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Parsing the Resource Pie: Using STRTs to Measure Attention to Mediated Messages

Annie Lang
Indiana University

Samuel D. Bradley
Texas Tech University

Byungho Park
National University of Singapore

Mija Shin
Washington State University

Yongkuk Chung
Dongguk University

This study directly tests the hypothesis that secondary task reaction time (STRTs) measured during television viewing index available resources rather than resources allocated by the viewer, resources required by the message, or resources remaining in the system. An initial test of the hypothesis did not support the theoretical interpretation of STRTs as either available or remaining resources. A subsequent secondary analysis introduced a new measure of television message complexity called information introduced. The stimuli were recoded using this measure and reanalyzed to test the same hypothesis. Results of the secondary analysis yielded a pattern of STRT responses supporting the prediction that STRTs are indexing available resources.

Correspondence should be sent to Annie Lang, Department of Telecommunications, Indiana University, 316 Radio-TV Building, 1229 East 7th Street, Bloomington, IN 47405-5501. E-mail: anlang@indiana.edu

Many communication theories rely heavily on the concept of attention. During the past 30 years, attention to media has been measured using retrospective self-report (Chaffee & Schleuder, 1986), online self-report measures (Biocca, David, & West, 1994), physiological measures (A. Lang, 1990, 1994), eyes on screen (Alwitt, Anderson, & Lorch, 1980), audio and video preloads (Grimes, 1991; Grimes & Meadowcroft, 1995), and secondary task reaction times (Basil, 1994). This article focuses on the secondary task reaction time (STRT) as a covert measure of attention to ongoing media messages.

STRT methodology comes to us from cognitive science (Basil, 1994). It is based on limited capacity models of attention (Navon & Gopher, 1979, 1980; Schneider, Dumais, & Shiffrin, 1984) that assume people are information processors and that information processing requires mental resources. Attention occurs when people allocate mental resources to a task. Within this theoretical perspective, it is hypothesized that people can perform multiple tasks simultaneously, as long as the tasks do not require the same input or output systems, and the participant has sufficient mental resources available to perform the tasks.

In the STRT paradigm, participants perform two tasks, a primary and a secondary task. They are instructed to pay close attention to the primary task (e.g., television viewing), and they are told that their performance on the primary task matters the most. Participants are also given a secondary task (e.g., push a button as fast as you can when you hear a signal). The signal is called the secondary task probe. The elapsed time between the tone and when the participant pushes the button is called the STRT. Theoretically, as the primary task becomes more difficult, it requires more mental resources, leaving fewer unused resources to respond to the secondary task probe. Thus, as the primary task becomes increasingly difficult, the speed of the response to the secondary task probe, or the STRT, slows down.

There is a fairly long history in cognitive psychology of using secondary task methodology to track shifts in the allocation of mental resources to various cognitive tasks. However, when this method was taken out of the psychology laboratory and placed in the media laboratory, some counter-intuitive and downright confusing results emerged. First, Britton and his colleagues (Britton & Tesser, 1982; Britton, Westbrook, & Holgredge, 1978) used secondary task methodology to track attention during the processing of text messages. They had people read messages that differed in terms of complexity. They found, somewhat surprisingly, that simple messages resulted in *slower* STRTs than did complex messages. According to standard STRT theory, this implies that the simple messages required more resources—or resulted in fewer leftover resources—than did the complex messages. On the face of it, this seems unreasonable.

Similar results were found when STRT methodology was used to assess resource allocation to visually complex and visually simple television (TV) messages (Reeves & Thorson, 1986; Reeves et al., 1985; Reeves, Thorson, &

Schleuder, 1986; Schleuder, Thorson, & Reeves, 1988). Once again STRTs were slower in response to simple messages, implying that simple messages required or in some way used more mental resources than complex messages.

A. Lang and Basil (1998) reviewed the literature using STRT methodology to measure attention to mediated stimuli in an attempt to develop an explanation for this phenomenon. They suggested that the problem might reside with the conceptual definition of the resources being measured by the STRT. In the article, they define four pieces of the resource pie: a) resources required by the task; b) resources allocated to the task; c) resources remaining in the system during task performance; and d) available resources.

A. Lang and Basil illustrate these pieces of the resource pie with a shopping example. When you go shopping, you have a certain amount of money in your wallet—this is your *total resource pool*. When you buy something (equivalent to processing a media message), the item has a price. That price is the *resources required* (to process the message). When you offer the salesperson some amount of money, the money you offer is equivalent to the *resources allocated*. Hopefully, after offering this money, there was still some money left in your wallet—the money left in your wallet is your *remaining resources*. The difference between the price (resources required) and the sum offered (resources allocated) is your change, or your *available resources*. So in the media use situation, you have a total pool of resources. Processing the mediated message requires a certain level of resources. Through automatic and controlled mechanisms, you allocate a certain level of resources to the task at that point:

resources remaining = total resources – resources allocated, and

available resources = resources required – resources allocated.

A. Lang and Basil (1998) concluded that STRTs have been interpreted primarily as a measure of resources remaining in the system during task performance. They suggested that the counter-intuitive results found for complex TV messages might be explained by conceptualizing STRTs not as a measure of remaining resources but, rather, as a measure of available resources. They point out that as long as STRTs are thought of as a measure of remaining resources, then STRTs will vary only as a function of resources allocated (in a fixed pool model). Thus, the more resources allocated—the lower the resources remaining and the slower the STRT.

On the other hand, if STRTs measure available resources, than STRTs reflect the difference between resources allocated and resources required. Because this difference can be positive or negative, large, small, or zero, STRTs might get slower or faster as resources allocated increases depending on whether the allocated resources are required to process the message.

A. Lang and Basil provide evidence in support of this reconceptualization of STRTs from existing research comparing change in STRTs, orienting responses (ORs), and recognition memory in response to related and unrelated camera changes (CCs). This reinterpretation is based on three propositions derived from the literature: First, the relatedness of information presented before and after a CC is a manipulation of resources required. This proposition follows from research showing that when information following a CC is unrelated to the previous information and/or unexpected, it is more difficult to process than when it is highly related and/or expected. Second, CCs elicit ORs that result in an automatic and invariant allocation of resources to processing the CCs (Geiger & Reeves, 1993; A. Lang, Geiger, Strickwerda, & Summer, 1993). This proposition is based on orienting theory that suggests the strength and vigor of the OR is indicative of the level of resources allocated to a stimulus (A. Lang, 1990; A. Lang, 2000; Ohman, 1979, 1997); the proposition is also based on media research that shows variations in difficulty and complexity of CCs do not change the strength or vigor of the OR (A. Lang, Geiger, et al., 1993; Thorson & Lang, 1992). Third, recognition for information presented following a CC is a measure of encoding task performance and therefore indirectly indexes the relationship between resources allocated and resources required or available resources. As available resources increase (resources allocated–resources required), task performance should increase. Using these three proposition one can produce Table 1, which illustrates what should be happening to all the pieces of the resource pie if these propositions are true. In the example the total pool size and invariant allocation of resources to a CC are set, arbitrarily, to 50 and 30, respectively. As relatedness decreases from very high (*extremely related*) to very low (*extremely unrelated*), resources required increases from an arbitrary low level of 10 to a high of 30. Remaining resources and available resources are calculated for each level. Of particular interest is that remaining resources do not change as a function of relatedness, but available resources do. As resources required increase, available resources decrease. This means that if STRTs measure available resources, they should get slower as relatedness and therefore available resources decrease. Similarly, to the extent that recognition indexes available resources, recognition should also decrease. If, on the other hand, STRTs measure resources remaining, there should be no change in STRT as a function of relatedness.

Support for this analysis exists in a study done by A. Lang et al. (1993). Participants viewed TV messages that contained related and unrelated cuts. ORs, recognition, and STRT following the cuts were measured. Results showed that ORs did not vary as a function of relatedness, supporting the contention that resource allocation did not vary with relatedness. Recognition was lower following unrelated cuts than it was following related cuts, supporting the contention that available resources had decreased. STRTs were slower following unrelated

TABLE 1
Resource Predictions as a Function of Relatedness

Relatedness	*Total Pool*[a]	*Resources Allocated*[b]	*Resources Required*	*Resources Remaining*[c]	*Available Resources*[d]
Very high (edit)	50	30	10	20	20
High	50	30	15	20	15
Medium	50	30	20	20	10
Low	50	30	25	20	5
Very low (cut)	50	30	30	20	0

[a]Arbitraily set at 50 resource units.
[b]Arbitraily set at 30 resource units per camera change.
[c]Resources remaining = total pool resources allocated.
[d]Resources available = resources allocated-resources required.

cuts than they were following related cuts, suggesting that they were measuring available and not remaining resources.

Two other studies also provide support for STRT as a measure of available resources and provide the framework for the study reported here. These two studies are based on a distinction between two classes of CCs called cuts and edits. The distinction between cuts and edits—like the distinction between related and unrelated CCs—is based on the concept of resources required. Some CCs (called cuts in this research) completely change the visual scene in a single frame. Other CCs (called edits) simply switch from one camera to another in the same visual scene. Thus, on the face of it, cuts introduce a great deal more new information and therefore should require more resources than edits.

In the two studies being considered here, A. Lang and colleagues (A. Lang, Bolls, Potter, & Kawahara, 1999; A. Lang, Zhou, Schwartz, Bolls, & Potter, 2000) looked at recognition memory for messages that varied the number of CCs in a message. In one study they varied the number of cuts in the message, and in the other they varied the number of edits. If, as argued above, recognition indexes available resources, and if edits require fewer resources than cuts, then these studies should show different patterns of recognition or available resources as the number of CCs increases. Table 2 illustrates some of the possible outcomes of this manipulation.

Table 2 assumes that cuts and edits require the same number of resources at all levels of pacing, that is, increasing the rate of CCs does not make the task of encoding the information being introduced by the CCs more difficult. As can be seen in the table, resources remaining always decreases, as a function of number of CCs (e.g., resources allocated) and does not change as a function of type of CCs. Thus, if STRTs are measuring remaining resources, they should always

TABLE 2
Recognition as a Function of Available Resources
(Total Pool of Resources = 80)

Type of Camera Change	*Number of Camera Changes*	*Resources Allocated*[a]	*Resources Required*	*Resources Remaining*	*Resources Available*
Section I: Assumes that a cut requires 4 units of resources allocation an edit only 1					
Edit	3	15	3	65	12
Edit	6	30	6	50	24
Edit	12	60	12	20	48
Cut	3	15	12	65	3
Cut	6	30	24	50	6
Cut	12	60	48	20	12
Section II: Assumes that cuts require 6 units of resources and edit only 1					
Cut	3	15	18	65	–3
Cut	6	30	36	50	–6
Cut	12	60	72	20	–12

[a]Assumes a camera changes elicits an automatic allocation of 5 resource units.

decrease as number of CCs increases, and relatedness should have no effect on the size of the STRT. Available resources, on the other hand, vary as a function of both the number of CCs and the type of CCs. In section 1 of Table 2, the assumption is that for both cuts and edits sufficient resources are allocated to the CCs to encode the new information. Therefore, available resources increases for both cuts and edits. However, because cuts require more resources than edits, the increase is greater for edits than cuts. Thus, the prediction would be that recognition memory should increase as a function of number of CCs and that it should increase faster for edits than for cuts. Of particular interest here is that the prediction for STRT in this case is that STRTs should also get *faster* as number of CCs increases and that the increase should be greater for edits than for cuts. Because a great deal of research measuring STRTs does indeed show faster STRTs in response to structurally complex TV messages, this prediction is a much better match for the existing data.

The second section of Table 2 assumes that cuts require more resources than are automatically allocated to a CC while the assumption for edits is not changed. If this is the case, then available resources should increase for edits but decrease for cuts. Thus, recognition memory should improve as the number of edits increases and get worse as the number of cuts increases, and STRT should get faster for edits and slower for cuts.

Another very real possibility, however, is that the assumption made in Table 2, that the speed or rate of CCs does not alter the resources required, is not true.

Consider a 30-sec message that has 3, 6, or 12 CCs. In the case where there are 3 CCs, the viewer has an average of 10 sec to process the information presented following each CCs. When there are 6 CCs, they have 5 sec; and when there are 12 changes, they have less than 3 sec. This speeding up of the task may very well make the task require more resources—in other words doing the task quickly may require more resources than doing the task slowly. If this is the case, then the resources required for each CC would increase as the number of CCs increased. Table 3 illustrates one such possibility.

In this table, resources required by a single CC is assumed to increase as the number of CCs increases. The increase is larger for cuts (the more difficult condition) than for edits. In the edits condition, as the number of CCs increases, allocated resources remain greater than required resources resulting in positive available resources. However, the increase in available resources associated with increased CCs is much smaller than when the resources required by a single CCs were assumed to be invariant. For the cuts condition, however, a greater increase in resources required as a function of number of CCs is posited, and the result is a sharp decrease in available resources resulting eventually in negative available resources, a fact that will be discussed a bit later.

What these examples tell us is that we should see different patterns of change in recognition as a function of variation in number of cuts compared to number of edits. In particular, there should always be more available resources at a given number of CCs for edits than for cuts. Therefore, recognition should improve faster or decrease more slowly for edits compared to cuts. Results from these two experiments do indeed conform to these expectations. Recognition increased as a

TABLE 3
Available Resources as a Function of Speed and Relatedness

Type of Camera Changes	*Number of Camera Changes*	*Resources Allocated (10/cc)*	*Resources Required /cc*[a]	*(total)*[b]	*Resources Remaining 150–RAll*	*Resources Available RAll–RReq*
Edit	3	30	2	(6)	120	24
Edit	6	60	3	(18)	90	42
Edit	12	120	6	(72)	30	48
Cut	3	30	4	(12)	120	18
Cut	6	60	10	(60)	90	0
Cut	12	120	15	(180)	30	–60

[a]The resources required per camera change increases with number of camera changes. This number is the resources required per camera change at this number of camera changes per time unit.

[b]This number is the total resources required at this level of camera changes, that is, number of camera changes times the resources required per camera change.

function of number of edits per message (A. Lang et al., 2000) and increased at medium levels and then decreased as a function of the number of cuts (A. Lang et al., 1999).

The final question to be considered is what happens when either remaining or available resources are zero or negative? In other words, when the task demands exceed the resources available (or the total resources in the system), what happens to both task performance (recognition) and STRT? For task performance, the answer is integral to the secondary task methodological paradigm. When there are insufficient resources available to perform a task, performance decreases, and cognitive overload is said to have occurred. The performance decrease is considered to be evidence that cognitive overload has occurred meaning that there are insufficient resources available (or allocated) to perform the task completely. In the case of CCs, recognition is being used to index how well information following a CC is encoded. As long as sufficient resources are allocated to the task, recognition performance should not decrease. However, if insufficient resources are allocated to perform the task resulting in cognitive overload (e.g., available resources are less than 0), then recognition should decrease. Indeed, evidence indicates that this is the case. At high levels of resources required (e.g., hyphen fast-paced messages), recognition memory for messages has been shown to decrease compared to medium and low levels (Bolls, Muehling, & Yoon, 2003; A. Lang, Schwartz, Chung, & Lee, 2004; Lee, Angelini, Schwartz, & Lang, 2003). Thus, when cognitive overload occurs, recognition task performance should decrease.

The question of what happens to STRTs, however, is not so easily answered. One possibility is that STRTs will continue to get slower. A second possibility is that once the primary task is overloaded, some level of resources will be automatically shifted to the secondary task—irrespective of primary task difficulty—to keep both tasks going. In this case, STRTs might be relatively fast or slow, but they would become fairly invariant. Once cognitive overload had occurred, STRTs would cease indexing resources available to the primary task and instead become an index of resources actually allocated to and available for performing the secondary task. In this case, one would expect to see STRTs become steady and cease to vary with changes in resources allocated and required. They might also become quite fast because the secondary task is easy and resources would now be allocated to performing it.

The study reported here is primarily designed to test whether STRTs measure available or remaining resources, however, it may also shed some light on what happens to STRTs when the primary task reaches a state of cognitive overload. In this study, participants viewed messages that varied either number of cuts or number of edits per message. The participants' primary task was recognition for audio information contained in the messages. Recognition data should be an indirect index of available resources, and decreases in recognition can be interpreted as a sign of insufficient resources being allocated to the task, or cognitive overload. We predict that:

H1: STRTs should be slower during and recognition should be lower for messages containing cuts compared to messages containing edits (in cases where cognitive overload has not occurred).

H2: The effect of number of CCs on STRTs and recognition will be greater for messages containing cuts compared to messages containing edits in cases where there is no sign of cognitive overload.

In addition to these hypotheses, there is the empirical question of what happens to STRTs during cognitive overload? In other words, at the point where performance on the primary task decreases, what happens to STRTs?

RQ1: What happens to STRTs under conditions where primary task performance decreases?

METHOD

Design and Stimulus Materials

This study used a type of CCs (2) × number of CCs (3) × message (6) × order of presentation (4) mixed design. Order of presentation was the only between-subject factor. The other variables were within-subjects factors. Type of CCs had two levels, cuts and edits. Number of CCs had three levels, low, medium, and high. Message is the repetitions factor and represents the six messages in each category.

To construct stimulus tapes, 36 messages between 30 and 60 sec long were selected from a pool of TV messages and feature films. Half of the messages contained CCs that were classified as edits, and the other half contained CCs classified as cuts. Within each half there were 6 messages at each level of number of CCs (low, medium, and high). Four different counter-balanced presentation orders were created, and participants were randomly assigned to one of the four orders.

Independent Variables

Cuts and edits. A cut is defined as a change from one visual scene to a completely new visual scene within a semantically related message (A. Lang et al., 1999). An edit, on the other hand, is defined as a change from one camera shot to another within the same visual scene (A. Lang et al., 2000).

Number of camera changes. The number of CCs had three levels: low, medium, and high, which varied by number of structural features (i.e., cuts or edits). The low condition messages had fewer than 4 CCs, 4-9 CCs or 10+ per 30 seconds.

Dependent Variables

Secondary task reaction times. STRT was measured by recording the time in milliseconds from the onset of the STRT probe to the moment the participant responded to it by pressing a key on the computer keyboard. The STRT probe was a 200 millisecond 1,000 Hz audio tone. One tone was placed in each third of each message resulting in three tones per message with the caveat that tones did not occur in the first 5 or the last 5 sec of a message. The tones were placed so that they occurred at least 500 msec before or after a cut or an edit.

Recognition. Recognition was assessed using a four-alternative forced-choice recognition test administered on laptop computers using MediaLab software (Jarvis, 2002). There were two questions per message that focused on the audio content of the messages only. The questions were presented randomly.

Participants

Sixty-nine college students (42 women) at Indiana University, Bloomington participated in this study and received extra credit for a course in which they were enrolled.

Procedure

Each participant performed the experiment individually using a Dell Latitude C840 notebook computer equipped with headphones and a 15-in LCD monitor. Each participant was instructed to pay attention to each message and asked to remember the content from the video clip because he or she would be given a memory test later. This was considered the primary task. Participants were also instructed to respond to the audio tone as quickly as possible each time they heard it by pressing the enter key on the keyboard (secondary task). After a 2-message practice session, participants were asked to perform the assigned tasks for all 36 messages. After viewing, participants were given a distractor task, completed the recognition test, and were thanked and dismissed. After all data were collected, outliers beyond the range of two times the interquartile range beyond the quartiles were removed. This is preferable to replacements based on standard deviations because the outliers themselves go into the computation of the standard deviation. In total, 298 of 7,452 (3.9%) of outliers were replaced with the maximum allowable value.

RESULTS

Before testing the hypotheses, it is necessary to determine at what points cognitive overload occurred. To do that, we must examine the recognition data. As long as recognition accuracy is increasing or remaining the same, this indicates that cognitive overload has not occurred. It is only when recognition data decline that cognitive overload is thought to occur. Overall, there was a significant type of CCs × number of CCs interaction, $F(2, 132) = 27.647$, $p < .01$, $\eta^2 = .295$ shown in Figure 1. For the edits condition, task performance in the low and medium conditions does not differ significantly while recognition in the high condition is significantly better than low and medium. In the cut condition, recognition improves significantly from low to medium, but there is no significant difference between medium and high. Thus, performance on the primary task is stable or improving—indicating no cognitive overload and all conditions can be included in the analysis.

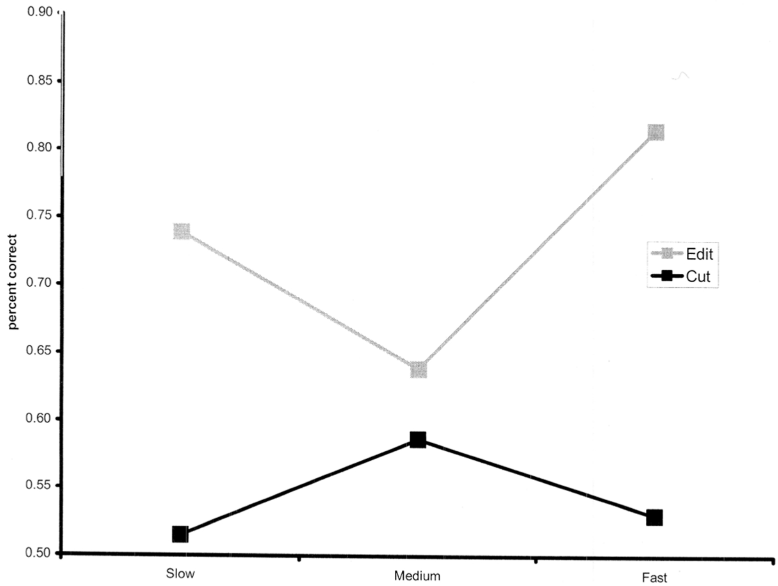

FIGURE 1 Recognition as a function of pacing and type of cut.

H1

This hypothesis predicted that STRTs should be slower in messages containing cuts compared to messages containing edits when there is no evidence of cognitive overload. The main effect of the type of CCs factor was significant, $F(1, 67) = 17.517$, $p <.001$, $\eta^2 = .20$ but not in the predicted direction. The mean STRT during messages containing edits was 463.88 msec compared to 451.18 msec for messages containing cuts. Thus, contrary to expectations, STRTs were slower for messages containing edits than they were for messages containing cuts.

H2

This hypothesis predicted that the change in STRT would be greater for messages containing cuts compared to messages containing edits. The two-way type of CCs × number of CCs interaction was significant, $F(2, 134) = 63.32$, $p < .00$, $\eta^2 = .48$, and is shown in Figure 2. While the change in STRTs was larger for cuts than for edits, it is not in the predicted direction (given that there is no evidence of cognitive overload). STRTs go faster as number of CCs increased for cuts, and they got slower and then leveled off for edits.

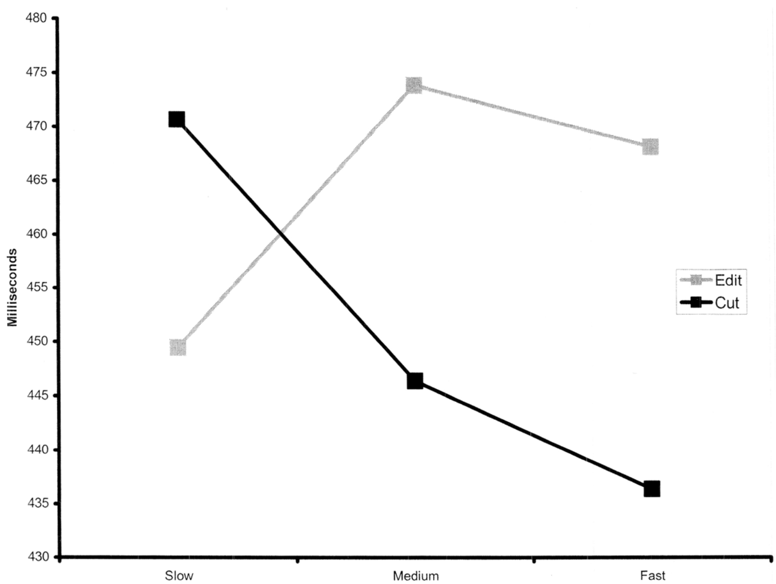

FIGURE 2 STRTs as a function of pacing and type of cut.

RQ1

This research questions asks what happens to STRTs during cognitive overload. Given that there is no clear evidence of cognitive overload, these data shed no light on this question.

DISCUSSION

Unfortunately, the results do not clearly support an interpretation of STRTs as either available or remaining resources. The recognition data support the contention that the participants are doing what they are supposed to be doing. Recognition memory, as predicted, is better for messages containing edits than it is for messages containing cuts, strongly supporting, as expected, that messages containing cuts are more difficult to process. Similarly, recognition memory shows the expected interaction with number of CCs. That is, increases in number of CCs resulted in an increase in recognition test performance for edits—where available resources are expected to continue to exist but not for cuts.

However, the results for the STRT data do little to support the contention that STRTs are measuring available resources though they do seem to make clear that STRTs are not measuring remaining resources. If STRTs were measuring remaining resources, then there should have been no difference in remaining resources between cuts and edits, and STRTs should have gotten slower as number of CCs increased. But STRTs did differ as a function of type of CCs, and they got faster (not slower) as the number of CCs increased.

This does not mean, however, that the case for available is better. If STRTs were measuring available resources, then they should have been faster for edits than for cuts, but instead they were faster for cuts compared to edits.

Given that these data do little to clarify exactly what is going on when using the STRT methodology with mediated stimuli, it may make sense to ask where the problem lies. There are basically three choices. First, the specific theory about which aspect of resource allocation is being measured by STRTs could be wrong. STRTs may not measure remaining resources or available resources. Second, the larger methodological theory behind the STRT measure could be wrong. In other words, STRTs may not be measuring resource allocation, at least not during the presentation of mediated messages. Third, the test we set up in this experiment may be seriously flawed. Obviously, this third choice is the most comforting. Before proceeding to rework either the specific or the methodological theory, it seems logical to examine where the manipulation in this experiment may have gone wrong. The most likely problem lies with the operationalization of resources required. In other words, the problem may lie with using cuts and edits to manipulate resources required.

This choice was made based on the assumption that a cut would always require more resources than an edit. Yet this may not be true. Two categories, cuts and edits, are being used to stand in for a continuous variable. The continuous variable is resources required to process the information following the CCs. Resources required could range from a very small number (e.g., when the information following a CC is almost identical to the information that precedes the CCs) to a very large number (e.g., when there is almost no information following the CC that is related to or similar to the information that preceded the CC).

The assumption in the previous work using cuts and edits is that if the CC occurs in the same visual scene, it will always require fewer resources to be processed than if it introduces a new visual scene. However, this is not necessarily a tenable assumption. For example, under the coding rules in the literature, a CC from a long shot of a crowd to a close-up of a person in the crowd is considered to be an edit. However, a great deal of new information is introduced by this CC. On the other hand, the CC from a person who says "let's go into the kitchen" to that person in the kitchen is considered to be a cut; yet, despite the new visual scene, there is not a great deal of new information introduced (I^2) by this CCs. Therefore, it is possible that there is a great deal of variation in the amount of I^2 following edits and following cuts and that there is some overlap between these two categories.

Therefore, to clarify the results found in the previous analysis, the decision was made to develop a new measure of resources required that would assess resources required more finely. The new measure called information introduced (I^2) measures the amount of information introduced by each individual CC on a seven-point scale. Then, the stimulus materials used in this study were re-coded using the new measure and the data were reanalyzed.

Development of the New Measure

The first step was to develop a measure of the amount of I^2 by a CC that would better capture the continuous nature of the underlying concept of information required. Some attempt was made when developing this measure to consider dimensions of information that might cross media. In other words, even though in the case of TV CCs much of the information load is carried on the visual track, there are dimensions of change that need not be inherently visual and that would transfer when developing a similar measure for other media. To determine what dimensions to code, the resource allocation literature was examined to determine what types of information are theorized to require more resources. Based on that literature review, seven dimensions were chosen: object change, novelty, relatedness, distance, perspective, form change, and emotion. A brief description of each follows.

Object change. The first coding dimension is related to the focal object in the scene. Following a CC, the focal point of the scene could be the same object or it could be a different object. Introducing new information requires the allocation of resources. A large body of research supports that our visual attention system gives high priority to new objects abruptly appearing (e.g., Yantis & Jonides, 1990) resulting in automatic allocation of cognitive resources (Kahneman, 1973). Thus, if the focal point of the scene is different from the focal point of the previous scene, it should require more resources than if the focal point stays the same.

Novelty. When coding this dimension, the question is whether the new focal point of the scene is new or old. However, novelty is context-dependent. What is new or novel depends on what preceded the CC. If the focal point or object in the scene following a CC was not previously seen in the message (either in the background or as a focal point of the message), then the new information is considered to be novel. If, however, the focal point following a CC has been seen previously, then it is not novel. Thus, an object can only be novel one time in a message. More resources (attention) will be needed to process novel information than old information (see Johnston, Hawley, & Farnham, 1993; Johnston, Hawley, Plewe, Elliott, & DeWitt, 1990; Johnston & Schwarting, 1997). Novelty thus adds an additional resource requirement (e.g., Berlyne & Ditkofsky, 1976).

Relatedness. The concept of relatedness comes from work by Geiger (e.g., Geiger & Reeves, 1993). He suggested that the resources required to process information following a CC depended on how much the new information was related to the old information (in the previous scene). Relatedness could come from context, story, or continuity. As discussed earlier, unrelated scene changes require more processing resources than do related scene changes (A. Lang et al., 1993). Narrative messages consisting of more than two temporally and or causally related events have been found easier to process (fewer resources required) and better remembered than nonnarrative messages (Graesser, 1981; A. Lang, Sias, Chantrill, & Burek, 1995; Thorson, 1989). Because TV messages are a composition of continuously changing visual images and narratives, fewer resources should be required when newly introduced information builds on previous information—that is, when new information fits the viewers' expectations (Geiger & Reeves, 1993). In short, these types of relatedness are predicted to reduce the resources required to process the message. If the story, context, or expectations associated with the type of message lead one to expect the information following the CCs, then the information is related. If it does not follow logically from context or expectation, it is not related. Unrelated information should increase resources required.

Distance. Research investigating looming suggests that as objects become closer, they are more compelling than objects that are further away. A recent study shows that looming objects compel attention, but receding objects do not, though both of them are moving objects that are thought to capture attention (Franconeri

& Simons, 2003). The authors of the study suggest this may be so because approaching objects are behaviorally more urgent compared to receding objects. Research examining screen size further supports the notion that larger objects may require more resources than smaller ones (Reeves, Lang, Kim, & Tatar, 1999). From an evolutionary perspective this makes sense because closer objects are generally either more dangerous, or, if they are desirable, they are more available. Therefore, closer objects should require more resources to process than objects that are further away. Therefore, if the information following a CC is closer than the information that preceded the CC, that should require more resources to process.

Perspective. Among film directors, photographers, and artists, a change in camera angle and perspective is known to produce certain psychological effects (Andrew, 1976; Eisenstein & Leyda, 1949). Research also shows that camera perspective can influence the viewer's evaluation of televised events (Kepplinger & Donsbach, 1987), perception and impressions (Garramone, 1986), and memory (Anderson & Pichert, 1978; Garramone, 1986; Kepplinger & Donsbach, 1987; Kraft, 1987, 1991). In particular, Kraft (1987) revealed that camera angle is significantly related to the recall of the physical and personal characteristics of characters the ability to recall the gist of the story. Little research has investigated systematically how a change in camera angle and perspective would influence the allocation of cognitive resources. However, it is reasonable to think that any change in perspective would require additional resources because a new look from the camera introduces new or additional information to the viewer. In addition, the camera can change perspective in ways that human beings cannot. When the camera does things that people cannot do, it is thought to require additional resources to process the stimulus. Thus, if the information following the CC is seen from a different perspective than it was preceding the CC, this should require additional resources to process.

Emotion. A great deal of research shows that emotional (e.g., positive or negative) content requires more resources to be processed compared to nonemotional (e.g., calm) content (e.g., A. Lang, 1991; A. Lang et al., 1999; A. Lang, Dhillon, & Dong, 1995; A. Lang, Newhagen, & Reeves, 1996; P. J. Lang, Bradley, & Cuthbert, 1990; P. J. Lang, Greenwald, Bradley, & Hamm, 1993; McKenna & Sharma, 1995; Newhagen & Reeves, 1992). Therefore, if the material following the CC is emotional and the information preceding the CC is not, that should require additional resources. The dimensional view of emotion (P. J. Lang et al., 1993) identifies two primary dimensions underlying all human emotions, arousal (ranging from calm to arousing) and valence (ranging from positive to negative). The view posits that differences (changes) in these two dimensions change emotional experiences. Thus, if the emotion changes, from positive to negative, or from low arousal to high arousal, this should require additional processing resources.

Form change. This dimension considers the formal features associated with the information immediately following the CC. If the information is presented with a new set of formal features following the CC, the change in form should require additional resources. Examples of form change include change from color to black-and-white, moving pictures to still pictures, pictures to text, live-action to animation, and the addition of videographics or frames to the screen following a CC (e.g., Fox et al., 2004; Lang, Borse, Wise, & David, 2002; Thorson & Lang, 1992). If the information following the CC has a new set of formal features associated with it, that information should require additional resources.

As stated previously, the new measure developed was called information introduced (I^2). The amount of I^2 by a CC was equal to the sum of the dimensions. For each dimension, if the scene that followed the CC contained the type of information determined to require more resources, it was coded 1 on that dimension. If it did not contain the type of information defined as requiring more resources, it received a 0 on that dimension. Then, for each CC, these numbers were summed across dimensions. Therefore, a CC could have a score on I^2, ranging from 0 to 7.

Next, two variables were created. First, the number of CCs was summed for each message and divided by the number of seconds per message resulting in the variable CCs per second (CC/sec), which was the operational definition of resources allocated. Second, I^2 was summed across CCs for each message and divided by message length in seconds resulting in information introduced per second (I^2/sec), which is the operational definition of resources required. These new variables were then used to test the hypothesis that STRTs measure available resources. Because number of CCs indexed resources allocated to the task and I^2 by a CC was an index of resources required, CC–I^2 should correspond to varying levels of available resources. This means that the messages can be sorted into levels of CCs and I^2. Within each level of CCs (or resource allocation), the messages can then be split into messages with different levels of I^2, which will then manipulate available resources.

Thus, as the number of CCs increases, the level of resources allocated increases, and the level of resources remaining should be decreasing. If STRTs are measuring resources remaining in the system, then STRTs should get slower as the number of CCs increases, and this slowing of STRTs should be the same for both high I^2 and low I^2 messages.

If, on the other hand, STRTs are measuring available resources, then a different pattern of STRTs would be expected for messages with high or low levels of information and, within each level of resource allocation, there should be more available resources for messages with a low level of I^2 compared to messages with a high level of I^2. Therefore:

H3: As information per second increases, STRT should increase (if there is no cognitive overload).

H4: STRTs should increase more, as number of CCs/sec increases for messages with high information per sec, compared to messages with low information per sec (given no cognitive overload).

METHOD

Recoding the Stimuli

A group of coders was trained to use the new coding instrument. Ten percent of the messages were coded, and results were compared. Following this initial coding, the coding instructions were changed, and coders were retrained. Following the retraining, all of the messages were recoded. Each message was coded by at least two coders.

To code the messages, coders first watched the entire message to understand the context of the message. Next, they viewed the message and stopped at each CC and scored each of the seven dimensions as requiring more resources (1) or not (0). If the information following the scene change had a new focal object, was novel, was closer, was seen from a different perspective, had new form, resulted in a change in emotion, and was not related to previous information, that CC would receive a 7. On the other hand, if the scene following a CC had the same focal object at the same distance from the same perspective in the same form, was not new, represented no change in emotion, and was related to the previous scene, it could receive a 0.

Following coding, the number of CCs and the sum of all I^2 by all CCs was calculated for each message for each coder. Inter coder reliability for the number of CCs per message was 100%. For I^2 (which has values ranging from 0 to 160), the correlation between the two coders was .97. When the values were not exactly equal, the two coders were averaged to arrive at the amount of I^2 per message. Then, for each message, these numbers were divided by the number of seconds in the message because messages differed slightly in length. Thus, the final variables used in this analysis were CCs/sec and I^2/sec.

As can be seen in Table 4, though in general the original coding of slow medium and fast is relatively in line with the new CCs/sec value, the cuts and edits distinction is not particularly related to the new I^2/sec variable. For example, for messages with I^2/sec values greater than 1—of which there are 11—five of them were previously coded as edits and six of them were previously coded as cuts.

TABLE 4
Recoded Messages

	Original Coding		*New Coding*			
Type of Camera Change	*Production Pacing*	*Arousing Content*	*Information per Second*	*Camera Changes per Second*	*Valence*	*Arousing Content*
Edits	fast	arousing	2.52	.80	+/–	2.00
Cuts	fast	arousing	2.31	.90	+	1.25
Cuts	fast	arousing	2.29	.72	–	2.00
Edits	fast	arousing	1.76	.60	+	1.00
Cuts	fast	calm	1.70	.53	+	1.00
Edits	fast	arousing	1.41	.49	–	2.00
Cuts	fast	calm	1.37	.42	0	0
Edits	fast	calm	1.37	.45	+/–	1.00
Cuts	fast	calm	1.31	.38	+	.50
Edits	medium	arousing	1.28	.40	–	2.00
Cuts	fast	arousing	1.20	.40	+	2.00
Edits	medium	arousing	.98	.27	+	1.50
Edits	medium	arousing	.98	.33	–	1.50
Cuts	medium	arousing	.97	.40	–	2.00
Cuts	slow	arousing	.93	.37	–	2.00
Cuts	medium	arousing	.82	.23	–	2.00
Edits	fast	calm	.68	.28	–	1.25
Cuts	medium	calm	.66	.21	+	.50
Cuts	medium	calm	.66	.19	+	1.00
Edits	medium	calm	.64	.20	0	0
Edits	medium	calm	.63	.18	+	.50
Edits	slow	arousing	.54	.35	–	2.00
Cuts	medium	calm	.48	.13	+	.75
Cuts	medium	arousing	.48	.17	+	2.00
Edits	medium	calm	.48	.21	+	1.00
Edits	fast	calm	.37	.18	–	1.00
Edits	slow	calm	.23	.08	0	0
Edits	slow	calm	.18	.08	0	.50
Cuts	slow	arousing	.17	.07	+	1.0
Cuts	slow	calm	.13	.03	0	.25
Edits	slow	calm	.09	.03	0	0
Cuts	slow	calm	.00	.00	0	0
Cuts	slow	calm	.00	.00	0	0
Cuts	slow	arousing	.00	.00	+	2.00
Edits	slow	arousing	.00	.00	+	.00
Edits	slow	arousing	.00	.00	–	2.00

To test the hypotheses, the original 36 messages were split into three groups of 11 messages. Three messages (I^2/sec = .48) were not included in the analysis to create equal size groups that had significant variance on I^2/sec. The high I^2/sec group had scores ranging from 1.20 to 2.52. The medium group had scores ranging from .54 to .98. The low group had scores ranging from 0 to .37. The main effect of information group on the I^2/sec scores was significant, $F(2, 30) = 75.16$, $p < .001$, $\eta^2 = .83$.

RESULTS

H3

This hypothesis predicted that in cases where there is no cognitive overload, STRTs should be slower as I^2/sec increases. The main effect of I^2/sec was tested on the recognition data to determine whether cognitive overload had occurred. This effect was significant, $F(2, 132) = 10.13$, $p < .001$, $\eta^2 = .13$, and the means are shown in Table 5. Recognition increases significantly from low to medium levels of I^2/sec. At high levels of I^2/sec, mean recognition is between the low and medium levels. It is significantly lower than the high level but does not differ significantly from the low level. This indicates that cognitive overload may have begun at the high level of I^2/sec.

Next, the main effect of I^2/sec on STRTs was tested. The main effect was significant, $F(2, 134) = 4.00$, $p < .02$, $\eta^2 = .06$, and the means are also shown in Table 5. The pattern of STRTs mirrors the recognition results. As I^2/sec increases from low to medium, STRTs get slower. When recognition falls off at the high level of information, STRTs get faster though there are no significant differences among pairs of means for the STRT data.

These results tell us two things. First, that as global complexity increases from low to medium, STRTs appear to get slower. Second, there is the suggestion that STRTs may get faster as a result of cognitive overload, because STRTs were faster for high compared to medium information messages, and the recognition data indicates that cognitive overload has occurred during high information messages.

TABLE 5
Main Effect of Information/Second on Recognition and STRTs

Information/ Second	*% Correct*	*STRT*
Low	.59a	455.41a
Medium	.66b	465.02a
High	.62a	460.66a

H4

This hypothesis predicted that, in cases with no cognitive overload, STRTs should get slower as CCs/sec increase and that the change should be greater for messages with high I^2/sec compared to messages with low I^2/sec. This is tested by the I^2/sec × CCs/sec interaction on both the recognition and STRT data. First, the recognition data were examined to determine whether cognitive overload occurred. To calculate this interaction, a median split was done on the 11 messages in each I^2/sec group based on their CCs/sec scores. The middle message was dropped in each group. As a result, for this analysis, at each level of I^2/sec (low, medium, and high) there are five messages with a slow or low number of CCs/sec and 5 messages with a higher or faster number of CCs/sec. The predicted interaction was significant, $F(2, 132) = 4.17$, $p < .02$, $\eta^2 = .06$, and is shown in Figure 3. In this figure, at each information level, recognition actually increases from low to high CCs/sec.

Next, the same CCs/sec × I^2/sec interaction was run on the STRT data. Again, the interaction was significant, $F(2, 134) = 6.21$, $p < .001$, $\eta^2 = .09$ and is shown in Figure 3. As predicted, STRTs get slower as CCs/sec increases, and the change is greater for messages with medium and high I^2/sec than it is for messages with low I^2/sec. This pattern of results matches what would be expected if STRTs were in fact measuring available resources and not remaining resources.

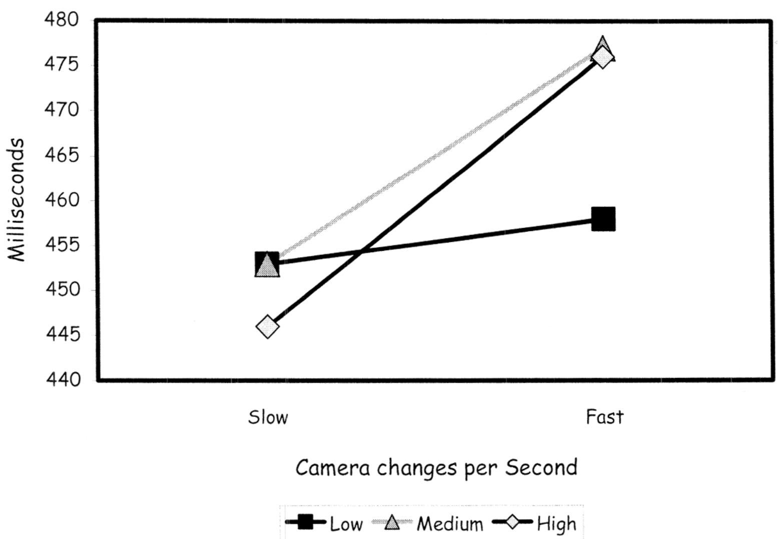

FIGURE 3 Recognition as a function of information .per second and camera changes per second.

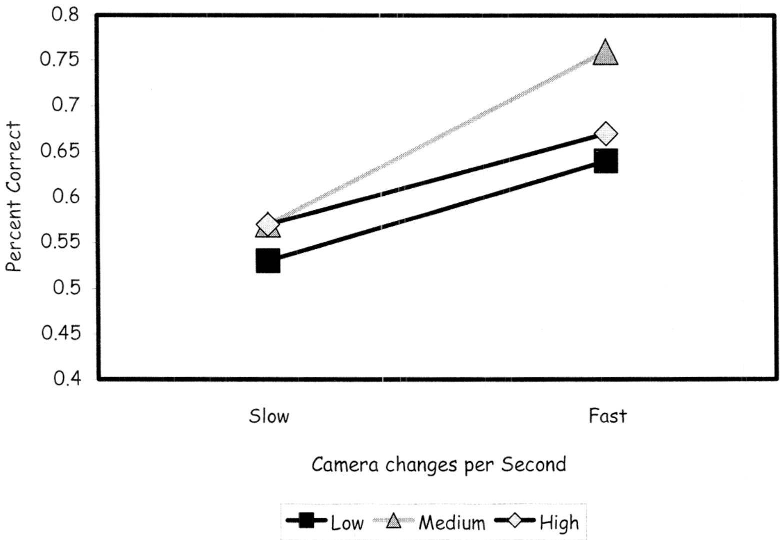

FIGURE 4 STRT as a function of information per second and camera changes per second.

GENERAL DISCUSSION

In general, the pattern of results found in the secondary analysis presented here support the interpretation that STRTs are measuring available resources. If STRTs were indexing remaining resources, then two things should be true. First, there should always be slower STRTs when there are more CCs/sec because as CCs/sec increases, resources allocated increases, and therefore resources remaining must decrease. Second, STRTs should not vary as a function of I^2. While in general, STRTs did get slower as CCs increased, that increase in STRT did vary as a function of I^2.

Similarly, If STRTs were measuring resources required by the message, then, STRTs should not vary as a function of resources allocated (e.g., number of CCs), and they should always get slower as I^2 increases. But these data show STRT varying as a function of number of CCs and, in the low information group, there is virtually no change in STRT as a result of I^2.

Instead, the pattern that appears in these data is the pattern predicted if STRTs are measuring available resources. If STRTs measure available resources, then they should vary in response to changes in both allocated and required resources—which they do. At each level of I^2 (low, medium, and high), task performance is better for high levels of CCs compared to low. Similarly, at each information level STRTs are slower at high compared to low CCs. However, the difference is smallest for low information as would be expected if STRTs are measuring available resources because increasing the number of CCs increases resources allocated, but the low level of I^2 means that there is very little change in resources required, resulting in a high level of available resources, and thus, the fastest STRTs. With increasing levels of I^2, resources required increases faster than resources allocated resulting in fewer available resources and slower STRTs.

Of most significance here is that when both the level of resources allocated and the level of resources actually required are taken into consideration when coding media complexity, the STRT results are in line with basic limited capacity theories and secondary task methodological theory that demands that increased complexity or difficulty result in slower STRTs. These data do not require us to provide explanations for why messages that are, on the face of it, more complex, difficult, and information heavy result in fast STRTs. Instead, as long as both the calls for automatic allocation of resources and the requirements for those resources are considered, we see STRTs that are slower for the more information heavy messages. Future research should replicate these results and take into consideration how they might interact with other variables that have been shown to affect STRTs such as emotional valence and arousal (A. Lang et al., 1995).

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