Imposing Cognitive Load to Unmask Prepared Lies: A Recurrent Temporal Pattern Detection Approach

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Abstract

According to Vrij, the differences between liars and truth tellers are greater when interviewees report their stories in reverse order than in chronological order. We intend to explore such influences on the organization of behavior within the framework of the T-pattern model. This model grants the possibility to measure and compare behavior patterns between liars and truth tellers, not easily detectable without the use of such tools. Recalling stories in reverse order will produce cognitive overloading in subjects, because their cognitive resources are already partially spent on the lying task; this should emphasize non verbal differences between liars and truth tellers. During the experiment, we asked female students to report specific autobiographical episodes. We videotaped them as they reported the stories in chronological order or in reverse order after asking to lie about one of the stories. We focused in analyzing how people organize their communicative styles during both truthful and deceptive interactions.. We coded the video recordings, after establishing the ground truth, using Theme Coder 5 software. We are currently analyzing datasets using Theme 6 software.

Keywords. T-patterns, Theme, non-verbal cues to deception, cognitive load, lie detection.

Introduction

Achieving high information assurance is complicated due to human fallibility in deception detection [1]. Two studies [2, 3] reveal that although people show a statistically reliable ability to discriminate truths from lies, overall accuracy rates average 54% or only a little above chance. Moreover, the average total accuracy rates of professional lie catchers (56%) is similar to that of laypersons.

A meta-analysis of cues to deception [4], which included above 130 studies published in English examining nonverbal cues to deception, reveals that many conflicting results have been found. Since no diagnostic cue to deception occurs, it could be that a diagnostic pattern does arise when a combination of cues is taken into account [3].

Moreover, cues to deception are typically faint and unreliable [4]. A contributing factor is that the underlying theoretical explanations for why such cues occur, like nervousness and cognitive load, also apply to truth tellers [5]. Studies in the past have focused on eliciting and amplifying emotions [3] for example by asking questions, but it is uncertain whether this procedure will necessarily raise more concern in liars than in truth tellers. Conversely, only a few efforts focused on unmasking the liars by applying a cognitive lie detection approach [6,7].

Instead of searching for universals in cues to deception, we focused in analyzing how people organize their communicative styles during both truthful and deceptive interactions. According to Vrij, the differences between liars and truth tellers are greater when interviewees report their stories in reverse order than in chronological order [6]. The innovativeness of the present work consists in using the methodological approach used in [8, 9], that is, the T-pattern model approach. We intend to explore the influences on the organization of behavior within the framework of the T-pattern model. This model grants the possibility to measure and compare behavior patterns between liars and truth tellers, not easily detectable without the use of such tools [1, 2, 3]. Recalling stories in reverse order will produce cognitive overloading in subjects, because their cognitive resources are already partially spent on the lying task [6]; this should emphasize non verbal differences between liars and truth tellers.

Methods

Participants

16 Students, all females, aged from 21 to 26. After being recruited, all participants gave their informed consent both to audio and video recording.

Instruments

Both audio and video recording equipment.

Setting

The present study was carried at the University of Milano-Bicocca in an audio-isolated laboratory room equipped with four cameras, set to video-record participants' full-lengths and close-ups. The cameras were connected with a 2 channel quad device (*split-screen* technique).

Procedure

We asked participants to consider two specific episodes, regarding the last time they had been to a party and the last time they went out for pizza. One of these two episodes had to be the truth, the other a lie. They were given 20 minutes to prepare the two stories, knowing that after they would have to report both episodes to another person (a confederate), who didn't know which was the lie. We asked half of the students to tell the pizza episode first, while the other half did the opposite. All of them were told to lie during the first episode. We controlled motivation by telling them that, if they succeeded in telling the lie (meaning, the other person couldn't tell which episode was a lie and which was the truth), they would receive extra credits.

In the first experimental condition, the interviewer asked the interviewee to report both episodes in chronological order. In the second condition, the interviewer asked to report both episodes in reverse mode (starting from the end of the story and going back to the beginning).

The time frame for the experimental task was 10 minutes for each participant (5 minutes per episode), marked by audio signals.

Manipulation check

To establish the ground truth and verify cognitive load manipulation and motivation, we asked the subject to complete a questionnaire after the experiment was finished. Later, we watched the video recordings with the participants and asked them when they lied (veracity status).

T-patterns and Theme 5

Data analysis is performed using Theme 5 software distributed by Noldus Information Technology [9]. Theme detects statistically significant time patterns in sequences of behaviors. The term T-pattern stands for temporal pattern; they are based on the timing of events, relative to each other. T-pattern detection [8, 12, 13] was developed for finding temporal and sequential structure in behavior. The algorithm implemented in the software detects repeated patterns of intra- or inter-individual behavior coded as events on one-dimensional discrete scales.

A minimal T-pattern consists of two event types. An event type is a category of observable behavior whereas an event is an instance of behavior occurring at a particular time unit without a duration [8]. Two event types are considered a T-pattern if they both occur at least twice in the behavior record in the same order and their occurrence times are invariantly distributed over time, i.e. their time distances are unlikely random [8].

Post-detection tools can be applied for filtering and analyzing patterns, for example based on their occurrence frequency (how often the pattern is repeated), length (number of events that comprise a pattern) or behavioral content.

Data analysis

The coding grid was built basing on literature review of non verbal cues in lie detection. [3, 4, 10]. We considered body movements (head, trunk, arms, hands, legs and feet), gestures (rythmic, iconic, metaphoric and deictic), self-contacts, gaze and facial micro-movements (FACS action units) [11].

2 minutes observation intervals were considered for subsequent analysis. Videos were coded frame by frame using Theme coder 5 software distributed by Noldus Information Technology [9]. Each behavior occurrence was regarded as a case of an event-type that occurs at a particular point on a discrete time scale, but has no duration otherwise. The occurrences of each event-type within the selected observation period form the so called "T-dataset". To assess inter-rater reliability of the T-dataset, Cohen's Kappa was calculated on 10% of the same video materials independently coded by two coders, using a "blind" coding procedure. Although differing through categories, inter-coder reliability was found to be good to satisfactory (ranging from .70 to .92; $p < .05$). When disagrements were identified or the agreement was not perfect, the specific cases were discussed and agreed by both coders.

Results

On-going work. We are currently analyzing datasets.

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