity of one stimulus interrupts the sustained channel-activity of another stimulus (e.g., inhibition of the sustained-channel activity of the target by the transient-channel activity of the mask in backward masking). Masking by integration, on the other hand, occurs as a result of combined sustained-channel activity, such that sustained activity of the mask integrates with the sustained activity of the target.

Several experimental paradigms have been used to study visual masking in schizophrenia. Commonly, the procedures involve high-energy masks relative to a low-energy and spatially overlapping target (Breitmeyer and Ogmen, 2000). ("Energy" in this context refers to the product of stimulus contrast and duration.) Under these conditions, the masking effect occurs from target and mask integration at short intervals, and interruption at longer intervals. Such procedures, therefore, involve both integration and interruption processes and produce monotonic masking functions, in which subjects' performance increases with increasing intervals (Breitmeyer and Ganz, 1976).

Another procedure, designed to isolate integration and interruption processes, uses relatively weak (i.e., low-energy) masking stimuli, compared to the targets. Because the visual representation formed by integrating the target with a weak mask is still interpretable, the effects of integration on visual processing of the target are minimized, and masking effects occur primarily through interruption (Green et al., 1994a). This masking paradigm typically produces a non-monotonic (i.e., U-shaped) function that can demarcate the point at which target processing is interrupted by the mask (i.e., the point of the strongest masking effect) (Ganz, 1975; Michaels and Turvey, 1979; Stewart and Purcell, 1974).

More recently, a third procedure has been introduced into schizophrenia research in which the mask surrounds, but does not spatially overlap, the target (Rassovsky et al., 2004). It is called paracontrast (for forward masking) and metacontrast (for backward masking). As there is no spatial overlap between target and mask, this procedure is very effective in isolating the interruption mechanisms (Ganz, 1975). A graphical representation of subjects' performance using this paradigm also produces a non-monotonic function (Merritt et al., 1986; Rassovsky et al., 2004; Rassovsky et al., in press).

Despite the theoretical distinctions among the various paradigms, it remains unclear whether these procedures provide different information regarding visual processing that are relevant to understanding deficits in schizophrenia. To directly address this issue, we collected data from a sample of schizophrenic patients using these paradigms, as well as one that involves locating a target instead of identifying it. This task should rely less on sustained channels for the response and more on transient channels. We postulated that the extent to which different masking procedures yield distinctive information regarding the underlying visual processes would be reflected in the number of latent variables needed to explain the observed performance. If some of the procedures are yielding redundant information, they should load on a single factor.

Based on the aforementioned theoretical considerations, four competing models were constructed using the eight masking parameters: 1) a model in which all masking parameters load on a single factor; 2) a two-factor model that has a factor for monotonic masking functions and one for non-monotonic masking functions; 3) a three-factor model: one for monotonic masking functions, a second for non-monotonic functions with spatially overlapping target and mask, and a third for non-monotonic functions with non-overlapping target and mask; and 4) a four-factor model: one for monotonic masking functions of target location, a second for monotonic masking functions of target identification, a third for non-monotonic masking functions with spatially overlapping target and mask, and a fourth for non-monotonic masking functions with non-overlapping target and mask. The four models were compared using the structural equation modeling approach. This approach is conceptually analogous to a combination of confirmatory factor analysis and multiple regression (Ullman, 2001), as it allows the assessment of a common variance between latent variables and their indicators, as well as the variance or covariance among latent variables, within a theoretical framework.

2. Methods

2.1. Subjects

Participants were part of the project “Early Visual Processing in Schizophrenia” (Green et al., 1994a; Green et al., 1994b). All schizophrenia patients were outpatients recruited through outpatient clinics at the VA Greater Los Angeles Healthcare System and through presentations in the community. All participants gave written informed consent after receiving a full explanation of the research according to procedures approved by the Institutional Review Boards of UCLA and the VA Greater Los Angeles Healthcare System.

Participants were administered the Structured Clinical Interview for DSM-IV (SCID-P) (First et al., 1997) and met the DSM-IV diagnostic criteria for schizophrenia (AmericanPsychiatricAssociation, 1994). All interviewers were trained to administer the SCID by the Diagnostic Core of the Mental Illness Research, Education, and Clinical Center (MIRECC) Treatment Unit, and were required to obtain a Kappa of .75 for key psychotic and mood items before proceeding to interview participants independently. Patients were excluded if they had an identifiable neurological condition, any signs of mental retardation, or met criteria for substance dependence in the last 6 months.

The present study included 75 schizophrenic patients (92% male). Mean age of the sample was 46.65 (SD = 9.53; range = 24–61) and mean education was 12.98 (SD = 1.75; range = 8–18). The sample had a mean illness chronicity of 21.23 years (SD = 11.01; range = 3–39). The patients were clinically stable outpatients. Patients’ mean score for thinking disturbance cluster (hallucinations, unusual thought content, and conceptual disorganization) on the Brief Psychiatric Rating Scale (BPRS) (Overall and Gorham, 1962) was 2.46 (SD = 1.31; range = 1–6). Their mean BPRS score for the withdrawal/retardation cluster (blunted affect, emotional withdrawal, and motor retardation) was 1.97 (SD = .87; range = 1–3.67).

2.2. Testing procedures

A specially designed computerized system with a high refresh rate was used to administer the masking procedures. Although the procedures closely approximated previously-used computerized visual masking tasks from the same research program (Green et al., 2002; Green et al., 2003b; Rassovsky et al., 2004), the tasks for the current study differed in two key ways. First, the present tasks were programmed using E-Prime software (Psychology Software Tools Inc., Pittsburgh, PA). Second, the tasks were administered on a Dell Pentium computer with a 17 in. Sony Multiscan 200PS monitor, driven at 160 Hz with a refresh rate of 6.25 ms (our previous studies used 150 Hz with a refresh rate of 6.67 ms). Stimuli were presented as dark on a light background. Background luminance, measured with a hand-held meter with diffuser against the screen, was lx = 89.

Prior to the masking procedures, a thresholding procedure was used to equate participants' unmasked target identification using a staircase method (Wetherill and Levitt, 1965). The duration of the target was set at two screen sweeps (12.5 ms) and was held constant throughout the procedures. During this thresholding procedure, the contrast of the target (i.e., the gray scale value) was systematically increased or decreased based on subject's performance to achieve 84% performance accuracy. This contrast level was used for all subsequent masking procedures.

A fixation symbol (a small cross) was presented for 300 ms, starting 400 ms before target onset. The target was a square with a gap that could appear at the top, the bottom, or on the left side (see Fig. 1). Targets could appear at any one of four locations on the screen (upper left, upper right, lower left, lower right). Target location was 1.03° of visual angle from fixation, and it subtended 0.23° of visual angle. Intervals between target and mask were measured by stimulus onset asynchronies (SOAs), which is the time interval between the onset of the target and the onset of the mask. In forward masking, the mask preceded the target and in backward masking, the mask followed the target. In every masking condition, there was an SOA of 0, but it was not included in the analyses. Twelve trials were presented in a randomized fashion at each SOA (3 types of targets time 4 locations).

Four masking conditions were used:

1) In the target location, high-energy masking condition, participants were asked to indicate where the target appeared. The energy of the mask was twice the energy of the target (i.e., four screen sweeps for the mask and two for the target). The mask was a composite square made up of four smaller squares (see Fig. 1) and appeared at each of the four possible target locations, overlapping the area occupied by the target (Green et al., 2003b). The SOAs were spaced in 12.5 ms increments from −75 to +75 ms. In all, 12 SOAs were included in the analyses.
2) In the target identification, high-energy masking condition, participants were asked to identify the target. Target and mask were the same as in the previous condition. The energy of the mask was again twice the energy of the target. The SOAs were spaced in 12.5 ms increments from −75 to +75 ms, with additional intervals at −112.5 and +112.5 ms (total of 14 SOAs were included in the analyses).
3) In the target identification, low-energy masking condition, participants were again asked to identify the target. Target and mask were the same as in the previous conditions. The energy of the mask was half the energy of the target (i.e., one screen sweep for the mask and two for the target). The SOAs were again spaced in 12.5 ms increments from −75 to +75 ms, with additional intervals at −112.5 and +112.5 ms (total of 14 SOAs were included in the analyses).
4) In the target identification, equal energy paracontrast/metacontrast condition, participants were also asked to identify the target. The target was the same as in the previous conditions. The energy of the mask was equal to that of the target (two screen sweeps). As can be seen in Fig. 1, the mask was a square that surrounded, but did not overlap, all possible areas in which the target could appear (Rassovsky et al., in press). The SOAs were spaced in 12.5 ms increments from −75 to +100 ms (total of 14 SOAs were included in the analyses).

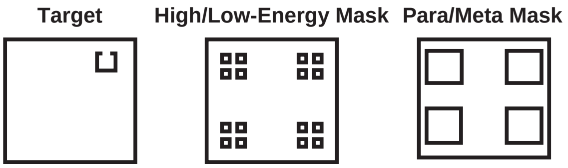

Fig. 1. Masking stimuli. The target was a square with a gap that could appear at the top, the bottom, or on the left side. Targets could appear at any one of four locations on the screen (upper left, upper right, lower left, lower right). The high/low-energy mask was a composite square made up of four smaller squares and appeared at each of the four possible target locations, overlapping the area occupied by the target. The paracontrast/metacontrast mask was a square that surrounded, but did not overlap, all possible areas in which the target could appear.

2.3. Statistical analyses

Pearson bivariate correlations (two-tailed) were calculated to examine zero-order correlations among the masking parameters. The structural equation modeling technique was then used to examine four models hypothesized to explain the factorial structure of the visual masking parameters (Bentler, 1996). The first

Table 1
Pearson correlations among masking variables

	1	2	3	4	5	6	7	8
1. F-Hi-Loc	–	.441**	.294*	.310**	.247*	.341**	.205	.314**
2. B-Hi-Loc		–	.313**	.283*	.205	.248*	.150	.256*
3. F-Hi-ID			–	.487**	.654**	.649**	.528**	.577**
4. B-Hi-ID				–	.478**	.608**	.442**	.569**
5. F-Lo-ID					–	.788**	.748**	.702**
6. B-Lo-ID						–	.628**	.654**
7. P-Eq-ID							–	.862**
8. M-Eq-ID								–

F-Hi-Loc = forward condition, high-energy mask, target location; B-Hi-Loc = backward condition, high-energy mask, target location; F-Hi-ID = forward condition, high-energy mask, target identification; B-Hi-ID = backward condition, high-energy mask, target identification; F-Lo-ID = forward condition, low-energy mask, target identification; B-Lo-ID = backward condition, low-energy mask, target identification; P-Eq-ID = paracontrast, equal energy, target identification; M-Eq-ID = metacontrast, equal energy, target identification.
$*p<.05$, $**p<.01$ (two-tailed).

model had one latent variable with all eight indicators: forward condition, high-energy mask, target location (F-Hi-Loc); backward condition, high-energy mask, target location (B-Hi-Loc); forward condition, high-energy mask, target identification (F-Hi-ID); backward condition, high-energy mask, target identification (B-Hi-ID); forward condition, low-energy mask, target identification (F-Lo-ID); backward condition, low-energy mask, target identification (B-Lo-ID); paracontrast, equal energy, target identification (P-Eq-ID); and metacontrast, equal energy, target identification (M-Eq-ID). The second model had two latent variables representing the monotonic/non-monotonic distinction. “Monotonic” indicators included F-Hi-Loc, B-Hi-Loc, F-Hi-ID, and B-Hi-ID; “non-monotonic” indicators included F-Lo-ID, B-Lo-ID, P-Eq-ID, and M-Eq-ID. The third model had three latent variables representing the monotonic/non-monotonic, as well as the overlapping/non-overlapping, distinctions. “Monotonic” indicators were the same as in the two-factor model. “Non-monotonic/overlapping” indicators included F-Lo-ID and B-Lo-ID; “non-monotonic/non-overlapping” indicators included P-Eq-ID and M-Eq-ID. The fourth model had four latent variables representing the monotonic location/identification distinction, the monotonic/non-

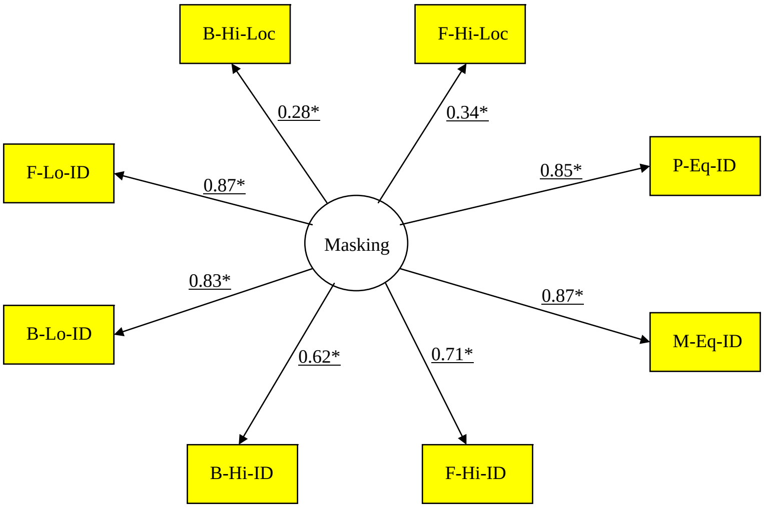

Fig. 2. Structural equation model, with one latent variable and eight indicators. Circle represents the latent variable, and rectangles represent measured variables (defined in Table 1). *Estimated parameters. Underlined coefficients (presented in standardized form) are significant at the .05 level. CFI = .85, χ^2 (20, N = 74) = 70.18, $p<.001$.

monotonic distinction, and the overlapping/non-overlapping distinction. "Monotonic/location" indicators included F-Hi-Loc and B-Hi-Loc. "Monotonic/identification" indicators included F-Hi-ID and B-Hi-ID. "Non-monotonic/overlapping" and "non-monotonic/non-overlapping" indicators were the same as in the third model.

The hypothesized models were estimated with EQS Structural Equation Package (Bentler, 1996), using maximum likelihood solution. This software reports many of the indices that have been described in the literature for evaluating model fit (e.g., Bentler–Bonett Normed Fit Index, Bentler–Bonett Non-Normed Fit Index, Comparative Fit Index, Bollen Fit Index, McDonald Fit Index, Lisrel GFI Fit Index, Lisrel AGFI Fit Index, Root Mean-Square Residual, Standardized RMR, and Root Mean-Square Error of Approximation). As the fit indices were consistent in ranking the candidate models, we report in this paper only two commonly reported indices, the chi-square and the Comparative Fit Index (CFI). A good fitting model is typically indicated by a non-significant chi-square. However, because the chi-square is very sensitive to sample size, it often rejects good-fitting models (Ullman, 2001). Therefore, the Comparative Fit Index (CFI) was also included (Bentler, 1990). The CFI ranges from 0 to 1 and values greater than .95 typically indicate good model fit (Hu and Bentler, 1999). As only one participant had missing data, listwise deletion method was used in the analyses (i.e., excluding the participant with the missing data).

3. Results

3.1. Zero-order correlations

Pearson bivariate correlations (two-tailed) for the masking variables are reported in Table 1. As can be seen in Table 1, most variables had significant zero-order correlations with each other at the .05 level.

3.2. Structural equation models

The independence model, testing whether or not the observed data fit the expected data, was rejected, χ^2 $(28, N=74)=363.27$, $p<.001$. (The chi-square for the independence model should always be significant, indicating that there is a relationship among the variables. The independence

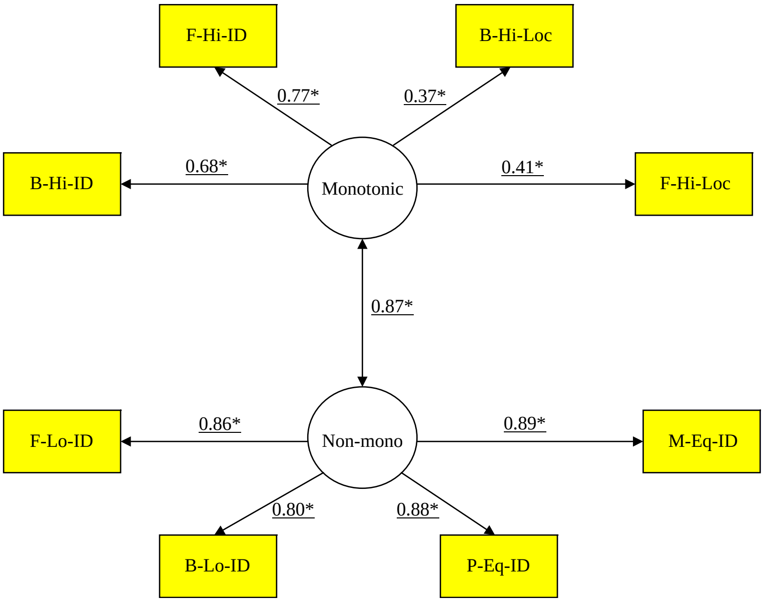

Fig. 3. Structural equation model, with two latent variables representing the monotonic/non-monotonic distinction. *Estimated parameters. Underlined coefficients (presented in standardized form) are significant at the .05 level. CFI=.86, χ^2 $(19, N=74)=65.18$, $p<.001$.

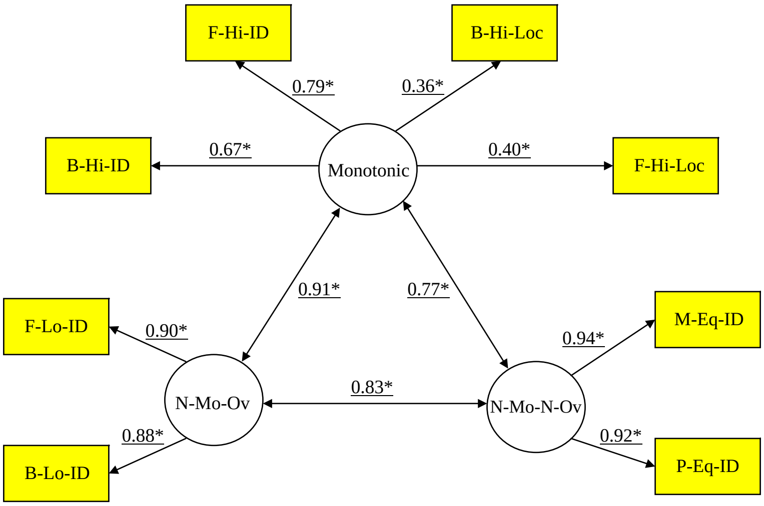

Fig. 4. Structural equation model, with three latent variables representing the monotonic/non-monotonic, as well as the overlapping/non-overlapping, distinctions. N-Mo-Ov = non-monotonic function, overlapping target and mask; N-Mo-N-Ov = non-monotonic function, non-overlapping target and mask. *Estimated parameters. Underlined coefficients (presented in standardized form) are significant at the .05 level. CFI = .95, χ^2 (17, N = 74) = 35.60, $p < .01$.

model was the same for all four models.) Next, the first hypothesized model, with one latent variable and all eight indicators, was tested. Although all indicators had moderate-to-high loadings on the latent variable, and all were significant at the .05 level, the first model fit the data only modestly, CFI = .85, χ^2 (20, N = 74) = 70.18, $p < .001$ (see Fig. 2).

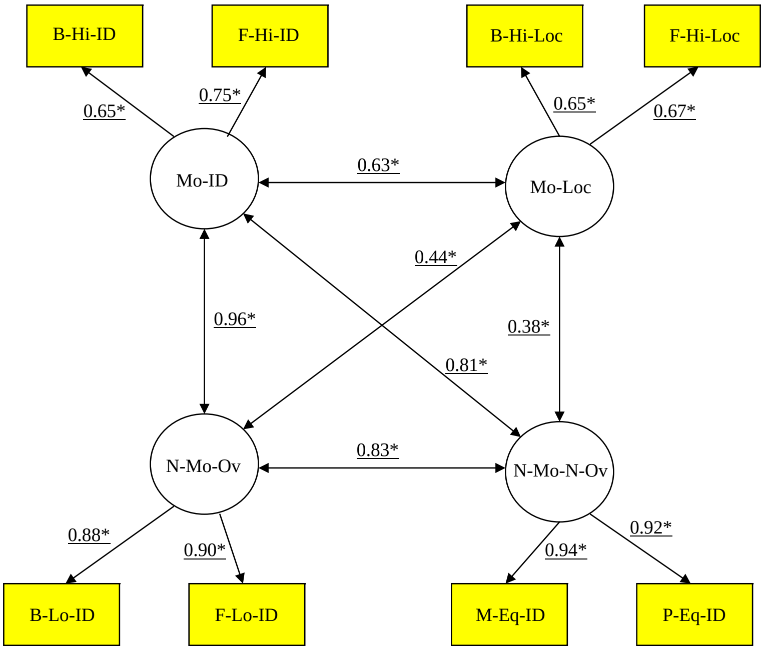

Fig. 5. Structural equation model, with four latent variables representing monotonic location/identification, monotonic/non-monotonic, and overlapping/non-overlapping distinctions. Mo-ID = monotonic function, target identification; Mo-Loc = monotonic function, target location. *Estimated parameters. Underlined coefficients (presented in standardized form) are significant at the .05 level. CFI = .97, χ^2 (14, N = 74) = 24.51, $p = .04$.

The second hypothesized model, with two latent variables representing the monotonic/non-monotonic distinction, also provided only a moderate fit for the data, CFI=.86, χ^2 (19, N=74)=65.18, $p<.001$. Again, all indicators had moderate-to-high loadings on their respective latent variables, and all were significant at the .05 level (see Fig. 3). Furthermore, a high covariance was found between the two latent variables (standardized coefficient=.87, $p<.05$). This model offered a modest, but statistically significant, improvement over the first model, χ^2 (1, N=74)=5.00, $p<.05$.

The third hypothesized model, with three latent variables representing the monotonic/non-monotonic, as well as the overlapping/non-overlapping, distinctions, provided a good fit for the data, CFI=.95, χ^2 (17, N=74)=35.60, $p<.01$. All indicators had moderate-to-high loadings on their respective latent variables, and all were significant at the .05 level (see Fig. 4). As seen in Fig. 4, a high covariance was found among the three latent variables, with all standardized coefficients significant at the .05 level. This model offered a significant improvement over the first model, χ^2 (3, N=74)=34.58, $p<.001$, and the second model, χ^2 (2, N=74)=29.58, $p<.001$.

Finally, the fourth hypothesized model, with four latent variables representing monotonic location/identification, monotonic/non-monotonic, and overlapping/non-overlapping distinctions, provided an excellent fit for the data, CFI=.97, χ^2 (14, N=74)=24.51, p=.04. All indicators had moderate-to-high loadings on their respective latent variables, and all were significant at the .05 level (see Fig. 5). A high covariance was found among the four latent variables, with all standardized coefficients significant at the .05 level. This model offered a significant improvement over the first model, χ^2 (6, N=74)=45.67, $p<.001$, over the second model χ^2 (5, N=74)=40.67, $p<.001$, and over the third model, χ^2 (3, N=74)=11.09, $p<.05$.

4. Discussion

In the present study, we employed several experimental paradigms to examine whether the underlying structure of visual masking performance in schizophrenia reflects hypothesized differences in the underlying visual mechanisms. Using structural equation modeling we compared four competing models: 1) a model in which one latent variable is hypothesized to underlie all eight masking indicators; 2) a model with two latent variables representing the monotonic/non-monotonic distinction; 3) a model with three latent variables representing the monotonic/non-monotonic, as well as the overlapping/non-overlapping, distinctions; and 4) a model with four latent variables representing monotonic location/identification, monotonic/non-monotonic, and overlapping/non-overlapping distinctions. We found that the four-factor model provided the best fit for the data.

The current results are consistent with the dual-channel masking model of visual processing (Breitmeyer, 1984; Breitmeyer and Ganz, 1976). As predicted by this model, the measured variables with mask energies higher than their target energies loaded heavily on the latent monotonic factor. The monotonic functions in forward and backward masking can be attributed to a very strong masking by integration in the sections of the masking curves that are closest to an SOA of 0 (Breitmeyer, 1984). For pattern masking, this process occurs when the sustained activity of the mask integrates with the sustained activity of the target. Such sustained-channel activity has been recently attributed to cortical oscillations in the gamma range (Green et al., 2003a; Purushothaman et al., 2000). In location masking, a similar process occurs when the transient activity of the mask integrates with the transient activity of the target.

Conversely, the variables with low energy or non-overlapping masks loaded on the latent non-monotonic factor. Non-monotonic functions do not involve sustained on sustained integration in the short masking intervals. They can be produced by a mask that surrounds but does not spatially overlap the target, or by an overlapping mask that is of less energy than the target. Masks that have a low energy activate sustained channels only weakly, thus yielding little if any pattern masking by integration; however, they strongly activate transient channels (Breitmeyer, 1984). With non-overlapping target and mask of equal energy, the non-monotonic paracontrast masking functions result from intrachannel inhibition of the sustained activity of the target by the sustained activity of the preceding mask, whereas the non-monotonic metacontrast masking function results from interchannel inhibition of the sustained activity of the target by the transient activity of the mask.

In addition, the non-monotonic factor was subdivided further into overlapping and non-overlapping factors. This again would be predicted; because there is no overlap between target and mask in metacontrast, one would expect strong non-monotonic masking results, and also stronger interruption processes than in the overlapping low-energy masking condition (Ganz, 1975). Finally, the monotonic factor was subdivided into target location and target identification factors. This is also consistent with the dual-channel masking model, in which transient channels would be mainly involved in conveying information about target location, whereas sustained channels would be mainly responsible for the more detailed analysis needed to identify the target (Breitmeyer and Ganz, 1976).

It should be noted that in the best fitting model, all of the paths linking the latent variables were statistically significant, and the inclusion of these paths resulted in improved model fit. This pattern of correlations suggests that, even though the four-factor model provides the best fit, there are common underlying mechanisms that all four of the factors share. The stimuli for all of these tasks were small, faint, and very briefly presented. Hence, all the tasks rely on a shared capacity for speeded visual processing.

The current results did not reveal redundancy in the four masking procedures. Despite likely dependence on a common mechanism, each procedure appears to yield somewhat different information about underlying visual processes. Overlapping, high-energy masking procedures are useful to examine overall differences in visual information processing, without separating interruption from integration mechanisms. Inclusions of target location and identification tasks are useful for tapping separate visual channels needed to conduct the task. Overlapping, low-energy procedures are a useful counterpart to the overlapping, high-energy procedures for evaluating non-monotonic functions. Finally, the paracontrast/metacontrast procedure can be effectively employed for specifically isolating the mechanism of interruption. Using structural equation modeling, this study supported the utility of these various masking procedures and suggested that each paradigm offers unique insight into visual processing deficits in schizophrenia.

Acknowledgements

This research was supported by NIMH grants MH-43292 and MH-65707 to Dr. Green, and by the Department of Veterans Affairs, VISN 22 Mental Illness Research, Education, and Clinical Center (MIRECC). Additional statistical support was provided by Sun Hwang, M.S., M.P.H.

References

American Psychiatric Association, 1994. Diagnostic and Statistical Manual of Mental Disorders, 4 ed. American Psychiatric Press, Washington, DC.

Bentler, P.M., 1990. Comparative fit indexes in structural models. Psychological Bulletin 107, 238–246.

Bentler, P.M., 1996. EQS: Structural Equations Program Model. BMDP Statistical Software, Los Angeles.

Braff, D.L., Saccuzzo, D.P. and Geyer, M.A., 1991. Information Processing Dysfunctions in Schizophrenia: Studies of Visual Backward Masking, Sensorimotor Gating, and Habituation. In: et al. (Eds.), Neuropsychology, Psychophysiology, and Information Processing. New York, NY, US, Elsevier Science, pp. 303-334.

Breitmeyer, B.G., 1984. Visual Masking: An Integrative Approach. Oxford University Press, New York.

Breitmeyer, B.G., Ganz, L., 1976. Implications of sustained and transient channels for theories of visual pattern masking. Saccadic suppression, and information processing. Psychological Review 83, 1–36.

Breitmeyer, B.G., Ogmen, H., 2000. Recent models and findings in visual backward masking: a comparison, review, and update. Perception and Psychophysics 62, 1572–1595.

Cadenhead, K.S., Serper, Y., Braff, D.L., 1998. Transient versus sustained visual channels in the visual backward masking deficits of schizophrenia patients. Biological Psychiatry 43, 132–138.

First, M.B., Spitzer, R.L., Gibbon, M., Williams, J.B.W., 1997. Structured Clinical Interview for DSM-IV Axis I Disorders—Patient Edition. New York State Psychiatric Institute, New York.

Ganz, L., 1975. In: Friedman, M.P. (Ed.), Temporal Factors in Visual Perception, Handbook of Perception, 5. Academic Press, New York, pp. 169–232.

Green, M.F., Nuechterlein, K.H., Mintz, J., 1994a. Backward masking in schizophrenia and mania: I. Specifying a mechanism. Archives of General Psychiatry 51, 939–944.

Green, M.F., Nuechterlein, K.H., Mintz, J., 1994b. Backward masking in schizophrenia and mania: II. Specifying the visual channels. Archives of General Psychiatry 51, 945–951.

Green, M.F., Nuechterlein, K.H., Breitmeyer, B., 2002. Development of a computerized assessment for visual masking. International Journal of Methods in Psychiatric Research 11, 83–89.

Green, M.F., Mintz, J., Salveson, D., Nuechterlein, K.H., Breitmeyer, B., Light, G.A., Braff, D.L., 2003a. Visual masking as a probe for abnormal gamma range activity in schizophrenia. Biological Psychiatry 53, 1113–1119.

Green, M.F., Nuechterlein, K.H., Breitmeyer, B., Tsuang, J., Mintz, J., 2003b. Forward and backward visual masking in schizophrenia: influence of age. Psychological Medicine 33, 887–895.

Hu, L.-T., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Structural Equation Modeling 6, 1–55.

Merritt, R.D., Balogh, D.W., Leventhal, D.B., 1986. Use of a metacontrast and a paracontrast procedure to assess the visual information processing of hypothetically schizotypic college students. Journal of Abnormal Psychology 95, 74–80.

Michaels, C.F., Turvey, M.T., 1979. Central sources of visual masking: indexing structures supporting seeing at a single, brief glance. Psychological Research 41, 1–61.

Overall, J.E., Gorham, D.R., 1962. The brief psychiatric rating scale. Psychological Reports 10, 799–812.

Purushothaman, G., Ogmen, H., Bedell, H.E., 2000. Gamma-range oscillations in backward-masking functions and their putative neural correlates. Psychological Review 107, 556–577.

Rassovsky, Y., Green, M.F., Nuecherlein, K.H., Breitmeyer, B.G., Mintz, J., 2004. Paracontrast and metacontrast in schizophrenia: clarifying the mechanism for visual masking deficits. Schizophrenia Research 71, 485–492.

Rassovsky, Y., Green, M.F., Nuecherlein, K.H., Breitmeyer, B.G. and Mintz, J., in press. Modulation of attention during visual masking in schizophrenia. American Journal of Psychiatry.

Rund, B.R., 1993. Backward-masking performance in chronic and nonchronic schizophrenics, affectively disturbed patients, and normal control subjects. Journal of Abnormal Psychology 102, 74–81.

Saccuzzo, D.P., 1974. Backward Masking as a Measure of Attention in Schizophrenia. Kent State U.

Saccuzzo, D.P., Hirt, M., Spencer, T.J., 1974. Backward masking as a measure of attention in schizophrenia. Journal of Abnormal Psychology 83, 512–522.

Saccuzzo, D.P., Schubert, D.L., 1981. Backward masking as a measure of slow processing in schizophrenia spectrum disorders. Journal of Abnormal Psychology 90, 305–312.

Schuck, J.R., Lee, R.G., 1989. Backward masking, information processing, and schizophrenia. Schizophrenia Bulletin 15, 491–500.

Stewart, A.L., Purcell, D.G., 1974. Visual backward masking by a flash of light: a study of U-shaped detection functions. Journal of Experimental Psychology 103, 553–566.

Turvey, M.T., 1973. On peripheral and central processes in vision: inferences from an information-processing analysis of masking with patterned stimuli. Psychological Review 80, 1–52.

Ullman, J.B., 2001. Structural Equation Modeling. In: Fidell, L.S. (Ed.), Using Multivariate Statistics, 4 ed. Allyn and Bacon, Boston, pp. 653–771.

Wetherill, G.B., Levitt, H., 1965. Sequential estimation of points on a psychometric function. British Journal of Mathematical and Statistical Psychology 18, 1–10.