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Exploring detection of contact vs. fantasy online sexual offenders in chats with minors: Statistical discourse analysis of self-disclosure and emotion words☆

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ABSTRACT

This exploratory study is the first to identify content differences between youths' online chats with contact child sex offenders (CCSOs; seek to meet with youths) and those with fantasy child sex offenders (FCSOs; do not meet with youths) using statistical discourse analysis (SDA). Past studies suggest that CCSOs share their experiences and emotions with targeted youths (self-disclosure grooming tactic) and encourage them to reciprocate, to build trust and closer relationships through a cycle of self-disclosures. In this study, we examined 36,029 words in 4,353 messages within 107 anonymized online chat sessions by 21 people, specifically 12 youths and 9 arrested sex offenders (5 CCSOs and 4 FCSOs), using SDA. Results showed that CCSOs were more likely than FCSOs to write online messages with specific words (first person pronouns, negative emotions and positive emotions), suggesting the use of self-disclosure grooming tactics. CCSO's self-disclosure messages elicited corresponding self-disclosure messages from their targeted youths. These results suggest that CCSOs use grooming tactics that help engender youths' trust to meet in the physical world, but FCSOs do not.

1. Introduction

Unwanted online sexual solicitation of minors is a growing problem. In 2015, the Internet Crimes Against Children (ICAC) taskforce conducted over 54,000 investigations and 61,000 forensic exams resulting in the arrest of more than 60,000 offenders (US Department of Justice, 2017). However, according to the Federal Bureau of Investigation, 750,000 adults seek sex with youths daily (Rodas, 2014). Internet crimes against children are further complicated by the differences among online child sex offenders. Some are contact-driven; they want to meet with the minor in the physical world (contact child sex offender, CCSO; also known as hands-on child sex offender, Briggs, Simon, & Simonsen, 2011). Others are online solicitors who are fantasy-driven, uninterested in meeting the minor in the physical world (fantasy child sex offender, FCSO; also known as Internet solicitors, Briggs et al., 2011).

Compared to FCSOs, CCSOs are typically a greater threat to children. Whereas FCSOs might psychologically harm children, CCSOs can both physically and psychologically harm children. Furthermore, CCSOs are much more likely than FCSOs to be repeat offenders (McCarthy, 2010). Also, CCSOs' cognitive distortions can help them deny the harm they cause their victims, so some researchers

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believe that challenging and addressing CCSOs' cognitive distortions during treatment can reduce their recidivism rates (Blumenthal, Gudjonsson, & Burns, 1999). Successful treatment strategies require understanding the risks associated with the offender, so risk assessment of CCSOs and FCSOs is critically important (Haldaman, 2012). As CCSOs pose a more immediate and continuous threat to children compared to FCSOs, detecting CCSOs and preventing contact sex crimes is a higher priority for law enforcement than finding FCSOs. However, law enforcement officers are swamped with cases involving solicitations of minors and lack a cost-effective way to determine whether an offender is a CCSO or an FCSO.

This exploratory study is the first to identify content differences between the online chats of CCSOs and FCSOs based on their goal-motivated (meet youth vs. not meet youth) grooming tactics via statistical discourse analysis (SDA, Chiu & Lehmann-Willenbrock, 2016). Past studies focused on sociodemographic (e.g., age, race) and criminological differences between contact-driven and fantasy-driven child sex offenders, relying on their subjective responses to surveys and interviews (Babchishin, Hanson, & Hermann, 2011). In contrast, we capitalize on CCSOs' and FCSOs' different goals to identify a self-disclosure tactic for building trust with youths (Medaris & Girouard, 2002). Furthermore, we analyze objective data, namely chats, to test whether CCSOs self-disclose more than FCSOs do and whether sex offender self-disclosures induce youth disclosures. Specifically, the current, exploratory study tested whether CCSOs are more likely than FCSOs to disclose their experiences and emotions, thereby encouraging youths to share their experiences and emotions (modeling theory, Singer, 2013), in order to build mutual trust (trust attraction, Dindia, 2002) toward an eventual meeting. In this exploratory study, we conducted a linguistic analysis of 36,029 words in 4,353 messages within 107 anonymized online chat sessions by 21 people, specifically 12 youths and 9 arrested sex offenders (5 CCSOs and 4 FCSOs) with SDA (Chiu & Lehmann-Willenbrock, 2016). By helping law enforcement detect CCSOs, we can prevent sex offenses against children.

2. Theoretical framework

After summarizing possible differences between online and offline sex offenders, we discuss different types of online sex offenders. As some online sex offenders seek to meet youths for sex (CCSOs), while others do not (FCSOs), their different goals can yield differences in their grooming tactics. We discuss one set of grooming tactics, namely disclosures of own experiences and emotions, and explicate why CCSOs are more likely than FCSOs to use them.

2.1. Sex offenders and routine activities theory

Online and offline child sex offenders are not homogenous. According to Routine Activities Theory, criminal behavior requires: (a) motivated offenders, (b) available targets, and (c) weak monitoring (Cohen & Felson, 1979). In the case of off-line child sex offenders, they must have high motivation to identify and engage with accessible victims face-to-face, compared to the Internet child sex offender who may anonymously identify and engage a large number of minors with little effort or motivation (Briggs et al., 2011).

Technological advancements, including social networking sites, enable child sex offenders to chat simultaneously with any number of children anywhere at any time (Afuah & Tucci, 2003). The Internet facilitates communication and information sharing (Criddle, 2006), which aids in the identification of available target youths by searching chat rooms, screen names, and profiles (Davidson & Gottschalk, 2011). Furthermore, CCSOs network with other sex offenders, who model possible sex offenses, encourage them, and share strategies and tactics to commit them (e.g., identify victims, groom them for sex, and avoid detection, Holt, Blevins, & Burkert, 2010).

As the Internet's apparent anonymity suggests little monitoring, it attracts people to experiment with taboos, including sex with children (Laulik, Allam, & Sheridan, 2007). Also, the Internet enables people to interact while providing little information about themselves, so this thin bandwidth facilitates deception (e.g., 29% of sex offenders lied about their age, Malesky, 2007). As societal costs are much higher for CCSOs than for FCSOs, CCSOs face much more severe punishment and are more concerned about potential external monitors, as suggested by the shorter durations of their chats with youths (Martellozzo, 2012; McCarthy, 2010; Walby, 2004).

2.2. Differences between CCSOs and FCSOs

Hence, the Internet's attributes suggest that some online sex offenders differ from offline sex offenders in their commitment and aims (Babchishin et al., 2011). Before the Internet's added sex offense opportunities, less motivated people might not have committed sex offenses, as suggested by online sex offenders' sparser crime records before a sex offense arrest and lower recidivism rates, compared to offline-only sex offenders (Babchishin et al., 2011). Also, each online offender might have different aims, such as: (a) impulsive/curiosity viewing/downloading of child pornography; (b) creating or distributing child pornography solely for profit; (c) cybersex (Briggs et al., 2011; DeHart et al., 2016); or (d) contact sex offenses (Krone, 2004; Lanning, 2010).

Within the Routine Activities Theory framework, CCSOs and FCSOs differ on motivations, targeted victims and concerns about monitoring. Whereas CCSOs are motivated to have physical sex with youths, FCSOs seek cybersex with them. Hence, CCSOs target youths who are willing to meet with them in the physical world, while FCSOs only need youths to engage with them online, not necessarily in the physical world. As CCSOs can cause severe damage with their contact sex offenses, society proscribes much harsher penalties for them, so they are often concerned about external monitors (Martellozzo, 2012; McCarthy, 2010; Walby, 2004). In contrast, FCSOs' sex offenses cause less damage, so they face smaller punishments and are less concerned about external monitors (Martellozzo, 2012; McCarthy, 2010; Walby, 2004).

Complicating matters, people can commit multiple sex offenses, commit different offenses depending on the victims (e.g., based

on hair color), and change their sex offenses over time (DeHart et al., 2016). Such differences across online sex offenders and across time can limit the potential of using fixed demographic profiles to identify specific types of sex offenders. Indeed, while studies have reported some demographic differences with descriptive statistics, none of these are statistically significant (e.g., Briggs et al., 2011).

In contrast, studies have reported significant differences in CCSOs' and FCSOs' behaviors. Specifically, CCSOs are more likely than FCSOs to use illicit drugs, have committed a sex crime, download child pornography, masturbate to it, view child models, read erotic stories, and chat with others about sexual interest in children (both online and face-to-face, McCarthy, 2010). In contrast, FCSOs are more likely than CCSOs to teach a youth about sexual behaviors, engage in exhibitionism with a web camera, masturbate in front of a youth, and encourage a youth to masturbate and have cybersex (Briggs et al., 2011). Hence, we propose that examining specific behaviors, namely differences in grooming tactics, might be more effective than focusing on demographics.

2.3. Self-disclosure as a grooming tactic

Unlike FCSOs, CCSOs seek to meet with a youth for physical sex, so we propose that CCSOs likely use grooming tactics to engender their target youths' trust, such as disclosing one's experiences and emotions (self-disclosures; other examples of grooming tactics are flattery, bribes, and threats, Whittle, Hamilton-Giachritsis, Beech, & Collings, 2013). Through self-disclosures, speakers encourage listeners to disclose their own experiences, which kindles a closer relationship built on mutual trust (modeling theory, Singer, 2013). CCSOs who disclose their experiences and emotions (including sexual ones) suggest that doing so is normal and encourage targeted youths to emulate them by disclosing their own experiences and emotions.

A person's self-disclosures also create shared information with listeners (Tardy & Dindia, 2006), show vulnerability, and indicate that he or she likes and trusts them with this information (Joinson & Paine, 2007). With this shared information, the speaker and listener(s) have more in common, so they are more likely to interact and like each other (homophily bias, Brechwald & Prinstein, 2011).

Self-disclosures, especially of negative experiences and emotions, increase vulnerability and indicate trust by the revealer (personalized disclosure, Bazarova, 2012; Miell & Duck, 1986) as the listener can potentially misuse this information (Joinson & Paine, 2007). Thus, sharing negative experiences rather than positive ones is more likely among friends than acquaintances or strangers, as it renders one even more vulnerable and creates a high expectation of trustworthiness in the listener (Bazarova, 2012). Beyond negative experiences, discussing negative emotions further increases one's exposure and suggests greater trust and intimacy (Tolhuizen, 1989). Furthermore, youths who are lonely, shy, physically abused, sexually abused or otherwise traumatized are more likely to receive online aggressive sexual solicitations (Mitchell, Finkelhor, & Wolak, 2007; Peter, Valkenburg, & Schouten, 2005), suggesting that some child sex offenders target vulnerable children who might be attracted to someone who shares and understands their negative feelings.

By disclosing negative emotions, the revealer displays esteem and trust in the listener, so the former encourages the latter to reciprocate (trust attraction hypothesis or disclosure-liking, Dindia, 2002; Shamdasani & Jung, 2011). Thus, after a disclosure, the listener is more likely to trust the discloser more, thereby reciprocating experiences and emotions, which ignites a cycle of disclosures (social exchange theory, Cook, Cheshire, Rice, & Nakagawa, 2013; Tardy & Dindia, 2006). In addition, the original discloser may further highlight parts of the listener's information to show that they have more commonalities, or reveal additional related stories, all of which can further increase homophily bias (Brechwald & Prinstein, 2011). This cycle of disclosures can help participants like and trust one another more, thereby building closer relationships.

3. The current study

As CCSOs and FCSOs show no statistically significant demographic differences (e.g., Briggs et al., 2011), past studies often surveyed or interviewed them after they were arrested for sex offenses, so the validity of these data depend on their honesty and accuracy. In contrast, our study identifies a grooming tactic within their chats, objectively determines differences in its usage by CCSOs and FCSOs, and tests for a mechanism by which it influences youths' behaviors with a novel statistical method, SDA. Successfully determining grooming tactics that differentiate CCSOs and FCSOs can help law enforcement identify CCSOs and prevent sex offenses against children.

Within the Routine Activities Theory framework, CCSOs and FCSOs have different motivations, different targets, and different concerns about monitoring. CCSOs desire to have physical sex with youths willing to meet with them, and potentially harsh penalties increase their concern about external monitoring. In contrast, FCSOs seek fantasy sex with youths who need not be willing to meet with them, and weaker penalties reduce their concern about external monitoring. Based on the above criminology studies and social psychology studies, we expect to find that CCSOs are more likely than FCSOs to use self-disclosures of their experiences and emotions (especially negative ones) to build trust with target youths and eventually meet with them. Hence, we hypothesize the following.

The online chat messages of CCSOs are more likely than those of FCSOs to have:

H-1a. … first person pronoun(s) (I, me, …)

H-1b. … negative emotion word(s) (sad, mad, …)

H-1c. … positive emotion word(s) (glad, happy …)

H-1d. … both negative emotion word(s) and first person pronouns

H-1e. … both positive emotion word(s) and first person pronouns

By self-disclosing their experiences and emotions, CCSOs encourage youths to self-disclose their own emotions and experiences, which builds trust with the CCSOs. Hence, we hypothesize that self-disclosures increase the likelihood of reciprocal self-disclosures of the same type. Specifically, a message with the following types of words is more likely to be followed by a responder's message with the same types of words:

H-2a. A message with first person pronoun(s) is more likely than other messages to be followed by a message with first person pronoun(s)

H-2b. A message with negative emotion word(s) is more likely than other messages to be followed by a message with negative emotion word(s)

H-2c. A message with positive emotion word(s) is more likely than other messages to be followed by a message with positive emotion word(s)

H-2d. A message with both negative emotion word(s) and first person pronoun(s) is more likely than other messages to be followed by a message with both negative emotion word(s) and first person pronoun(s)

H-2e. A message with positive emotion word(s) and first person pronoun(s) is more likely than other messages to be followed by a message with both positive emotion word(s) and first person pronoun(s)

Thus, through a grooming process of self-disclosures, the CCSO increases the likelihood of meeting face-to-face with the youth in the real world. In contrast, a FCSO who does not seek to meet the youth is less likely than a CCSO to use this self-disclosure grooming tactic. (Unlike CCSOs, FCSOs are more likely to teach youths about sexual behaviors or use web cameras for exhibitionism to encourage a youth to reciprocate, Briggs et al., 2011) See Fig. 1 for a summary of the hypotheses.

4. Methods

To address our hypotheses, we analyzed online chats between youths and sex offenders (Black, Wollis, Woodworth, & Hancock, 2015). We coded each message in multiple ways with a customized, computer annotation program. Then, we explored our hypotheses with SDA (Chiu & Lehmann-Willenbrock, 2016).

4.1. Sampling and procedure

In contrast to past studies using data with police posing as children (e.g., Black et al., 2015), the authors solicited online chats between offenders and minors from the ICAC task forces and affiliations in the United States. The Ventura County Sheriff's Department (in California) and the Iowa Department of Public Safety shared anonymized online chat conversations by 21 people (12 youths, 5 arrested CCSOs and 4 arrested FCSOs; 36,029 words in 4,353 instant text messages within 107 online chat sessions) for this study. The majority of the cases were from 2015 and 2016 with one from 2007; all of the offenders were male, but no other demographic information was available. The data included both male and female victims, but all demographic information remained anonymous to the researchers. The data were treated in accordance with the ethical standards set forth by the American Psychological Association (APA), and this study received Institutional Review Board approval under protocol #1602017226.

Statistical power differed for each level (e.g., message, chat session, and individual; Konstantopoulos, 2008). For the 4,353

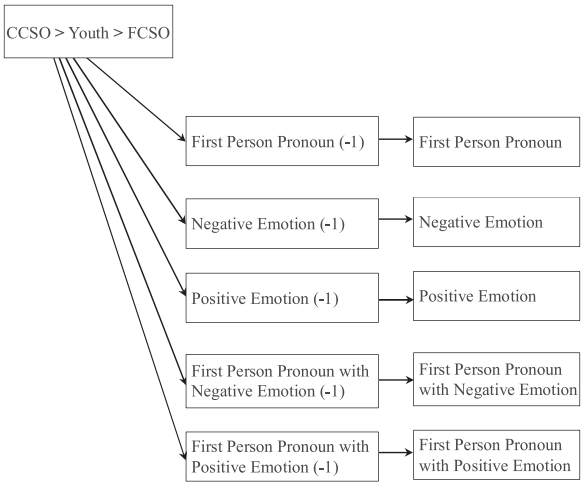

Fig. 1. Explanatory Model of relations among individuals and message attributes.

messages, statistical power exceeded 0.99 for an effect size of 0.1. Also, the statistical power of 107 online chat sessions was 0.88 for an effect size of 0.3, while that of 21 individuals (9 sex offenders and 12 youths) was 0.85 for an effect size of 0.6. Hence, we have statistical confidence in all results at the message and session levels and in significant results at the individual level. However, we lack confidence in non-significant results at the individual level.

As all identifiable information was removed from the dataset (e.g., names, addresses), we developed the following nomenclature. Within the online chat conversations, the agencies replaced the name of the offender with either "predator" for CCSOs or "solicitor" for FCSOs, and the youth's name was replaced with "victim." The agencies also replaced any other identifiable information with an appropriate name to assist with coding and content analysis (e.g., address, phone number). Finally, the agencies removed all photos/files, including child pornography sent during the online chat conversations, replacing them with a description so that we could annotate the person requesting an image, the person sending an image, and the content of the image.

4.2. Variables

4.2.1. Individual-level variables

Based on our agencies' identification of the participants, we created the dichotomous variables *CCSO* and *FCSO*. *CCSO* has a value of one for a message written by a CCSO or a value of zero otherwise. Each message is likewise coded for *FCSO*. A message by a youth is indicated by zero values for both *CCSO* and *FCSO*.

4.2.2. Message-level variables

Each message occurred at a specific time and together form an ordered sequence. Hence, *message order* is the position of a message within this sequence. For example, the 37th message in a conversation between a sex offender and a youth has a *message order* value of 37.

We wrote a computer program to create three variables indicating whether each message contained any words from these three categories: *first person personal pronouns* (e.g., I, me), *negative emotion words* (e.g., sad, angry) or *positive emotion words* (e.g., happy, joy; linguistic inquiry and word count [LIWC] categories, Pennebaker, Francis, & Booth, 2001). Then, we created two variables indicating whether messages had *first person pronoun with negative emotion words* or *first person pronoun with positive emotion words*. As the LIWC negative emotions category included sex-related words, we addressed this confound by creating and testing variables for negative emotions without sex-related words (e.g., "dick" was removed from the negative emotions category since it is also a sex-related word). Additionally, we supplemented LIWC's sexual words category with words found in the online chats pertaining strictly to sex (e.g., jerk off).

4.3. Analysis

We use *statistical discourse analysis* (SDA, Chiu & Lehmann-Willenbrock, 2016), to test: (a) whether the likelihood of each type of self-disclosure in a message differs among CCSOs, FCSOs and youths, and (b) whether a type of self-disclosure in a message is more likely to precede a similar self-disclosure in the next message. Integrating analyses of data at multiple levels and across time, SDA combines multilevel analysis and time-series analysis to model (a) how variables at various levels (message, chat session, person, etc.) are related to attributes of a message, and (b) how attributes of previous messages (or their sequences) are related to attributes of the current message.

Statistically analyzing social interaction processes presented several difficulties (regarding the data set, outcome variables, and explanatory variables), each of which is addressed with a specific statistics strategy within SDA (Chiu & Lehmann-Willenbrock, 2016). For details, see Appendix A (in Supplementary material; Benjamini, Krieger & Yekutieli, 2006; Chiu & Khoo, 2005; Graham, 2009; King & Zeng, 2001; Ljung & Box, 1979; MacKinnon, Lockwood & Williams, 2004; Peugh & Enders, 2004; Wise & Chiu, 2011).

4.3.1. Explanatory model

We began with a variance components model (with random intercepts) with no explanatory variables (Goldstein, 2011).

$$\mathbf{Word\_in\_Message}_{yijk} = \mathrm{F}(\beta_y + \mathbf{f}_{yjk} + \mathbf{g}_{yk}) + \mathbf{e}_{yijk} \quad (1)$$

The probability that word type y (first person pronoun; negative emotion; positive emotion; first person pronoun with negative emotion; first person pronoun with positive emotion) occurs at message i of session j in dyad k is the expected value of $\mathbf{Word\_in\_Message}_{yijk}$ via the Logit link function (F) of the overall mean β_y, and the unexplained session and dyad components (residuals, $\mathbf{f}_{yjk}$, $\mathbf{g}_{yk}$).

Then, we add explanatory variables regarding the person who wrote the current message, the message number (reflecting time), word types in the previous message, and their interactions.

$$\begin{aligned}\mathbf{Word\_in\_Message}_{yijk} = \mathrm{F}(&\beta_y + \mathbf{f}_{yjk} + \mathbf{g}_{yk} + \beta_{ypjk}\mathbf{Person}_{yijk} + \beta_{ymjk}\mathit{Message\_number}_{yijk} \\ &+ \beta_{ywjk}\mathbf{Word\_in\_other\_person's\_last\_message}_{yijk} + \beta_{yxjk}\mathbf{Interactions}_{yijk}) + \mathbf{e}_{yijk}\end{aligned} \quad (2)$$

Using messages written by youths as the baseline, we entered two explanatory variables, CCSO and FCSO (**Person**), to test hypotheses regarding differences in self-disclosures across people (H-1a, b, c, d, e). Wald tests identified significant effects (likelihood

Table 1
Summary Statistics (N = 4353 messages).

Variable	Proportion	Minimum	Maximum
First Person Pronouns (I, me, etc.)	0.351	0	1
Negative Emotion (angry, sad)	0.125	0	1
Positive Emotion (happy, joy)	0.319	0	1
I + Negative Emotion	0.069	0	1
I + Positive Emotion	0.128	0	1
Contact Child Sex Offender[a] (all males)	0.300	0	1
Fantasy Child Sex Offender[a] (all males)	0.202	0	1
Youth	0.498	0	1

[a] Compared to youths in online chats.

ratio tests were not reliable for multilevel analysis of dichotomous outcomes, Goldstein, 2011). Non-significant variables were removed. Next, we tested whether the likelihood of self-disclosures differed in earlier or later messages (*Message_number*). Then, we tested whether self-disclosure grooming tactics (hypotheses H-2a, b, c, d, e) elicited reciprocation by adding the following explanatory variables regarding the other person's last message: first person pronoun (−1), negative emotion (−1), positive emotion (−1), first person pronoun with negative emotion (−1), and first person pronoun with positive emotion (−1) (**Word_in_other_person's_last_message**). Lastly, we tested for interactions among explanatory variables. For cross-level interactions, we use a random coefficients model (see Appendix for details in Supplementary material).

An alpha level of 0.05 was used. The odds ratio of each variable's total effect (E = direct + indirect) was reported as the percentage increase or decrease (+E% or –E%) in the outcome variable (Kennedy, 2008). We examined residuals for both good fitting representatives of our theoretical framework and substantial outliers. The above analysis was repeated using Probit (rather than Logit) to test the robustness of the results to different assumptions regarding the distribution of the residuals.

5. Results

5.1. Summary statistics

Among these 4,353 messages, 35% had first person pronouns, 13% had negative emotions, and 32% had positive emotions. Few messages had both first person pronouns and negative emotions (7%), while more messages had both first person pronouns and positive emotions (13%). See summary statistics in Table 1.

5.2. Explanatory model

SDA results showed that use of specific categories of words, suggesting self-disclosure grooming tactics to engender trust, differed substantially across CCSOs, FCSOs, and youths, and slightly across time (see Table 2).

These grooming tactics were used more often by CCSOs and less often by FCSOs (CCSO > FCSO). CCSOs used first person pronouns in 13% more of their messages than FCSOs did (supporting hypothesis H-1a). For example, CCSO ID#2's message has a self-disclosure, marked by the first-person pronoun "I."

CCSO #1: I wonder how long till he's here
CCSO #1 explicitly expresses his uncertainty and suggests concern (I wonder) regarding when his friend will arrive (how long till he's here).

Likewise, CCSOs used LIWC negative emotion words in 6% more of their messages than youths did. In contrast, FCSOs used negative emotion words in 13% fewer of their messages than youths did. Hence, CCSOs used negative emotion words substantially more often than FCSOs did (supporting hypothesis H-1b). The following CCSO's message has the LIWC negative emotion words "worried" and "missing."

CCSO #2: *smiles* too tired, worried and missing my girl a lot
CCSO #2 begins by expressing positive emotion (*smiles*) but also reports exhaustion (too tired) and substantial negative emotions (worried and missing … a lot). As this message has the first-person possessive "my," it is also a self-disclosure.

CCSOs used LIWC positive emotion words in 6% more of their messages compared to both youths and FCSOs did (supporting hypothesis H-1c). The following CCSO's message has the LIWC positive emotion words "cute" and "fun."

CCSO #3: Your hella cute id like to have some fun with u
CCSO #3 compliments the youth (Your hella cute) and expresses his desire to enjoy her company (id like to have some fun with u), both of which suggest his positive emotions. As this message has a first-person pronoun within a contraction (id ~ I'd), it is also a self-disclosure.

CCSOs and FCSOs differed more in their use of both self-disclosures and emotion words in the same message. CCSOs used a first-person pronoun with negative emotion in 31% more of their messages compared to FCSOs (supporting hypothesis H-1d; see above CCSO #2 message). CCSOs used a first-person pronoun with positive emotion in 7% more of their messages than FSCOs and youths

Table 2
Statistical Discourse Analysis Results of Modeling First-person Pronoun, Negative Emotion, Positive Emotion, and First-person Pronoun Combinations with Each of the Latter Two.

	Modeling 5 types of words in each message				
Explanatory variable	First Person Pronoun (I)	Negative Emotion	Positive Emotion	I + Negative Emotion	I + Positive Emotion
Contact Sex Offender [a]	0.053	0.278*	0.233*	0.170	0.277*
	(0.087)	(0.125) **+6%**	(0.093) **+6%**	(0.169)	(0.128) **+7%**
Non-Contact Sex Offender [a]	-0.552***	-0.519**	0.051	-1.478***	-0.235
	(0.109) -13%	(0.180) -13%	(0.107)	(0.353) -31%	(0.166)
Message Order (Time)			-0.001**	0.000	-0.001*
			(0.000)	(0.000)	(0.000)
First Person Pronoun (-1)	0.414***				0.308**
	(0.080) **+10%**				(0.119) **+8%**
Negative Emotion (-1)		0.648***			
		(0.154) **+16%**			
Positive Emotion (-1)			0.683***		0.492***
			(0.085)**+16%**		(0.119) **+12%**
First Person Pronoun (-1) * Negative Emotion (-1)				1.063***	
				(0.239)**+24%**	
Variance explained	0.016	0.018	0.023	0.041	0.021

Note. Values represent unstandardized parameter coefficients (with standard errors in parentheses), positive odds ratios in bold and negative odds ratios in red. Each model has a constant term.
*$p < .05$, **$p < .01$, ***$p < .001$
[a] Compared to youths in online chats.

did (supporting hypothesis H-1e; see above CCSO #3 message). Furthermore, positive emotion, first-person pronoun with negative emotion, and first-person pronoun with positive emotion, were all slightly more likely to occur in earlier online chat messages (b = -0.001 for all models).

Self-disclosures of experiences, positive emotions or negative emotions all increased the likelihood of reciprocation with corresponding messages, reflecting their impacts as grooming tactics. After a message with a first-person pronoun, it was 10% more likely in the responder's next message (supporting hypothesis H-2a). After CCSO #1's two messages with self-disclosures (indicated by "I" and "me"), Youth #1's next message also has a self-disclosure ("I").

CCSO #1: I wonder how long till he's here
CCSO #1: Not for me for him
Youth #1: I am fully confident that he can handle himself
Sensitive to CCSO #1's concern about his friend's arrival, Youth #1 comforts CCSO #1 by expressing a strong belief (I am fully confident) in his friend's ability (he can handle himself).

A message with a negative emotion was 16% more likely to be followed by such a message by the responder (supporting hypothesis H-2b). After CCSO #2's message with two LIWC negative emotions ("worried" and "missing"), Youth #2's message also has two LIWC negative emotions words ("sorry" and "stress").

CCSO #2: *smiles* too tired, worried and missing my girl a lot
Youth #2: I am sorry i didnt mean to put so much stress on u
After CCSO #2 expresses his negative emotions, Youth #2 expresses regret and responsibility (I am sorry) over any unintended contribution to it (i didnt mean to put so much stress on u). As Youth #2's message also has first-person pronouns (I and i), it is also a self-disclosure.

After a message with a positive emotion, it was 16% more likely in the responder's next message (supporting hypothesis H-2c). After CCSO #3's message with two LIWC positive emotion words ("cute" and "fun"), Youth #2's message also has two LIWC positive words ("Haha" and "okay").

CCSO #3:Your hella cute id like to have some fun with u
Youth #3:Haha okay mister
After CCSO #3 compliments Youth #3 and expresses his desire to enjoy her company, Youth #3 expresses laughter (Haha) and accepts his offer (okay), playfully addressing him with excessive formality (mister).

A message with a first-person pronoun and a negative emotion was 24% more likely to be followed by such a message by the responder (supporting hypothesis H-2d). See above message sequence example of CCSO #2 and Youth #2.

In contrast, first-person pronoun and positive emotion showed separate independent links to the likelihood of both occurring in the next message. After a message with a first person pronoun, the next message is 8% more likely to have a first person pronoun and positive emotion words. After a message with a positive emotion word, the next message is 12% more likely to have a first person pronoun and positive emotion words. Hence, the results only partially supported hypothesis H-2e.

All other interactions were not significant. Notably, interactions with CCSO or FCSO were not significant. Models with alternate variables or distribution assumptions (Probit rather than Logit) yielded similar results. Residuals showed no substantial outliers. Past studies have shown that message attributes explain much more of the variance of many dependent variables than individual, group, or topic characteristics (see Chiu, 2008; Chiu, Molenaar, Chen, Wise, & Fujita, 2013; Chiu & Lehmann-Willenbrock, 2016), suggesting that studies using coarser units of analysis (individual, group, or topic) are accounting for less than 1% the variance at the message level. Hence, the message-level variance explained by the models in this study are likely greater than those in past studies.

6. Discussion

This exploratory study is the first to differentiate CCSOs and FCSOs based on their goal-motivated (meet youth vs. not meet youth) grooming tactics via linguistic and statistical discourse analysis. Our exploratory results suggest that CCSOs are more likely than FCSOs to write online messages with specific types of words (first-person pronouns, negative emotions, and positive emotions). Furthermore, such messages are more likely to be immediately followed by a message of the same type by the other participant (reciprocation). These results are consistent with the view that CCSOs use grooming tactics to help engender youths' trust to meet in the physical world, whereas FCSOs do not. If these results are replicated in larger studies, they suggest several theoretical, methodological, and practical implications.

6.1. Theoretical implications

These exploratory results suggest that CCSOs differ from FCSOs in their self-disclosures, especially for negative emotions, and that self-disclosures elicit youths' self-disclosures. The significant differences in CCSO vs. FCSO use of first-person pronouns suggest differences in self-disclosures, which are consistent with their different motivations and target victims within the Routine Activities Theoretical framework (Krone, 2004; Lanning, 2010). As CCSOs seek physical sex with youths, they self-disclose more than FCSOs do, suggesting that it is a grooming tactic to help targeted youths trust them enough (trust attraction, Dindia, 2002) to meet. In contrast, FCSOs' less frequent use of self-disclosures suggests that they do not use this strategy as they do not seek to meet their targeted youths. Instead, FCSOs are more likely than CCSOs to teach youths about sexual behaviors or use exhibitionism to encourage a youth to reciprocate, on the way to cybersex (Briggs et al., 2011).

This difference in tactics shows how we can differentiate CCSOs from FCSOs by their behaviors (Briggs et al., 2011; McCarthy, 2010). Moreover, as sex offenders might change from FCSO to CCSO (or vice-versa), examining their behaviors over time can reflect these changes, whereas analysis of fixed sociodemographic characteristics cannot (DeHart et al., 2016).

CCSOs' and FCSOs' different uses of emotion words suggest different grooming tactics. In each online message, CCSOs are more likely than FCSOs to use positive emotion words (LIWC category words; Pennebaker et al., 2001), even more likely to use negative emotion words, likelier still to use positive emotion words with first person pronouns, and mostly likely to use negative emotion words with first person pronouns. These results are consistent with the view that self-disclosures of emotions (especially negative ones) increase vulnerability to and show trust in the listener, thereby encouraging the listener to reciprocate (personalized disclosure, Bazarova, 2012). These results suggest that CCSOs are more likely than FCSOs to use self-disclosures of emotions (especially negative ones) as grooming tactics.

Reciprocation of first person pronouns or emotion words suggest the effectiveness of self-disclosures, especially of emotions, in building closer relationships. After a message with a first-person pronoun, positive emotion word, or negative emotion word, the next person's message was more likely to have a word of the same type. These results support the claim that self-disclosures, especially those with emotion words, ignite cycles of self-disclosures and enhance participants' social relationships (social exchange theory, Cook et al., 2013). Furthermore, they suggest that CCSOs effectively use self-disclosures, especially of their negative emotions, to build trust with targeted youths.

6.2. Methodological implications

We showcase a new approach to studying sex offenders' online chat messages via identification of goals and corresponding behaviors, automatic computer coding, and statistical discourse analysis. In addition to past studies of CCSO vs. FCSO demographics and other individual characteristics, we can identify their different goals (e.g., meet vs. not meet targeted youth), test for differences in their corresponding behaviors (e.g., grooming tactics), and evaluate their impact (reciprocation of behaviors). First, we consider the goals of different sex offenders; for example, CCSOs aim to meet targeted youth, but FCSOs do not. Based on these different goals, we expect sex offenders to use different tactics; for example, CCSOs are more likely than FCSOs to use self-disclosure grooming tactics. As noted above, analyzing sex offenders' behaviors allows a researcher to study changes in their sex offences across time.

Then, we seek behavioral indicators of these tactics that a computer algorithm can identify. In this case, we used first person pronouns and categories of positive emotion words and negative emotion words (Pennebaker et al., 2001). This automatic categorization process can both sharply reduce human labor costs and increase coding reliability (Gaesser & Chiu, 2015). As most conversation tactics did not necessarily use a specific set of words, actual instances of such tactics are likely undercounted; hence,

human examination of a representative subsample serves as a quality check. Also, if any undercounting is sufficiently similar across participants, then statistical comparisons can yield meaningful results (reducing confidence in non-significant results but retaining confidence in significant results, Kennedy, 2008).

Next, we used a new statistical method, statistical discourse analysis (Chiu & Lehmann-Willenbrock, 2016), to test: (a) whether CCSOs, FCSOs and youths differ in their use of the above categories of words in text messages; and (b) whether the occurrence of these words in a message is related to their presence (or absence) in subsequent messages. The following are examples of the classes of research questions that statistical discourse analysis can address. First, which factors at various levels (including dyadic outcomes) affect the likelihoods of specific words (or categories of words) in a message? Second, how do words in recent messages (or their sequences) affect the likelihoods of specific words in each message? Lastly, how do the links between independent variables and dependent variables differ across time? Answers to such questions can improve our understanding of how words in recent messages and their sequences are related to the likelihood of words in subsequent messages for different individuals, dyads, groups, time periods and contexts.

This methodology is amenable to both large scale data and incorporation into mixed methods (Chiu, McVee, & Rinker, 2017). As we implemented both the categorization of messages and statistical analysis in computer programs, this type of analysis can easily scale up to large data sets, and is not limited by human coding. Furthermore, statistical discourse analysis examines residuals to identify both outliers and well-fit data for qualitative exploration of both possible exceptions to the theory and its best empirical representatives—all of which can inform mixed methods studies.

6.3. Practical implications

If our exploratory results are replicated, they can inform both undercover police training and allocation of their time, and serve as the basis for a digital forensics tool that detects CCSOs. Currently, some police officers pose as youths and chat online with potential CCSOs in Internet sex stings (a preventative law enforcement practice) but have difficulty differentiating between CCSOs and FCSOs (Martellozzo, 2012). If larger studies replicate our results, then we have identified specific self-disclosure grooming tactics that CCSOs often use but FCSOs rarely use. Notably, CCSOs use self-disclosures slightly earlier than average, so analyzing online chats offers the promise of identifying CCSOs before the hands-on child sex offense occurs. Hence, undercover police officers can be trained to recognize the presence or absence of self-disclosures (especially involving negative emotions) to help differentiate CCSOs from FCSOs and devote their limited time and resources to investigating the former rather than the latter.

In addition to informing undercover police training and resource allocation, our theory, methodology, and results take a step towards building a digital forensics tool that automatically analyzes online chats to detect CCSOs (Seigfried-Spellar, Ringenberg, Chiu, & Rogers, 2017). By identifying grooming tactics that CCSOs frequently use but FCSOs rarely use, our computer/statistics algorithms can quickly scan online chats and compute the probability that each suspect is a CCSO, thereby reducing police officers' time, efforts, and emotional costs. Such a digital forensics tool can automatically scan online forums, alert police of suspicious message sequences, and potentially prevent sex offenses against youths.

6.4. Limitations and future studies

This exploratory study's limitations include its small sample, limited context, likely undercounting of self-disclosures, imprecise categorization of expressed emotions, omission of other possible explanatory variables and possible mis-categorization of CCSOs and FCSOs. As obtaining and anonymizing texts between actual children and sex offenders is difficult and slow, we analyzed this preliminary data and are collecting more data to test whether larger samples across diverse contexts yield similar results.

Undercounting of disclosures might differ across online chats. If the undercounting is sufficiently similar across participants, then it is measurement error, like mis-categorizations. While measurement errors reduce confidence in non-significant results, they do not change the interpretation of significant results, which retain their usual meaning (Kennedy, 2008).

Furthermore, omission of other possibly significant explanatory variables such as demographics (e.g., age) or grooming tactics can cause *omitted variable bias* (Kennedy, 2008). Hence, future studies should explore inclusion of more demographic information and other grooming tactics into the explanatory model.

Lastly, it is possible that the ICAC mis-categorized some sex offenders (e.g., as FCSOs rather than CCSOs). Mis-categorization errors would reduce the likelihood of statistical differences between the two groups, thereby increasing the likelihood of non-significant results. Hence, we have less confidence in our results showing non-significant differences but retain full confidence in our results showing significant differences.

7. Conclusion

In their online chats with youths, arrested contact-driven child sex offenders were more likely than arrested fantasy-driven child sex offenders to use specific categories of words in their messages in this exploratory study. Specifically, contact-driven child sex offenders were more likely than fantasy-driven child sex offenders to use first-person pronouns, negative emotion words, positive emotion words, first-person pronouns with negative emotion words, and first-person pronouns with positive emotion words. The exploratory findings are consistent with self-disclosure as a grooming tactic for CCSOs: building trust in order to meet their victims in the physical world.

These online messages suggestive of self-disclosures also elicited reciprocation. After a message with a first-person pronoun,

positive emotion word or negative emotion word, the next person's message often had some words from the same category(ies), suggesting that self-disclosures elicited other's self-disclosures. These preliminary results are consistent with the claim that contact sex offenders effectively use self-disclosures, especially of their negative emotions, to build trust with their victims.

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Appendix A. Supplementary data

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References

Afuah, A., & Tucci, C. L. (2003). *Internet business models and strategies* (2nd ed.). New York, NY: McGraw-Hill.

Babchishin, K. M., Hanson, R. K., & Hermann, C. A. (2011). The characteristics of online sex offenders: A meta-analysis. *Sexual Abuse: A Journal of Research and Treatment, 23*(1), 92–123. http://dx.doi.org/10.1177/1079063210370708.

Bazarova, N. N. (2012). Public intimacy: Disclosure interpretation and social judgments on Facebook. *Journal of Communication, 62*(5), 815–832. http://dx.doi.org/10.1111/j.1460-2466.2012.01664.x.

Benjamini, Y., Krieger, A. M., & Yekutieli, D. (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika, 93*, 491–507. http://dx.doi.org/10.1093/biomet/93.3.491.

Black, P. J., Wollis, M., Woodworth, M., & Hancock, J. T. (2015). A linguistic analysis of grooming strategies of online child sex offenders: Implications for our understanding of predatory sexual behavior in an increasingly computer-mediated world. *Child Abuse & Neglect, 44*, 140–149. http://dx.doi.org/10.1016/j.chiabu.2014.12.004.

Blumenthal, S., Gudjonsson, G., & Burns, J. (1999). Cognitive distortions and blame attribution in sex offenders against adults and children. *Child Abuse and Neglect, 23*, 129–143. http://dx.doi.org/10.1016/S0145-2134(98)00117-3.

Brechwald, W. A., & Prinstein, M. J. (2011). Beyond homophily: A decade of advances in understanding peer influence processes. *Journal of Research on Adolescence, 21*(1), 166–179. http://dx.doi.org/10.1111/j.1532-7795.2010.00721.x.

Briggs, P., Simon, W. T., & Simonsen, S. (2011). An exploratory study of internet-initiated sexual offenses and the chat room sex offender: Has the internet enabled a new typology of sex offender? *Sexual Abuse: A Journal of Research and Treatment, 23*(1), 72–91. http://dx.doi.org/10.1177/1079063210384275.

Chiu, M. M. (2008). Flowing toward correct contributions during groups' mathematics problem solving: A statistical discourse analysis. *Journal of the Learning Sciences, 17*(3), 415–463. http://dx.doi.org/10.1080/10508400802224830.

Chiu, M. M., & Khoo, L. (2005). A new method for analyzing sequential processes: Dynamic multi-level analysis. *Small Group Research, 36*, 600–631. http://dx.doi.org/10.1177/1046496405279309.

Chiu, M. M., & Lehmann-Willenbrock, N. (2016). Statistical discourse analysis: Modeling sequences of individual behaviors during group interactions across time. *Group Dynamics: Theory, Research, and Practice, 20*(3), 242–258. http://dx.doi.org/10.1037/gdn0000048.

Chiu, M. M., McVee, M., & Rinker, T. (2017). *Statistical interpretive discourse analysis in educational research: A mixed methods approach to a wicked problem from the radical middle.* Manuscript submitted for review.

Chiu, M. M., Molenaar, I., Chen, G., Wise, A. F., & Fujita, N. (2013). Micro-analysis of collaborative processes that facilitate productive online discussions: Statistical discourse analyses of three cases. In M. Clara, & E. B. Gregori (Eds.). *Assessment and evaluation of time factors in online teaching and learning*Hershey, PA: IGI Global. http://dx.doi.org/10.4018/978-1-4666-4651-3.ch009 pp. 232–263.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*, 588–608. http://dx.doi.org/10.1007/BF01561001.

Cook, K. S., Cheshire, C., Rice, E. R., & Nakagawa, S. (2013). Social exchange theory. In Susan T. Fiske, Daniel T. Gilbert, & Gardner Lindzey (Eds.). *Handbook of social psychology*Netherlands: Springer. http://dx.doi.org/10.1002/9780470561119 pp. 61–88.

Criddle, L. (2006). *Look both ways: Help protect your family on the Internet.* Washington, DC: Microsoft Press.

Davidson, J., & Gottschalk, P. (2011). Characteristics of the Internet for criminal child sexual abuse by online groomers. *Criminal Justice Studies, 24*(1), 23–36. http://dx.doi.org/10.1080/1478601X.2011.544188.

DeHart, D., Dwyer, G., Seto, M. C., Moran, R., Letourneau, E., & Schwarz-Watts, D. (2016). Internet sexual solicitation of children: A proposed typology of offenders based on their chats, e-mails, and social network posts. *Journal of Sexual Aggression, 23*(1), 77–89. http://dx.doi.org/10.1080/13552600.2016.1241309.

Dindia, K. (2002). Self-disclosure research: Knowledge through meta-analysis. In M. Allen, R. W. Preiss, B. M. Gayle, & N. A. Burrell (Eds.). *LEA's communication series. Interpersonal communication research: Advances through meta-analysis*Mahwah, NJ: Lawrence Erlbaum Associates pp.169–185.

Gaesser, A. H., & Chiu, M. M. (2015). Affective curriculum for gifted: Factors influencing students' experiences. *Paper Presented at the Annual Meeting of the American Educational Research Association* (April).

Goldstein, H. (2011). *Multilevel statistical models.* Sydney, AU: Edward Arnold.

Graham, J. W. (2009). Missing data analysis: Making it work in the real world. *Annual Review of Psychology, 60*, 549–576. http://dx.doi.org/10.1146/annurev.psych.58.110405.085530.

Haldaman, C. D. (2012). The relationship between cognitive distortions and risk to sexually re-offend in adolescents: Comparing three levels of treatment. *PCOM Psychology Dissertations* Paper 249.

Holt, T. J., Blevins, K. R., & Burkert, N. (2010). Considering the pedophile subculture online. *Sexual Abuse: A Journal of Research and Treatment, 22*(1), 3–24. http://dx.doi.org/10.1177/1079063209344979.

Joinson, A. N., & Paine, C. B. (2007). *Self-disclosure, privacy and the Internet. The Oxford handbook of Internet psychology*. Oxford: Oxfordhttp://dx.doi.org/10.1093/oxfordhb/9780199561803.013.0016 pp. 237–252.

Kennedy, P. (2008). *Guide to econometrics.* New York, NY: Wiley-Blackwell.

King, G., & Zeng, L. (2001). Logistic regression in rare events data. *Political Analysis, 9*, 137–163. http://dx.doi.org/10.1093/oxfordjournals.pan.a004868.

Konstantopoulos, S. (2008). The power of the test in three-level cluster randomized designs. *Journal of Research on Educational Effectiveness, 1*, 66–88. http://dx.doi.org/10.1080/19345740701692522.

Krone, T. (2004). A typology of online child pornography offending. *Trends & Issues in Crime and Criminal Justice, 279*, 1–6.

Lanning, K. (2010). *Child molesters: A behavioral analysis for professionals investigating the sexual exploitation of children.* Alexandria, VA: National Center for Missing & Exploited Children.

Laulik, S., Allam, J., & Sheridan, L. (2007). An investigation into maladaptive personality functioning in Internet sex offenders. *Psychology, Crime and Law, 13*, 523–535. http://dx.doi.org/10.1080/10683160701340577.

Ljung, G., & Box, G. (1979). On a measure of lack of fit in time series models. *Biometrika, 66*, 265–270. http://dx.doi.org/10.1093/biomet/65.2.297.

MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate*

Behavioral Research, 39, 99–128. http://dx.doi.org/10.1207/s15327906mbr3901_4.
Malesky, L. A. (2007). Predatory online behavior: Modus operandi of convicted sex offenders in identifying potential victims and contacting minors over the Internet. *Journal of Child Sexual Abuse, 16*(2), 23–32. http://dx.doi.org/10.1300/J070v16n02_02.
McCarthy, J. A. (2010). Internet sexual activity: A comparison between contact and non-contact child pornography offenders. *Journal of Sexual Aggression, 16*(2), 181–195. http://dx.doi.org/10.1080/13552601003760006.
Medaris, M., & Girouard, C. (2002). *Protecting children in cyberspace: The ICAC Task Force program (NCJ 191213)*. Washington, DC: U.S. Department of Justice.
Martellozzo, E. (2012). *Online child sexual abuse: Grooming, policing and child protection in a multi-media World.* New York, NY: Routledge.
Miell, D., & Duck, S. (1986). *Strategies in developing friendships. Friendship and social interaction.* New York, NY: Springer pp. 129–143.
Mitchell, K., Finkelhor, D., & Wolak, J. (2007). Youth Internet users at risk for the most serious online sexual solicitations. *American Journal of Preventive Medicine, 32*, 532–537. http://dx.doi.org/10.1016/j.amepre.2007.02.001.
Pennebaker, J. W., Francis, M. E., & Booth, R. J. (2001). *Linguistic inquiry and word count: Liwc 2001.* Mahwah, NJ: Lawrence Erlbaum Associates.
Peter, J., Valkenburg, P. M., & Schouten, A. P. (2005). Developing a model of adolescent friendship formation on the Internet. *CyberPsychology & Behavior, 8*, 423–430. http://dx.doi.org/10.1089/cpb.2005.8.423.
Peugh, J. L., & Enders, C. K. (2004). Missing data in educational research: A review of reporting practices and suggestions for improvement. *Review of Educational Research, 74*, 525–556. http://dx.doi.org/10.3102/00346543074004525.
Rodas, E. (2014). *The multi-facets of cyber-sex trafficking: A call for action and reform from society.* Unpublished manuscript.
Seigfried-Spellar, K. C., Ringenberg, T., Chiu, M., & Rogers, M. K. (2017). Distinguishing contact child sex offenders vs. non-contact solicitors: Toward a digital forensics tool for automatic analysis of their chats with minors. *Presented at the LEIU/IALEIA annual training conference in Bloomington, MN*.
Shamdasani, P., & Jung, K. (2011). Relationship quality between in-groups and out-groups. *The International Business & Economics Research Journal, 10*(6), 33–52. http://dx.doi.org/10.19030/iber.v10i6.4371.
Singer, A. J. (2013). *Teaching to learn, learning to teach.* New York, NY: Routledge.
Tardy, C. H., & Dindia, K. (2006). Self-disclosure: Strategic revelation of information in personal and professional relationships. In O. Hargle (Ed.). *The handbook of communication skills*(3rd ed.). pp. 229–266.
Tolhuizen, J. H. (1989). Communication strategies for intensifying dating relationships: Identification, use and structure. *Journal of Social and Personal Relationships, 6*(4), 413–434. http://dx.doi.org/10.1177/0265407589064002.
US Department of Justice (2017). *Violent crime victimization.* December 14, Retrieved fromhttps://www.ojjdp.gov/ojstatbb/victims/faqs.asp.
Walby, S. (2004). *The cost of domestic violence.* London: UK Department of Trade and Industry.
Whittle, H., Hamilton-Giachritsis, C., Beech, A., & Collings, G. (2013). A review of online grooming: Characteristics and concerns. *Aggression and Violent Behavior, 18*(1), 62–70. http://dx.doi.org/10.1016/j.avb.2012.09.003.
Wise, A., & Chiu, M. M. (2011). Analyzing temporal patterns of knowledge construction in a role-based online discussion. *International Journal of Computer-Supported Collaborative Learning, 6*, 445–470. http://dx.doi.org/10.1007/s11412-011-9120-1.