IDENTIFICATION OF RELIABLE CUES FOR AN AUTOMATIC DECEPTION DETECTION SYSTEM

by

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A Dissertation Submitted to the Faculty of the

COMMITTEE ON BUSINESS ADMINISTRATION

In Partial Fulfillment of the Requirements
For the Degree of

DOCTOR OF PHILOSOPHY
WITH A MAJOR IN MANAGEMENT

In the Graduate College

THE UNIVERSITY OF ARIZONA

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THE UNIVERSITY OF ARIZONA
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ACKNOWLEDGEMENTS

I am mostly grateful for my dissertation advisors, Dr. Jay F. Nunamaker and Dr. Judee K. Burgoon, for the guidance and encouragement that help me overcome the difficulties during the many years of PhD study. Also thank my other major committee member, Dr. Leon Zhao, for the support throughout the study. Thanks to my minor committee members in the Department of Linguistics, Dr. Terry Langendoen and Dr. Mike Hammond for their valuable suggestions and feedback.

Many thanks to the research team at the Center for the Management of Information (CMI) for collaboration and support, as well as the Ford Foundation and the U.S. Air force for sponsoring the projects. Special thanks to: Ling Ming, Jinwei Chao, Betty Albert.

I also thank all the faculty members at the Department of Management Information Systems for their advice and support on my PhD study, especially Dr. Mohan Tanniru.

I would like to thank to my colleagues, fellow PhD students and friends for their support and help through the tough journey, particularly Yilu Zhou, Jason Li, Gang Wang, Yiwen Zhang, and Harry Wang.

Finally, I am extremely grateful and greatly indebted to my parents, husband, and my son for their unconditional love and support. They are always the energy sources to support me to work hard, and overcome the difficulties during my study and for the rest of my life.

DEDICATION

To my parents, Wei Qin and Si Xu; my dearest husband, Xiangyu Zhang and our lovely son, Brian

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ABSTRACT

An automatic deception detection system (ADDS) is to detect deceptive human behavior with machine extractable evidences (i.e., cues). One of the most prominent challenges for building a ADDS is the availability of reliable cues. This study represents one of the first attempts to address the system's reliability by identifying the set of reliable cues in order to improve the system performance (detection accuracy).

This study addresses two critical challenges of existing machine cues, irreproducibility and inconsistency. First, in order to mitigate the irreproducibility, the study introduces a set of machine measurable cues to estimate the commonality of related machine cues. These more reproducible cues are referred to as the macro cues which can be applied for automatic pattern recognition. Second, in order to address the consistency, the study separates cues based on the controllability, and defines the strategic cues as those can easily be manipulated by deceivers during interaction. The strategic cues fluctuate during deception and thus are less consistently reliable as predictors for the ADDS. On the contrary, the nonstrategic cues are more consistent. This study also considers other moderator effects that influencing the ADDS performance: time and the condition of interviewer's immediacy (ERIMD).

The macro cues are automatically estimated from the micro cues based on the predefined relational models. The empirical data support the relationship models between macro and micro cues. Results show that macro cues mitigate the irreproducibility problem by reducing the variability in the single cues. However, the results also show

that using macro cues as predictors in the discriminant analysis does not perform better than micro cues, and thus imply the needs to adjust weights of important components when constructing the macro cues. In terms of the consistent cues, results show that the nonstrategic cues are relatively more consistent than strategic ones in ADDS performance. Furthermore, the study suggests that particular detection methods must be tailored according to the feature of strategic and nonstrategic cues.

The findings have many potential implications. One is to use the macro cues to recognize the dynamic patterns in deceptive behaviors. Specifically, truthtellers increase the certainty, immediacy, and tend to decrease the cognitive load; but deceivers behave the opposite. The other is to rely on the characteristics of strategic cues to manipulate the communication environment to improve the ADDS performance. This concept is also referred to as the Proactive Deception Detection (PDD). In the current study, the interviewer's immediacy is a controllable environment factor for PDD. The high ERIMD increase the system performance because it has higher overhead added to the deceptive behavior to trigger more abnormal cues. In sum, methods and results of this study have multiple impacts in information assurance and human-computer interaction.

CHAPTER 1

INTRODUCTION

1.1 Background of Deception Detection

Deception is ubiquitous in everyday life. Most people tend to think of deception as a blatant untruth or a bald-faced lie. For example, if somebody stole money and then continued to assert “I didn’t take it” when being confronted about the theft, she would be telling a bald-faced lie. However, the concept of deception is much broader than bald-faced lies. It also includes white lies, exaggerations, evasions, fabrications, and equivocations. By nature, once a person intends to create a false impression to other people out of certain motives, she is deceiving. Given the broad scope of deception, it has been reported that people tell an average of one to two lies a day (DePaulo, Kashy, Kirkendol, Wyer, & Epstein, 1996; Hancock, Thom-Santelli, & Ritchie, 2004), thus supporting the fact that deception is a widespread phenomenon.

Failing to detect deception can damage interpersonal relationships, impede criminal justice, reduce business profits, and jeopardize national security. According to the Federal Trade Commission (FTC), individuals and businesses suffered approximately $52.6 billon in losses in 2004 due to deception-related issues, or social engineering.

It is unquestionable that detecting deception is very meaningful in human life. Unfortunately, deception detection in general is a very difficult thing to do. It is still unclear if there is a good scientific solution. Even though there are many findings on indicators of deception, the accuracy of lie detection by human beings is not satisfactory across most studies of detecting deceit. The accuracy percentages of lie detection range from 45% to 60%, which is low considering that 50% accuracy is expected by chance alone (DePaulo, Stone & Lassiter, 1985; Vrij, 2000; Zuckerman, DePaulo & Rosenthal, 1981). Literature review further shows that people are particularly poor at detecting lies (44% accuracy rate) (Vrij, 2000). It has been predicted that truth bias, stereotypical thinking, and processing ability all have an influence on human judgment (Chaiken, 1980; Fan, Wagner, & Manstead, 1995; Bond, 2006; Buller, Burgoon Afifi, White, & Buslig, 1999; Buller, Burgoon, White & Ebesu, 1994; Zuckerman & Driver, 1985).

Human judgment also does not improve significantly through training. It has been shown that training can increase one's confidence in judgment but often not one's accuracy (Fan, Wagner & Manstead, 1995; Kassin et al., 2005), and findings vary significantly and substantially from study to study with important methodological limitations (Frank and Feeley, 2003). Some professional detectors, such as police interrogators, are more confident in their judgment, but their accuracy is not significantly better than that of students who've participated in lie-detection studies because of the professionals' strong biases, such as truth or deception biases (Garrido, Masip, & Herrero, 2004). Even in the case when training can assist human deception detection, the effect is modest and requires extensive time, practice, and feedback.

Furthermore, the development of information technology brings new challenges to the traditional ways for humans to detect deception. Specifically, digital communication is faster and more versatile than face-to-face communication. Deceivers have the choice to convey messages by writing an email, making a phone call, or sending a video segment; all of these methods of communication make it easier for deceivers to disguise their intent. Consequently, the anonymity afforded by these communication methods confers an advantage on deceivers to create even more influential digital deception. Without an efficient deception filter in place, the sheer volume of information communicated at such a fast pace will heavily burden the capabilities of information processing, thus making humans extremely vulnerable to various forms of deception. Therefore, the sheer number of digital lies creates a need for a digital cure.

1.2 Automatic Deception Detection: New Opportunities and Challenges

Fortunately, research has shown that automatic deception detection techniques are promising in their ability to mitigate the human shortcomings, because a system is not affected by human biases and therefore can make fair judgments. Thus far, several automatic deception detection studies have been independently conducted in different research laboratories. Existing systems can detect deception from verbal or nonverbal evidences collected from linguistic style, voice, and gestures. For example, the linguistic system utilized at Cornell University can detect deceptive patterns in text-based, computer-mediated communication (Hancock, Curry, Goorha & Woodworth, 2005; Newman, Pennebaker, Berry & Richard, 2003). An example of detection deception from nonverbal evidence is VoicePrism (www.voiceprism.com), which captures the abnormal cognitive activities and emotion fluctuation present in vocal signals when someone is lying.

The current study is based on the automatic deception detection prototype designed by Zhou and colleagues (Zhou, Twitchell, Qin, Burgoon, & Nunamaker, 2003; Zhou, Burgoon, & Twitchell, 2004; Qin, Burgoon, & Nunamaker, 2003). This system was originally designed to capture verbal features. But the concept of the current proposed research model is base on the prospect of combining automatically extracted nonverbal features with automatically extracted verbal features. Specifically, the system starts by parsing messages for deceptive indicators, which are also referred to as **cues**. Next, indicators are used for classification when patterns of the indicators are formed with certain statistical or machine learning methods. The extracted patterns are compared with truthful patterns. If the observed pattern is significantly different from the truthful one, the system judges the message as deceptive; otherwise, as truthful. Furthermore, empirical results show the effectiveness of the automatic deception detection system: when a series of tests was performed with different sets of experimental testing data, the system was able to automatically detect deception within a range of 65% to 85% (i.e., on average, 75 out of 100 deceptive message can be spotted) (Qin, Burgoon, & Nunamaker, 2003; Zhou, Twitchell, Qin, Burgoon, & Nunamaker, 2003; Zhou, Burgoon, & Twitchell, 2004). The result is much better than the average human performance, which is only 54% (Bond & DePaulo, 2005).

The two, critical, functional components for the Automatic Deception Detection System (ADDS) are **cues extraction** and **classification,** and the first component is a prerequisite for the second. Hence, from the viewpoint of the design of an ADDS, this study refers to **machine cues** as being those that can be automatically extractable and then used for automatic classification.

Currently, the machine cues used in the ADDS have been adapted from the deceptive indicators suggested by deception theory. Most of the existing verbal cue auto-extraction techniques are based on single word counting and simple dictionary look-ups (Hancock, Curry & Goorha, 2005; Neumann et al., 2003; Pennebaker et al., 2003; Zhou et al., 2003). Likewise, most of the current nonverbal cues are based on simple audio and kinesic feature extraction such as pitch and body movements (Meservy, Jensen Kruse, Burgoon, & Nunamaker, 2005; Qin et al., in progress). From the perspective of classification, the current status of existing machine cues is that of being single measurement cues. Although some higher-order cues are defined as composites of several single cues, they are treated as several single cues rather than a composite in classification. For example, verbal immediacy was referred as any indication of separation, non-identity, attenuation of directness, or change in intensity of interaction among the communicator, the listener, the object of communication, or the communication (Wiener & Mehrabian, 1968). In a ADDS research conducted by Zhou and the colleagues, verbal immediacy has been considered as a promising indicator to detect deception. Specifically in Zhou's study, verbal immediacy is comprised of four major components (temporal words, spatial words, voice, and modifiers). But in the classification, it is the four indicators, rather than a composite measure, that are considered as predictors (e.g., in the discriminate analysis). One contribution of current study is to systematically study the relationships between the composites and the corresponding single measurements and then automatically estimate the value of the composite variables by calculating the commonality in the component single variables. The composite variables are applied in classification. This study provides an approach to handling a large number of features for an automatic deception detection system.

When compared to human ability, a machine is more advanced in its ability to detect deception on many levels. First, a machine can handle the sheer volume of messages generated from computer-based communication. Second, machine judgment is fair and not affected by first impressions or relationships. Humans, on the other hand, tend to rely on mental shortcuts to make convenient judgments instead of sufficiently considering all the relevant information (Buller, Burgoon, Afifi, White, & Buslig, 1999; Chaiken 1980), and humans are easily affected by stereotypical thinking and truth biases (Bond 2006).

Although machine detection is theoretically very promising, it is also facing great challenges. One of the most critical challenges is the **availability of reliable cues**. As aforementioned, the ADDS's mechanism is to use the machine extractable cues to estimate the deceptive intent. Hence the quality of cues is a fundamental condition for the system.

The selection of current machine cues (micro cues) has been based on comprehensive literature review and empirical support; for example, a study done by Zhou et al. (2003) specifies the process of selection cues in detail. However, the estimation process—from the objective and concrete machine cues to the subjective, abstract, dynamic, and complicated intents— is by no means a direct cause-effect one.

Instead, many effects may interact with the cues, affecting the machine's reliability in detecting deception. For example, the number of words is not a reliable cue since deceivers talk more to appear plausible when they have rehearsal time (Zhou et al., 2003) but talk less otherwise (Blair, Burgoon, & Qin, 2004). Therefore, it would make no sense to detect deception simply based on the word count without comprehensively considering other effects.

The most direct outcome of using unreliable cues is an unreliable system. If the unreliable cues were used by a system to construct a baseline to detect deception, it is possible that the baseline would work well in one scenario but fail in another, because the machine cues are easily affected by environment factors/moderators in the latter scenario. Hence, reliable cues are one of the most fundamental conditions of constructing an automatic deception detection system.

Perhaps the most straightforward method is to construct baselines specifically for each scenario. But in this case, reliability is obtained with an extremely high overtaxed by considering every possible scenario. Hence, a more realistic method is to identify a set of cues that is generally more reliable than others so that the system performance is reliable in general. This method is especially advantageous when detecting messages from a completely unknown scenario.

Thus far, very little research has studied the issue of reliable cues specifically in reference to automatic deception detection systems. The current study represents one of the first attempts to address the system's reliability by identifying the set of reliable cues.

Specifically, this study addresses two of the most common cases of unreliable cues; each has unique characteristics. The first type of unreliability—**irreproducibility**—happens when the same deception can be expressed in a variety of ways (behaviors) so that the corresponding micro cues are not reproducible from one way of expression to another, thus making it possible to cause contradictory results when classifying the same deceptive intent because the micro cues vary with expressions. The second type of unreliability—**inconsistency**—happens when a cue fails to be consistently statistically significant in distinguishing deception from truth from one scenario to another.

In the following subsections, more details of the two types of unreliability are discussed: their causes and results, methods for handling them, and their resultant implications.

1.2.1 Addressing the Irreproducibility with Macro Cues

Irreproducibility

The major task of an ADDS is to estimate deceptive intent with machine cues. On one hand, deceptive intent is subjective, abstract, and semantically meaningful (interpretable) and on the other the machine cues are objective, concrete, and devoid of semantic meaning. The relationship between the two is one-to-many: one intent can be expressed through innumerable patterns, each pattern consists of a set of behaviors, and each set of behaviors, in turn, can be measured with the micro-level machine cues.

When people tell lies, they may be nervous and have to think hard. Although the internal status is the same—high cognitive load—the outside expressions could be different: one person could pause more frequently and use a variety of different content words to explain themselves; while another person could pause less frequently and use fewer content words. Because the values of micro cues differ, when the system uses the two different micro cues as predictors, the classification results are potentially different from one person to another, even though expressions in the two persons show a commonality of high cognitive load.

Figure 1.1 demonstrates the concept of irreproducibility. The dynamic instead of static patterns are used for demonstration in order to show clearly how the values of micro cues are not reproducible from situation 1 to 2.

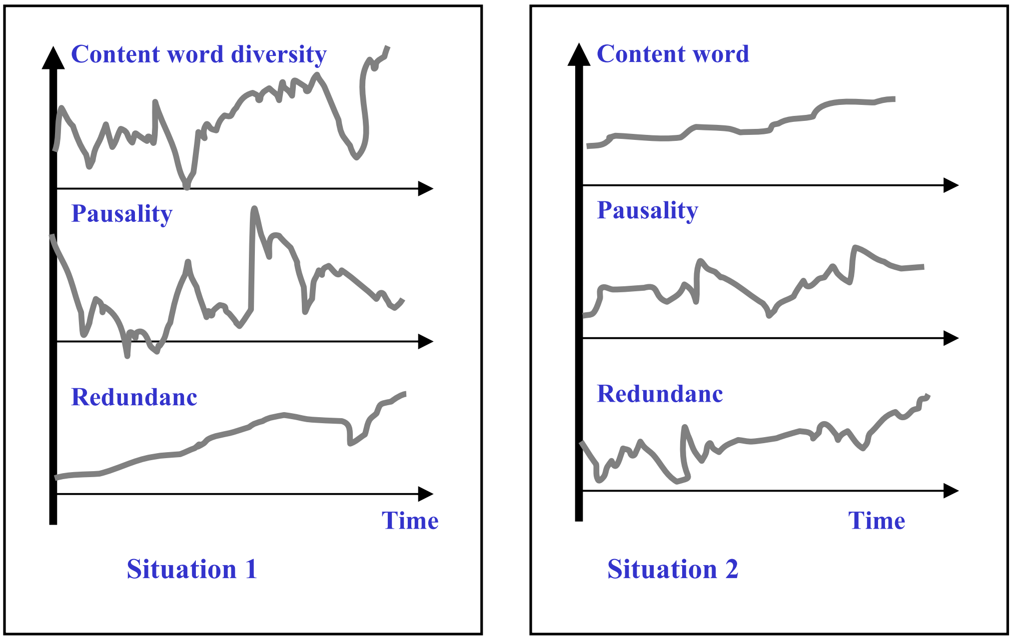


Figure 1.1 Subsets of Micro Cues in Two Situations of the Same Deceptive Intent

As shown, although both of the two persons are deceptive and show a similar cognitive load in each situation, the presentation of micro cues might be different.

Specifically, the content word diversity, the pausality, and redundancy are not reproducible.

One negative impact of using the irreproducible micro cues in automatic deception detection is that it can cause contradictory results; i.e., one is classification as truth and the other is deceptive. In other words, the system is unreliable in that it is affected by the variability in the behaviors.

Estimate Composite Cues with Macro Cues

It is the hidden behavior meanings that really matter: we are less interested in the value of content words' diversity and pausality than knowing that the cognitive load is high.

Therefore, irreproducibility can be mitigated if the hidden information of the related micro cues is extractable. Consider the example in Figure 1. Content word diversity, pausality, and redundancy are three components of a higher order, abstract composite cue, cognitive load, which is estimated with the commonality in the three micro cues. For demonstration purposes, the assumption is made that the cognitive load only consists of three micro cues. For this example, the approximate value of cognitive load estimated for the two situations is shown in Figure 1.2, where the patterns are more reproducible. The combination of Figures 1.1 and 1.2 demonstrates how the irreproducibility issue can be effectively handled by adding a middle layer between the deceptive intent and the micro cues. This middle layer is also known as the layer of **macro cues**, each of which is a higher-order, abstract, and meaningful composite of a set of related micro cues and is estimated with the commonality in the micro cues.

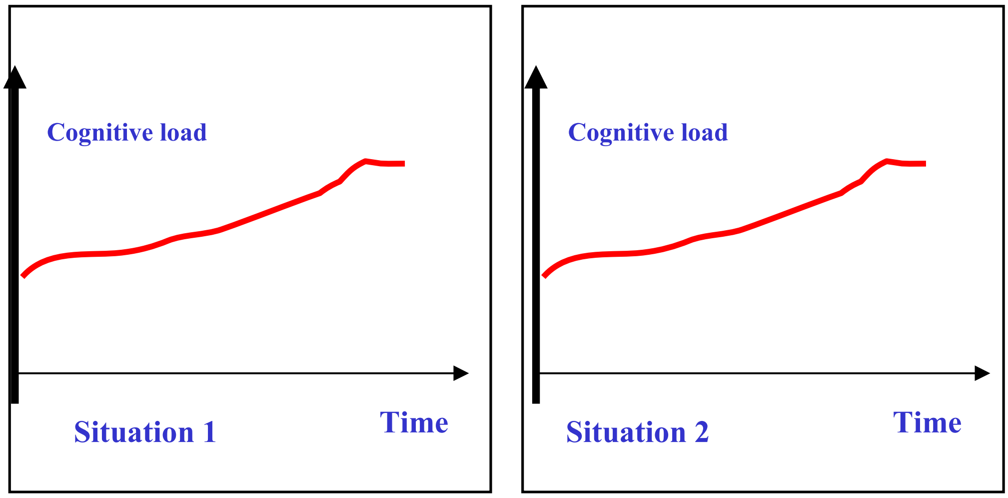


Figure 1.2 The Macro Cue Extracted from the Micro Cues

The macro cues are the conceptual composite variables that capture the commonality of the set of related micro cues. The biggest challenge of constructing macro cues is the different operationalizations for the same conceptual variable. For example, the meta-analysis conducted by DePaulo and the colleagues (2003) categorizes cues into several categories: engaging, immediate, uncertain, pleasant, tense, and unusual contents. Each category contains around 5-15 micro-level cues. According to DePaulo, verbal immediacy is measured by generalizing terms, self-reference, mutual and group references, other references, verbal immediacy (temporal) and verbal immediacy (all categories). But according to Newman (Newman, Pennebaker, Berry & Richards, 2003), verbal immediacy is operationally measured with a single cue of **self-reference**.

Therefore, the primary method for addressing irreproducibility is to create systematic relations between macro and micro cues. Focusing on deception detection, this study presents one of the first attempts to propose and statistically validate a relational model between macro and micro cues related to deception. **The first research question**

is how to automatically construct macro cues from micro ones? Specifically, this question actually includes 3 sublevel questions: Is there a relational model between macro and micro cues that can be statistically supported by empirical data? How can macro cues be automatically estimated by machines? How do macro cues compare with micro cues in terms of automatic classification?

Implication of Macro Cues: Recognizing Deceptive Patterns Cross-Sections

Because macro cues are the abstract cues that are semantically meaningful to humans (i.e., they represent the meanings humans assign to clusters of cues), one important implication of using macro cues is in recognizing deceptive patterns over time.

Deceptive behavior is dynamic and interactive in nature. According to the Interpersonal Deception Theory (IDT) (Buller & Burgoon, 1994, 1996), deceptive behavior fluctuates during communication rather than remaining stable. This theory has been confirmed by more recent studies. Specifically, Granhag and Stromwall (2002) examined the verbal and nonverbal behaviors of deceivers and truth tellers across the three interrogations They concluded that deception-related patterns vary in four nonverbal and verbal behaviors, and deceivers showed more declines in smiles, self-manipulation, pauses, and gaze aversion than truthtellers. Burgoon and Qin (2006) also found that deceivers showed different patterns over time from truth tellers, and that the differences between them diminish over time; thus, the best time to detect deception is at the beginning phase of communication.

Consistent with the IDT, this study considers deception a dynamic and interactive behavior. Because the macro cues contain certain behavior meanings, they can be used to recognize the behavior patterns. Specifically, the **second research question is**: Do the communication patterns of deceptive behavior differ from the patterns of truthful behavior?

1.2.2 Addressing the Inconsistency by Categorizing Nonstrategic and Strategic Cues

In this study, a cue is **statistically significant in deception detection if it** is statistically significant in separating truth from deception in a classification analysis such as discriminant analysis. In reality, there is no perfect cue that can successfully detect deception generated from all people under all contexts at all times. A refined goal, therefore, is for a cue to be as reliable as possible in detecting deceit within many contexts. (For example, finding a cue that is reliable in either high or low stakes deception; or deceptive messages exchanged between close friends or strangers; or deceptions happening in different phases of communication). Specifically in this study, a **consistent** cue is one that, when compared to other cues, is statistically significant in detecting deception in two separate time frames. Number of words is an example of an inconsistent cue because its discriminability and even the direction of the relationship (truth greater than deception or deception greater than truth) varies from one time frame to the next.

Identifying a set of consistent cues is never easy in reality. Deception typically occurs in interpersonal communication contexts where the mutual influence of senders and receivers occurs. Deceivers must constantly adjust their behavior in response to feedback from receivers. In order to maintain a truthful look, deceivers manage behavior through strategically manipulating information, impression, and behavior. During this process, deceivers constantly manipulate some cues based on the interaction and feedback between both interlocutors, and thus the cues are fluctuating frequently. For example, deceivers may first adopt nonimmediacy to distance themselves from their message. Later during the interaction, if deceivers sense their performance provokes suspicion in receivers to the extent that they appear to violate expectations for normal conversational behavior (Burgoon, Buller, Dillman et al., 1995), they are motivated to offset these changes strategically to maintain sufficient conversational immediacy. If the deceivers are successful, then their behavior -- which is represented in cues -- will appear very similar to truthful behavior. There are also some cues that are less controllable. These cues are termed the nonstrategic cues because they happen unconsciously. Nonstrategic cues include *heavier cognitive load* and *psychological arousal* when deceiving.

It is important to note that the more easily a cue can be strategically manipulated, the more it fluctuates during communication and therefore the cue is less consistent as a reliable predictor for detecting deception. This study investigates the consistency of machine predictors. Specifically, the **third research question is**: Are nonstrategic cues more consistent in detecting deception than strategic cues?

Improving the Performance of the ADDS

Central to the idea of differentiating between strategic and nonstrategic cues is that deception is a dynamic and interactive process. The performance of deceivers will be more effective if they develop a more innocent appearance, whether this is achieved over time or by sufficiently adjusting self-behavior during the interaction process.

Because deception is an interpersonal rather than intrapersonal behavior, factors in the surrounding environment can affect it, such as time and the reactions of interlocutors. These factors may cause inconsistency in performance of cues. Thus there seems to be an invariable inclination to view these moderator effects as unwanted features. To the contrary, a renewed interest has been brought to taking advantage of the moderating factors. Central to this new perspective is the idea that since the moderators can affect the differentiating power of cues, the detecting environment therefore should be manipulated in such a way that the differentiating power is maximized. This can be illustrated with the time effect: if deceit can more easily be detected at the beginning phase of communication, it would be more accurate for the system to consider cues in the early phase rather than later. In this study, this idea is noted as “proactively” detecting deception, which warrants the following discussion: given the moderating factors on linguistic cues, is it possible to manipulate the communication environment in such a way that the machine cues can significantly differentiate deceit from truth?

Effect of Time in Deception Detection

The first factor investigated in this study is time. There have been very few studies conducted to investigate the time effect on deception, and the results are not consistent. White and Burgoon (2001) examined the nature of adaptability and mutual influence in human interaction. Interpersonal deception theory and interaction adaptation theory were used to study patterns of interaction that occur across time in truthful and deceptive conversations. Their results showed that deceivers felt more anxious and were more concerned about self-presentation than truth tellers. White and Burgoon concern examined the adaptation in interaction from the aspect of Interaction adaptation theory (IAT; Burgoon, Stern, et al., 1995). Specifically, IAT proposes that adaptation in interaction is responsive to the needs, expectation, and desires of communicators and affects how communicators position themselves in relation to one another and adapt to one another's communication. They found that deceivers increased involvement over time but also reciprocated increases or decreases in receiver involvement. Their results inspire this current hypothesis that deceivers adjust their behavior base on the interlocutors' reactions during conversation. One direct outcome of such adjustments would be shown in the changes in the strategic cues in the deceiver's behavior. According to White and Burgoon, the communication patterns were moderated by deception and continuously changed over time. From the perspective of deception classification, the more similarity there is in the patterns between truth tellers and deceivers, the more difficult it is to detect deceit. Hence, a further investigation of the machine cues would be necessary in deciding the time effect on the deception detection. A more recent study (Burgoon & Qin, 2006) found that deceivers adapted their ways of communication in ongoing interactions to the extent that, eventually, they converged their communication toward that of truthful respondents. The result is that in later phases of an interaction, deceptive behavior became indistinguishable from truth norms. However, it is also possible that in the beginning of the communication, both deceivers and truth tellers are settling into their own interaction pattern. This self-adjusting process is more related to each interlocutor finding his or her own comfort zone rather than resulting from mutual influences between the interlocutors. This process reflects an actor effect rather than a partner effect, and therefore it reflects little of deceptive effects. In the early phase, the deceptive effect is overshadowed by the self-adjusting effect and takes over only after the self-adjusting effect becomes stable. Under this speculation, it is posited that detecting deception is more evident in the later phase of conversation. The **fourth research question is**: what time phase is better for detecting deception: the beginning or later?

Effect of Interlocutors' Immediacy on Deception Detection

The second factor is related to the interactive process of communication. Interpersonal Adaptation Theory predicts the default pattern as reciprocity in interaction. Deceivers are aware of the situational expectations and are inclined to follow the pattern of normal behavior (Burgoon, Stern, & Dillman, 1995). In the case where the interlocutors increase involvement or immediacy, the normal expectation is for the deceptive sender to respond by increasing involvement (Buller, Burgoon, White, & Ebesu, 1994; White & Burgoon, 2001). However, deceivers are also expected to experience more cognitive burdens than normal (truthful) senders when they manage to suppress leakage. So, their ability to enact additional responses designed to strategically reciprocate high involvement is limited. Thus, the reasoning leads to an interesting and also the **fifth research question**: when the interlocutor's immediacy is high, does the leakage of deceptive cues increase so that the performance of automatic deception detection is improved?

CHAPTER 2

RELATED THEORY BACKGROUND AND HYPOTHESES

2.1 Deception: an Interpersonal Act of Communication

There is no doubt that the first and most important question to be asked in researching automatic deception detection systems (ADDS) is: What is deception? If there is no working concept or definition of "deception," then ADDS research in its entirety will be based on nothing: there will be no object of interest, no idea of what is detectable, and thus no methodology to detect it.

Even though the definition of deception serves as a foundational work for ADDS, it is often underestimated and has frequently been left out of discussions in almost all previous ADDS research. When given a passing thought, the concept of "deception" seems familiar and trivial. However, among the numerous attempts made by scholars of deception research to capture the idea of deceptive communication, this concept has run the gamut with significantly different foci.

The **definition of deception** in this work is: *a message knowingly transmitted by a sender to foster a false belief or conclusion by the receiver* (Buller & Burgoon, 1996).

The nature and feature of deception and its detection are decided by two key elements, namely **intent** and **interaction.**

The element of **intent** concerns whether deception is communicated consciously (thus intentionally) or occurs at the subconscious level. DePaulo defines intentional deception succinctly: “deceivers are, by definition, deliberately misleading others … they are not doing so mindlessly or mistakenly” (DePaulo, 1988, p.153). In contrast, other scholars argued that deception requires neither deliberativeness nor consciousness (Bavelas, Black, Chovil, & Mullett, 1990; Bond & Robinson, 1988).

The element of **intent** in deception directly affects the method of detection. If the sender conveys false deception subconsciously and has no doubt about the content, her performance will be similar to when she’s telling the truth: there will be no negative emotion (fear, guilt), no cognitive challenges for maintaining content consistency, no arousal that results in greater pupil dilation, and so on. In this case, all cues usually related to deception, such as arousal, emotion, and cognitive aspects (Zuckerman et al., 1981; Ekman, 1969, 1985; Buller & Burgoon, 1996; DePaulo et al., 2003) will be ineffective. The possible method used to detect subconscious lies could be the content-related analysis. Reality monitoring (RM), for example, is an applicable technique that studies the difference between real experience and imagination (Johnson, Hashtroudi, & Lindsay, 1993). Because the outcomes of the deliberate deception are more malicious and serious than others, most of the scholars have focused their attention on the idea of intent as a key defining characteristic of deception. In other words, the first key aspect of definition of deception is intentional.

Interaction is another key aspect of deception definition simply because deception is an interpersonal, dynamic, and adaptive communication process. A representative perspective is Interpersonal Deception Theory (IDT, Buller & Burgoon, 1994, 1996). Interactive deception encompasses the entire communication process, usually between two participants. Demonstrated in figure 2.1, the deceptive sender sends out a false message and **constantly and strategically** adjusts her behavior according to the receiver's feedback.

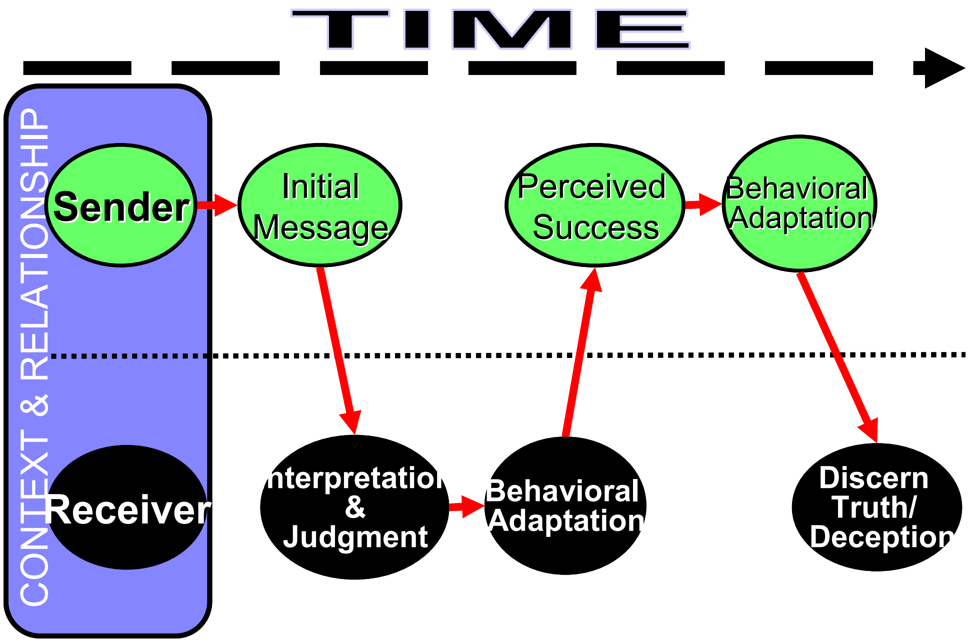


Figure 2.1 Interactive Deception

By contrast, much deception research has implicitly taken an individualistic and static approach, focusing either on deceiver or detector behavior rather than on the effect of interaction (Buller, Comstock, Aune, & Strzyzewski, 1989; Toris & DePaulo, 1985; Vrij & Winkel, 1991; Weiler & Weinstein, 1972).

For this current focus on automatic deception detection, methods will be significantly different depending on whether the deception is defined as individualistic and static or interpersonal and interactive. The former emphasizes the self-reactive effect such as becoming emotional while committing deception, and it relies on related cues to deception behavior. Detection performance is affected by the individual and their internal psychological processes such as goals and motivations, but not directly affected by the interactive and external effect such as the interlocutor's suspicion.

By contrast, the latter detection methods for the interactive deception are much broader than those for the individual deception: besides the individual, static aspect, it addresses the importance of the interactive, dynamic effect.

Furthermore, in order to handle the interactive deception, two classes of behaviors must be taken into consideration—strategic and nonstrategic. According to the interactive metaphor, strategic behaviors are treated differently from nonstrategic behaviors. Strategic behavior occurs when senders actively respond to receivers' feedback by deliberately adjusting self-behavior, and the nonstrategic cues are the subconscious reactions that follow the deception process. Consequently, a good method to use in detecting interactive deception should be adaptive to strategic and nonstrategic cues according to their unique features. Furthermore, since the interactive deception emphasizes that the deceivers constantly and strategically adjust themselves according to the feedback they receive, it can be concluded that both interlocutors influence the deceptive effect. Under this assumption, the idea of "proactive detection" is plausible, meaning increasing detection accuracy by manipulating some interactive factors to enlarge the deceptive effect.

To summarize the above discussion, deception communication is intentional, dynamic and interactive. Hence such deception should be the object of interest of a powerful and flexible ADDS. However, all of the current ADDS research does not explicitly define deception, and it fails to sufficiently address the interactive aspect of deception. For example, Newman simply defined deception as “telling a false story … requires describing events that did not happen or attitudes that do not exist.” (Newman, Pennebaker, Berry & Richards, 2003, P665) This definition does not consider the “interaction.” Even in the ADDS research where the interactive effects were studied (Hancock, Curry, & Goorha, 2005; Zhou et al., 2003), the authors did not distinguish strategic and nonstrategic indicators as two very difference classes of indicators.

The current study presents the first attempt to systematically examine detection methods regarding the intentional and interactive deception from the perspective of automatic deception detection. And following IDT, deception discussed in current study has two key features: intentional and interpersonal. Under this definition, two categories of cues are further specified. Specifically from the viewpoint of intentional, cues are differentiated into macro and micro where macro cues contain more intent than micro ones. Furthermore, in terms of human controllability, cues are separated into strategic and nonstrategic.

2.2 Categorizing Cues into Macroscopic and Microscopic Features

This study can be considered an extended one of the ADDS investigated previously by Zhou and colleagues (Zhou et al., 2003). Hence, it follows that some machine cues have been defined previously. Furthermore, this current study extends upon previous studies by defining new, automatically extractable cues (categories), which are more sophisticated and have advanced features. A further contribution is the categorization of cues into macroscopic and microscopic levels and the method used to automatically extract the macro cues.

As aforementioned in the first section, cues can be categorized into two levels in terms of the behavioral meanings contained: micro cues are the currently-defined machine cues that are directly applied into automatic classification. And the macro cues are the commonality patterns that can be automatically extracted from the related micro cues.

In the next subsections, the definitions of micro cues are first introduced and then the relationship between macro and micro cues and the hypotheses are presented. This is followed by a comparison between micro and macro cues.

2.2.1 Micro Cues

Micro cues can take verbal or nonverbal forms. Verbal micro cues have been defined and directly used as predictors for classification in previous ADDS studies (Zhou et al., 2003, 2005; Qin et al., 2003, 2004; Blair et al., 2004; Burgoon & Qin, 2006). These include the syntactic, semantic, and lexical (vocabulary) features used in text-based messages or transcripts of recorded face-to-face communication. Research suggests that by counting and categorizing the words people use to communicate, we can determine their underlying thoughts, emotions, and motives (Newman et al., 2003). For example, deceivers' messages typically lack vivid and specific details because they do not have the relevant corresponding experiences from which to provide details.

The techniques for extracting verbal cues include word counting and dictionary searching for words representing semantic meaning. There are three affect cues that encode the semantic meaning of activation, pleasantness, and imagery. The Whissell dictionary (1986, 2001) measures the affect terms on a scale of 1 to 3, with 1 (e.g., least emotion-laden) being the lowest and 3 (e.g., most emotion-laden) being the highest.

Most of the verbal cues listed in Tables 2.1 and 2.2 have been discussed in detail in previous studies (e.g., see Zhou et al., 2003, for a review). Table 2.1 lists the definitions of verbal cues that are covered by the current study. The measurement process will be discussed in the next chapter.

Nonverbal cues include vocal and kinesic cues, as listed in Table 2.2. Currently the nonverbal cues are semi-manually coded and the details are introduced in the chapter of Method. However, it can be shown in the discussion section that they are extractable by existing techniques (Jensen et al., 2005; Mann, Vrij, & Bull, 2006).

Table 2.1 Verbal Micro Machine Cues

1. Average sentence length: (total # of words) divided by (total # of sentences)
2. Average word length: (total # of characters) divided by (total # of words)
3. Pausality: (total # of punctuation marks) divided by (total # of sentences)
4. Modifier: describes word or make the meaning of the word more specific. There are two parts of speech that are modifiers- adjectives and adverbs.
5. Passive voice: the form of a verb used when the subject is being acted upon rather than doing something.
6. Self references (singular first personal pronouns)
7. You-references (second-person singular or plural pronouns)
8. Group references (first personal plural pronouns)
9. Other reference (third personal pronouns)
10. Content word diversity: variety of words that express lexical meaning (total # of different content words) divided by (total # of content words)
11. Lexical diversity: (total # of different words) divided by (total # of words), which is the percentage of unique words in all words.
12. Redundancy: (total # of function words) divided by (total # of sentences), where function word is a word expressing a primarily grammatical relationship.
13. Specificity: sum of spatial and temporal details
14. Sensory: sensory experiences such as sounds, smells, physical sensations and visual details
15. Imagery: words that provide a clear mental picture
16. Pleasantness: positive or negative feelings associated with the emotional state.
17. Activation: the dynamics of emotional state

Table 2.2 Nonverbal Micro Machine Cues

1. Nonfluency: the frequency of disruptions in speech, including vocalized pauses ("ah," "um," "uh"), nonvocalized pauses and other forms of speech disturbances such as repetitive sounds, garbled speech, and stutters
2. Tempo: pace of speech, measured as the ratio of the number of words to the duration
3. Adaptor: cues often associate with nervousness, e.g., self-grooming, touching oneself, playing with hair, shift body balance back and forth, fidgety movement
4. Illustrator: movements that accompany speech and accent, emphasize, trace the rhythm of the speech. Functional hand and arm movements designed to modify and/or supplement what is being said verbally
5. Position shift (rigidness): the frequency of shifting position, the lack of position shift represent the rigidness status of the person
6. Shrug (total of head and shoulder shrug): the frequency of raising the shoulders or head as a gesture of doubt, disdain, or indifference.
7. Speaking nods: head movements during speaking turn
8. Back channel nods: affirmative head movements during listening

2.2.2 Macro Cues

The micro cues defined in 2.2.1 are not independent. In fact, many of them need to be combined as demonstrations of **the same** behavior meaning. The concept of aggregating micro cues has been demonstrated in Figure 1.1 and 1.2 in Chapter 1, where the level of cognitive loading in text messages can be objectively measured by the combined patterns of the pausality, content word diversity, and redundancy used in the message. Such commonality extracted from a set of related micro cues becomes the macro cues, which contain more meaning in their composite form than the micro cues.

The primary question is this: how to define related micro cues? In other words, the different micro cues that fell into the same categories should contribute to the measurement of higher-order and abstract behavior meanings that they have in common — meaning, macro cues. There are six macro cues investigated: verbal specificity/certainty, verbal immediacy/involvement, verbal arousal/cognitive load, nonverbal specificity/certainty, nonverbal immediacy/involvement, and nonverbal arousal/cognitive load.

Although there are six macro cues, there are actually two sets of similar concepts defined for the verbal and nonverbal channels, respectively. Therefore, it is sufficient to define specificity/certainty, immediacy/involvement, and arousal/cognitive load.

1. **Specificity / Certainty**: the strategy of conveying the message in a complete and clear manner. Higher certainty implies the information is veridical and that the sender is withholding nothing.
2. **Immediacy / Involvement**: the strategic performance to prevent leakage and detection. Immediacy concerns the degree of directness and intensity of interaction between communicator and the referred object and event. Involvement is strategic management of behavior engagement of the speaker in the communication. Deceivers strategically suppress and restrain behavior by applying nonimmediacy language and maintain sufficient involvement. Deceiver's behavior often disengages self from the message interlocutors, and lack of spontaneity.
3. **Arousal/Cognitive load**: The display of the cues that betray a heightened state of physiological arousal and the cues that reflect the complex cognitive factors involved in deception.

A set of related micro cues are categorized into the three subsets of macro cues, and the major task of the current study is to validate the categorizing of micro cues into the macro cues. The connections between micro and macro cues are referred to as the **relational models**.

Specifically, research question 1 studies the validity of the proposed relational models between micro and macro cues and offers a comparison of automatic extracted macro and micro cues:

Research Question 1.1: What are the relationships between the micro machine cues and the three macro cues of specificity/certainty, immediacy/involvement, and arousal/cognitive load? And research question 1.2: How do macro cues compare with micro cues in terms of detection classification?

Relational Models between Macro and Micro Cues

The relational models are further separated into verbal and nonverbal groups as shown in Figures 2.2 and 2.3, respectively.

Verbally speaking, the micro cues of modifiers, specificity, sensory details, and imagery are a form of measurement when someone manages information and decides how many details should be revealed. One common way of creating a deception is to withhold truthful information and abbreviate a risky interchange. Deceivers may do this by reducing the amount of specificity in content details (Bavelas, Black, Chovil, & Mullett, 1990; Hopper & Bell, 1984). Therefore, the cues of modifiers, specificity, sensory details, and imagery are measurements of the certainty or specificity of messages.

The reference usage is associated with immediacy. For example, the use of the self-reference is a subtle proclamation of one's ownership of a statement. Wiener and Mehrabian (1968) argued that liars should be more nonimmediate than truth-tellers and refer to themselves less often in their stories. Using a more passive voice also has the similar function of dissociating themselves from the contents (Zhou et al., 2003). Use of pleasant terms is associated with involvement, in that deceivers could strategically use more pleasantness in an effort to manage the information being given as well as their image.

The third category of verbal cues is associated with the cognitive complexity involved during communication. During communication, a deceiver is continually performing multiple tasks to convey deceptive ideas and yet still appear truthful. When the greater part of brainpower is used to convey a difficult lie, other behavior is less controllable and is therefore a potentially leaky clue of the deception. The complexity, diversity, and redundancy cues belong to this category. The leakage could also come from arousal, which contains the terms of activation. More precisely, arousal refers to the amount of physical and physiological activation experienced by the actor. Verbally, activation represented by language can be measured on a scale of 1 to 3 with 3 being the most activated status (Whissell, Fournier, Pelland, Weir, & Makarec, 2002).

Two hypotheses about the verbal micro cues can be posited as:

Hypothesis 1.1.1: The micro verbal cues are associated with the three macro verbal cues, as shown in Figure 2.2. Hypothesis 1.1.1 states there is a level of higher-order composite variables to represent the commonalities of the micro cues. In other words, the micro cues can be grouped into a macro level cue, and the existence of the grouping relationship between micro and macro cues can be statistically validated. Once hypothesis 1.1.1 is supported and there exists a validated relational model between micro and macro cues, the next question will be to investigate whether the relationship is positive or negative, which can be specified as the following:

Hypothesis 1.1.2: Specifically on the direction of the relationship,

increased verbal specificity/certainty is associated with:

(a) more modifiers, (b) more specificity terms, (c) more sensory terms, and (d) more imagery;

more verbal immediacy/involvement is associated with:

(e) less passive verbs, (f) more first person singular pronouns, (g) more you reference, (h) more third person pronouns, (i) less first person plural pronouns, and (j) more pleasantness terms;

and, More verbal cognitive load/activation is associated with:

(k) less content word diversity, (l) more pausality, (m) more redundancy, (n) less average word length, (o) more activation.

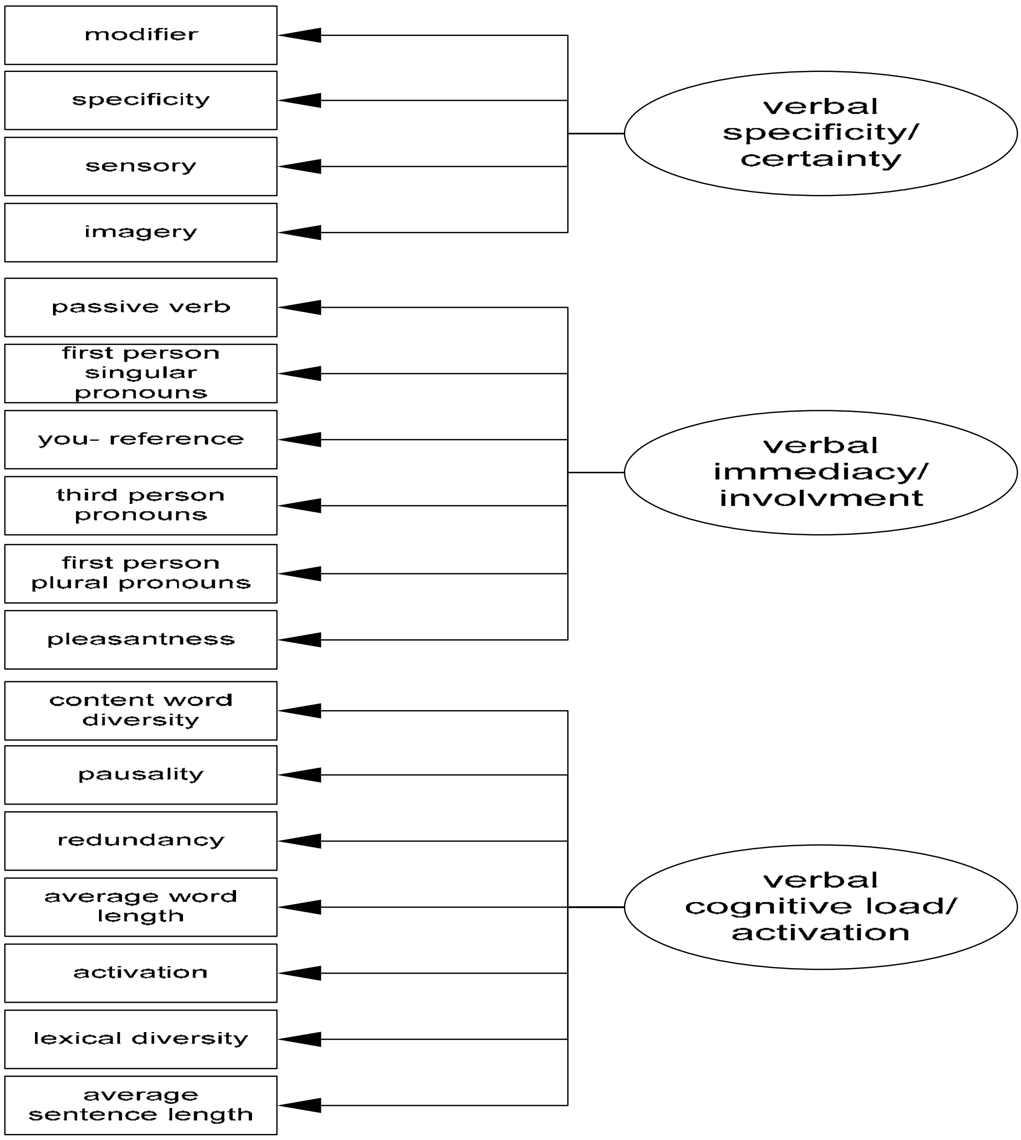


Figure 2.2 Relational Models of Verbal Macro and Micro Machine Cues

Similar to verbal cues, a relational model can be constructed between nonverbal macro and micro cues.

Speaking nods, illustrators, and shrugs are cues that are related to the certainty of information presented . According to DePaulo et al (2003), speaking nod is a cue showing certainty. Specifically, speaking nods represent a tendency to agree the comments and communication. One that nod more often tend to show certainty on the comments during the conversation. Secondly, the purpose of illustrators is to clarify by use of examples or comparisons, thus the more use of illustration implies that speakers tend to reduce ambiguity and represent themselves in a more certain way. The last but not the least, shrug belongs to the gestures displaying the doubt or indifference. In the meta research done by DePaulo and the colleagues, shrug is one of the cues in the uncertain category. Besides shrug, the other cues in the uncertain category are: tentative constructions, verbal and vocal uncertainty (impressions), amplitude, and chin raise (DePaulo et al, 2003).

Less involvement can be represented as rigidity (less position shift) while more back channel nods serve as a cue of more engaging (involvement) and help conversation flow naturally (DePaulo et al., 2003; Koper & Sahlman, 2001; Heilveil & Muehleman, 1981).

Vocal cues reflect the difference between deceivers and truth tellers with respect to memory processes and cognitive efforts (Vrij, 2000; Burgoon, Buller & Woodall, 1996). According to Vrij, the cognitively difficult tasks such as deception may produce overt indicators of speech distraction or slower tempo in speech utterance (Vrij, 2000; Vrij, et al, 2000). The nonfluency indicators include vocal pause, nonvocal pause, and other nonvocal pause. Vocal pauses such as “ah,” “um,” and “er” occur especially when the spoken content is complex (Berger, Karol, & Jordan, 1989; Christenfeld, 1994; Schachter et al., 1991). Nonvocal pause indicates state anxiety/activation, and the other nonvocal pauses are stuttering and omitting relevant words, indicating the cognitive overload (Kasl & Mahl, 1965; Mahl, 1987). Furthermore, adaptors and position shift could be indicators of an activated mood (Mehrabian, 1971).

Specifically, the hypotheses of the nonverbal relational model are:

Hypothesis 1.2.1: The micro nonverbal cues are associated with the three nonverbal macro cues, as shown in Figure 2.3.

Hypothesis 1.2.2: More specifically, **increased nonverbal specificity/certainty is associated with**

(a) speaking nods, (b) more illustrators, and (c) more shrugs;

More nonverbal immediacy/involvement is associated with:

(d) more back channel nods, (e) more position shift/less rigid;

and, **More nonverbal cognitive load/activation is associated with:**

(f) less tempo, (g) more nonfluency, (h) more adaptor, and (i) less position shift.

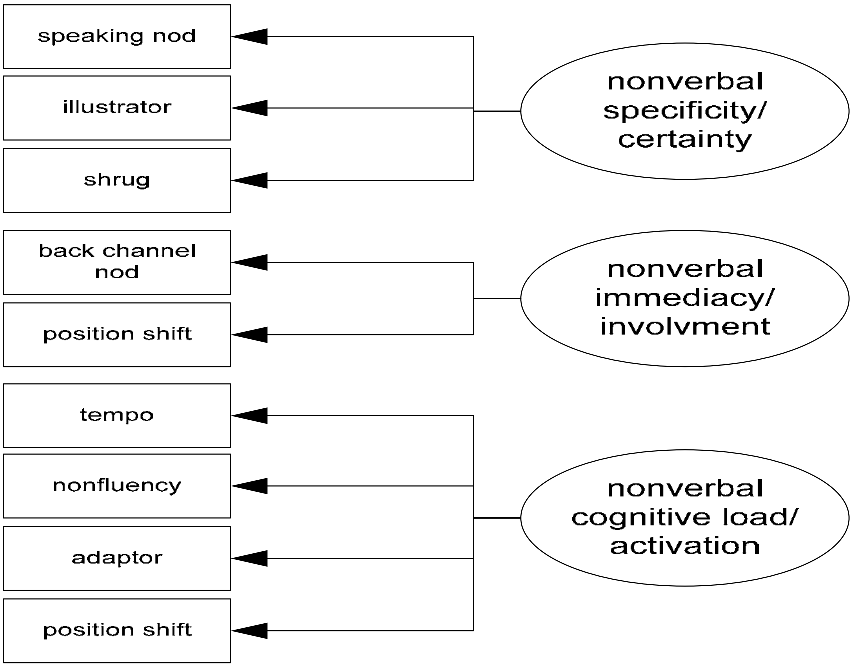


Figure 2.3 Relational Models of Nonverbal Macro and Micro Machine Cues

As will be shown in Chapter 3, the proposed relational models can be validated through a series of Confirmatory Factor Analyses (CFA). The macro cues can be automatically estimated from the regression of the factor scores.

Comparison between Macro and Micro Cues

From the perspective of system design, discussion of macro versus micro cues is mainly on the quality of the cues as the predictors for deception classification. Specifically, the criteria for selecting the cues include being able to answer these questions: do they encode sufficient information to represent meanings in behavior? How are they affected by behavior variability? Does the information they encode have enough distinguishing power to detect deception?

The distinction between the macro and micro cues is parallel to that between the distal cues and proximal percepts in the Brunswikian lens model (Brunswik, 1956; Scherer, 1978). Distal cues are concrete behaviors (e.g., words, tempo) that are ostensible and can be measured objectively. They are antecedent to and causally related to proximal percepts, which are abstract qualities (e.g., verbal immediacy) that encode the meanings or functional value of behaviors.

The current definitions of macro and micro are different from the notation of "micro and macro measurement" in the study of Burgoon and Baesler (1991). In the study "Choosing between Micro and Macro Nonverbal Measurement: Application to Select Vocalic and Kinesic Indices," Burgoon and Baesler define macro and micro according to the "amount of behavior that is to be present" (Burgoon & Baesler, 1991, p. 59). Specifically, the micro measurement is a microscopic unit of behavior: either event-based or time-based at very small intervals; and macro measurement is based on larger time intervals or events. For clarity, Burgoon and Baesler's "macro" and "micro" are denoted as molar and molecular measurement. It is possible that current micro cues can be measured at a molar level, which is their "macro" level. One such example is the number of words a person uses during the entire conversation. Word-number is a micro cue because it does not represent much behavior meaning. However, it is a molar measurement because it is based on a large conversation sampling. Thus, the key component of the current macro/micro definition is the encoded meanings rather than physical measurement unit.

Macro cues have the advantage for the ADDS. First, using macro cues as predictors potentially reduces behavior variability in the micro cues, thus improving the irreproducibility problem. Second, macro cues contain behavior meanings and thus are more interpretable in making and testing hypotheses. In this study, macro cues are applied in pinpointing abnormal behavior patterns.

However, micro cues could outperform macro cues in many ways. First, there is an inevitable risk that, during the aggregation process, some valuable information that is unique for particular micro cues is now masked in the corresponding macro cues. Therefore, it is possible that using macro cues could degrade the detection accuracy. Second, micro cues are simple and can be directly measured by machine. In fact, current techniques on automatic deception detection are based on micro cues.

Thus, a systematic comparison of macro and micro cues is necessary and critical. From the perspective of automatic deception detection, this study constructs a relational model between micro and macro cues, and investigates the method to **automatically estimate macro cues**. The focus is on investigating the quality of automatic macro and micro cues as predictors for ADDS.

2.2.3 Applying Macro Cues to Investigate the Adaptation Patterns of Deception and Truth

During the interaction process, deceivers adjust self-behavior according to feedback received from the listeners. When compared with truth tellers, it can clearly be seen that deceivers have different needs, expectations, and desires to appear truthful.

These different motives in deceivers imply that they may have different interaction patterns than truth tellers.

If the general patterns of truth and deception can be identified, a plausible method of detecting deception is to investigate the trend of an unknown behavior and see if it follows the truth or deception pattern.

In ADDS, the pattern comparison is difficult to perform with only micro cues, since patterns of micro cues are messy due to variability. In other words, even for two closely related micro cues (e.g., redundancy and average sentence length, which both represent the verbal cognitive load), the patterns could be significantly different. Fortunately, one critical application of automatic macro cues is to perform pattern comparison, because macro cues represent the common trends in the micro cues.

Specifically, the second research question is to compare the truth and deception patterns over time:

Research Question 2: Do the dynamic patterns of deceptive behavior differ from the patterns of truthful behavior?

The hypothesis is:

Hypothesis 2: Deceivers show different behavior patterns than truth tellers in terms of verbal and nonverbal specificity/certainty, immediacy/involvement, and cognitive load/activation.

2.3 Categorizing Cues into Strategic and Nonstrategic

Just as one cue can be categorized into macro or micro, it can also be categorized according to strategic or nonstrategic. Only now the theme of categorizing is not according to the intents contained, but whether the cue is easy to control by humans. Figure 2.4 demonstrates the two methods of categorization, where the horizontal level represents macro and micro and the vertical level represents the strategic and nonstrategic.

In the section 2.2.2, three macro cues were defined in both verbal and nonverbal cues: specificity/certainty, immediacy/involvement, and cognitive load/activation, and each group contained a set of related micro cues. The same set of macro cues and related micro cues can also be categorized according to strategic and nonstrategic.

First, the definition of specificity (and related micro cues) falls into the strategic cues. Specifically, the strategic activities happen when deceivers attempt to control the way they deceive by information, behavior, and image management. At the information and image management level, the tactics include introducing uncertainty and vagueness to the information being supplied, thereby distancing speakers from what is being said. At the behavior management level, the tactic is to disengage from the conversation and reduce involvement in the interaction. Therefore, specificity and immediacy are strategic cues that humans intentionally manipulate to strategically adjust self-behavior naturally over time or interactively in response to the interlocutor’s feedback.

Second, the cognitive load (and related micro cues) belongs to the nonstrategic category since it reflects the deceptive feature that Ekman and Friesen (1969) called "leakage" – inadvertent, often involuntary telltale signs of arousal (Zuckerman, et al., 1981; Buller & Burgoon, 1994, 1996). They are less controllable and represent an automatic, psychological reflection of the deception effect.

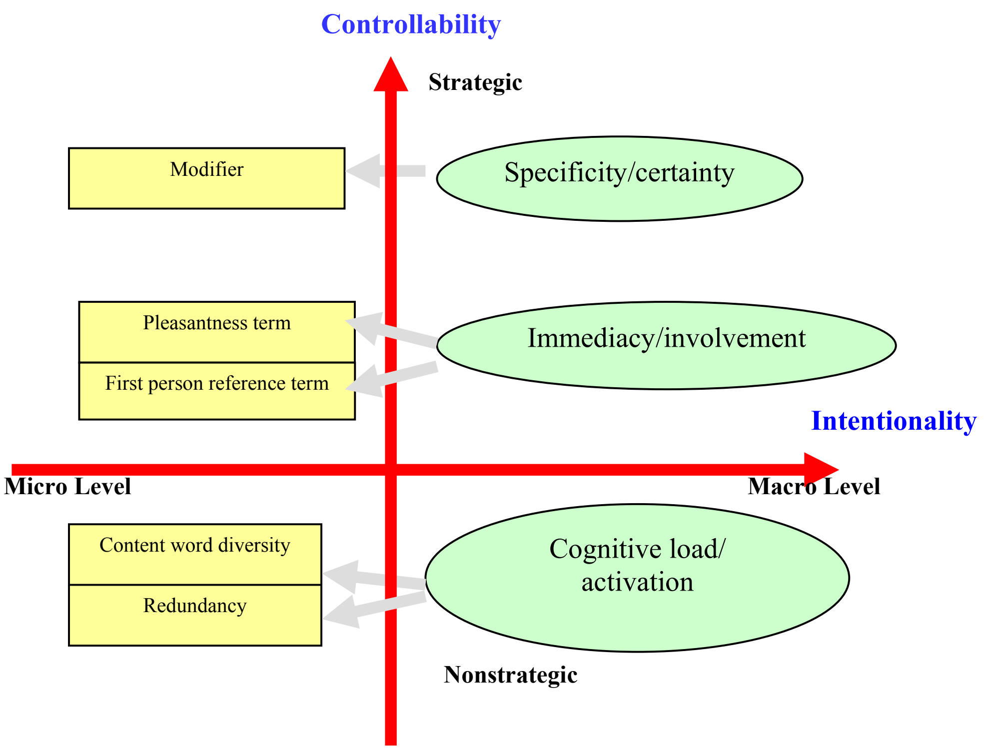


Figure 2.4 Comparing the Categories of Macro vs. Micro and Strategic vs. Nonstrategic

Consistent Predictors

In order to evaluate the cues in their performance of deception classification, discriminant analysis is chosen as a method of classification because it can handle the classification problem where the dependent variable is categorical data. Furthermore, discriminant analysis is similar to constructing the regression function, which uses the independent variables (cues) to predict the categorical dependent variable (deception or truth). Hence, a cue is statistically significant when its coefficient is significant in the regression function (also known as discriminant function). This study is part of the deception-related research that uses the significance of coefficients in regression functions to decide the statistical reliability of the cues in detecting deception (A similar method has been adopted previously; e.g., Kam, 2003). In this study, a **consistent** cue is one that is statistically significant in detecting deception in two separate time phases. Consequently, a consistent cue means it is significant in discriminant analysis in the two time phases.

This study categorizes cues into strategic and nonstrategic and posits that the two sets of cues should perform differently in terms of consistency. The research question is:

Research Question 3: Are the nonstrategic cues more reliable in detecting deception?

The strategic cues are the ones that deceivers show by constantly adjusting behavior during interaction. Such cues are expected to fluctuate frequently because deceivers constantly manipulate them to appear truthful. In some cases, when deceivers can sufficiently adjust their behavior, they manipulate the strategic cues to appear truthful. For example, when the deceivers are allowed to rehearse their lies, they create more specific details to present in their message (Zhou et al., 2003).

By contrast, nonstrategic cues are less controllable. The nonstrategic cues reflect the simultaneous and psychological effect following the deception intent. Therefore, it is reasonable to assume that the less controllable cues are the more stable ones for use in detecting deception than strategic ones. Zuckerman and Driver (1985) supported this hypothesis empirically in their comprehensive meta-analysis in seeking to identify reliable indicators. They found out that among 22 cues in visual, paralanguage, verbal, and general forms, the indices of pitch, speck errors, and speech hesitations are the most reliable cues in determining deceit. Interestingly, the three cues are related with the cognitive load/activation and in the less controllable vocal channel. A more recent example is the meta analysis done by DePaulo et al. (2003), where liars have been shown to be more preoccupied and more cognitively taxed than truth tellers. For example, the level of involvement in their words and in their voice shows discrepancies between deceivers and truth tellers. When social actors could not plan their presentations, the response latencies of deceivers were greater than those of truth tellers; and when presentations were sustained for greater lengths of time, liars' latencies to respond were grater. Overall for the general case of deception detection, the promising cues fall into the categories of cognitive load and involvement.

Specifically, the hypotheses for RQ3 which concerns the consistent cues can be listed as:

Hypothesis 3: (a) With other conditions being equal, for both verbal and nonverbal cues, the nonstrategic cues are more reliable than strategic ones in detecting deception. (b) the hypothesis in 3(a) also holds for the micro level cues.

Current study judge the consistency based on the controllability of the cues. In other words, the easier the cues be strategically manipulated, the more reliable the cues are. From this perspective, the degree of reliability of the three categories depends on the level of strategic in the cues. The specificity/certainty is relatively the most controllable (i.e., strategic) cues since they reflect the behaviors that deceivers strategically manage to modify the extent to which a message if complete, clear, relevant, veridical, and personal. On the contrary, cognitive load/arousal is the most nonstrategic is a display of cues which “inadvertently leak information about psychological process” (Burgoon, Buller, & Woodall, 1996, p435). The level of strategic of the category of immediacy/involvement lies in the some where between the other two categories.

Time (Cross-Section) Effects on Automatic Deception Detection

It is important to consider the dynamic effects on detection performance. In order to address the dynamic impact, two important dynamic components need to be considered (Burgoon & Qin, 2006): the communication-adjust process that happens in all forms of communication and the deception-adjust process that happens in deceivers. The communication-adjust process means the process of acclimating to the situation, the setting, the interlocutor, and so forth. For example, as people start to talk together and become more comfortable, they will probably increase their level of involvement. The deception-adjust behavior in deceivers refers to the fact that deceivers continuously adjust their performance according to responses received so as to maintain an innocent appearance.

The combined effect of communication-adjustments and deception-adjustments determines whether the beginning or the later phase is best for detecting deception. As shown in many cases, the self-adapting process happens in the early phase of communication when it will probably mask the deception effects (difference between T and D). In the later phase, however, when the self-adapting tends to be stable, it could be easier to identify deception if deceivers did not sufficiently adjust their behavior.

However, the opposite pattern might also be correct. It is possible that deceivers adapt their ways of communication in ongoing interactions to the extent that, eventually, they converge their communication toward that of truthful respondents. Under such situations, deceptive behavior becomes indistinguishable from truthful behavior. Hence, detecting deception would be less successful in the later phase than in the beginning.

The fourth question addresses this mixed effect:

Research Question 4: How does time affect the power to discriminate between truth and deception?

Specifically,

Hypothesis 4: The performance of deception detection is influenced by time.

Interlocutors' High Immediacy Effect on Automatic Deception Detection

The last research question is related to the effect of interlocutors' high immediacy effect on the performance of deception detection.

Deceivers are aware of the situational expectations and are inclined to follow the normal pattern of behavior. For example, the normal reaction of a speaker for the increased involvement in the interlocutor is to reciprocate and maintain the higher level of involvement. However, in a particular case of deception, deceivers could so busy in handling the contents of the conversation and suppress leakage that they do not react sufficiently and fail to maintain the involvement in the same level as a normal speaker (truth tellers) will perform otherwise, thus generating a discrepancy between deceivers and truth tellers.

From the perspective of ADDS, the greater the discrepancy, the easier for a system to detect. Furthermore, a more charming idea is how to manually control the factors such that the discrepancy would increase. This study considers the interlocutor's immediacy effect, and study the consequence to enacting a high immediacy condition on the deceptive behavior. Hence, the fifth research question is:

Research Question 5: How does an interlocutor's high immediacy affect the performance of deception detection?

Specifically,

Hypothesis 5: Detecting deception under high interlocutors' immediacy improves the deception detection performance.

CHAPTER 3

METHOD

3.1 Deception Interview Experiment

Participants

Age, experience, and personal character have been proved to affect deceptive behavior as well as deception judgment (Mann, Vrij, & Bull,2002, 2004; Goodman, Luten, Edelstein, & Ekman, 2006; Johnson, Barnacz, Yokkaichi, Rubio, Racioppi, Shackelford, Fisher, & Keenan, 2005). Naturally speaking, people who experience more cases of deception will attune to the patterns of truth and deceptive, and thus become better subjects for the purpose of experiment. A legitimate estimation of such experience is age. In current study, in stead of the traditional undergraduate students, 30 of the total (N=122) subjects were recruited from the nontraditional undergraduate students whose age was greater than 25. Further more, for a more realistic context setting and study the performance of people involved with real forensic contexts (Granhag & Stromwall, 2004), 90 subjects were solicited from a county courthouse. Differences of the student and nonstudent group were not considered.

Although sex differences were not considered as a factor in the present study, all participants in the study consisted of almost the same number of female and male. The sample consisted of 50.8% (n=62) females and 49.2% (n=60) males. In terms of the age and education distribution, 37% were age 19 to 30, 30% were age 30 to 40, and 33% were older than 40; 5% had high school education or less, 81% had (some) college education, and 14% had graduate level education. The student-participants received extra credit and other members recruited from courthouse were paid for their participation.

In order to situate the experiment under interactive contexts, participants were paired randomly to create 61 dyads. Subjects in one dyad interact with each other in the form of interviewing: one is assigned as interviewee and the other is interviewer. In order to avoid the differences in the dyads cause by same or cross sex pairing, almost then same number of cross- (n=32) and same- gender dyad (n=29, 15 were female-female) were formed.

Procedure

The experiment is a comprehensive one which investigate not only deceptions in dynamic and interactive contexts, but also record the individual social skills (emotional expressivity, emotional sensitivity, emotional control, social expressivity, social sensitivity, and social control) as well as the individuals communication attitude (trait suspicion scale and unwillingness to communicate scale) (Buller, Burgoon, White, & Ebesu, 1994; Burgoon, Buller, Ebesu, & Rockwell, 1994). A throughout investigation of the comprehensive experiment is valuable to understand relationships between individual difference and deception behavior. However, the current study is particularly interested in the macro and micro level cues and patterns during dynamic and interactive contexts. Therefore, the following description of experiment process will focus on the main body.

Those sections related to the assessment of individual characteristics are only briefly introduced.

The student participants signed up during class for designed time slots. The nonstudent participants were offered $10/hour for the assignment. The criteria of selection nonstudent participants include balancing the number of male and females and availability during certain time blocks. All participants were required to complete a pretest questionnaire and return the mail in sealed envelope to experimenter. The pretest questionnaire was designed to assess individual traits on three areas, consisted of the social skill inventory, trait suspicion scale and communication attitudes inventory, as well as the demographic information mostly for descriptive purposes: gender, age, race, ethnicity and education.

After arriving at the experiment site, participants were given a general overview of the project and signed consent forms. They were then randomly assigned the role of interviewee or interviewer, and then separated. Both will be told the main purpose of the interaction is to examine how people interact when discussing personal topics and that the interaction will be videotaped. They were separated and given different instructions.

Interviewers reviewed a list of 12 questions (on education, occupation, personal relationship and political attitudes) that they would be answering during the interview and then received the deception induction: They were told that their primary goal was to keep the interaction flowing and they should ask follow up questions and to continue to ask until they have fully understood their partners' answers. In addition, they were given instructions in low, normal or high immediacy. The immediacy could be in the way of proximity, facing, faze, bogy orientation, lean. Interviewers were told that people vary in the degree to which they disclose information about themselves. If they misrepresent, are ambiguous, conceal information on one question they are likely to do it on others. What is interested is how well the interacting process can detect when people are deceiving. Their task as interviewers was to determine whether the interviewee is deceiving on all, some, or none of the questions. During the interview, interviewers were told to provide two ratings at the end of each question period, 1 on how truthful they think the interviewee was and 1 on how confident they are of their assessment. The degree of truthfulness and confidence were ranked on 0 to 10 point scale. The continuous measurement strategies were used to obtain judgments because studies have shown that receivers are more sensitive to changes in the credibility of senders and messages when making continuous than dichotomous rating (Burgoon et al., 1996). Interviewers also required to fill in questionnaire to evaluate interviewee’s immediacy, pleasantness, composure, formality and dominance. Interviewers were informed that the interviewees would be simultaneously assessing their own performance as interviewees and will be led to believe that interviewers are merely also rating their own communication ability.

Interviewees were required to alternate between truthful and deceptive responses to the 12 questions, which form four blocks—three questions each. Interviewees alternated between truth (T) and deception (D) answers throughout blocks following one of two orders: TDTD or DTDT. In other words, each block included all truthful or all deceptive responses so that three D questions followed three T questions or vice versa. Questions on which they were to be lie were starred on the answer sheets. During the interview, the interviewees were asked to provide two ratings at the end of each question period, 1 on how truthful they were and 1 on how successful they think they were in getting the interviewer to believe them. They were also requested to answer questionnaire for assessing interviewer's immediacy, dominance, composure, pleasantness, and formality. They were told that interviewers were merely also rating their own communication ability.

Interviewers and interviewees were ushered into the interaction room, given their respective rating forms on clip boards and told to keep the clipboards on the floor during the actual conversation.

Interactions were videotaped and continue until all 12 questions have been answered. In current setting, each interview takes approximately 15 minutes. The transcription and the videotapes were later decoded to extract verbal and nonverbal cues. The assessment of truthfulness level and confidence level were used to study the human heuristic effect and deception judgment, and compare human performance with machine.

3.2 Independent Measurement

Truthful and Deception Condition

The first independent measurement is the interviewee's truthful or deception condition of answering. Because of the special design of experiment, interviewees start with truth or deception and alternately between the two conditions. Unlike the interviewer's immediacy, the truth/deception condition has both within- and between-subject effects. For the purpose of clearly identify dynamic effect and condition effect, this study considers the truth/deception condition effect with between-subject analysis.

One group is deceivers and the other is truthful tellers. In other words, only block 1 and block 3 are studied so that there are half of the subjects deceive all the time (D group), comparing with the other half that speak truth (T group). In other words, the T group is serving as the norm for detecting deceit.

Time Effect

The time effect considered in this study is actually the block effect. Because only 2 blocks are considered, they are also referred to as block 1 and 2. Block 1 is the starting phase and block 2 happens later. Therefore, it is the cross section analysis instead of time series analyses performed to evaluate dynamic effect. Current study follows the method used in previous study to evaluate dynamic effect through cross section analysis (Burgoon, & Qin, 2006). Furthermore, since the sequence effect is out of scope of current discussion, the two blocks where the deception and truth switch orders are left out (for detail reviews, see Burgoon and Qin, 2006).

Interviewer's immediacy

The third independent measurement is interviewers' immediacy which is measured in three levels: low, medium and high. Interviewers were told to manipulate level of immediacy by adjusting behaviors such as lean toward/away, eye contact, etc.

3.3 Dependent Measurement

The dependent measurements are the micro verbal and nonverbal cues, and macro level cues estimated with latent variable scores from confirmatory factor analysis.

Machine micro level cues are the basic analysis unit of automatic deception detection. The current extraction prototype completely automatically extract verbal cues, and semi-automatically extract nonverbal cues. The extraction process is described as following:

Verbal Micro Cues

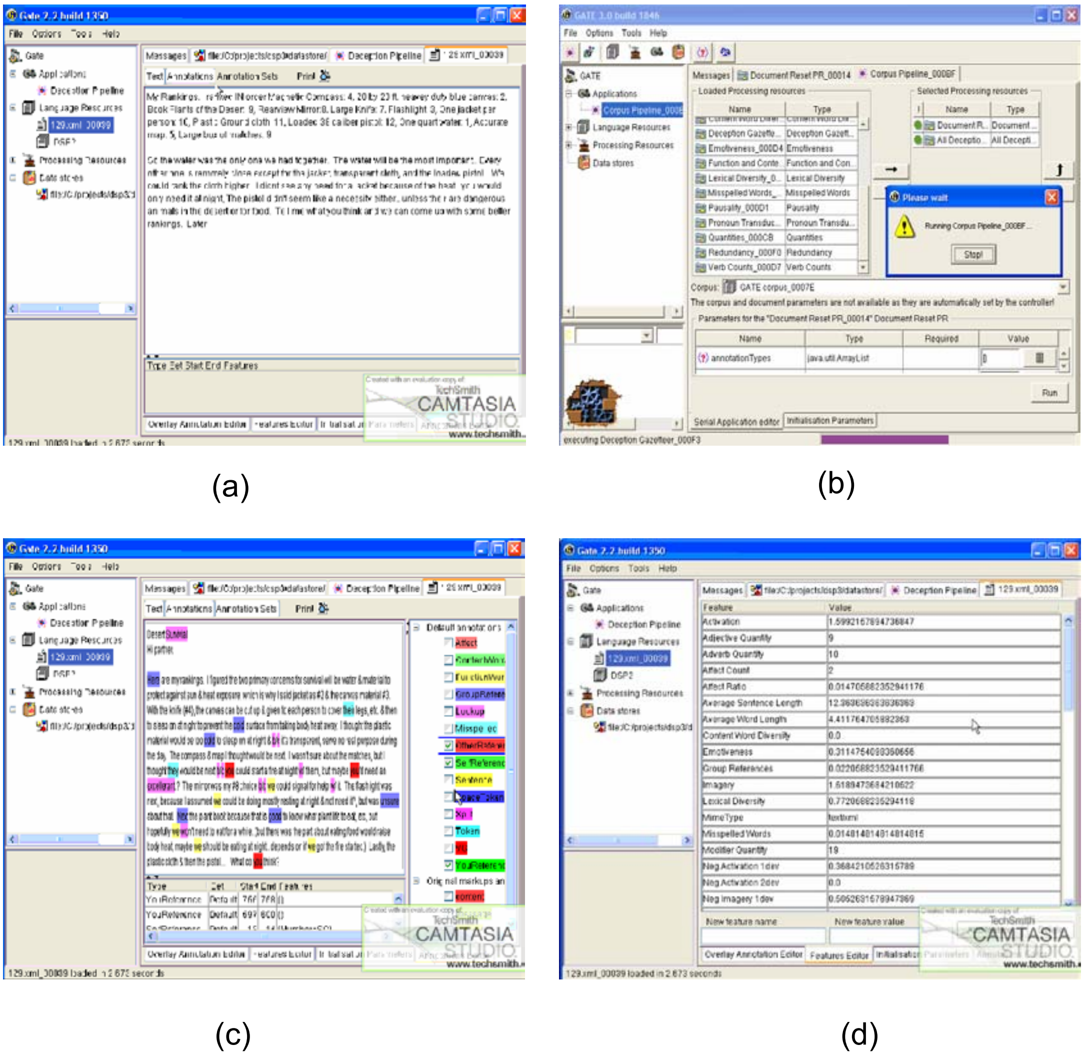
According to previous review, there are 17 verbal micro cues:

1. Average sentence length: (total # of words) divided by (total # of sentences)
2. Average word length: (total # of characters) divided by (total # of words)
3. Pausality: (total # of punctuation marks) divided by (total # of sentences)
4. Modifier: describes word or make the meaning of the word more specific. There are two parts of speech that are modifiers- adjectives and adverbs.
5. Passive voice: the form of a verb used when the subject is being acted upon rather than doing something.
6. Self references (singular first personal pronoun)
7. You-references
8. Group references (first personal plural pronoun)
9. Other reference (third personal pronoun).
10. Content word diversity: (total # of different content words) divided by (total # of content words), where content word primarily expresses lexical meaning.
11. Lexical diversity: (total # of different words) divided by (total # of words), which is the percentage of unique words in all words.

12. Redundancy: (total # of function words) divided by (total # of sentences), where function word is a word expressing a primarily grammatical relationship.
13. Specificity: sum of spatial and temporal details
14. Sensory: sensory experiences such as sounds, smells, physical sensations and visual details
15. Imagery: words that provide a clear mental picture
16. Pleasantness: positive or negative feelings associated with the emotional state.
17. Activation: the dynamics of emotional state

Before automatic extraction process, the interviewee's statements were transcribed into text format by paid coders. The text statements are later process by a modified natural language processing (NLP) tool. NLP analyzes language by sub-sentential, sentential and discourse processing. The sub-sentential process can be further defined in phonological analysis, morphological analysis, syntactic parsing, and semantic analysis. The morphological analysis determine the part-of-speech in the sentence, the syntactic parsing decides the structure of a sentence following syntactic grammar. Semantic analysis of current techniques may produce many ambiguities, therefore not covered in current study. A shallow parsing has been tested to provide good results in practice. During shallow parsing, some phrasal constituents are identified and cues can be calculated from the constituents.

In the current investigation, a shallow parser—General Architecture for Text Extraction for parsing (Bontcheva, Cuningham & Tablan, 2002)—is applied to identify components of language. For some semantic cues such as pleasantness terms, a plug-in dictionary is used to look up words. The dictionary— Whissell dictionary— collects more than 8,000 words with scaled values for affect-related indicators (Whissell, 2001). Figure 3.1 demonstrates the extracting process.



(a) (b) (c) (d)

Figure 3.1 The Extracting Process Using GATE

Shown in the figure, a testing text message is first input into GATE, as in (a). Then a cope line is constructed between the message and the cues program, as in (b), the message is scanned and the cues are being calculated. In Figure (c) the cues are identified and can be seen marked in the interface. Finally in figure (c), the cues can be output into a text file and ready for further analysis.

After text based messages are processed by GATE, the output excel file contains the verbal cues and ready for further analysis.

Nonverbal Micro Cues

As listed below, the nonverbal cues are in either vocal or gesture format:

1. Nonfluency
2. Tempo
3. Adaptors
4. Illustrators
5. Position shift percentage
6. Back channel nods percentage
7. Speaking nods percentage
8. Shoulder and head shrug percentage

The cues are referred to as minor level cues because they bear a small amount of meanings of behavior. But they are also known as “machine” coded ones in the study even though the data were mainly coded by human. One reason is that great potentials have been seen in other studies that they are highly automatically extractable (Auto id and other projects). In the discussion section, the automatic extraction methods and related results will be discussed to show how these nonverbal cues are extracted by machine.

Before the automatic techniques are sufficiently tested and become routine, it is still more reliable for human coder to extract the cues. Further more, with the assistance of a program call Coaching Behavior Assessment System (CBAS; Smith, Smoll, & Hunt, 1977), the coding process is fast and efficient especially for the small sample exploratory study. The extraction process is described as following:

The Coaching Behavior Assessment System (Smith, Smoll, & Hunt, 1977) was designed as an observational measure to use during practices and games. During process of observation (games or videos), coders can recode certain actor's behaviors by pressing down a predefined key when the action begins and release the key when it ends. The system was modified for this study to recode the nonverbal cues during communication. The coders received trainings of definition of the cues. Furthermore, two or more coders were assigned to code the same cues to ensure reliability.

The duration based vocal cues—talking and turn switch time—were recoded as latencies of such behavior. But in order to filter out the general duration effect that long interviews section have longer talk time and silence time, the two cues were standardized by dividing the total interviewing duration. Hence the unit of the talking time and turn switch silence time is duration percentage. The vocal pause, nonvocal pause and other nonvocal pause were recoded as the number of occurrences of such events.

For recoding of adaptors and illustrators, coders were requested to code separately for left hand and right hand behavior. For example, coders press the key “r” and “u” for the left and right hand illustrators, respectively. And release when the behavior stops. The left hand and right hand behaviors were later summed to form the general kinesics’ cues of “adaptor” and “illustrator”. Data were originally recorded in frames (1 sec = 30 frames), and then standardized by dividing the total frames of the interview section. Hence, the measurement unit of the six gesture cues becomes frame percentage.

Macro Cues Estimation

As discussed earlier, three macro cues are hypothesis to represent global dimension of specificity/certainty, cognitive load/activation, and immediacy/involvement. Each dimension consists of a set of micro level cues. Because of the channel differences, it is reliable to defined the macro cues for both verbal and nonverbal cues. In other words, there are 6 macro cues that are estimated by machine:

1. Verbal specificity/certainty
2. Verbal cognitive load/activation
3. Verbal immediacy/involvement
4. Nonverbal specificity/certainty
5. Nonverbal cognitive load/activation
6. Nonverbal immediacy/involvement

In hypothesis 1, two relational models are defined where the micro cues are expected to associate with a macro cues. Unlike the micro cues, the macro cues are not directly observable. They are also referred to as the latent variables.

Task in this section is to estimate the macro cues, and then evaluate whether the estimated macro cues are related to the micro ones as in the predefined model. This task is similar with factor analysis where one factor score is assigned to some closely related observed variables. Thus, the regular factor analysis does not specify the relationship between the factors and the predicted variables. However, current study required the factors must be estimated from the observed cues according to some prediction relationships.

According to the requirements, the method of Confirmatory Factor Analysis (CFA) were chosen to evaluate the predefined relationship between observed and latent variables and estimate the latent variables.

CFA is a special case of factor analysis to study how well the observation variables can be explained by a smaller number of factors. CFA have similarity and difference with the most familiar factor analysis using principle component analysis (Exploratory factor analysis, or EFA). EFA exploratory discover simple patterns in the relationship among the variables and see whether a small number of factors can explain largely or entirely of the observed variables. These representative factors are also referred to as the latent variables/structures/dimensions. Similar with EFA, CFA also belongs to factor analysis whose purpose is to uncover the latent structure of a set of variable by reducing attribute space to a smaller set, and to study the contribution of each attributes to the latent variables. But unlike EFA, CFA seeks to determine if the number of factors and the loadings of measured (indicator) variables on them conform to what is expected on the basis of pre-establish decisions. In other words, CFA is appropriate when the researcher posit expectations about which variables will load on which factors (Kim and Mueller, 1978b:55).

A path diagram is better to demonstrate with a path diagram in which squares represent observed variables and circles represent the latent concepts. A standard cause-effect representation can demonstrate in single headed arrows, and covariance between two latent variables can be represented with double-headed arrows, as shown in the following figure (http://www.indiana.edu/~statmath/stat/all/cfa/cfa1.html).

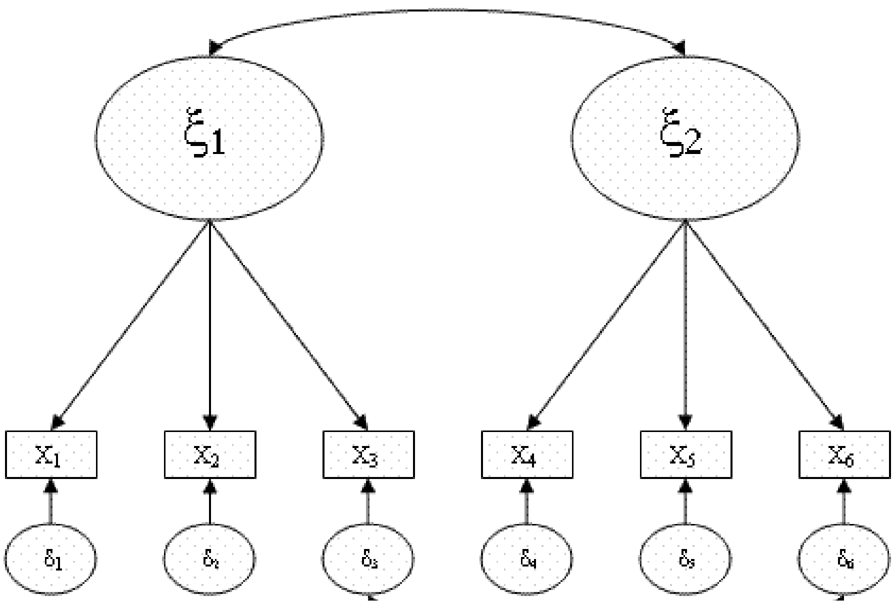


Figure 3.2. A Path Diagram for Illustrating CFA Modeling

shows a simple CFA scenario which contains two latent factors, and each containing three observation variables. Specifically, the two ξ (ksi) denotes the two latent variables.

Demonstrated within current context, each of the latent variable, ξ, represents one machine macro level dimensions. And each of the observation variables X represents the micro level cues such as talking time, number of words, etc. The circles labeled δ (delta) represent the measurement errors of observed variables. In factor analysis, it is always assume that latent variables and the measurement error cause the presentation of the observation variables. As shown in the figure that the single arrows are pointed from ξ and δ.

Shown in the figure, it is also assumed that the two latent variables are correlated, denoted with a double-headed arrows. Taken in current contexts, it is to assume that the verbal uncertainty is correlated with verbal immediacy.

The estimation of CFA is based on the following equation:

$$\mathbf{\Sigma} = \Lambda \Phi \Lambda' + \Theta$$

Where the $\mathbf{\Sigma}$ is the covariance matrix of x; where Φ represents the covariance matrix of the $\boldsymbol{\xi}$ factors and Θ represents the covariance matrix of $\boldsymbol{\delta}$ (Bollen, 1989, pg. 236). Estimation proceeds by finding the parameters $\hat{\boldsymbol{\Lambda}}$, $\hat{\boldsymbol{\Phi}}$, and $\hat{\boldsymbol{\Theta}}$whose predicted $\hat{\boldsymbol{\Sigma}}$ is as close to the sample $\mathbf{x}$ covariance matrix as possible. The maximum likelihood is a standard fitting functions to determine parameters and fit the model.

The technique to perform CFA is through Structural Equation Modeling (SEM, see Rex B. Kline for a detail review). SEM is a similar, but much more powerful technique of multiple regression. Unlike the general regression, SEM is capable to answer a set of interrelated research questions in a single, systematic, and comprehensive analysis by modeling the relationships among multiple independent and dependent constructs simultaneously, while the most first generation regression models such linear regression, LOGIT, and MONOVA can analyze only one level of linkage between independent and dependent variables at a time (Bollen, 1989). In other words, SEM is capable to generate a layer of latent variables, if needed, to capture the complicated cause-effect relationship between dependent and independent variables.

```
The code for CFA for verbal macro cues

System file from File
'C:\research_name\EXP5_8_22\CFA\computescore\vb1try.DSF'
Latent Variables:  vb1cog vb1unc vb1imd
Relationships
s1img s1modi s1spec s1senra = vb1unc
s1convd s1redun s1pau s1act s1awl= vb1cog
s1pvrat s1self s1you s1other s1goup s1plsan = vb1imd
PSFFile
'C:\research_name\EXP5_8_22\CFA\computescore\vb1try.psf'
LISREL output: AD = OFF FS
Path Diagram
End of Problem
```

Among the three popular statistical packages for doing SEM—LISREL, AMOS, and EQA, LISREL is the most common tools used for IS research (Gefen, Straub, & Boudreau, 2000). Current analysis uses LISREL in performing the CFA. The sample code for predicting verbal uncertainty is as following:

As shown in the sample code, the structural of relationships between latent variables (verbal cognitive load, verbal certainty, and verbal immediacy) and observation variables (micro level verbal cues) are predefined in the syntax.

The machine macro level cues are estimated by latent variable score, which can be generated automatically from the syntax:

PSFFile 'C:\research_name\EXP5_8_22\CFA\computescore\vb1try.psf'.

The automatic estimated latent variables have been standardized such that the mean is 0 and 2/3 of the data is within the range [-1, 1].

Furthermore, the latent variable can also be estimated from the weighted linear combination of the observed variable, where the weighted scores is the Ksi matrix obtained from the CFA. This method is valuable to estimate the latent variables for a new single observation.

CHAPTER 4

RESULT

4.1 Manipulation Checks

Interviewers' immediacy

In order to check whether interviewers follow the requirement of manipulation check, one General Linear Model (GLM) analysis is applied on each of the six interview sections, with the dependent variable is the interviewee's rating (of interviewers' immediacy) and the independent variable is the assignment of immediacy level that the interviewer need to follow. For simplicity, the interviewer's immediacy is denoted as "ERIMD", and has three values— low, medium and high. The results of GLM tests confirmed that the interviewers have manipulated the interview immediacy as required by the experiment instructions. Specifically, the GLM results showed that all tests on ERIMD are significant for all six interview sections, with $36.327 \le F(2, 57) \le 69.618$, and all p-values <0.0001. Furthermore, a series of pairwise comparisons show that the actual ERIMD has significant difference based on the experiment assignment, for example, the interviews who were assigned high immediacy were actually observed to have more immediacy than those who assigned medium or low ERIMD. Table 4.1 shows the results of the pairwise comparison.

Table 4.1 Pairwise Comparison of Observed Interviewer's Immediacy on Different ERIMD Values

Observed Interviewer Immediacy (Block1)	(I) erimmed	(J) erimmed	Mean Difference (I-J)	Std.	T-value	P-value
	low	mid	-0.975	0.287	-3.399	0.001
		high	-2.397	0.287	-8.360	<.0001
	mid	low	0.975	0.287	3.399	0.001
		high	-1.423	0.279	-5.090	<.0001
	high	low	2.397	0.287	8.360	<.0001
Question 1		mid	1.423	0.279	5.090	<.0001
	low	mid	-1.192	0.286	-4.170	<.0001
		high	-2.930	0.286	-10.251	<.0001
	mid	low	1.192	0.286	4.170	<.0001
		high	-1.738	0.279	-6.238	<.0001
	high	low	2.930	0.286	10.251	<.0001
Question 2		mid	1.738	0.279	6.238	<.0001
	low	mid	-1.382	0.260	-5.315	<.0001
		high	-3.096	0.260	-11.908	<.0001
	mid	low	1.382	0.260	5.315	<.0001
		high	-1.714	0.253	-6.765	<.0001
	high	low	3.096	0.260	11.908	<.0001
Question 3		mid	1.714	0.253	6.765	<.0001
Observed Interviewer Immediacy (Block2)	(I) erimmed	(J) erimmed	Mean Difference (I-J)	Std.	T-value	P-value
	low	mid	-1.784	0.295	-6.044	<.0001
		high	-3.534	0.295	-11.975	<.0001
	mid	low	1.784	0.295	6.044	<.0001
		high	-1.750	0.288	-6.085	<.0001
	high	low	3.534	0.295	11.975	<.0001
Question 1		mid	1.750	0.288	6.085	<.0001
	low	mid	-1.815	0.304	-5.975	<.0001
		high	-3.529	0.304	-11.618	<.0001
	mid	low	1.815	0.304	5.975	<.0001
		high	-1.714	0.296	-5.789	<.0001
	high	low	3.529	0.304	11.618	<.0001
Question 2		mid	1.714	0.296	5.789	<.0001
	low	mid	-1.837	0.300	-6.127	<.0001
		high	-3.580	0.303	-11.800	<.0001
	mid	low	1.837	0.300	6.127	<.0001
		high	-1.743	0.296	-5.890	<.0001
	high	low	3.580	0.303	11.800	<.0001
Question 3		mid	1.743	0.296	5.890	<.0001

The table shows that interviewer's immediacy is the highest when ERIMD is high and the lowest when ERIMD is low. All tests are significant, thus it can be concluded that the manipulation of interviewer's immediacy were sufficient.

Truth and Deception

Truthtellers' and deceivers' ratings of their self-enacted truth or deception, respectively, confirmed that the truth/deception manipulation was indeed successful. For the six interview sections, 91.817 <= F(1, 56) <= 198.763, all significant p-value (<0.0001). Table 4.2 shows the pairwise comparison for each section (question). Results confirmed that the manipulation of deception and truth was successful.

Table 4.2 Pairwise Comparison between Truth tellers and Deceivers

		Mean Difference Truth-Deception	Std. Error	T-value	P-value
Block 1	Question 1	6.659	0.695	9.581	<0.0001
	Question 2	7.222	0.647	11.162	<0.0001
	Question 3	6.74	0.478	14.100	<0.0001
Block 2	Question 1	6.388	0.733	8.715	<0.0001
	Question 2	6.786	0.511	13.280	<0.0001
	Question 3	7.577	0.667	11.360	<0.0001

4.2 Preliminary Analysis

A preliminary analysis is important for the following analysis. The purpose is to "clean" the data by filtering out redundant information. Data cleaning is a standard process before performing major analysis. Furthermore, in one of the previous study, Qin and colleagues have proved cleaning the data was valuable for classifying deception (Qin et.al., 2003). Specifically, Qin found out that, when two or more variables are highly correlated (such as word and verb counts), keeping only one of the data can significantly improve classification accuracy.

Deleting redundant variables is even more meaningful in current experiment analysis where the sample size is small, but the redundant variables consume degree of freedom without providing useful information. Hence using the redundancy variables increases the risk of rejecting significant hypothesis, i.e., the type II error.

An effective way to relieve redundancy is through Pearson Correlation Coefficient tests (Qin et al., 2003). Specifically if the correlation is significantly high within two variables, only one should be kept. Table 4.3 is a list of highly correlated variables. In this study, the threshold value of correlation is 0.85, i.e., the two variables are considered strongly correlated when the Pearson Correlation Coefficient is greater than 0.85. The choice of the threshold is based on the empirical study done by Qin and the colleagues (2003) where two cues are considered redundant when the correlation is greater than .85, in which case one of two cues was deleted. According to the study, getting rid of redundant cues significantly improved the deception detection rate (Qin et al, 2003).

Table 4.3 Pearson Correlation Coefficient of Highly Correlated Variables

Kept Variable	**Deleted Variable**	**Block 1**	**Block 2**
Content word diversity	Lexical diversity	0.916**	0.865**
Redundancy	Average sentence length	0.951**	0.908**

**: Significant at 0.01 level.

As shown in table 4.3, two pairs of variables are strongly significantly correlated in both block 1 and 2 ($p<0.01$). The first pair is content word diversity and lexical diversity. Specifically, content word diversity is the number of different content words divided by the total number of content words, while content words are words with lexical meanings. Therefore, content words are similar to the lexical words, thus the two diversity measurements are highly related. The other related pair is redundancy and average sentence length. In order to reduce redundancy, the lexical diversity and average sentence length were deleted in the following analyses.

4.3 Test the Relational Model between Macro and Micro Cues

The first research question (RQ1) is to validate the relational model between minor and macro cues, as shown in the two hypotheses H1.1 and H1.2. After the preliminary analysis, the refined relational models are displayed in figure 4.1 and 4.2, where the redundant variables were deleted.

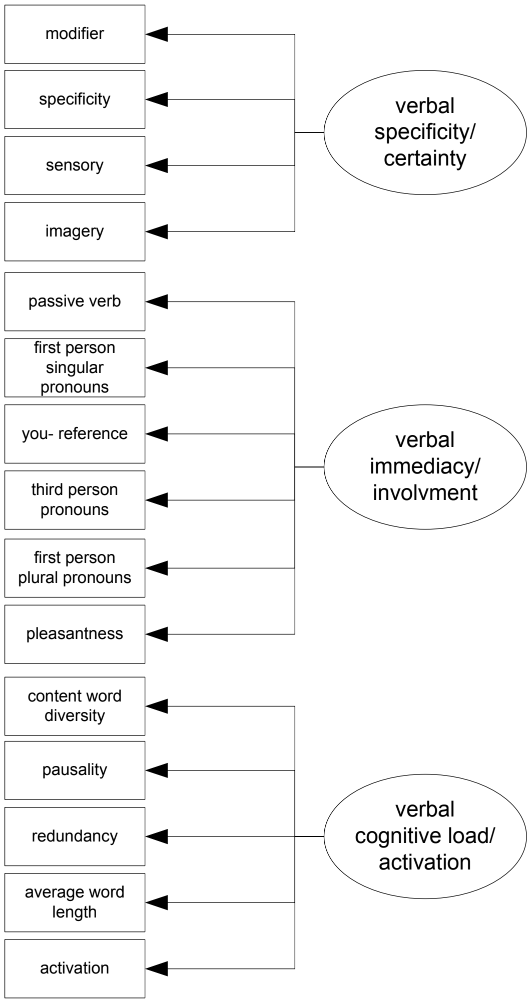


Figure 4.1 The Relational Model between Verbal Macro and Micro Cues

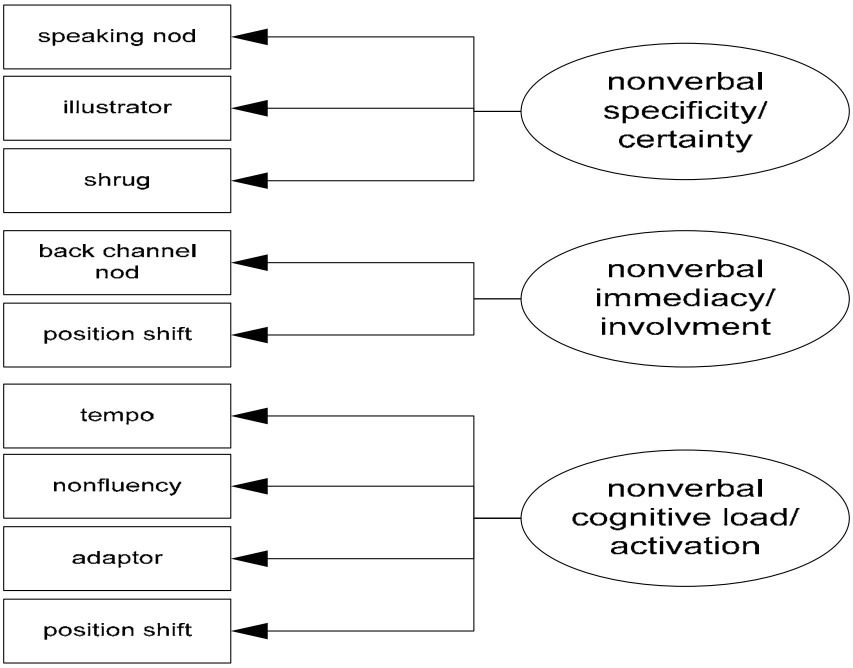


Figure 4.2 The Relational Model between Nonverbal Macro and Micro Cues

A series of Confirmatory Factor Analysis (CFA) were performed to validate the claimed relationship between the macro and micro cues, where Hypothesis 1.1 and Hypothesis 1.2 discuss verbal and nonverbal cues, respectively.

The Verbal Relational Model

Hypothesis 1.1.1 proposes a relational model between verbal macro level and micro level cues and states that the model is consistent in both time blocks. In order to test H1.1.1, two CFAs are performed, one for each time block. In block 1, the test yields a χ^2 = 186.43, df = 87. The ratio of χ^2 to the degree of freedom equal to 2.14 (<3), hence supporting H1.1.1.

In order to address the small sample tests as in current study, a modified model goodness-of-fit criterion—the ratio of χ^2 to the degree of freedom—is used in stead of the general criterion of a nonsignificant χ^2 value (Jöreskog & Sörbom, 1989). The modification of criterion is necessary because χ^2 is very sensitive to large sample size (>150) and the power of the test (Jöreskog & Sörbom, 1989). A commonly acceptable criterion for the small sample test is to report the ratio of χ^2 to the degree of freedom (Hair, et al., 1998). Specifically in the studies of Information Systems (IS) area, researchers have confirmed that a reasonable goodness-of-fit criterion for CFA is the ratio of χ^2 to degrees of freedom is smaller than 3:1 (Chin & Todd, 1995; Gefen, Straub, & Boudreau, 2000).

Using the modified goodness-of-fit criterion, the ratio of χ^2 to the degree of freedom equal to 2.14 and 1.81 for CFA tests conducted for block 1 and 3, and both ratio is less than 3. Hence H1.1.1 and H1.2.1 are supported and the relational models are empirically validated for this study.

Hypothesis 1.1.2 specifies the directions of relationships between macro and micro verbal cues. This hypothesis is tested from the loading coefficients generated by CFA, as shown in table 4.4. The loading coefficients (the Lambda-x matrix) specify the relationships between macro and micro cues: first, the higher the absolute value in the loading coefficient of one micro cue means the micro cue contributes more in the construction of the macro cue; second, the positive (or negative) sign of the coefficient means that the micro cue is positively (or negatively) associated with the corresponding macro cue. Most loading coefficients are significant at the 0.05 level based on t-values.

Furthermore, the loading coefficients tests on block 1 and 2 are similar, implying that the relational model is consistent in two different time blocks.

Table 4.4 Factor Loading Coefficient of Verbal Macro on Micro Cues

Verbal Cue	Block 1			Block 2		
	Speci-ficity/ Certainty	Imme-diacy/ Invol-vement	Cognitive load/ Activation	Speci-ficity/ Certainty	Imme diacy/ Invol-vement	Cognitive load/ activation
Modifier	24.63*			42.48*		
Sensory	0.01*			0.01*		
Specificity	0.01*			0.01*		
Imagery	0.02*			0.02*		
Passive verb		<0.0001			<0.0001	
First person singular pronouns		0.01*			0.01*	
You reference		<0.0001			<0.0001	
First person plural pronouns		<0.0001			<0.0001	
Third person pronouns		<0.0001			<0.0001	
Pleasantness		-0.03*			-0.04*	
Pausality			1.93*			2.05*

Average word length			0.05*			0.07*
Content word diversity			-0.01*			-0.01*
Redundancy			2.72*			2.5*
Activation			-0.01*			-0.01*

*: Significant in 0.05 level

Table 4.4 confirmed most of the hypothesis 1.1.2. Because the situations in block 2 are similar to block 1, only block 1 on the left part of the table are demonstrated.

Specifically, for the verbal specificity/certainty, H1.1.2(a),(b),(c) and (d) are supported because all the loading coefficients are positive. In other words, more verbal specificity/certainty is associated with more number of modifiers, sensory terms, specificity, and imagery terms.

Furthermore, the number-of-modifier shows a dominant loading factor in the macro cue of specificity/certainty than other cues in the same category: sensory, specificity and imagery terms. The empirical result implies the characteristics of the specificity/certainty are highly biased towards that of the number-of-modifiers. Therefore the effectiveness of the macro cue as predictor to detect deception is also highly influenced by the effectiveness of this single micro cues, generating a potential lack of fairness when using the macro cues. However, conclusions can not be made based on results of single experimental study; future research is needed to investigate the construct of the macro cues.

For the verbal immediacy dimension, results are mixed. H1.1.2(f) on self person singular pronounss are supported: more immediacy is associated with more use of self reference. However, H1.1.2(j) is not supported, implying that people who show more immediacy verbally tend to use fewer pleasantness terms.

However, nonsignificant tests are also seen on relationships between macro and micro cues of verbal immediacy. The nonsignificant hypotheses include H1.1.2(e) on passive verbs, H1.1.2(g) on you-reference, H1.1.2(h) on third person pronouns, and H1.1.2(i) on first person plural pronouns. For all of the four cases, the loading coefficients are less than .001 and thus imply a weak association between these micro cues and the corresponding macro cue. However, a close look at the variables reveals that the weak association is possibly caused by the fact that most of the values in the four variables are 0's. Hence, this current study does not have sufficient non-zero variables for testing hypotheses H1.1.2 (e)(g)(h), and (i).

The relational models on verbal cognitive and the micro cues are partially supported by empirical data. Specifically, H1.1.2 (l), (m), and (k) are consistent with the results. More cognitive load is associated with more pausality, redundancy, and less diversity of content words. Unexpectedly, H1.1.2 (n) and (o) are not supported. Higher cognitive load is associated with longer words, and less activation term.

The Nonverbal Relational Model

As expected, H1.2.1 on the relational models of nonverbal macro and micro cues are strongly supported. For block 1, the χ_2 = 22.52, degree of freedom = 16, the ratio of χ_2 to the degree of freedom = 1.4 < 3, RMSEA = 0.085. Further more, even for this small sample test, result yields an nonsignificant p-value > 0.1. Similarly for block 2, the χ_2 = 24.45, degree of freedom = 16, the ratio of χ_2 to the degree of freedom = 1.5 < 3, and the p-value = 0.08, RMSEA =0.096. Overall, the results of the CFA analysis have validated the proposed relational models between the nonverbal macro and micro cues.

Specifically, speaking nods, illustrators, and shrug are related to the same macro cue, the nonverbal certainty. Back channel nods and body rigidness are associated with the nonverbal immediacy. And tempo, nonfluency, adaptors, and positions shifts are naturally grouped together to reflect one macro cues, denoted as nonverbal cognitive load.

Similar with verbal cues, hypotheses 1.2.2 on directions of relationships are tested with loading coefficients. Results are shown in table 4.5.

Table 4.5 Factor Loading Coefficient of Nonverbal Macro on Micro Cues

Nonverbal Cue	Block 1			Block 2		
	Specificity	Immediacy	Cognitive load/	Specificity	Immediacy	Cognitive load
Speaking nod	0.73*			0.73*		
Illustrator	2.05*			2.23*		
Shrug	0.38*			0.17*		
Back channel nod		0.31*			0.07*	
Position shift /rigid		-1.21	-0.27		-3.32	-3.72
Tempo			-9.94*			-6.21*
Nonfluency			19.33*			39.28*
Adaptor			1.07			-0.24

*: significant in 0.05 level

H1.2.2 (a) and (b) are supported in that nonverbal certainty is positively related with speaking nod and illustrator and shrug. H1.2.2 (c) is not supported: because more shrugs is positively associated with certainty expression. The H1.2.2(c) is based on the idea that shrug is similar with “I don’t know”, thus expressing an intent of uncertainty. The result suggests that shrug could also have another explanation that involve with certainty expression— "what has been said is right, and I don't care". The current experimental data supports the second explanation.

H1.2.2 (d) and (e) are confirmed that, as expected, more immediacy/involvement is associated with more back channel nods, and less rigid.

Last but not least, the hypothesis on cognitive load and activation, H1.2.2(f)(g) and (i) are supported. The nonverbal cognitive load is associated with less rigidness (less position shift), slower pace of talking, and more nonfluency. Interestingly for the relationship between adaptors and the overall level of nonverbal cognitive load, inconsistent patterns are found from block 1 to 2. In block 1, higher cognitive load results in more adaptors; but in block 2, the pattern is opposite. Hence the relationships between adaptor and the cognitive load can not be decided with the current empirical data.

4.4 Comparing the Cross Sections Patterns of Deception and Truth Behavior

Section 4.3 shows that a series of CFA tests have successfully validated the proposed relational model between the macro and micro cues. Furthermore, an important implication of CFA test is to use the latent factor scores as an estimation of the macro cues.

Comparing with the micro cues, the macro cues have two superior features. First, macro cues are more reproducible, since macro cues extract the commonality of the related micro cues and reduce the variability in single micro cues. Second, macro cues contain more behavior meanings than micro cues. Hence macro cues can be used to investigate the deceptive patterns over time, and compare them to the truthful ones.

RQ2 studies the difference of deceptive and truthful behavior cross sections. Specifically, hypothesis 2 is that deceivers show different behavior patterns than truth norm in terms of verbal nonverbal certainty, immediacy, and cognitive load.

Macro cues are better than micro ones to demonstrate behavior patterns since it is an abstract aggregation of micro cues. An example can be demonstrated with table4.6 and 4.7, which are the means and standard deviation of macro and micro cues of the verbal immediacy. Modifier, sensory, specificity, and imagery terms are cues representing the level of verbal specificity/certainty. However, the behavior patterns extracted form the individual micro cues are inconsistent. Specifically from block 1 to 2, the increasing usage of modifier in deceptive message implies a pattern of increasing specificity; but the decreasing imagery level implies the opposite pattern of specificity. The reason of the contradiction is that none of the single micro cues can represent the verbal immediacy. Because the macro cues are the higher order abstract from the related micro one, it summarize on the information that contain in several micro cues and shows an “overall” impression. In this case, the macro cue shows a pattern of decreasing verbal specificity/certainty. The complete means and standard deviation tables are in the appendix.

Table 4.6 Mean (Standard Deviation) of the Macro Cue of Verbal Specificity

		Block 1	**Block 2**
Verbal specificity/certainty	T	.095(.185)	.328(.162)
	D	-.107(.183)	-.34(.16)

Table 4.7 Mean (Standard Deviation) of the Micro Cues in the Verbal Immediacy

		Block 1	**Block 2**
Modifier	T	44.6(5.14)	86.17(7.48)
	D	38.9(5.08)	55.27(7.39)
Sensory	T	.017(.001)	.022(.002)
	D	.014(.001)	.014(.002)
Specificity	T	.016(.001)	.026(.002)
	D	.014(.001)	.016(.002)
Imagery	T	1.392(.009)	1.378(.008)
	D	1.374(.009)	1.336(.008)

Hypothesis 2 states that deceptive behavior has different cross section patterns than truthful one. In order to test H2, a series of General Linear Model (GLM) analysis were performed on the six macro level cues. The GLM has a design of 2(block) by 2(condition) repeated measurement. H2 will be supported if the within subject interaction effects between block and condition (block X condition) are significant. Table 4.8 summarizes the GLM results on the interaction effects.

Table 4.8 Within Subject Interaction Effect of Time by Condition

Time* condition interaction	**F-value**	**P-value**	η_p^2
Verbal specificity/certainty	4.521	0.038	0.071
Verbal immediacy/involvement	4.203	0.045	0.066
Verbal cognitive load/activation	0.656	0.421	0.011
Nonverbal specificity/certainty	0.016	0.899	0
Nonverbal immediacy/involvement	8.45	0.005	0.133
Nonverbal cognitive load/activation	4.397	0.041	0.074

. Consistent with H2, most of the macro cues show significant interaction effects of time by condition. In other words, deceivers and truthtellers have different cross section (block) patterns. Furthermore, figure 4.3 shows how the patterns are different between truth and deception condition over time.

Specifically from block 1 to 2, the verbal specificity increases in truth condition and decreases in deception. And the trends between two conditions differ significantly with $F(1,59)=4.521$, $p=.038$, $\eta_p^2 = .071$. Comparing to the truthteller who naturally become more certain and specific over time, the deceiver tend to have less specificity and certainty. Similarly, the nonverbal specificity show similar patterns comparison between truth and deception, although the pattern differences are not significant, because the interaction effect is not significant with $F(1,59)=0.016$ and $p=.899$.

For the immediacy/involvement, both interactions are significant: For verbal: $F(1, 59)= 4.203$, $p=0.045$, $\eta_p^2 = .071$; and for nonverbal: $F(1, 55)= 8.45$, $p=0.005$, $\eta_p^2 = .133$.

Deceivers decrease the verbal and nonverbal immediacy form block 1 to 2, while the truthtellers perform oppositely.

For the cognitive load/activation, situation is similar with the specificity cue except that the significant interaction effect becomes the nonverbal macro cues: $F(1, 55)=4.397$, $p=0.041$, $\eta_p^2 = .074$. Presenting in both verbal and nonverbal behaviors is the trend of increasing cognitive load in deceivers and the opposite in truthtellers.

In summary, the results support the hypothesis 2 that during conversation, deceptive evolves differently than truthful behaviors. Further more, this study shows that the patterns are automatically estimated with macro cues. Therefore, one implication of calculating macro cues is to automatic detect deception dynamically by investigating the behavior patterns over time.

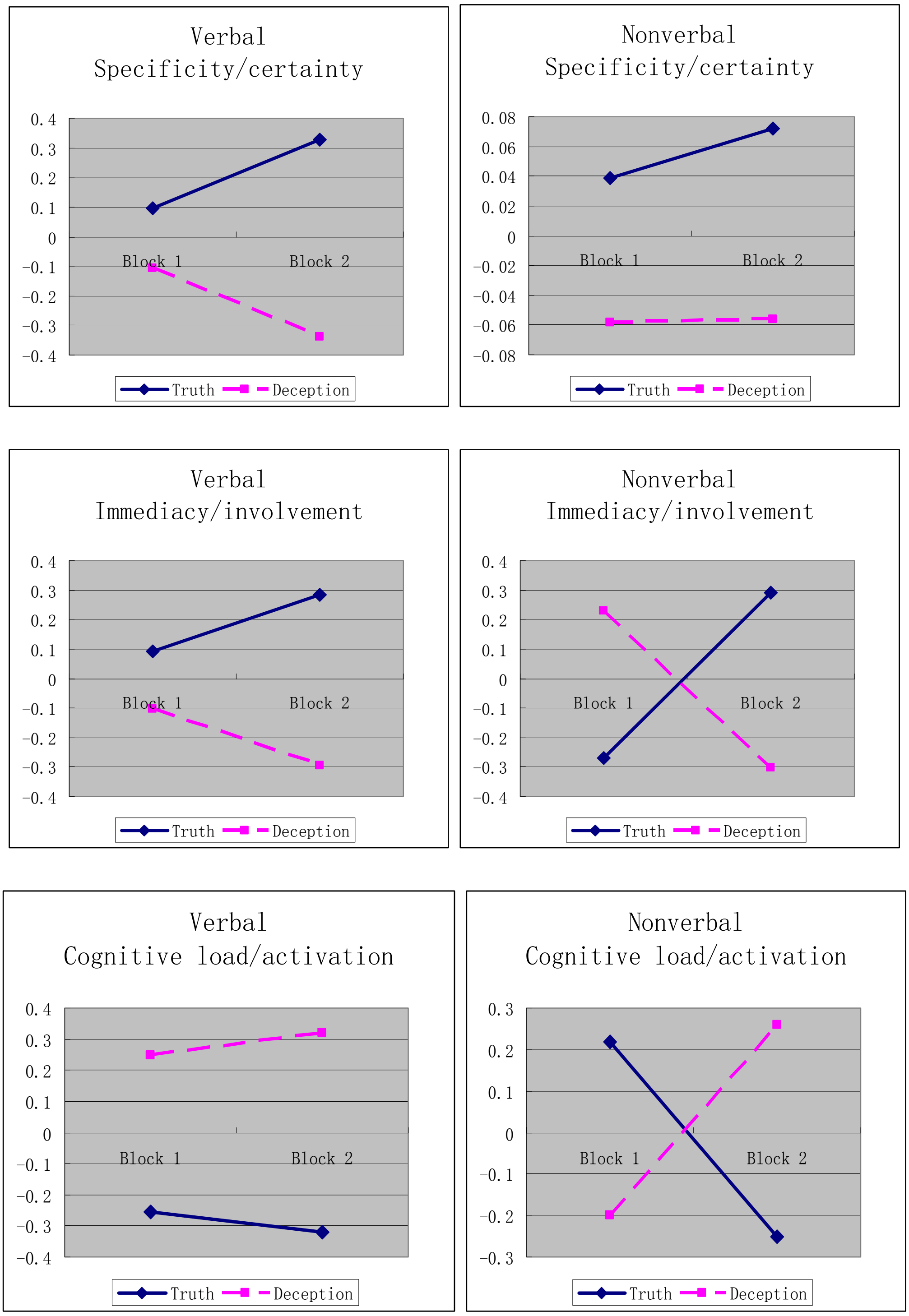


Figure 4.3 Macro Cues Mean Cross Section Comparison

4.5 Effects Influencing the Performance of the ADDS

Results from section 4.4 show that both deception and truth behavior change from block 1 to 2. The next critical question then arises from the perspective of system building: if things are changing, are some cues are consistent than others? More importantly, what are the effects influencing the ADDS performance?

These questions have been addressed in research question 3, 4 and 5. Each question has its own focus: RQ3 studies features of consistent cues, and RQ 4, and 5 study the block and the interlocutor's immediacy effects on the ADDS performance. Consistent with previous chapters, the interlocutor's immediacy is noted as ERIMD.

Specifically, hypothesis 3(a) predicts that cues in the category of verbal and nonverbal cognitive load/activation are more consistent than cues in the other two categories as predictors to detect deception. Hypothesis 3(b) states that the Hypothesis 3(a) holds for both macro and micro cues.

Hypothesis 4 posits that the deception detection is influenced by time, and detecting deception is more successful in some time phase than others.

Hypothesis 5 predicts that the deception detection under high ERIMD is more successful.

The three research questions study effects to improve system performance, i.e., the accuracy of the automatic classification. Therefore the most critical method to test the hypotheses is to study the effects through discriminant analysis. For example, as aforementioned a cue being consistent means it is statistically significant as predictors in the discriminant analysis to classify deception.

Hence, in order to evaluate the consistency of cues and other modality effects on the ADDS performance, a series of discriminant analyses have been performed. Results are shown in table 4.9 and 4.10, where table 4.9 lists the cues that are significant predictors in the discriminant analyses and table 4.10 shows the accuracy of the detection. The predictors in these discriminant analyses include both verbal and nonverbal cues. Results in table 4.10 are the overall accuracy after cross-validation. The truth- and deception- detection accuracy are very close to the overall accuracy within the range of ±3%. Hence only the overall-accuracy results are shown in this study.

Table 4.9 Statistically Significant Cues for the Automatic Deception Detection

	Block 1		Block 2	
	Normal ERIMD	High ERIMD	Normal ERIMD	High ERIMD
Macro level predictors	Verbal cognitive load, nonverbal immediacy	Nonverbal cognitive load	Verbal immediacy	Nonverbal cognitive load
Micro level predictors	Content word diversity	Modifier, Average word length, Pleasantness, Speaking nod, Back channel nod	Average word length , Content word diversity	Pleasantness, Self-references

Table 4.10 Classification Rate of Macro and Micro Cues as Predictor

	Block 1		Block 2	
	Normal ERIMD	High ERIMD	Normal ERIMD	High ERIMD
Macro level predictors	60%	65%	61%	80.%
Micro level predictors	67%	91%	64%	81.%

Further more, this study also conduct the second method to investigate system performance, which is less direct than the discriminant analysis. The analysis is to estimate the discrepancy between truth and deception behaviors by mean difference of the macro and micro cues. The difference is also noted as (T-D). Central to this method is the idea that: if the difference of (T-D), representing the mean difference in one cue, is significantly different than 0, then the cue is potentially useful to detect deception from truth. Consequently, if block 1 generates more of such cues than block 2, then the first time phase potentially benefits the classification of deception, and vice versa.

In order to address the difference of (T-D), a series of GLM tests are conducted with the design of 2(condition) by 2(block) by 3 (ERIMD) repeated measurement. Table 4.11 (4.12) shows the pairwise comparison on macro (micro) cues between truthteller and deceiver in block 1 and 2.

Table 4.11 Pairwise Comparison of (T-D) Mean Difference for Macro Cues

	Mean Difference (T-D)	
	Block 1	**Block 2**
Verbal Cognitive load/activation	-0.502*	-0.643*
Nonverbal Cognitive load/activation	0.418	-0.6*
Verbal Immediacy/involvement	0.197	0.577
Nonverbal Immediacy/involvement	-0.502	0.592*
Verbal Specificity/certainty	0.202	0.668*
Nonverbal Specificity/certainty	0.096	0.128

*: significant in .05 level.

Table 4.12 Pairwise Comparison of (T-D) Mean Differences for Micro Cues

		Mean Difference (T-D)	
		Block 1	**Block 2**
Verbal **Cognitive load/activation**	Pausality	-1.029*	-1.501*
	Average word length	-0.035	-.085*
	Content word diversity	.014*	.025*
	Redundancy	-1.695	-1.396
	Activation	0.006	0.006
Nonverbal **Cognitive load/activation**	Position shift	-2.035	-2.675
	Tempo	-3.914	-5.207*
	Nonfluency	10.361	21.227*
	Adaptor	-0.763	-1.245
		Mean Difference (T-D)	
		Block 1	**Block 2**
Verbal **Immediacy/involvement**	Passive verb	0.002	0.002
	First person singular pronouns	0.013	0.014
	You reference	0.004	0.01
	First person plural pronouns.	0	0.003
	Third person pronouns	0.001	0.003
Nonverbal **Immediacy/involvement**	Back channel nod	-.228*	-0.002
	Position shift	-2.035	-2.675
		Mean Difference (T-D)	
		Block 1	**Block 2**
Verbal **Specificity/certainty**	Modifier	5.603	30.897*
	Sensory	0.002	.007*
	Specification	0.002	.009*
	Imagery	0.018	.042*
Nonverbal **Specificity/certainty**	Speaking nod	0.574	0.747
	Illustrator	0.106	0.276
	Shrug	-0.259	0.033

Specifically, results of RQ3, 4 and 5 are discussed in the following subsections:

Consistent Cues

Hypothesis 3 investigates the consistent cues: cues that are statistically significant in the discriminant analysis. According to the description, there are no specific requirements on the ERIMD. Therefore for RQ3, only the column of the normal ERIMD situation in table 4.9 and 4.10 are considered.

In the results of discriminant analysis, table 4.9 shows that the strategic macro cues—verbal and nonverbal specificity/certainty—are not significant for both blocks. Specifically, the verbal cognitive load and the nonverbal immediacy are significant in block1; and the verbal immediacy is significant in block 2. Furthermore when consider the difference between truth and deception condition, table 4.11 shows the different (T-D) verbal cognitive load is consistently significant in both blocks, where the deceiver's language shows more cognitive load than truth tellers. In summary, the results strongly suggest that the nonstrategic macro cue of verbal cognitive load is the most consistent cues for the ADDS under general ERIMD.

Comparing table 4.9 and 4.11, it can be found that the significant cues in the discriminant analysis are not always identical to the cues providing significant (T-D). This is due to the different mechanism between the discriminant analysis and the pairwise comparison. Basically, the discriminant analysis is a classification method which uses a stepwise method what all variables are entered and removed base on the Wilk's lambda in comparing whether adding a new (and removing an existing) variable improve the accuracy of the discriminant function, and the comparison process will continue until the best combination of variables are selected. By contrast, pairwise comparison is not a classification method, where a series of F-tests test the difference between truth and deception conditions for each variable. In other words, the discriminant analysis compares all variables while the pairwise comparison only considers a single variable at a time in distinguishing deception from truth. For the current empirical data, although verbal cognitive load is potentially good in detecting deception, it can contribute little more than the verbal immediacy in the discriminant analysis.

However, the verbal cognitive load cue does not show up in block 2 in the discriminant analysis does not mean it is not consistent. Its potential as good predictors has been supported by the pairwise F-tests, which showed that the difference of this cue between truth and deception condition was significant. From the viewpoint of the system design, what is more important is to consider the unknown situation, i.e., how to classify a new message based on existing knowledge. The current study suggests a more conservative yet "safer" method is to detect deception based on the cognitive load and immediacy cues.

The tests of the micro level cues also show that the nonstrategic cues are better than strategic ones. Specifically, the significant micro cues are the nonstrategic cues of content word diversity and average word length. The content word diversity turns out to be a consistent predictor. Hence hypothesis 3(b) is supported.

Table 4.10 shows the classification rate with macro and micro cues as predictors, respectively. It is shown that micro cues provide better accuracy than macro ones. When predicting with macro cues, performance of the ADDS is similar in both blocks at around 60.5%; when predicting with micro cues, the performance in block 1 is better in block 2.

The result shows that, for the discriminant analysis, using micro cues as predictors provides better accuracy than macro cues. The worse performance in the macro cues as predictors can be explained by the construction. As aforementioned, the macro cue is the higher-order abstraction to estimate the commonality of related micro cues. It mitigates the irreproducibility problem by reducing the variability in the single cues. However, reproducibility is not identical to consistency in detection deception. In other words, one cue has identical values in two situation does not guarantee it is a statistically significant predictor in the discriminant analyses. On one hand macro cues try to maximize the commonality of micro cues, but on the other, it is the unique feature of a single micro cue that contributes more in the discriminant analysis.

For example, table 4.9 shows the statistically significant predictors where the content word diversity is a very effective predictor. However, the loading coefficient table 4.4 reveals that content word diversity contributes only a small in the construction of the macro cue of verbal cognitive load. Thus it is understandable that macro cues does not behave as reliable as the micro cues since it is the unique feature of the content word diversity that contribute more in the discriminant analysis but the valuable features are not sufficiently considered in the macro cues, i.e., verbal cognitive load.

Time (Cross-sections) Effects

It has been shown in table 4.8 that deception and truth patterns change over blocks. The current section further investigates whether the early or and late phase benefits the automatic deception detection.

In order to test hypothesis 4, an Analysis of Variance test was performed to compare the accuracy of discriminant analysis in block 1 and 2 shown in table 4.10. The result is nonsignificant with $F(1, 6)=.006$, $p=.942$. Therefore hypothesis 4 is not supported, and the ADDS performance is only slightly different in block 1 and 2.

In addition, the pairwise comparison table, 4.11 and 4.12 are used to investigate the block effects on the deception and truth condition difference (T-D). For the macro cues in table 4.11, there are no significantly more non-zero (T-D) on block2 than block 1, with $F(1,10)=3.462$, $p=.092$. Similarly for the micro cues in table 4.12, $F(1,44)=3.845$, $p=.056$.

In summary, the hypothesis 4 does not receive significant support in the current study. According to hypothesis 2, both the deception and truth behavior are not stable cross section, but it cannot be concluded which block benefits the ADDS performance.

Although the overall comparison does not show significant advantages of blocks, the comparison of individual cues reveals that the difference (T-D) is significant in one block over the other. From table 4.11, the verbal cognitive load is significant in both block 1 ($F(1, 55)=4.007$, $\eta_p^2 = .068$, $p=.05$) and block 2 ($F(1, 55)=6.821$, $\eta_p^2=.11$, $p=.012$). Only significant in block 2 are the three macro cues, nonverbal cognitive load ($F(1, 51)=4.67$, $p=.035$, $\eta_p^2=.084$), nonverbal immediacy ($F(1, 51)= 6.007$, $p=.018$,

η_p^2=.105), and verbal specificity (F(1,55)= 8.644, p=.005, η_p^2=.14). Summarizing the significant patterns found on the macro cues, deceivers are more cognitive loaded, less involved and specific in messages than truthtellers. The current findings are consistent with traditional deception research (Vrij, 2000).

Interlocutor's High Immediacy Effect

The effects of high ERIMD on the ADDS performance have been shown in table 4.10. The performance under high ERIMD is much higher than the normal ERIMD: the average accuracy under ERIMD is 79% (mean of the four values for both micro and macro, block 1 and block 2); while the average accuracy for the general ERIMD is only 63%. Furthermore, an Analysis of Variance (ANOVA) test shows that the superior performance on high to general ERIMD is statistically significant, with $F(1, 6) = 8.54$, p=.027.

Finally, in an attempt to investigate the ERIMD effects on deception behavior, patterns of truth and deception comparison are shown in figure 4.4 (a)(b)(c). The aforementioned GLM test is used to investigate the interaction effects between ERIMD and the deception/truth condition. Although the GLM results show the between subject interaction condition * ERIMD are not significant in most cues, figure 4.3(a)(b) and (c) still illustrate some very interesting findings.

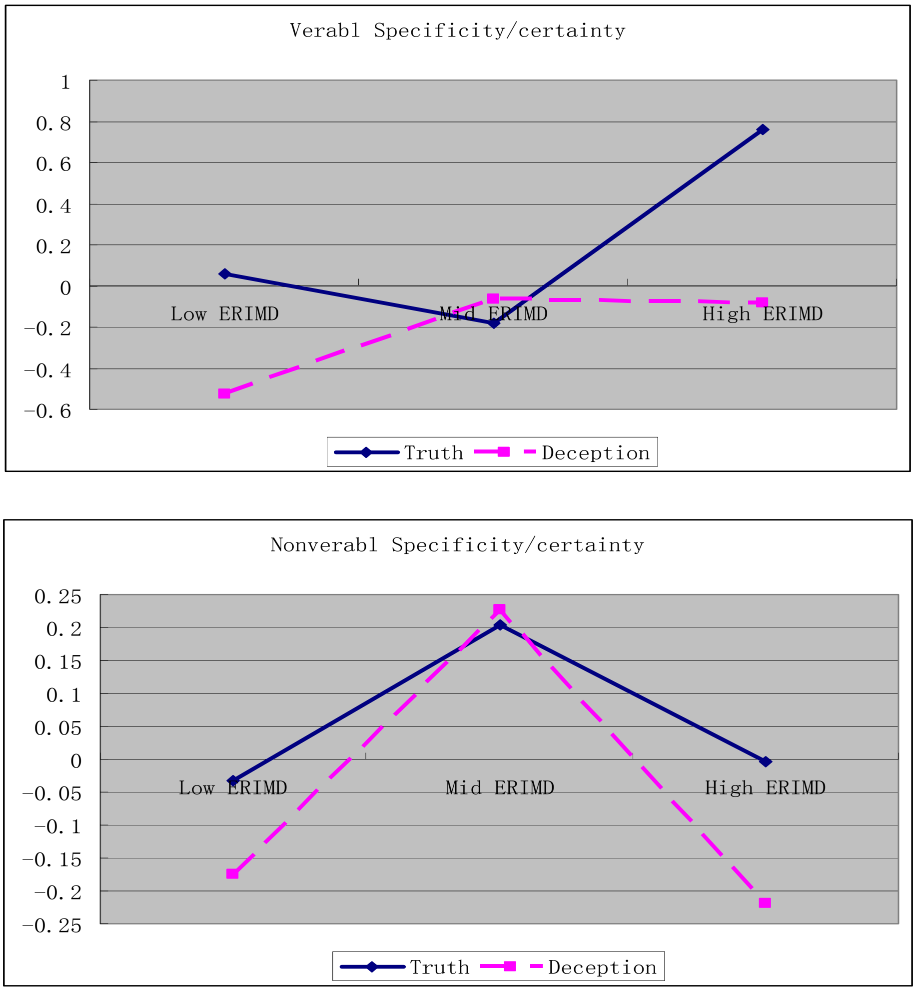


Figure 4.4 (a) Specificity/certainty Comparison of Truth and Deception by ERIMD

As shown in figure 4.4(a), in term of the specificity/certainty, the high and low ERIMD show different patterns than the medium ERIMD: in both high and low ERIMD situation, deceivers are less specific and confident than truth tellers. But in the medium ERIMD, the pattern is opposite. Such observations are true for both verbal and nonverbal cues.

The patterns suggest that, under the high or low ERIMD, deceivers are more conservative in managing information. They tend to not disclose more details (less specificity) and not make much commitment (less certainty). But when the conversation environment are medium in immediacy, they may feel more comfortable and thus be less conservative and not afraid to manage the contents to be as close to telling the truth as possible.

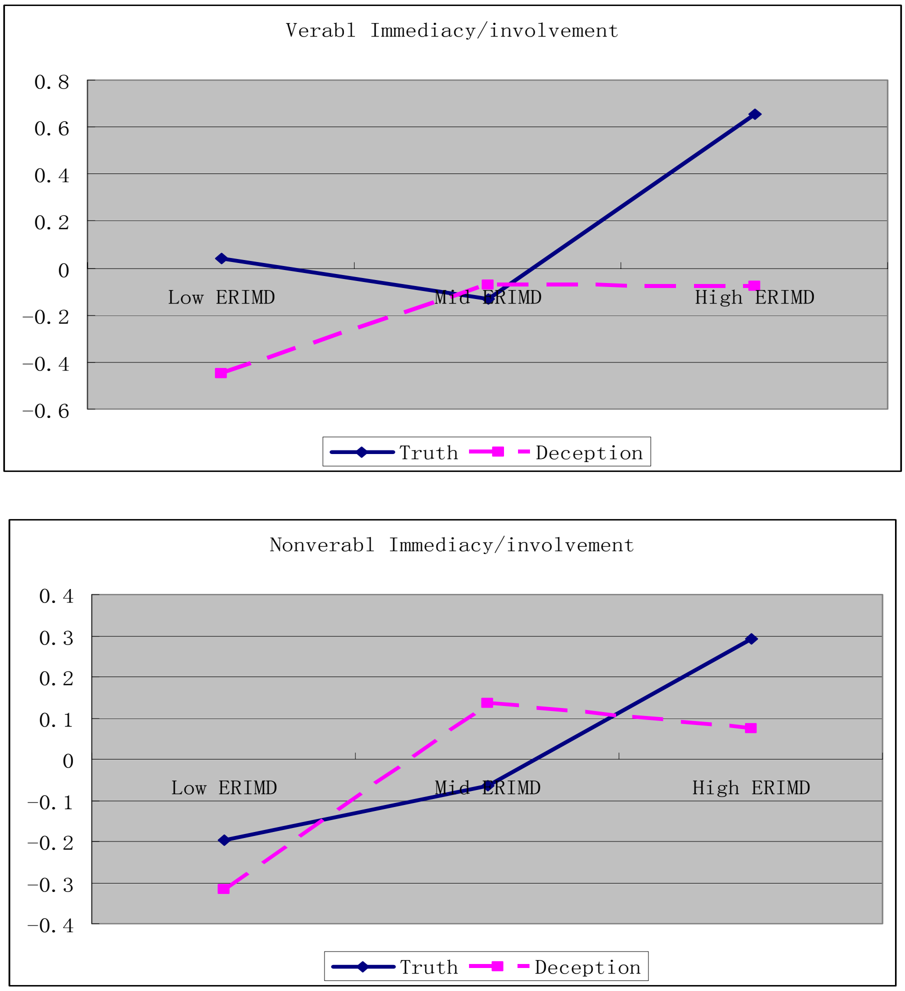
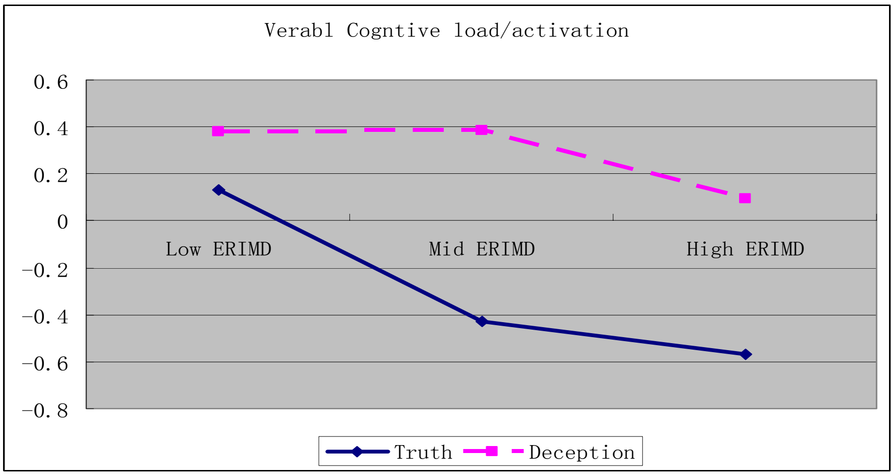


Figure 4.4 (b) Immediacy/involvement Comparison of Truth and Deception by ERIMD

Shown in figure 4.4(b) are patterns of the macro cues of verbal and nonverbal immediacy. Similarly to specificity: in the high or low ERIMD situation, deceivers are trying to disengage themselves from their interlocutors. But when the conversation is under medium ERIMD, they adapt their behavior to appear truthful by increasing involvement.



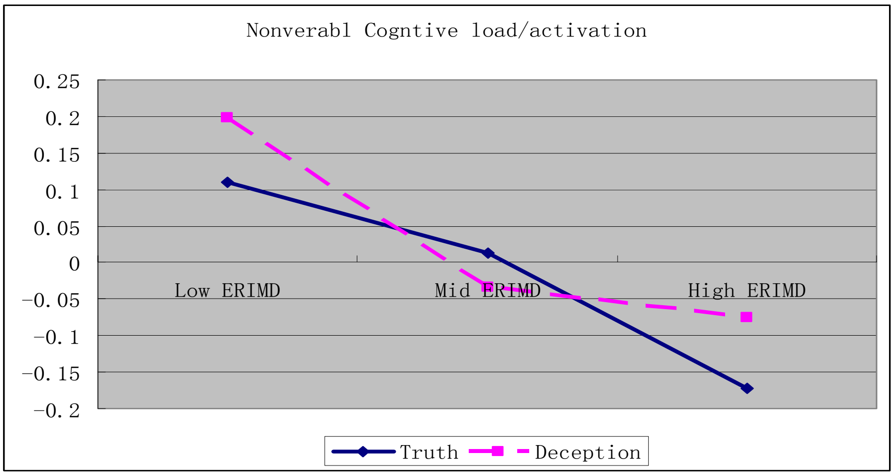


Figure 4.4 (c) Cognitive load/activation Comparison of Truth and Deception by ERIMD

In the upper part of figure 4.4(c), deceivers are consistently more cognitive loaded than truth tellers in all high, medium, and low ERIMD. The difference between cognitive load and the other macro cues—immediacy and specificity—implies that nonstrategic cues more stable due to low controllability. Unfortunately this statement is not supported by the nonverbal macro cue of cognitive load. One possible reason is the discrepancy between verbal and nonverbal channels.

The cognitive load in the nonverbal cues are easier to control than in the verbal cues, thus deceivers are able to manipulate the cues representing the cognitive load/activation. However such explanation is contract with study done by Zuckerman and Diver (1981) where the author claimed that the verbal channel is less controllable than nonverbal cues. Further research is needed to further investigate the ERIMD effect on deception.

CHAPTER 5

DISCUSSION

This study presents one of the first attempts to systematically study features of machine cues and identify reliable cues specifically for automatic deception detection systems. The targeted deception is defined as the false messages intentionally transmitted by deceivers, where the deceivers are able to constantly adjusting self behavior according to feedbacks during interaction. The key features of the deception are intentional and interpersonal. Consequently, good machine cues to detect detection should be able to effectively address the intentional and interpersonal aspects of the deception.

In order to improve the ADDS performance (detection accuracy), this study addresses two critical challenges of existing machine cues, irreproducibility and inconsistency. From the viewpoint of system design, the cause of irreproducibility is to use the lower order, objective, and meaningless micro cues to directly estimate the subjective, abstract, and meaningful intent. Hence this study mitigates the irreproducibility by introducing a set of machine measurable cues to estimate the commonality of related machine cues. These more reproducible cues are referred to as the macro cues which can be applied for automatic pattern recognition. In order to address the consistency, the study separates cues based on the controllability, and defines the strategic cues as those can easily be manipulated by deceivers during interaction. The strategic cues are fluctuate during deception and thus less consistently reliable as predictors for the ADDS. On the contrary, the nonstrategic cues are more consistent. This study also considers other moderator effects that influencing the ADDS performance: blocks and the ERIMD.

The contribution of the study is introducing the concepts of macro vs. micro, strategic vs. nonstrategic cues for the ADDS. The following sections will further discuss the features, advantages, and limitations of the concepts, and the effects to improve the ADDS performance.

5.1 Macro Cues vs. Micro Cues

Macro cue is a higher-order, abstract, and meaningful composite of a set of related micro cues and is estimated with the commonality in the micro cues. The Table 5.1 summarized the comparisons of macro and micro cues. Macro cues are composite, abstract and contain more behavior meanings. The macro cue mitigates the irreproducibility by aggregating related micro cues. As discussed later in this section, macro cues have many implications in detecting deception. Hence one important contribution of this study is to automatically extract the macro cues.

The study defined three macro cues in both verbal and nonverbal forms: cognitive load/activation, immediacy/involvement, and specificity/certainty. Hypothesis 1 proposes the relational models that connecting the micro cues with the three macro cues. The empirical results support the validity of the relational models.

Table 5.1 Comparisons between Macro and Micro Cues

Comparison	Micro Cues	Macro Cues
Relationships	A macro cue represents the commonality in a set of related micro cues	
Component	Single	Composite
Abstract	No	Yes
Contained Meaning	Low	High
Reproducibility	Low	High
Machine Extractable	Yes	Yes

According to the CFA tests, there are significant associations between the micro and macro cues: messages that show more specific contents have more modifiers, sensory terms, temporary and location terms, and imagery descriptions; messages that show the tendency for the speakers being immediate or involved contain more self-references. And one will show the cognitive load in the message by using more pausality, redundancy, shorter words, and less content words diversity. In terms of the gestures and vocals, the certainty intent is presented with more nods, illustrators, and shrugs; more immediacy/involvement intent is associated with more usage of back channel nods and relaxed movements or less rigidness; and the internal status of cognitive load is often positively associated with less position shift, slower talking pace, and nonfluency.

However, the results show that using macro cues as predictors in the discriminant analysis does not perform better than using micro cues. The results imply that, although macro cues mitigate the irreproducibility problem by reducing the variability in the single cues, they are not necessary the statistically significant predictor in detecting deception. One plausible reason is that during the construction process where macro cues aggregate the common trends in the micro ones, some valuable information are missing, especially when the valuable information is unique on the micro cues. Therefore, in order to improve the ADDS performance, it is highly desirable to increase the weights of certain important micro cues in constructing the macro ones. Specifically in this study, the content word diversity is a promising micro cue whose weight should be increase in the macro cues of verbal cognitive load.

Implications of Macro Cues

Macro cues are more advanced than micro cues in many aspects because macro cues are the higher order, abstract cues that contain behavior meanings. For example, macro cues can be used in automatic pattern recognition and then flagging deception from abnormal behavior patterns.

Deceptive behavior is not constant over time. In accord with the principles of IAT (Burgoon, Stern, & Dillman, 1995), communicators must manage their own needs, expectations, and desires while accommodating and adapting to the dynamic interaction landscape. Due to the difference of needs, expectation and desires, deceivers are expected to act differently not only at the beginning, but also during the process of the communication. Therefore the deception and truth patterns differs (White & Burgoon, 2001).

Consequently, a good method to automatic detect deception over time is to compare the patterns between target behavior with the truth norm. Specifically, hypothesis 2 is posited to detect the cross sections deception by comparing the patterns of deceivers and truthtellers.

As demonstrated in the results, using micro cues in the pattern comparison is likely to provide irreproducible (i.e., contradictory) results. Therefore the macro cues are used to recognize the cross-section patterns. From block 1 to 2, deceptive develop almost opposite patterns of the truthtellers. The hypothesis 2 was also supported because of the significant interaction effects between blocks and conditions. Specifically, truthtellers increase the certainty, immediacy, and tend to decrease the cognitive load; but deceivers behave the opposite way.

However, the method of cross-section instead of time series analysis restricts the generality of the results. Because the process is too short to represent the whole process, it is possible that current patterns are just a temporary trend. Although current study shows a diverging tendency, the IDT suggests that deceivers' and the truthtellers' behaviors are converging so that deception is harder and harder to detect because of the self-adjusting effects. Overall, the deceptive patterns are complicated and nonlinear. It is possible that the difference between deceiver and truthtellers, (T-D), first increase and then decrease. What is more valuable for a ADDS is to identify the transition point where deceivers start to converge since it will be the best time to detect deception with the largest (T-D).

Another important implication of macro cues is to use the channel discrepancy to detect deception. The macro cues are separated according to verbal and nonverbal forms because cues present in textual, vocal and gesture channels have different features. The difference in channels is supported by the Channel Discrepancy Theory (Zuckerman & Friesen, 1974). Zuckerman and Friesen investigated the channel discrepancy between facial and body expressions. Central in the Channel Discrepancy Theory is the idea that cues from two channels could display inconsistent patterns during deceits. In current study, the channels are verbal and nonverbal. Thence the discrepancy could occur between the verbal and nonverbal cues. For example, deceivers might express happiness in language along with a fake smile on the face. One important implication of the discrepancy in the cues from different channels is to detect deception. However, using current micro cues are more irreproducible and provide less meaningful comparisons between channels. Being more reproducible and meaningful, Macro cues are more valuable in applying the discrepancy theory to detect deception.

5.2 Strategic vs. Nonstrategic Cues

Another contribution of the study is to further categorize the machine cues strategic and nonstrategic and hypothesize that the nonstrategic cues are relatively more consistent than strategic ones in ADDS performance.

The results suggest that verbal cognitive load and the content word diversity are the most consistent predictor for the ADDS, respectively in the macro and micro level.

Overall, it is supported that strategic cues are less reliable in detecting deception because the strategic ones are influenced by the constantly adaptation effect, while the nonstrategic cues are stable because they reflect the simultaneous and psychological effect. The study suggests the conservatively reliable cues to detect unknown cases to be those in the nonstrategic category.

However, the results do not mean that the strategic cues are worthless. Rather, the idea is that particular detection methods must be tailored according to the feature of cues. The changes in strategic cues reflect a self adjusting activity that deceivers perform to mimic truth tellers. If the self-adjusting is within a reasonable range, the deceivers could act like truth tellers. But when the self-adjusting is over certain threshold, difference of (T-D) becomes more obvious and thus benefits the detection. In other words, behaviors presenting in the strategic cues could be overdone that look fake, in which case the strategic cues become the good predictors to classify deception. The advantages of strategic cues have been supported by previous study. For example, according to Burgoon and the college, deceivers often manage to prevent leakage and detection by suppressing and restraining behavior that might expose ulterior motives. If carried to an extreme, "behavior management can produce over-controlled, rigid presentation, inexpressiveness, and a lack of spontaneity" (Burgoon, Buller & Woodall, 1996, p 435). Verbal strategic cues can also be a good predictor. Most of the verbal strategic cues belong to the information management. As demonstrated in figure 5.1, In case of high ERIMD, the difference between truth and deception performance, i.e., the value of (T-D) is larger than both medium and low ERIME condition. In other words, the difference between truth teller's and deceiver's behavior is the most vivid in high ERIME. Consequently and validated by the empirical results, the ADDS performs better in the high than the other two conditions. Specifically, table 4.9 and 4.10 show that, under high ERIMD, strategic micro cues play a role in the classification and dramatically improve the detection accuracy.

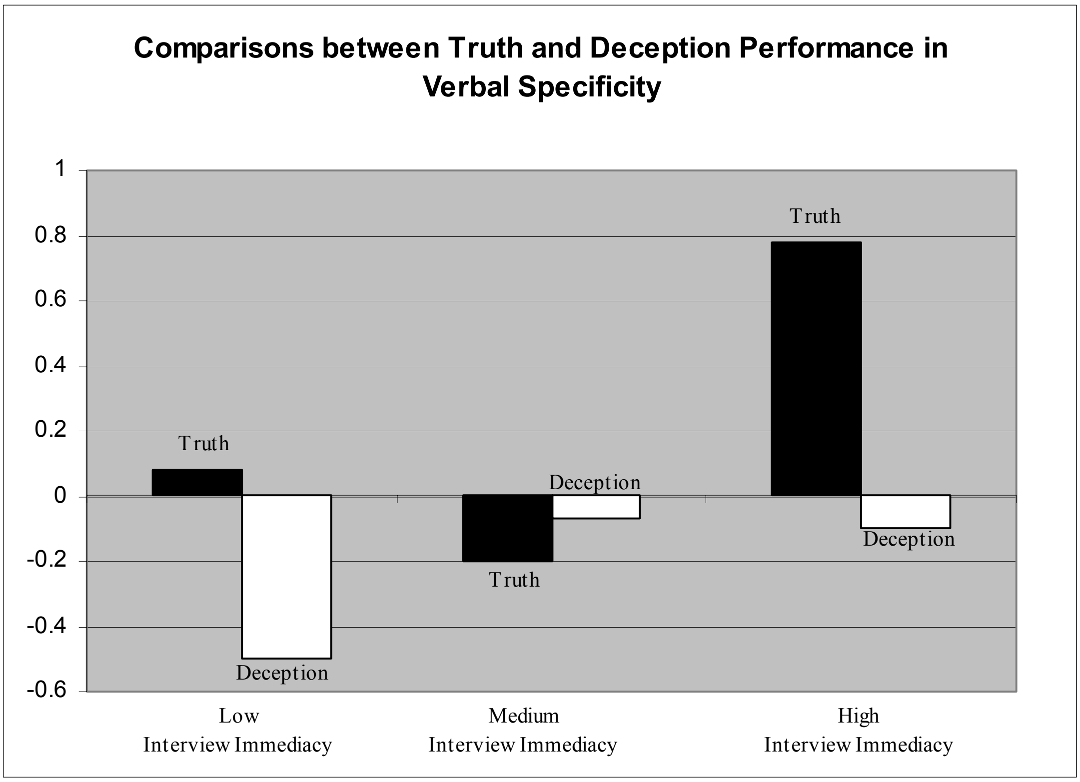


Figure 5.1 Demonstrating the Over-reacted Behavior Represented in the Verbal Specificity

Proactively Detect Deception

As demonstrate in this study, the high ERIMD is a controllable effect that potentially improve the ADDS performance. Thus it is posited the ADDS performance can be improved through manipulate the communication environment. This concept is also referred to as the **Proactive Deception Detection (PDD).**

In the current study, the ERIMD is a controllable environment factor for PDD. The high ERIMD increase the system performance because it has higher overhead added to the deceptive behavior to trigger more abnormal cues. Specifically in the high ERIMD case where the interlocutors increase involvement or immediacy, on one hand deceivers experience cognitive burdensome than normal (truth) senders when they manage to suppress leakage; on the other hand deceivers are expected to respond to the increasing ERIMD by increasing self involvement (Buller, Burgoon, White, & Ebesu, 1994; White & Burgoon, 2001). Hence their ability to enact additional responses designed to strategically reciprocate high involvement is limited and they failed to behave normal and fully respond to the high ERIMD. Consequently cues of cognitive load (e.g., less content word diversity) would increase; cues of content specificity (e.g., modifiers) would decrease; cues of involvement (e.g., self-reference) would also decrease.

The block effect is the other PDD effect investigated in this study. The idea is to searching for the best detecting point. Specifically, hypothesis 4 studies whether the starting phase (block1) is different from the later phase (block2) in the ADDS performance. However, the hypothesis does not receive significant support: the system performance is not significantly different. Identifying the best detecting point is a longitudinal analysis. The cross-section analysis is only a rough estimation. In order to precisely measure the changing point, time series analysis is needed for the future research.

5.3 Limitations and Future Study

Current study has several limitations. First, as an extended work of the previous ADDS research conducted in the University of Arizona (i.e., Zhou et al, 2003), this study defined the relational model and constructed the macro cues based on the micro cues defined in table 2.1 and 2.2. In other words, the definition of the macro cues and the corresponding relational models have been tailored for the defined micro cues. It is possible that a micro cue is measured differently from one study to another, even when the names of the micro cue are the same. Therefore, risk exists when applying the current relational model in other study or other ADDS where the cues are defined and measured differently. For example, the relational model might not be validated. Hence remodeling is necessary when applying the techniques to address the cues-reliability cues issue for another ADDS and when new micro cues are introduced.

The second limitation is related with the labels of the macro cues. For the sake of consistency, labels of the macro categories have been the same —specificity/certainty, involvement/immediacy, cognitive load/activation—for both verbal and nonverbal cues. However, a more accurate way of labeling macro cues is to consider verbal and nonverbal as different modalities, since cues in the two channels contain special features.

Specifically for the nonverbal cues, “expressivity” is a more appropriate label for the specificity/certainty category to represent the corresponding micro level cues: speaking nod, illustrator, and shrug. Expressivity refers to the use of vocal variation, facial expression, movements and gestures. Expressivity in ones’ behavior can enhance the listener's understanding (Murray, 1997). Therefore expressivity is close to certainty because both are methods to make one more understandable to the interlocutors.

For the verbal cues, "complexity" is a more accurate label for the cognitive load/activation in the verbal category, where the corresponding micro cues include content word diversity, pausality, redundancy (average sentence length), and activation terms. The idea is that more cognitive load generates more complexity, but the connection was not obvious, especially for the associated micro cues in the category.

Furthermore, the label "cognitive load/activation" should be separated into two difference concepts—cognitive load and activation. Each should has its corresponding micro cues. Future study is needed to study characteristics of both cognitive load and activation by considering a more comprehensive set of micro cues.

The third limitation is related with the cross-section design to address the dynamic effect of deception. Time series and longitudinal designs have the potential to increase the precision of measurement and should be considered.

However, using longitudinal analysis also raises questions about the frequency of measurements and the size of observational windows that are needed to accurately gauge interaction dynamics. The future study should also address the influence of measurements and methods on dynamic effects.

The definition of strategic and nonstrategic cues is based on the controllability. The current study has not compared the controllability caused by different channels. Specifically, controllability relates to an encoder's awareness of cues in a channel and ability to recall, repeat, or display a planned sequence of cues (Burgoon, Buller, &

Woodall, 1996). It is possible that one cue that is easy to manipulate in one channel is harder so in anther, since verbal channel has different controllability than nonverbal (Buller, Burgoon, Buslig, & Roiger, 1994; Caso, Vrij, Mann, & Leo, 2006; DePaulo, Zuckerman, & Rosenthal, 1980; Knapp, Hart, & Dennis, 1974; Zuckerman & Driver, 1985). In other words, the verbal specificity may be much less controllable than nonverbal specificity cues. Therefore the nonverbal specificity cues are not consistent cues. In order to further specify the consistent cues for the ADDS, the features of the communication channels should be investigated.

Finally but not the least, in order to improve the accuracy of ADDS, content analysis is necessary where semantic cues are measured. These cues are the potentially powerful indicators of deception. For example, if the cues show the content is contradict, the message is deceptive. A more sophisticated direction of ADDS research is to construct the semantic forensic natural language processors to analyzing the meanings of the discourse and compare the content to the previously set facts and to the knowledge of the world.

To conclude, the result of a more reliable ADDS can range from being able to reliably detect real and imminent dangers to national security, to saving the lives of innocent civilians and protecting the health and welfare of the general public.

APPENDIX

Mean (Standard Deviation) of Verbal Macro and Micro Cues

		Block 1	**Block 2**
Verbal specificity/certainty	**T**	**.095(.185)**	**.328(.162)**
	D	**-.107(.183)**	**-.34(.16)**
Modifier	T	44.6(5.14)	86.17(7.48)
	D	38.9(5.08)	55.27(7.39)
Sensory	T	.017(.001)	.022(.002)
	D	.014(.001)	.014(.002)
Specificity	T	.016(.001)	.026(.002)
	D	.014(.001)	.016(.002)
Imagery	T	1.392(.009)	1.378(.008)
	D	1.374(.009)	1.336(.008)
Verbal immediacy/involvement	**T**	**.094(.155)**	**.283(.137)**
	D	**-.104(.153)**	**-.294(.136)**
Passive verb	T	.004(.001)	.009(.002)
	D	.002(.001)	.007(.002)
First person singular pronouns	T	.09(.006)	.086(.006)
	D	.076(.006)	.072(.006)
You reference	T	.004(.001)	.01(.002)
	D	.004(.001)	.007(.002)
First person plural pronouns	T	0(0)	.006(.001)
	D	0(0)	.002(.001)
Third person pronouns	T	.002(.001)	.019(.002)
	D	.001(.001)	.016(.002)
	T	1.945(.007)	1.898(.006)

Pleasantness	D	1.964(.007)	1.931(.006)
Verbal cognitive load/activation	**T**	**-.255(.178)**	**-.321(.175)**
	D	**.247(.176)**	**.322(.173)**
Pausality	T	6.833(.292)	5.842(.326)
	D	7.862(.289)	7.343(.322)
Average word length	T	4.067(.032)	3.995(.028)
	D	4.102(.031)	4.08(.027)
Content word diversity	T	.335(.004)	.353(.004)
	D	.321(.004)	.328(.004)
Redundancy	T	9.516(.663)	9.217(.607)
	D	11.211(.655)	10.613(.6)
Activation	T	1.633(.004)	1.653(.004)
	D	1.627(.004)	1.647(.004)

Mean (Standard Deviation) of Nonverbal Macro and Micro Cues

		Block 1	Block 2
Nonverbal specificity/certainty	**T**	**.039(.186)**	**.072(.197)**
	D	**-.058(.17)**	**-.056(.181)**
Speaking nod	T	.432(.263)	3.941(.277)
	D	3.558(.26)	3.195(.274)
Illustrator	T	2.399(.352)	2.802(.362)
	D	2.293(.348)	2.525(.358)
Shrug	T	.405(.124)	.384(.103)
	D	.664(.123)	.351(.102)
Nonverbal immediacy/involvement	**T**	**-.27(.197)**	**.291(.178)**
	D	**.231(.181)**	**-.301(.163)**
Back channel nod	T	.677(.074)	.595(.069)
	D	.905(.073)	.597(.068)
Position shift /rigid	T	3.978(.894)	4.038(1.197)
	D	6.012(.884)	6.713(1.183)
Nonverbal cognitive load/activation	**T**	**.219(.191)**	**-.251(.174)**
	D	**-.2(.175)**	**.258(.159)**
Tempo	T	20.808(2.318)	12.516(1.673)
	D	24.722(2.129)	17.723(1.537)
Nonfluency	T	48.014(4.014)	79.808(6.759)
	D	37.653(4.544)	58.581(6.208)
Adaptor	T	4.974(.728)	5.827(.952)
	D	5.737(.719)	7.072(.941)
Position shift /rigid	T	3.978(.894)	4.038(1.197)
	D	6.012(.884)	6.713(1.183)

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