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Comparing Thin Slices of Verbal Communication Behavior of Varying Number and Duration

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Abstract

Objective—The aim of this study was to assess the accuracy of thin slices to characterize the verbal communication behavior of counselors and patients engaged in Motivational Interviewing sessions relative to fully coded sessions.

Methods—Four thin slice samples that varied in number (four versus six slices) and duration (one- versus two-minutes) were extracted from a previously coded dataset. In the parent study, an observational code scheme was used to characterize specific counselor and patient verbal communication behaviors. For the current study, we compared the frequency of communication codes and the correlations among the full dataset and each thin slice sample.

Results—Both the proportion of communication codes and strength of the correlation demonstrated the highest degree of accuracy when a greater number (i.e., six versus four) and duration (i.e., two- versus one-minute) of slices were extracted.

Conclusion—These results suggest that thin slice sampling may be a useful and accurate strategy to reduce coding burden when coding specific verbal communication behaviors within clinical encounters.

Practice Implications—We suggest researchers interested in using thin slice sampling in their own work conduct preliminary research to determine the number and duration of thin slices required to accurately characterize the behaviors of interest.

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Keywords

Thin Slices; Behavioral Coding; Patient-Provider Communication; Behavioral Intervention; Motivational Interviewing; Obesity

1. Introduction

Understanding the mechanisms by which counselors evoke intrinsic motivation and behavior change in their patients is an important focus of Motivational Interviewing (MI) research [1]. A body of literature supports the link between client communication behavior and treatment outcomes, but the specific counselor communication behavior that elicit specific client behavior is less well understood [1]. Understanding the intricacies of the interactions that occur between a MI counselor and a patient requires a careful, objective examination of the specific communication behaviors exhibited during a clinical encounter and accurate classification of these behaviors [2, 3]. Ideally, this type of research occurs through the systematic analysis of video- or audio-recordings, a resource-intensive endeavor. To illustrate, Moyers and Martin [3] coded 63 MI sessions using the SCOPE code system. Training coders to an acceptable level of reliability required 60 hours of training over six weeks. The authors did not provide details about the duration of time required for coding the 63 sessions, but do note that the analysis required two coding passes and six coders. Thus, the resource intensity of this type of research is inherently limiting progress in this important scientific area. Thus, a major goal for MI research, and, more generally, any research intensively examining clinical interactions, is to identify strategies that reduce the resources needed to conduct high quality research.

Thin slice sampling of recorded interactions might be a useful strategy to reduce coder burden [4], but only if the thin slices sampled accurately represent the characteristics of the entire interaction the researcher is trying to understand. The literature suggests a high degree of accuracy when using thin slices to make global assessments [e.g., 5, 6–14], but only three studies have examined the accuracy of thin slices to identify and characterize specific behaviors [i.e., 4, 15, 16]. The purpose of the present study is to examine the extent to which thin slices accurately represent verbal communication behaviors between adolescent patients and MI counselors engaged in weight loss counseling.

1.1 Thin Slices

A thin slice is “a brief excerpt of expressive behavior sampled from the behavioral stream” [17]; in other words, it is a small segment, either randomly or strategically, extracted from an interaction. Thin slices have been used successfully in a number of research studies where raters are asked to make judgments about a person or the quality of an interaction. To illustrate, Place and colleagues extracted 10-second slices from 3-minute speed dating interactions [5]. Three discrete groups of raters (a total of 193 raters) viewed the thin slices and assessed each participant’s romantic interest in the other participant. All three groups demonstrated a high degree of accuracy (r = .65 – .88) in predicting romantic interest when compared to actual dating offers made after speed-dating.

Thin slice methods have been used to detect psychopathological personality characteristics [6–9], assess affective style [10, 11], recognize emotions [12], deduce sexual orientation [13], and estimate socioeconomic status [14]. Assessments based on thin slices have been linked to outcomes including physical, cognitive, and psychological functioning [18], surgical malpractice claims [11], student evaluations of teaching [17, 19], and sales performance and customer satisfaction [20]. Finally, thin slices have been used in a variety of contexts including naturalistic observations, including speed dating [5], classroom teaching observations [19], laboratory-based experiments [6, 9, 10, 13, 14, 17], and observations of clinical interactions, such as physical therapy sessions [18], office [11] and clinic visits [21], psychological diagnostic interviews [7, 8], and medical student interactions with standardized patients [22]. This literature on thin slices suggests a high degree of accuracy when using thin slices to make subjective judgments (i.e., global ratings), but offers less guidance regarding the utility of thin slices with observational coding schemes designed to identify and characterize specific behaviors, such as specific patient-provider verbalizations during clinical interactions.

Three studies examined the degree to which thin slices accurately represented specific behaviors previously identified using the usual labor intensive, but empirically validated, method of coding. Murphy [4] examined how well one, two, or three randomly selected 1-minute slices extracted from a 15-minute interaction captured nonverbal behaviors (gestures, nods, self-touches, smiles, gaze) when compared to the fully coded interaction. Her results indicated moderate to high correlations between the three thin slice samples and the full interaction, with correlations increasing with the number of slices extracted. Findings from this study, however, suggested that three slices were only marginally better than one or two slices (e.g., $r_{1\ slice}$ = .62 versus $r_{2\ slices}$ = .68 versus $r_{3\ slices}$ = .76), with the exception of lower frequency behaviors which demonstrated much stronger correlations when more slices were extracted (e.g., $r_{1\ slice}$ = .41 versus $r_{2\ slices}$ = .76 versus $r_{3\ slices}$ = .83).

Roter and colleagues [16] sampled three 1-minute thin slices (extracted at minutes one, five, and nine) from medical student-standard patient interactions lasting around 12 minutes in duration. The slices and the entire encounter were coded using the author's coding system for classifying verbal patient-physician communication, Roter Interaction Analysis System (RIAS). Each of the three 1-minute slices and a three-slice sum were compared to the fully coded encounter. The results indicated that the correlation between verbalizations coded in the entire encounter and each 1-minute slice were very variable, ranging from very small (−.02) to strong (.66); however, the correlations between the entire encounter and the three-slice sum were more consistent and of a larger magnitude (ranging from .27 to .82).

James and colleagues [15] tested the utility of thin slices to code interactions between mothers and infants (gaze and verbalizations). Each 18-minute encounter was divided into six 3-minute segments, three 6-minute segments and two 9-minute segments. They found 3- and 6-minute slices did not accurately represent the behaviors present in the full 18-minute observation, but the 9-minute slices did. James and colleagues also observed that lower frequency behaviors demonstrated wider variability in the behaviors coded in "thinner" (i.e., shorter) slices as compared to "thicker" slices. These results suggest thin slices might be a promising strategy to reduce coder burden when analyzing behavior within clinical interactions. However, with only three studies using dissimilar methods, there is very little guidance available to researchers interested in implementing thin slice sampling when coding specific behaviors in clinical settings.

This study builds upon this research by examining the accuracy of thin slices to identify and code the verbal communication behavior of counselors and adolescent patients engaged in a Motivational Interview (MI) counseling session targeting weight loss. The aim of this research study was to assess the extent to which thin slice samples of MI sessions accurately characterize the overall pattern of verbal communication behavior of counselors and patients relative to fully coded sessions. Specifically, we investigated both how many thin slices are needed and how thin can slices be to accurately characterize key communication behaviors relative to fully coded sessions? Based on the work of Murphy [4], Roter [16], and James et al [15], we expected to find greater accuracy when a greater proportion of the encounter was extracted. In other words, we expected greater accuracy when a greater number of thin slices were extracted (six versus four slices) and when "thicker" slices were extracted (2-minute versus 1-minute slices). This study is the first to examine the utility of thin slice sampling for coding MI sessions.

2. Method

This research is a secondary analysis of data collected as part of a study examining patient-counselor communication during Motivational Interviewing (MI) weight loss sessions with African American adolescents [23]. The goals of the parent study were to (1) develop an observational code scheme to characterize verbal communication behaviors and (2) identify specific counselor verbalizations effective at eliciting patient expressions of intrinsic motivation (i.e., change talk and commitment language) [1]. We provide a brief description of the parent study below; a detailed description, including methods, the development of the code scheme (Minority Youth - Sequential Coding for Observing Process Exchanges (MY-SCOPE)), and findings, has been reported elsewhere [23].

2.1 Participants

Adolescent patients and their caregivers were recruited from the adolescent medicine, pediatric medicine, and endocrinology clinics at a large urban teaching hospital with a small number (<20%) recruited from community-based sites, e.g., local health fairs and schools. Adolescent eligibility included age 12.0 to 17.0, self-identifying as Black with BMIs (kg/m2) ≥95th percentile. We excluded adolescents with obesity secondary to medication use (e.g., steroids), comorbid medical conditions preventing normal exercise, pregnancy or another medical condition where weight loss is contraindicated, comorbid thought disorders (i.e., schizophrenia), moderate/severe mental retardation, psychosis or current suicidality. All caregivers provided informed consent and adolescents provided assent. The university-affiliated Human Investigation Committee approved the research protocol.

Adolescents (N = 37) were, on average, 14.7 years old (SD = 1.63) and female (n = 27). At study entry, adolescents' BMI was 38.5 (SD = 8.33), corresponding to a BMI percentile of 98.6% (SD = 1.99%). Most caregivers were biological mothers (n = 33). Most were co-parenting, i.e., two-parent homes, (n = 25) and reported a median family income of

$16,000–$21,999 (*Minimum* = less than $1,000–$50,000, *Maximum* = $74,999). Three weight loss counselors (one Ph.D. psychologist, one Ph.D. dietitian and one Masters-level psychologist) highly trained in MI provided the MI treatment. Two (Ph.D.s) were members of the Motivational Interviewing Network of Trainers [24].

2.2 Procedure

In the parent study, families participated in one MI [25, 26] session targeting the nutritional and physical activity behavior changes necessary to promote and sustain weight loss [23]. We planned for sessions between the adolescent and MI counselor to last 20 minutes; the actual duration was closer to 30 (M = 29:21, *SD* = 8:21, *Minimum* = 15:34, *Maximum* = 45:47). All sessions were video recorded using state-of-the-art video recording technology that produces a split-screen image on a single monitor from simultaneously recording cameras trained on the adolescent and counselor [27]. Audio tracks were transcribed by a professional transcription service. Transcriptionists used the timestamp from the recording to enter the timing of specific verbalizations. Both video recordings and transcripts were used when coding the sessions.

2.3 Minority Youth - Sequential Coding for Observing Process Exchanges (MY-SCOPE)

A primary goal of the parent study was to develop a coding scheme to characterize the verbal communication behavior counselors use during MI sessions and the resulting patient verbal communication [23]. With the MY-SCOPE, counselor verbal utterances were coded as “MI-consistent” (e.g., reflections, open-ended questions, statements emphasizing the patient’s autonomy in decision-making) or “MI-inconsistent” (e.g., reflections of amotivational patient communication). Subsequent patient verbal utterances were coded as “change talk” (i.e., statements describing their own desires, abilities, reasons, and need for adhering to weight loss recommendations), “commitment language” (i.e., statements about their intentions or plans for adhering), and “counter-change talk” (i.e., amotivational statements).

Two coders completed the MY-SCOPE coding during the parent study. Initial coder training involved coding one session each week for a total of 10 sessions and weekly discussions of coding discrepancies. Initial inter-rater reliability (IRR) was assessed with Cohen’s kappa calculated across five co-coded sessions (k = .778). One primary coder coded all 37 sessions and a secondary coder coded 1 out of every 5 sessions. Once trained to reliability, the coders required eight months to code the 37 sessions achieving a coding rate of approximately 5 hours for every recorded hour. Overall, coders achieved an adequate level of IRR (k = .696) [28, 29].

2.4 Thin Slice Sampling

For the current study, four thin slice samples were extracted from the coded parent study data. To extract the first sample, we first divided the recordings into four equal segments. This was to ensure that slices were extracted from across the entire interaction (i.e., from the beginning, middle, and end of the interaction) and increasing the likelihood of accurately characterizing the evolving communication between the counselor and patient. More specifically, in MI, the counselor’s objective is to encourage patients to explore and resolve their ambivalence about behavior change. As patients become less ambivalent, their verbalizations change; thus, sampling one or two randomly selected minutes is less likely to accurately capture the full range of communication behavior observed over the course of the entire encounter. When extracting slices, we did not consider session content, but if a slice began or ended in the middle of an utterance, the entire utterance was extracted. This procedure resulted in a sample consisting of four 1-minute thin slices.

To empirically test the hypothesis that thin slices of a longer duration are more accurate than thin slices of shorter duration, our second sample involved extracting four 2-minute slices using used the same procedure (i.e., dividing the session into four segments and extracting a thin slice from the center of each segment). The third and fourth samples of thin slices were similarly extracted but, to extract a greater number of thin slices, the sessions were first divided into six equal parts. With an average duration of around 30 minutes, dividing the encounter into six sections would approximate sampling 1 minute every 5 minutes. Then, two thin slices, 1- and 2-minutes in duration, respectively, were extracted from the middle of each segment. This procedure resulted in two more samples of thin slices, one that included six 1-minute slices and a second that included six 2-minute slices. We did not examine 3-minute slices because the length of the shortest session was only 15:34 minutes; therefore, in some cases, 3-minute slices would result in coding nearly the entire session rather than thin slices of the session which defeats the purpose of using thin slices (i.e., reducing coding burden).

The final result was a total of four thin slice samples from the same 37 MI sessions. The first sample was comprised of four 1-minute slices for a total of four minutes of the total encounter which represented, on average, 14% of the session data. The second was composed of four 2-minute slices for a total of eight minutes and 27% of the data. The third consisted of six 1-minute slices for a total of six minutes of the encounters and 20% of the data. The fourth was comprised of six 2-minute slices and 41% of the data. Table 1 describes the proportion of the coded data extracted from the sessions.

2.5 Statistical Analysis Plan

We hypothesized that thin slice samples comprised of a greater number of slices (i.e. six versus four) and those of a longer duration (i.e., 2- versus 1-minute) would more closely match the pattern of verbal communication behavior coded in the full dataset. To test this hypothesis, we calculated the frequency distribution of the verbal communication behaviors in the fully coded parent dataset and compared it to the distribution extracted in each thin slice sample. Pearson's correlations were then computed using this frequency data to assess the strength of the relationship between the communication behaviors extracted in each thin slice sample and those in the fully coded dataset. The correlations represent a measure of reliability where the relationship between each thin slice sample and the entire encounter, including the thin slice, is assessed. Thus, we expected these part-whole correlations to be high. Interpreting the correlation coefficients as a reliability statistic suggests that correlations of a magnitude of at least .6 can be interpreted as adequate, ≥.7 good, and ≥.8 excellent [30]. All analyses were conducted in SPSS, version 21.

3. Results

A total of 6,796 verbal utterances were coded across the 37 treatment sessions, see Table 1. In the fully coded dataset just over one-third (38.2%) of the utterances were adolescents'. Similar proportions were extracted in each thin slice sample: 37.5% of the utterances were adolescents' when four 1-minute slices were extracted, 39.3% with six 1-minute slices, 38.6% with four 2-minute slices, and 39.0% with six 2-minute slices.

Examining the proportions of communication codes applied to the data revealed that the proportions extracted in each thin slice sample was very similar to the proportions represented in the fully coded session. For example, "change talk" represented 29.6% of the total number of adolescent utterances in the fully coded dataset, 31.4% in the four 1-minute slice sample (a difference of 1.8%), 31.7% when six 1-minutes slices were sampled (a difference of 2.1%), 29.5% when four 2-minutes slices were sampled (a difference of −0.1%), and 29.4% when six 2-minutes slices were sampled (a difference of −0.2%). The communication codes extracted in any thin slice sample varied at most 5.5% from the fully coded session.

Comparing the thin slice samples to one another revealed support for our hypothesis that samples consisting of a greater number and duration of thin slices would more closely match the fully coded dataset. In other words, the proportion of communication codes extracted in the thin slice samples was closer to the fully coded session when a greater number of thin slices were extracted (i.e., when 6 thin slices were extracted versus 4) and when the slices were longer in duration (i.e., when 2- versus 1-minute slices were extracted). To illustrate, "counter change talk" represented 10.6% of adolescent utterances in the fully coded dataset. The thin slice sample that most accurately represented this proportion was the sample of six 2-minute slices where 10.4% (a difference of −0.2%) of the adolescent utterances were characterized as counter change talk. In contrast, counter change talk represented 9.7% (a difference of −0.9%) of adolescent verbalizations in four 1-minute slice sample, 10.2% of the six 1-minute slice sample (a difference of −0.4%) and 11.3% of the four 2-minute slice sample (a difference of 0.7%). The six 2-minute slice sample demonstrated the highest degree of accuracy (the closest proportion) in 10 of the 20 communication behaviors coded.

The pattern among the correlations between the fully coded dataset and the thin slice samples, presented in Table 2, also demonstrated the expected pattern, with even stronger findings. The strength of the correlation between the fully coded dataset and the thin slice samples increased when a greater number of slices was extracted (i.e., 6 slices versus 4) and when "thicker" slices were extracted (i.e., 2-minute versus 1-minute slices). For 13 of the 20 communication behaviors coded, the strongest correlations were observed within the six 2-minute slices sample. As an illustration, consider the adolescent "commitment language" code. The four 1-minute slice sample demonstrated a moderate, statistically significant correlation with the fully coded dataset ($r = .474$, $p \leq .01$), the strength of the correlation increased when both a greater number of thin slices were extracted (six 1-minute slices: $r = .726$, $p \leq .001$) and when "thicker" slices were extracted (four 2-minute slices: $r = .701$, $p \leq .001$). But, the strongest correlation was observed when six 2-minute slices were sampled ($r = .760$, $p \leq .001$).

4. Discussion and Conclusion

4.1. Discussion

The results of this study suggest that thin slice sampling may be a useful and accurate strategy to reduce coding burden when characterizing verbal communication during clinical encounters with behavioral coding schemes. As expected, samples comprised of a greater number and duration of thin slices demonstrated the greatest accuracy with the six 2-minute slice sample demonstrating the greatest accuracy. Surprisingly, the four 2-minute slice sample demonstrated only slightly less accuracy than the six 2-minute slice sample. The proportions of five communication behaviors demonstrated greater accuracy in the four 2-minute slice sample than the six 2-minute slice sample with the overall differences between the two samples being quite small, on average 0.9%. Similarly, six communication behaviors coded in the four 2-minute slice sample represented the strongest correlation with the full dataset and, overall, the average difference between the samples of four versus six 2-minute slices was only .122. Coding four 2-minute thin slices, versus six 2-minute slices, would reduce the coding burden considerably. Specifically, coders would code 28% of the average 29 minute encounter when extracting 8 minutes versus 41% when extracting 12 minutes. These results suggest that using four 2-minute thin slices may provide a slightly lower level of accuracy than six 2-minute slices, but much greater utility when considering resource expenditures, i.e., coding duration and associated costs, both financial and quality.

Literature on the use of thin slices to code discrete verbal behaviors is quite limited. However, three studies have examined the use of thin slices to code behavior and demonstrate findings that are consistent with the current study's findings. When coding discrete nonverbal behaviors (gestures, nods, self-touches, smiles, gaze) among undergraduate students collaborations, Murphy [4] found the accuracy of thin slices increased when the number of thin slices extracted increased from 1 to 2 to 3 (all one minute in duration). Specifically, the three slice sample, which represented 20% of the 15 minute interaction, demonstrated the greatest accuracy in three of five nonverbal behavior categories (gaze, self-touch, and smile). But, like the results of the current study, when comparing the magnitude of correlations observed in each of the three thin slice samples, the differences were relatively small, with the exception of self-touch. In Roter's study [16] of patient-provider communication among medical students, the thin slice sample comprised of three slices was more strongly correlated with the entire encounter than any 1-minute thin slice. James et al [15] found "thicker" slices, those nine minutes in duration representing 50% of the 18 minute interaction, accurately represented mothers and infants dyads' eye gaze and vocalizations but shorter slices of three and six minutes were discrepant from patterns observed in the full interaction.

Limitations of the current study include extracting thin slices of previously coded data. If the thin slices were extracted and then coded, the results of the coding might vary. For example, a counselor's reflection of a patient statement might be miscoded if the preceding patient statement was not extracted. The relatively small sample size and specific context from which the observations were drawn might also limit generalizability. Although 1,776 behaviors were coded, these behaviors occurred within the context of 37 MI sessions between an African American adolescent and a weight loss counselor. Thus, these results might not generalize to other video-recorded data, other types of counseling sessions or clinical interactions with adults or other populations. Thus, there is a need to replicate this research with both larger and more diverse samples and to examine the utility of thin slices coded after, versus prior to, extraction.

4.2. Conclusion

Despite these limitations, this research adds to a very small literature suggesting thin slices might be a viable methodology for coding verbal behaviors. Our results suggest thin slice samples of counselor-patient interactions demonstrate a high degree of accuracy, relative to fully coded sessions, when characterizing verbal communication behavior in Motivational Interviewing sessions. We found the highest degree of accuracy when six 2-minute slices were extracted and only slightly lower accuracy when four 2-minute slices were extracted. This research has the potential to facilitate high quality research examining the complex, behavioral interactions that occur between clinicians and patients in a variety of settings, research that has been significantly limited by its resource intensive nature.

4.3 Practice Implications

Given the limited literature on the application of thin slices to behavioral coding schemes, both verbal and nonverbal, we suggest that researchers interested in using thin slices in their own work conduct preliminary research to determine the ideal number and “thickness” of slices required for their study context. In their discussions, both Murphy [4] and James et al [15] indicate the frequency of the target behavior is a critical issue. Thin slices sampling might not accurately detect and, therefore, might not be appropriate for behaviors with a very low base rate. A second consideration is the length of the observation to be coded. In this study, we could not examine thin slices greater than 2 minutes “thick” because, for some of the sessions, extracting slices of longer duration would result in coding the entire session thereby defeating the entire purpose of using thin slices, i.e., reducing coding burden. Although an individual decision is dependent on available resources and research goals, we suggest that if using thin slices does not reduce the coding burden by at least half, resource savings is minimal and the argument for using thin slices is weak.

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References

1. Apodaca TR, Longabaugh R. Mechanisms of change in motivational interviewing: A review and preliminary evaluation of the evidence. Addiction. 2009; 104:705–15. [PubMed: 19413785]
2. Moyers TB, Martin T. Therapist influence on client language during motivational interviewing sessions. J Subst Abuse Treat. 2006; 30:245–51. [PubMed: 16616169]
3. Moyers TB, Martin T, Houck JM, Christopher PJ, Tonigan JS. From in-session behaviors to drinking outcomes: a causal chain for motivational interviewing. J Consult Clin Psychol. 2009; 77:1113. [PubMed: 19968387]
4. Murphy NA. Using Thin Slices for Behavioral Coding. J Nonverbal Behav. 2005; 29:235–46.

5. Place SS, Todd PM, Zhuang J, Penke L, Asendorpf JB. Judging romantic interest of others from thin slices is a cross-cultural ability. Evol Hum Behav. 2012; 33:547–50.
6. Friedman JNW, Oltmanns TF, Turkheimer E. Interpersonal perception and personality disorders: Utilization of a thin slice approach. J Res Pers. 2007; 41:667–88.
7. Fowler KA, Lilienfeld SO, Patrick CJ. Detecting psychopathy from thin slices of behavior. Psychol Assess. 2009; 21:68–78. [PubMed: 19290767]
8. Oltmanns TF, Friedman JNW, Fiedler ER, Turkheimer E. Perceptions of people with personality disorders based on thin slices of behavior. J Res Pers. 2004; 38:216–29.
9. Borkenau P, Mauer N, Riemann R, Spinath FM, Angleitner A. Thin Slices of Behavior as Cues of Personality and Intelligence. J Pers Soc Psychol. 2004; 86:599–614. [PubMed: 15053708]
10. Oveis C, Gruber J, Keltner D, Stamper JL, Boyce WT. Smile intensity and warm touch as thin slices of child and family affective style. Emotion. 2009; 9:544–8. [PubMed: 19653777]
11. Ambady N, LaPlante D, Nguyen T, Rosenthal R, Chaumeton N, Levinson W. Surgeons' tone of voice: A clue to malpractice history. Surgery. 2002; 132:5–9. [PubMed: 12110787]
12. Elfenbein HA, Ambady N. On the universality and cultural specificity of emotion recognition: A meta-analysis. Psychol Bull. 2002; 128:203–35. [PubMed: 11931516]
13. Ambady N, Hallahan M, Conner B. Accuracy of judgments of sexual orientation from thin slices of behavior. J Pers Soc Psychol. 1999; 77:538–47. [PubMed: 10510507]
14. Kraus MW, Keltner D. Signs of Socioeconomic Status: A Thin-Slicing Approach. Psychol Sci. 2009; 20:99–106. [PubMed: 19076316]
15. James D, Wadnerkar M, Lam-Cassettari C, Kang S, Telling A. Thin Slice Sampling of Video Footage for Mother/Child Interaction: Application to Single Cases. J Psychopathol Behav Assess. 2012; 34:351–60. [PubMed: 22942556]
16. Roter DL, Hall JA, Blanch-Hartigan D, Larson S, Frankel RM. Slicing it thin: New methods for brief sampling analysis using RIAS-coded medical dialogue. Patient Educ Couns. 2011; 82:410–9. [PubMed: 21239135]
17. Ambady N, Gray HM. On being sad and mistaken: Mood effects on the accuracy of thin-slice judgments. J Pers Soc Psychol. 2002; 83:947–61. [PubMed: 12374446]
18. Ambady N, Koo J, Rosenthal R, Winograd CH. Physical therapists' nonverbal communication predicts geriatric patients' health outcomes. Psychol Aging. 2002; 17:443–52. [PubMed: 12243386]
19. Ambady N, Rosenthal R. Half a minute: Predicting teacher evaluations from thin slices of nonverbal behavior and physical attractiveness. J Pers Soc Psychol. 1993; 64:431–41.
20. Ambady N, Krabbenhoft MA, Hogan D. The 30-Sec Sale: Using Thin-Slice Judgments to Evaluate Sales Effectiveness. J Consum Psychol. 2006; 16:4–13.
21. Henry SG, Eggly S. The Effect of Discussing Pain on Patient-Physician Communication in a Low-Income, Black, Primary Care Patient Population. J Pain. 2013
22. Hall JA, Roter DL, Blanch DC, Frankel RM. Observer-rated rapport in interactions between medical students and standardized patients. Patient Educ Couns. 2009; 76:323–7. [PubMed: 19545973]
23. Idalski Carcone A, Naar-King S, Brogan K, Albrecht T, Barton E, Foster T, et al. Provider communication behaviors that predict motivation to change in African American adolescents with obesity. J Dev Behav Pediatr. 2013; 34:599–608. [PubMed: 24131883]
24. Madson MB, Loignon AC, Lane C. Training in motivational interviewing: A systematic review. J Subst Abuse Treat. 2009; 36:101–9. [PubMed: 18657936]
25. Miller, WR.; Rollnick, S. Motivational Interviewing: Preparing People for Change. 2. New York: Guilford; 2002.
26. Rollnick, S.; Miller, WR.; Butler, CC. Motivational interviewing in health care: helping patients change behavior. Guilford Press; 2007.
27. Albrecht TL, Ruckdeschel JC, Ray FL, Pethe BJ, Riddle DL, Strohm J, et al. A portable, unobtrusive device for videorecording clinical interactions. Behav Res Methods. 2005; 37:165–9. [PubMed: 16097357]

28. Landis JR, Koch GG. The measurement of observer agreement for categorical data. Biometrics. 1977; 33:159–74. [PubMed: 843571]

29. Wood, JM. Understanding and Computing Cohen's Kappa: A Tutorial. 2007. WebPsychEmpiricist Web Journal at http://wpeinfo/

30. Cohen, J. Statistical power analysis for the behavioral sciences. Hillsdale, NJ: Lawrence Erlbaum Associates; 1988.

Table 1

Frequency of Observed Communication Behavior in Thin and Fully Coded Slices

Adolescent Communication Behavior	**Full**	**Four 1-Minute Slices**	**Six 1-Minute Slices**	**Four 2-Minute Slices**	**Six 2-Minute Slices**
Change Talk	29.6%	31.4%	31.7%	29.5%†	29.4%
Commitment Language	14.9%	18.6%	14.3%†	18.0%	16.0%
Counter-Change Talk	10.6%	9.7%	10.2%	11.3%	10.4%†
Other	45.0%	40.3%	43.8%	41.3%	44.2%†
N	2698	424	650	800	1200
Counselor Communication Behavior					
Structure Session	6.7%	4.5%†	3.7%	3.8%	4.2%
Positive Information	7.1%	8.2%	8.6%	7.6%†	8.3%
Emphasize Autonomy	10.1%	10.5%	8.9%	10.3%	10.1%†
Elicit Feedback	4.1%	3.7%	4.5%	3.8%†	3.5%
Affirmation	9.2%	10.1%	10.2%	9.5%	9.4%†
Reflection of Change Talk	13.2%	13.7%	14.0%	12.9%†	13.7%
Reflection of Commitment Language	6.5%	6.7%	5.9%	7.4%	6.4%†
Reflection of Counter-Change Talk	2.5%	2.7%	2.0%	3.2%	2.4%†
Other Reflections	9.0%	9.1%	9.3%	9.0%†	8.8%
Summary	4.7%	6.5%	6.9%	6.0%	6.0%†
Open-ended Questions to Elicit Change Talk	9.3%	11.3%	9.7%†	10.8%	10.2%
Open-ended Questions to Elicit Commitment Language	4.4%	4.0%	4.7%	4.7%†	4.6%†
Open-ended Questions to Elicit Counter-Change Talk	2.1%	1.1%	2.1%†	2.0%	2.1%†
Other Questions	6.1%	0.6%	1.0%	1.2%	2.1%†
Other Statements	5.1%	4.4%	5.3%	5.1%†	5.4%
N	4361	706	1003	1275	1878
Proportion of Interaction Extracted					
M		14%	27%	20%	41%
Min, Max		9%, 26%	17%, 52%	13%, 39%	26%, 77%

† Denotes the thin slice sample that most accurately represents the communication behavior observed in the fully coded sample

Table 2

Correlation Between Thin Slices and Fully Coded Sessions

	Four 1-Minute Slices	Six 1-Minute Slices	Four 2-Minute Slices	Six 2-Minute Slices
Adolescent Communication Behavior				
Change Talk	.597***†	.261	.436**	.403*
Commitment Language	.474**	.726***	.701***	.760***†
Counter Change Talk	.601***	.639***	.741***	.822***†
Other	.585***	.652***	.749***†	.706***
Counselor Communication				
Structure Session	.401*	.485**	.475**	.498**†
Positive Information	.593***	.617***	.539**	.808***†
Emphasize Autonomy	.365*	.224	.376*	.499**†
Elicit Feedback	.627***	.640***	.752***†	.595***
Affirmation	.587***	.502**	.616***	.650***†
Reflection of Change Talk	.669***	.436**	.656***	.698***†
Reflection of Commitment Language	.455**	.581***	.790***†	.767***
Reflection of Counter-Change Talk	.472**	.591***	.753***	.578***†
Other Reflections	.574***	.585***	.718***†	.369*
Summary	.401*	.677***	.742***	.745***†
Open-ended Questions to Elicit Change Talk	.653***	.679***	.713***	.749***†
Open-ended Questions to Elicit Commitment Language	.310	.570***	.532**	.712***†
Open-ended Questions to Elicit Counter-Change Talk	.444**	.573***	.668***†	.606***
Close-ended Questions to Elicit Change Talk or Commitment Language	.645***	.587***	.681***	.863***†
Other Questions	.626***	.651***	.419**	.834***†
Other Statements	.128	.342*	.390*	.541**†

*denotes $p \leq .05$,

**denotes $p \leq .01$,

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*** denotes $p \leq .001$,

† Denotes the thin slice sample where the strongest correlation between the communication behavior in the fully coded sample and the communication behavior extracted in the thin slice sample was observed