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Pathways to Blunted Facial Affect in Negative Schizotypy: Social motivation and online cognitive resources

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PATHWAYS TO BLUNTED FACIAL AFFECT IN NEGATIVE SCHIZOTYPY: SOCIAL MOTIVATION AND ONLINE COGNITIVE RESOURCES

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Abstract

Schizotypy, a range of personality traits which confer liability for schizophrenia, is associated with significantly diminished social functioning and quality of life. Social dysfunction in all forms of schizotypy, including schizophrenia, is connected to blunted affect, or diminished expressivity, particularly facial expressions which are less frequent, intense, or long than typical. However, the mechanisms and treatments for blunted affect are, as yet, poorly understood and underdeveloped. In this project, two putative mechanisms of blunted affect were explored. The first involves cognitive load capacities, which are diminished in schizotypy, causing blunted affect – individuals do not have the cognitive resources to regulate their facial expressions in a socially productive way while managing competing demands (e.g., a dynamic social situation). The second pathway involves social motivation deficits, which are a characteristic trait of some forms of schizotypy, leading to fewer socially communicative expressions – essentially, individuals who are not socially motivated do not care to regulate their facial expressions. To maximize ecological validity, this study used an ambulatory assessment framework, where participants (N = 216, M_{age} = 19.68 , 76.9% women, 77.3% White) were asked to complete self-reports and cognitive tasks, as well as provide video of their facial expressions, while going about their daily lives. The two proposed mediators were modeled under an MSEM (multilevel structural equation modelling) framework to test the putative mechanisms for blunted affect. Contrary to hypotheses, metrics of expressivity were not related to self-reported negative schizotypy. Further, while metrics of expressivity suggesting blunted affect were related to decreased social motivation, they were also related, in a more tenuous fashion, to *increased* cognitive functioning. The results of this study suggest support for a more nuanced model of what blunted affect is – rather than a uniform decrease in expressivity, it may be a decrease in

socially engaging and affiliative expressions. As well, these results provide preliminary evidence that in the moment social motivation is a pathway to blunted affect. Limitations to this study are reviewed, including technological difficulties and limitations to generalizability borne from the sample characteristics.

Introduction

Schizophrenia, a serious mental illness, is one of the most debilitating maladies known to humankind (Üstün et al., 1999). It affects approximately 0.4% of the population worldwide (Saha et al., 2005) and 0.5% of Americans (Wu et al., 2006). However, approximately 10% of the population show some of the phenotypic characteristics of the disorder, otherwise known as schizotypy (Blanchard et al., 2000; Lenzenweger & Korfine, 1992; Verdoux & van Os, 2002). Symptoms of schizophrenia are related to lower subjective quality of life and general well-being (Galuppi et al., 2010; Norman et al., 2000), and can lead to serious and wide-ranging impairment, including in social functioning, vocational functioning, and independent living, (Addington & Addington, 2000; Dickinson et al., 2004; Vargas et al., 2014). Nonclinical high schizotypy individuals also show notable impairments in academic, social, and familial functioning (Jahshan & Sergi, 2007) and diminished quality of life (Cohen & Davis, 2009). Social functioning is particularly important to individuals with schizophrenia (Auslander & Jeste, 2002), and particularly concerning in high schizotypy individuals (Silvia & Kwapil, 2011), representing a crucial area for improved interventions.

This project explored several mechanisms for understanding one component of schizotypy, diminished facial expressivity, as a potential intervention target for improved social functioning. In schizophrenia and in schizotypy more broadly there are characteristic patterns of diminished facial expressivity where facial expressions appear muted or less evident than would be expected within a cultural context. In schizophrenia, these patterns are called in blunted affect, while in schizotypy they are called constricted affect, though there is no consensus in how these terms are distinguished from each other. For clarity, and to better connect to the broader

clinical literature, this project will use the term blunted affect. In setting the stage for this project, several key issues will be addressed. First, the issues regarding operationalization of key terms: schizotypy, blunted affect, and facial expressions. Then, relevant literature regarding the proposed mechanisms will be reviewed in both schizophrenia and schizotypy more broadly. Finally, these terms and concepts will be combined in specific hypotheses and aims for the present study.

Schizophrenia & Schizotypy

Schizophrenia involves three empirically-supported symptom clusters: positive symptoms, including delusions and hallucinations; negative symptoms, like avolition and blunted affect; and disorganized symptoms, such as disorganized speech (American Psychiatric Association, 2013). The positive symptoms represent additions to normal functioning, where negative symptoms represent reductions from normal functioning. There is general consensus of five negative symptoms clusters - avolition, or lack of motivation; anhedonia, lack of hedonic experience; asociality, lack of social motivation or interest; alogia, diminished speech production; and blunted affect, diminished expressivity (Kirkpatrick et al., 2006). As a category, negative symptoms drive functional impairments more than positive symptoms (Rabinowitz et al., 2012), but different negative symptoms have different relations with courses of illness and functioning (Ergül & Üçok, 2015). In particular, social deficits are influenced by asociality and blunted affect (Leifker et al., 2009). When designing treatments to support fulfilling social relationships then, targeting social motivation and blunted affect may be critical. But to effectively treat these symptoms, it is critical to understand the mechanisms which underly them.

While the clinical diagnosis of schizophrenia or schizophrenia spectrum psychopathology is relatively uncommon in the population (Wu et al., 2006), a much broader portion of the

population is on a “schizotypy-spectrum” – defined in terms of potential outcomes from adaptive/healthy to intermittent decompensation to chronic dysfunction. Schizotypy is a personality organization which reflects an underlying neurological predisposition to schizophrenia psychopathology, called schizotaxia, combined with social learning history (Lenzenweger, 2006; Meehl, 1962). Schizotypy is mostly commonly assessed using self-report questionnaires (e.g. Cohen et al., 2010; Kwapil et al., 2018). Individuals who score high on these questionnaires fall in the category of “psychometric schizotypy.” These questionnaires have significantly evolved since early conceptions nearly half a century ago (Chapman et al., 1976). Much like schizophrenia, schizotypy statistically coheres into positive, negative, and disorganized schizotypal traits (Cohen et al., 2010; Kwapil et al., 2018). The positive schizotypal traits reflect perceptual aberrations, like hallucinations or illusions, and unusual thought content, including odd ideas, magical thinking, and delusions. Negative schizotypy, as measured using self-report questionnaires, generally reflects anhedonia, often as it relates to social contexts, and can also reflect blunted affect (Cohen et al., 2010; Kwapil et al., 2012). Disorganization reflects disruptions in organizing or expressing thoughts and behavior, including a spectrum of severity from mild oddities and quirks through to confusing and incomprehensible speech (Kwapil et al., 2020).

As evidenced by each of the schizotypal traits being a spectrum, schizotypy is a multifinal personality organization, though the impact on quality of life can be quite substantial along the whole spectrum (Cohen & Davis, 2009). Different dimensions of psychometric schizotypy predict different clinical outcomes (Kemp et al., 2020), though negative schizotypy appears to be particularly important in predicting transition from lower risk states to higher clinical risk levels (Gooding et al., 2005; Kwapil, 1998). Studying negative schizotypy is

therefore particularly warranted in predicting and preventing higher risk clinical states. Negative schizotypy is characterized by social withdrawal, amotivation, and anhedonia, all of which are related to blunted affect (Gruzelier, 1996).

Blunted Affect

While blunted affect can refer to blunting of all expressive gestures, the core component of blunted affect is diminished facial affect, typically defined as an overall reduction in facial expression, or "significant lack of facial expressions when recounting emotional experiences" (Brief Negative Symptom Scale, Kirkpatrick et al., 2006). In this project and in much of the literature, while blunted facial affect is the specific construct of interest, it is referred to using the more general blunted affect. Blunted affect is present across the schizotypy spectrum, and is clinically significant in approximately one third of individuals with schizophrenia (Bobes et al., 2010). Blunted affect was identified over a century ago in individuals with schizophrenia (Bleuler, 1911/1950), though it is a transdiagnostic phenomenon. For example, individuals with depression, anxiety, borderline personality disorder, and schizophrenia all show what is commonly understood as a reduction, or flattening, of facial affect (Cooper et al., 2013; Gaebel & Wolwer, 2004; Renneberg et al., 2005). Blunted affect also can be a marker of potential risk for psychosis, as individuals are at high risk for psychosis, but have not had a psychotic episode yet, and who show increased blunted affect, are at increased risk for a psychotic episode in the next two years (Gupta et al., 2019). Individuals who score highly on self-reported schizotypy measures, particularly high negative schizotypy, both report higher blunted affect (Shi et al., 2012) and also show impaired emotion expression (Collins et al., 2005; Henry et al., 2009). As schizotypy is associated with lower quality of life, so is self-reported blunted affect in these individuals (Cohen & Davis, 2009).

Defining and Measuring Blunted Affect

Operationalizing Clinical Intuition. Numerous clinical interviews include a rating for flat or blunted affect with slightly different definitions. In general, these clinical interviews use operationalizations based on a decrease in the outward or observed expression of emotion or reduced reactivity or changes in response to stimuli or conversational matter (Andreasen, 1989; Axelrod et al., 1993; Kay et al., 1987; Kirkpatrick et al., 1989, 2006; Kring et al., 2013). Some interviews also consider restricted range of emotional expressions (Axelrod et al., 1993; Ventura et al., 1993), frequency of expression (Kring et al., 2013), or inappropriateness/incongruity of expressions (Andreasen, 1989; Kay et al., 1987). These definitions are based on clinical intuition of deviation from "normal." The use of clinically-rated blunted affect measures have provided many important insights, including much of the research on blunted affect in schizophrenia cited here. However, as measurement tools they have some limitations. They are typically based on single setting interactions (Kilian et al., 2015), power hierarchies in interactions with clinicians may affect the emotional expression of the individual being interviewed (Lorié et al., 2017), and they rely heavily on clinical judgement. If emotional expression is about communicating with a partner, clinical interviews evaluate the effectiveness of that communication, but only within a very particular circumstance.

Another avenue of measurement for blunted affect is self-report measures (e.g. Cohen et al., 2010; Krueger et al., 2012). These measures tend to capture two domains: internal experience and self-evaluated expressivity (e.g. "I am not good at expressing my true feelings by the way I talk and look"), and perception of other's reactions to one's own expressions (e.g. "People tell me it's difficult to know what I'm feeling"). These have the strength of a lifetime of experience in a variety of settings informing the ratings provided but are limited by self-perception and self-

conception. In sum, these two different measurement methods for blunted affect incorporate a variety of definitions – decreased outward expression in terms of intensity, frequency, and duration, reduced reactivity, context inappropriate displays, limited range, perceived lack of clear communication with others, and an internal experience of limited expression – but each measure has limitations.

It seems likely that some of these definitions of blunted affect are in fact subsumed within others. Limited range, or not showing a "normative" diversity of expressions can also be considered a subset of failure of providing context appropriate displays, as it is only normative to show a diversity of expression to a diversity of emotional experiences. Reduced reactivity may involve minimal outward expression of emotion, but simply within a particular context, or event which is expected to elicit emotion, like a joke or discussing a sad topic. Further, the self-report items are likely heavily influenced by observable features (Robinson & Clore, 2002) - internal experience of limited expression is likely influenced by decreased outward intensity, duration, and frequency of expression, and diminished observable characteristics of expression likely influence a lifetime of other's reactions to one's emotional displays, leading to a subjective report of being difficult to understand. As such, it seems that diminished outward expression in terms of intensity, duration, frequency, and variety of expressions shown in appropriately congruous contexts, are likely the core components of the definition of blunted affect.

Objectification of Facial Expressions. These four core components of the clinical definition of blunted affect can be measured using other tools than clinical judgement and self-report. Where clinical interviews and self-report measures of expressions focus on the "message" conveyed by facial expressions, and particularly the effectiveness of that message, other systems have focused on more objective and descriptive ratings- measuring the movements of the facial

muscles, and these descriptive ratings can then be combined to create different components of the definition of blunted affect. Measuring the movement of the facial muscles can be done in three ways – electromyography, trained raters, or computerized video analysis. Electromyography uses electrodes placed on key facial muscles to record movement and can provide objective and continuous information, even on movements which are too subtle or fleeting to be visible to the naked eye (Cacioppo et al., 1986). Trained raters can also code muscle movement from videos or pictures. Of the muscle coding systems, the most commonly known and used one is the Facial Action Coding System, first developed nearly fifty years ago and updated in 2002, which divides the face into Action Units based on what the facial muscles allow a face to do (Ekman et al., 2002). There are 27 total facial Action Units - some of these can be split into left- and right-side Action Units, providing substantial granularity, and facial Action Units can be combined into expressions. Further, when coding these Action Units, they can be coded as present or absent, or according to their intensity on a five-point scale, on each image frame (Cohn et al., 2007).

Another commonly used system if the Facial Expression Coding System (FACES), which gives information about the frequency, intensity, and duration of valanced facial expressions (Kring & Sloan, 2007). In this coding system, facial expressions are only rated according to valence rather than providing information on the discrete emotional category or muscles used in the facial expression. Further, intensity is rated on a four point, rather than five-point scale, where intensity is a function of how much of the face is involved, rather than the extent of movement of a given muscle, and duration is given in terms of seconds of expression. Muscle coding systems have already found nuance in the manifestation of expressions in schizophrenia. Particularly, frequency and intensity of expressions seem to be diminished in schizophrenia,

though these results are not uniform across studies – some studies even fail to find a correlation between blunted affect ratings and objectified measures, suggesting that there are nuances of perceived blunted affect which are not directly captured by human muscle coders (Trémeau, 2006).

These muscle coding systems were originally designed to be used by humans, but developments in the early twenty-first century allowed for machine vision coding of facial expressions. Computerizing these analyses provides two benefits. First, it is significantly less time and labor intensive than rating frames of a video by hand. Secondly, it allows the definition of blunted affect to be parsed more finely, combining discrete emotions from the FACS with the nuance of the FACES, to see exactly which of these components are atypical along the schizotypy spectrum or in specific contexts, without contamination from the other components in a clinician's estimation.

Findings from Objective Facial Affect Coding - Schizoptypy. Systems such as those mentioned above have been used to parse blunted affect in people high in schizotypy, and to create a more precise understanding of this phenomenon. Notably, it was found that individuals high in negative schizotypy do not have difficulty in suppressing their emotional displays, suggesting that downregulating expressions is possible, but that they do not increase or amplify their expressivity in response to task demands (Henry et al., 2009; Shi et al., 2012). As well, subgroups which show more severe blunted affect have been identified. In particular, men show fewer emotional expressions than women (Collins et al., 2005). These group differences are evident when independent raters evaluate expressivity (Collins et al., 2005; Henry et al., 2009), but interestingly are less evident in automated analysis which looked at mean activation (Cohen, Morrison, et al., 2013), suggesting differences in how trained raters and computer algorithms

identify blunted affect. This discrepancy between raters and automated analysis is not evident in schizophrenia, where even automated analysis shows lower mean expressivity in individuals with schizophrenia (Cohen et al., 2020). Individuals with psychometric negative schizotypy therefore appear to both show and report blunted affect but this lack of expression may be more subtle than evident in clinical severity schizophrenia. By studying the more subtle end of the schizotypy spectrum using automated analyses, a more nuanced understanding of blunted affect may be available.

Mechanisms of Blunted Affect

Using these more nuanced conceptualizations of blunted affect presents novel opportunities for exploring mechanisms and treatment targets for this central component of schizotypy. Across the schizotypy spectrum, mechanisms, and subsequently treatments, for blunted affect remain unknown (Galderisi et al., 2018). Early understandings of blunted affect suggested that it was driven by experiential deficits – individuals with blunted affect were not showing expressions simply because they were not experiencing strong emotions. However, blunted affect in individuals with schizophrenia is not driven by anhedonia or lack of emotional experience (Kring et al., 1993; Kring & Neale, 1996). There were two pathways relevant to blunted affect in schizotypy proposed in this project. The first hinges on having sufficient cognitive resources available in the moment to manage the social situation and effectively and appropriately express emotions (Cohen et al., 2012). The second reflects insufficient social motivation to produce facial expressions (Collins et al., 2005). Colloquially, one could consider these pathways to reflect ability and desire to produce expressions. The concept of sufficient cognitive resources, or online cognitive resources, is derived from the multiple resource theory and information processing perspective on cognition, which states that there are limited

processes, fuels, and structures available to complete simultaneous tasks (Granholm et al., 1996; Wickens, 2008). Online cognitive resources and social motivation were the mechanisms of interest in blunted affect across the schizotypy spectrum.

Online Cognitive Resources in Schizophrenia. With regard to cognition, it has been well established that individuals with schizophrenia on average show deficits of around one standard deviation in several domains, both those related to online cognitive resources, like executive functioning and attention, and more global cognition, such as memory, language, and intelligence quotient (IQ) when compared to controls (Fioravanti et al., 2005). Even individuals who are naïve to antipsychotic medications show a similar deficit in working memory, visual and verbal memory, processing speed, attention and executive functioning (Fatouros-Bergman et al., 2014), suggesting that these deficits are not due to medication side effects. Online cognitive resource deficits also do not appear to reflect ineffective or inefficient use of resources available, but rather fewer resources overall (Granholm et al., 1996). Cognitive deficits are considered both a hallmark feature of schizophrenia (Bowie & Harvey, 2006) and a potential indicator of the onset of further symptoms (Fusar-Poli et al., 2012). With regard to negative symptoms, cognitive deficits appear to be associated with expressive symptoms even in the early stages of the illness (Ergül & Üçok, 2015). Specifically, executive functioning, verbal learning and memory, and overall cognitive performance are associated with expressive deficits, even when accounting for motivational and pleasure deficits (Hartmann-Riemer et al., 2015). Attention and processing speed deficits in particular appear to be critically related to blunted affect (Cohen et al., 2013).

In the general population, there appears to be a direct relation between expressivity and cognitive resources. Lower working memory capacity is related to less control over expressions (Schmeichel et al., 2008), and situations which deplete cognitive resources, like dynamic social

interactions (Phillips et al., 2007) lead to less vocal expressivity (Huttunen et al., 2011), as well as fewer and less intense facial expression (Stone & Wei, 2011). This relation has also been observed and experimentally tested in schizophrenia, and tasks with high cognitive load resulted in more severe vocal expressive deficits (Cohen et al., 2014). Individuals who already have diminished cognitive resources may be left with insufficient resources for coordinating and displaying appropriate facial affect when also coordinating other tasks.

Online Cognitive Resources in Schizotypy. Individuals with psychometric schizotypy show a relative weakness in some domains of cognitive resources, particularly working memory and conceptual flexibility, components of executive functioning (Chun et al., 2013) and context integration (Chun et al., 2018). These deficits are more nuanced and less robust than the deficits found in clinical schizophrenia, though individual high in psychometric schizotypy self-report significant and robust cognitive complaints (Cohen et al., 2017). While perceived deficits are significant, the presence of deficits on clinical measures changes based on task used and subgroup (e.g. positive or negative), which can result in seemingly contradictory findings. Depending on which study is consulted and what task is used, schizotypy may not be associated with executive functioning deficits (Jahshan & Sergi, 2007; Spitznagel & Suhr, 2002), or perhaps only positive schizotypy is associated with executive function deficits (Moritz & Mass, 1997). Other studies have found that schizotypy is not associated with working memory deficits (Jahshan & Sergi, 2007), or that positive schizotypy is not associated with working memory (Lenzenweger & Gold, 2000) or that both positive and negative schizotypy are associated with poorer working memory (Gooding & Tallent, 2003; Schmidt-Hansen & Honey, 2009). Meta-analyses which collapsed across task type and subgroup of schizotypy found that the strongest associations were between schizotypy and impaired working memory and language, though there

was also some evidence that other domains like attention and cognitive flexibility were all also associated with schizotypy (Chun et al., 2013; Siddi et al., 2017). Another meta-analysis found that context integration deficits are associated with disorganized and negative schizotypy (Chun et al., 2018). The totality of research in this field suggests that cognitive resources are diminished in some way across the whole schizotypy spectrum, but that in psychometric schizotypy these impairments may be more nuanced – depending on task and schizotypy subgroup for a complete understanding. This nuance is often required in other domains of study in schizotypy – what may apply for individuals with high positive schizotypy may not hold true for individuals with more negative schizotypy. Compared to schizophrenia, less research has connected cognitive resources to blunted affect in schizotypy. However, when the cognitive requirements of a task increase, individuals with high negative schizotypal traits show increased constriction in their vocal affect (Cohen et al., 2012), suggesting that cognitive resources, particularly those for managing multiple tasks like working memory, may connect negative schizotypy to blunted affect.

Social Motivation in Schizophrenia. Social motivation, or the desire for, interest in, or pleasure from social interaction, may also play a significant role in blunted affect (Buck & Lysaker, 2014). Expressivity is inherently social, and in instance where individuals are insufficiently motivated by social relationships, they may expend fewer cognitive resources on socially appropriate and socially rewarded actions such as facial expressions. Social motivation is often measured at a trait level using clinical interviews or self-report (e.g Cohen et al., 2010; Strauss et al., 2012), and deficits in this kind of social motivation are a core negative symptom of schizophrenia (American Psychiatric Association, 2013). This kind of broad scale social motivation is what helps someone create relationships and initiate any given contact. However, social motivation can also be considered within an interaction – essentially, how much does one

enjoy this current interaction, and how much would you like this to continue or be repeated. This framework is analogous to research on general anhedonia, which has found that individuals with schizophrenia have intact consummatory anhedonia, but deficits in anticipatory anhedonia (Gard et al., 2007). If consummatory social motivation is impaired, then there may not be reason to produce expressions which would deepen social communication.

Social Motivation in Schizotypy. In many ways, a lack of social motivation, including social anhedonia, is the defining feature of negative schizotypy (Blanchard et al., 2011; Horan et al., 2007; Meehl, 1962). Social anhedonia, where social interactions are not rewarding, is separate from social anxiety, where social interactions are perceived as threatening (Silvia & Kwapil, 2011). Social anhedonia is also separate from physical or general anhedonia, which focuses on a lack of interest or pleasure more generally. High schizotypy individuals show social anhedonia similar to schizophrenia, but significantly less general anhedonia (Wang et al., 2014). Social anhedonia is distributed in the population, but generally increases with age, is more common in men, and varies with culture and location (Dodell-Feder & Germine, 2018). It is also consistently associated with poorer functioning (Silvia & Kwapil, 2011).

Social motivation deficits also show associations with blunted facial affect, such that individuals with social anhedonia are more likely to show blunted facial affect in an interview (Collins et al., 2005; Leung et al., 2010), and blunted affect and other behavioral signs of schizotypy provide information above and beyond self-reported symptoms in distinguishing between controls and individuals high in social anhedonia (Collins et al., 2005). When deconstructing possible components of affective expressivity which might be abnormal in blunted affect, individuals with social anhedonia show fewer positive expressions than those with higher social motivation. However, these expressions are of similar duration and intensity

as controls (Leung et al., 2010), suggesting that separating these definitions is crucial for understanding blunted affect, and also indicating that frequency is likely to be of particular importance.

People with social anhedonia self-report lower expressivity, and this lower self-report expressivity is not correlated to self-reported emotional experience (Leung et al., 2010). This finding is particularly of interest as it suggests that neither deficits in emotional experience nor deficits in social cognitive self-awareness are driving blunted affect. The research on social anhedonia and blunted affect in schizotypy has established a connection between trait social anhedonia and in-the-moment blunted affect but has not examined the ways that social motivation may fluctuate, even in individuals with low trait levels of social motivation, and how those fluctuations may influence in the moment expressivity. Two potential pathways therefore emerge. First, if social anhedonia is only present in anticipatory but not consummatory motivation deficits, essentially trait but not state social anhedonia, blunted affect may be driven by cognitive resource deficits. Thus, cognitive impairments would be the primary target for intervention. Alternatively, consummatory social motivation deficits may lead to less affective communication, particularly affiliative or social expressions. Indeed, when blunted affect is separated into the valence of expression, generally positive or affiliative expressions are more diminished (Alvino et al., 2007; Mandal et al., 1998; Riehle & Lincoln, 2017). In this case, a combination of increased emotional salience and motivation may be most helpful for guiding treatments and conceptual frameworks.

The Present Study

Thus, in reviewing the literature, some key ideas emerge. First, that blunted affect is present across the schizotypy spectrum; that this blunted affect is associated with social

functioning deficits; and that social functioning is a critical component of quality of life for individuals with schizophrenia. Further, in the laboratory, frequency, intensity, and duration of expressions have been the crucial summary features of objectifications of blunted affect. Finally, blunted affect, when rated by clinicians, seems to be connected to trait and state cognitive functioning and trait social motivation, and when operationalized as mean expressivity, is related to state cognition. From these facts, several questions follow. First, when outside the laboratory, how do frequency, duration, and intensity of expressions differ as a function of negative schizotypy? Second, what drives blunted affect, a lack of cognitive resources or a lack of affiliative desire? The driving concern of this study is understanding the mechanisms behind blunted affect in schizotypy to eventually create interventions which could improve social functioning.

This project aimed to objectify blunted facial affect in negative schizotypy to understand when, why, and how affective expression is different. To do so, this project used ambulatory assessment to obtain videos of individuals across the negative schizotypy spectrum in a variety of contexts while navigating their daily routines, along with their subjective self-report at the same time points, and state cognitive performance. By collecting information on both state and trait social motivation, and state cognitive resources, this project attempted to disentangle the influence of social motivation and cognitive resources on blunted affect.

Aims. First, the elements of expression which differ in conjunction with negative schizotypy, accounting for demographic or psychiatric confounds, were identified. Then, the two proposed pathways, with cognitive resource deficits or social motivation impairments connecting negative schizotypy to blunted facial affect were evaluated. To do so, this project collected ambulatory assessment data on social motivation, cognitive load, context, and other pertinent

variables, as well as self-filmed ("selfie") videos from individuals with psychometrically defined negative schizotypy. These videos were subjected to computerized analysis to objectify components of facial expressions, and these components were further analyzed and combined to created measures of facial expressivity including range, intensity, duration, and frequency of positively and negatively valenced expressions.

Hypotheses. High negative schizotypy was predicted to relate to diminished range, frequency, duration, and intensity of positive and negative expressions overall. Two potential pathways beginning with trait negative schizotypy and adding state social motivation and online cognitive resource deficits as drivers of blunted affect were tested with the hypothesis that these mediators would be significant.

Methods

Participants

Participants were recruited from Louisiana State University's Subject pool through the online SONA system. A total of 227 participants completed the baseline assessment, but ambulatory assessment data was only included in this study for 216. Participants were over 18 years of age and were eligible for research credit that could be applied to undergraduate psychology courses in partial fulfillment of a research assignment. For participant demographics, see Table 1. The sample was largely female, and White, and had relatively small variability in age. Three participants reported taking antipsychotic medications, or medications which are commonly used to treat psychotic spectrum disorders, and also having either an experience of psychosis themselves, or a first degree relative with psychosis.

Table 1. Descriptive Statistics for Participants and Study Variables.

	M(SD) or %	ICC
Age	19.68 (1.56)	
GPA	3.40 (0.47)	
Gender [a]		
Woman	76.9%	
Man	15.3%	
Nonbinary	3.2%	
Race & Ethnicity [b, c]		
Asian American & Pacific Islander	6.5%	
Biracial	17.3 %	
Black	16.7 %	
Hispanic/Latinx	13.4 %	
Indigenous/Native American/American Indian	3.7%	
Middle Eastern/North African	0.9 %	
White	77.3 %	
Verbal Fluency Videos Provided [d]	12.99 (8.79)	
Facial Analysis Videos Completed	12.01 (8.41)	
Facial Analysis Videos % Analyzable Frames [e]	83.21 (22.83)	

(table con't'd.)

	M(SD) or %	ICC
Average SPQ-BR Total [f]	1.62 (0.67)	
Average SPQ-BR Negative Schizotypy [f] (table con't'd.)	1.84 (0.72)	
Average SPQ-BR Constricted Affect [f]	1.27 (0.72)	
Average Brief Symptom Inventory (BSI) Total	2.01 (0.77)	
Average Brief Symptom Inventory (BSI) Depression	2.06 (0.98)	
Average Brief Symptom Inventory (BSI) Interpersonal Sensitivity	2.30 (1.10)	
Positive Expressions Duration	1586.04 (2913.93)	0.80
Positive Expressions Frequency	2.82 (3.28)	0.92
Positive Expressions Intensity [g]	0.30 (0.21)	0.86
Negative Expressions Duration	372.49 (506.06)	0.70
Negative Expressions Frequency	0.78 (0.89)	0.88
Negative Expressions Intensity [g]	0.10 (0.08)	0.86
Expressive Range	28.68 (4.43)	0.83
Positive Emotional Experience [h]	56.12 (26.71)	0.94
Negative Emotional Experience [h]	17.94 (20.00)	0.96
Self-reported Cognitive Functioning [h]	53.80 (26.43)	0.95
Verbal Fluency (unadjusted)	17.33 (8.18)	0.87
Social Motivation [i]	171.10 (99.72)	0.93

Note. [a] Three individuals identified as in ways that do not fit the below categories: heterosexual (2 individuals), and "prefer not to answer" (1 individual) [b] all participants who only identified their race solely as "not listed/write in below" identified as Hispanic/Latino. [c] Does not add to 100% as some participants identified with multiple categories [d] Includes any verbal fluency task where at least one word was provided, regardless of category match. [e] Only includes videos included in the larger study, which required a minimum of 10% of frames to be analyzeable. [f] Schizotypal Personality Questionnaire- Brief Revised; possible range 0-4. [g] possible range 0-1.0. [h] possible range 0-100. [i] possible range 0-300.

Measures

Trait Measures

Demographics. Participants were asked to self-identify their age, gender, ethnic and racial identity, grade point average, and any medications they are currently taking.

Psychological Symptoms. The Brief Symptom Inventory (BSI; Derogatis & Melisaratos, 1983) was included to identify potential psychiatric symptoms which could be confounds between schizotypy and facial expressivity. It is a 53-item self-report measure of nine primary

symptom dimensions (somatization, obsessive-compulsive, interpersonal sensitivity, depression, anxiety, hostility, phobic anxiety, paranoid ideation, and psychoticism) and several symptom composites, with items rated on a 5-point Likert scale ranging from 0 (not at all) – 4 (extremely). The interpersonal sensitivity and depression dimensions are of primary interest as they reflect symptom profiles which are associated with blunted affect. Internal reliability and test-retest reliability for the BSI is high, ranging from 0.71 – 0.85 for internal reliability and 0.68-0.91 for test-retest reliability over a 2-week interval. The BSI has also been validated against the MMPI, which found moderate convergent validity (r's 0.32 – 0.55).

***Negative Schizotypy*.** The Schizotypal Personality Questionnaire-Brief Revised (SPQ-BR, Cohen et al., 2010) is a 34-item Likert scale self-report measure of schizotypy traits. It has four superordinate factors, three of which tap a major domain of schizotypy: positive (cognitive-perceptual), negative (interpersonal), and disorganized, as well as a social anxiety factor. The interpersonal or negative schizotypy factor includes two subordinate factors: no close friends/constricted affect and social anxiety. The no close friends/constricted affect, with 6 items, was the primary metric of negative schizotypy in this sample (M = -0.79, SD = 0.78). This subscale has strong internal reliability (coefficient alpha =0.81, see Cohen et al., 2010 for full psychometric properties). Again, while the SPQ-BR refers to constricted affect, for clarity of communication, this project will refer to blunted affect throughout.

Ambulatory Measures

Online cognitive resources. Online cognitive resources were measured through an ambulatory verbal fluency task. Participants were prompted to name as many words as they can think of in one minute in a given semantic category. Semantic fluency is particularly relevant as a metric of variation in online cognitive resources in a schizotypy sample as executive functioning and

language domains are particularly impacted in schizotypy (Chun et al., 2013; Siddi et al., 2017), and are both represented in semantic fluency tasks (Aita et al., 2019).

A semantic fluency task allowed for variation in the stimuli to minimize practice effects. Animals, birds, clothing, college majors, colors, fruits, furniture, musical instruments, sports, vegetables, and vehicles were the categories collected. These categories were chosen based on pre-existing and validated tasks (Delis et al., 2012; Troyer, 2000) and studies which have specifically examined multiple presentations (Wilson et al., 2000) or categories of semantic fluency (Gollan et al., 2002), and found relative equivalence between these categories[1]. Categories were rotated through after each one has been administered once, such that each category was presented every other day, and never at the same time of day. This task was recorded using both audio and video. Audio was subjected to Microsoft Azure® Speech to Text, as automatic speech recognition, to create analyzable transcripts. Natural language processing was used to identify the number of elements provided in the semantic category (Holmlund et al., 2019).

The natural language processing proceeded in two steps. First, all words were filtered, which removed any punctuation, verbal stop words (e.g. “um,” “ah”), and expanded contractions. Each word is treated as a separate token, and the number of tokens for each assessment was counted automatically. Then, from each category, an overarching list of all words produced by all participants in response to that prompt was created, regardless of category relevance. Notably, each word is treated separately, which introduced some difficulties for compound concepts. For example, “redwing blackbird” might be included on the list as “redwing” “blackbird” or as “red” “wing” “blackbird”, or “redwing” “black” “bird” or as any combination thereof, depending on if

[1] Where the mean number of responses provided, or raw score corresponding to a scaled score of 10 in an approximate age range which includes the current study population is 15 ± 2.

multiple participants' responses were treated differently by the automatic speech recognition software. This overarching list was compared to a standard list of category relevant words stripped from Wikipedia for each category, to create two lists – a list of words that matched the Wikipedia list, and a list of words that did not. The list of words that did not match Wikipedia was hand checked for any false negatives, which were removed.

The most generous possible interpretation was used for checking this list to remove false negatives, particularly for "sound alike" potential errors in automatic speech recognition. For example, in the list of words that did not match from the "clothing" category was the word "abini," which was presumed to be an automatic speech recognition error which should have read "a beanie" which is a kind of hat and should be counted. As well, all subordinate categories were included, such as "cat," "kitten," "lion," as it was unknown whether those tokens came from the same individual's assessment. However, words did have to be category relevant examples. The Pokémon which had been provided by participants in the "animal" category were not counted, nor were brand names in the "clothing" or "vehicles" category unless the brand name also denotes a particular exemplar of that category (e.g. "converse" as clothing). For compound concepts, only ideas which could stand alone as an example of the category (e.g. "blackbird", or "bird" but not "red" or "black" alone) from above were retained. This list of "nonmatching" words was then compared to each single instance of assessment in each category, to count how many words from the instance of assessment were present on the list of nonmatching words. That number was then subtracted from the total number of tokens for that instance of assessment, to give the number of category relevant tokens, or the raw verbal fluency score.

To adjust for practice effects, this score was corrected using the Reliable Change Index which adjusts for practice effects (Troster et al., 2007), defined as:

$$X_{t2\ corrected} = X_{t2} + \frac{(X_{t2} - X_{t1}) - (M_{t2} - M_{t1})}{SD}$$

Where X_{t1} is the individual's score at a given timepoint, X_{t2} is their score at the subsequent administration of the same category, M_{ti} represents the group mean of that time point for that category, and *SD* is the standard deviation of the group test-retest difference for those two timepoints within that category. Each Reliable Change Index value for each assessment was then *z* transformed using the mean and standard deviation for that category, and then reverse-*z* scaled using the overall mean and standard deviation (across all categories and timepoints) to get data which was equivalently comparable across categories. Therefore, if someone scored 1 *SD* below the mean of that category, it would thus be treated as if they had an unscaled score which was 1 SD below the general mean.

Validation of this procedure for automatically transcribing and scoring verbal fluency assessments proceeded in four steps. Note that all validation was conducted on data not corrected for practice effects. First, test-retest reliability of these assessments was calculated (see Table 1). These assessments showed good test-retest reliability (Koo & Li, 2016). Then, a random subsample of 10 assessments from each verbal fluency category (k =110) were hand transcribed and scored, using the same overall scoring rules, but removing duplicate or repeated words. A two-way, random-effects, absolute agreement ICC(2,1) showed good reliability between automatic and hand scored data (ICC = 0.86, 95% CI = [0.50, 0.94]) (Koo & Li, 2016). A paired samples *t* test on this random subsample of verbal fluency assessments showed a significant difference between hand-scored and automatically scored data (t_{133} = -9.83, p < .001), such that

hand scored assessments received lower scores (*M*(*SD*) = 14.62 (6.22)) than automatically derived scores (*M*(*SD*) = 17.16 (7.93)).

Subsequently, several multilevel models nested by participant, representing possible threats to validity were evaluated – a model assessed the effect of category on number of words produced, and two separate models each assessed the effect of a demographic variable (race/ethnicity or gender) controlling for category. There were significant effects of category on number of words produced, such that relative to “animals,” all other categories except “colors” were associated with significantly fewer category relevant words with (*B(SE)'*s ranging from -1.80 (0.07) for vehicles to -0.35(0.7) for clothing). “Colors” was associated with significantly more words produced, relative to “animals” (*B*(SE) = 0.22 (0.07), $p < 0.01$). There were no significant effects of gender, controlling for category. Controlling for category, relative to White participants, Black participants were scored as producing fewer words (*B*(SE) = -0.37 (0.11), $p < .001$). One possible explanation for this finding is the possibility of more difficulty in the automatic speech recognition software in recognizing Black Southern accents, as most automatic speech recognition software is trained on White speakers.

The relation between verbal fluency and negative schizotypy was assessed with a multilevel model nested by participant and controlling for category. There was no significant effect of negative schizotypy on verbal fluency score. Finally, the convergent validity between this objective measure of cognition and subjective cognition (as described below in the *Momentary Reports* section) was assessed using a single multilevel model nested for participant, controlling for category. Subjective cognition was significantly, though modestly, associated with objective cognition (*B*(SE) = 0.06 (0.02), $p = .001$). These validation assessments suggest that the verbal fluency task was sufficiently reliable and valid to be used in future work, but that

the current categories are not entirely equivalent- hence why data was scaled relative to the category, and then transformed to be a raw number relative to the grand mean. Ideally automatic speech recognition software would be trained on a diversity of accents.

***Momentary Reports*.** Participants were asked to rate several items pertaining to their current state, including positive and negative affect items, their current social context, social motivation, and cognitive resources. These items are presented in Table 2. Affective items were adapted from the Positive and Negative Affect Schedule (Watson et al., 1988), a well-established measure with high reliability (Chronbach α = 0.85 and 0.89 for the Positive Affect and Negative Affect scales, respectively). The original version is given on a Likert scale, but for ambulatory assessment a slider was used. To measure subjective experience of online cognitive resources, two items from the Daytime Symptoms in Insomnia Scale (DISS, Buysse et al., 2007) were used. While this scale was designed for use in participants with insomnia, it has also been used in healthy adults. Composites for each self-report section were created using the average (positive affect, negative affect, self-report cognition) or the sum (social motivation) of every item in that section. Social motivation was summed rather than averaged for the theoretical reason that these domains tap different aspects (e.g. consummatory vs anticipatory, interest vs enjoyment) of social motivation, and summation is a better reflection of the responses on these items.

Table 2. Items in Momentary Assessments

Affective Experience: How ______ do you feel right now? [slider, 0 (Not at all) to 100 (Extremely)] [Positive affect] Amused, fun-loving, silly Content, serene, peaceful Happy, joyful, glad Love, closeness, trust [Negative affect] Angry, irritated, annoyed Sad, downhearted, unhappy Scared, fearful, afraid Ashamed, humiliated, disgraced
Cognitive Resources: [slider, 0 (Not at all) to 100 (Extremely)] *How clear-headed do you feel?* *How well can you concentrate?*
Social Context: Who are you interacting with? [select as many as are accurate] Significant other Family/ Roommates Friends Coworkers/ Classmates Doctor/ Therapist Strangers No one/ Alone
Social Motivation: [slider, 0 (Not at all) to 100 (Extremely)] How much are you enjoying this social interaction?/How much would you enjoy interacting with someone right now? How much do you think you will enjoy interacting with them next time/how much would you enjoy interacting with someone in the future? How interested are you in this social interaction/how interested are you in interacting with someone right now?
If interacting with another: *How are you interacting with them?* [select as many as are accurate] In person Phone Social video call School/Work video call Written electronic interaction (text, social media, etc.) Not interacting with anyone

Videos. Participants were encouraged to provide self-filmed "selfie" videos centered on their faces. They were asked to provide sixty seconds of video, following the probe "Describe, step by step, what you did in the last hour and how it made you feel. Please talk for a full 60 seconds," a minor modification from previously used procedures (Cohen et al., 2020).

Procedure

Due to the COVID-19 pandemic, this study proceeded entirely virtually. Individuals who registered for this study participated in an online survey-based assessment and seven days of ambulatory data collection.

Trait Measures Assessment. During the survey participants provided informed consent, then completed the demographics questionnaire, the BSI, and the SPQ-BR on Qualtrics. Participants automatically received an email which provided details on how to access the mobile application, and when they would receive ambulatory assessments. As well, this email provided a link to an instructional video on how to use the mobile application, and tips for how to film high quality videos, such as centering the video on one's face, removing large hats or opaque glasses before filming, and filming in circumstances with adequate light (e.g. turning a light on when it is dark in the room, not filming while backlit). They received two more reminder emails, one a day after completing the trait assessment, and one three days after completing the trait assessment.

Ambulatory/State Assessment. Participants were scheduled to receive six assessments per day, for seven days, for a maximum of 42 assessments per participant (see Power Analysis for rationale for proposed sampling rate). However, due to technical difficulties, the actual survey delivery rate was much more erratic, and many participants did not receive the proposed number of surveys, or surveys in the intended order, and due to technical difficulties, some

participants were granted an extension to complete more than the original intended number of surveys. Some participants had difficulty uploading the surveys and submitted surveys repeatedly. Surveys were removed if they had been submitted within five minutes of the previous survey (k =438). There was substantial variability in the number of surveys participants completed, ranging from one to 36 (M = 12.01, SD = 8.41) ambulatory assessments completed which included analyzeable video (i.e. ≥10% of frames analyzeable) and sufficient responses on the self-report metrics (e.g. any variability between adjacent sliders, to suggest that they had not simply clicked “next” and left the standard value in place), which was required for an assessment to be eligible for inclusion in this study. A total of 2594 assessments met these criteria. The ambulatory assessment included the online cognitive resources task, momentary ratings of mood, subjective cognition, social context, and social motivation, and self-filmed videos. See above for a brief review of questions and tasks provided during the ambulatory assessment phase.

Facial Analysis

Facial analysis was conducted using FaceReader 8.1, a proprietary software which provides continuous (frame by frame) analysis of a subset of the action units from the Facial Action Coding System, as well as several discrete emotions, and valence and intensity of expression (Noldus, 2019). FaceReader has been used in a number of studies, particularly in the domains of marketing and consumer science (e.g. Hadinejad et al., 2019; Maison & Pawłowska, 2017; Yu & Ko, 2017), but recent expansions have used it as a tool in the clinical psychological field (Cohen, Cowan, et al., 2020; Cowan, Cohen, et al., 2022; Cowan, Masucci, et al., 2022). FaceReader has consistently shown acceptable to high convergence with observer ratings (Lewinski et al., 2014) and is able to correctly identify target emotions 80-85% of the time, comparable to human raters (Lewinski et al., 2014; Skiendziel et al., 2019; Terzis et al., 2013).

When used to measure blunted facial affect, FaceReader scores for each frame can be averaged across an assessment window as a coarse assessment of overall facial affect. This coarse metric converges with clinical rantings of blunted affect, and even provides additional information in predicting functional outcomes over clinical ratings (Cohen et al., 2010). However, having continuous frame by frame data allows for much more fine-grained analysis and objectification of definitions of blunted affect.

***Objectifying Features of Blunted Affect*.** If the crucial basic domains of blunted affect are duration, intensity, frequency, and variety of expression, each of these can be objectified from the output obtained from FaceReader. To do so, however, it requires defining several features. First, what is an expression? In the FACS system, anything above an "A" rating is considered to be above "trace" expression (Ekman et al., 2002). In FaceReader, this translates to output above 0.26. Defining this as the minimum, a facial expression event can be the set of consecutive frames where expression intensity is above a 0.26. Duration of expression can be measured as the average length of each event, frequency can be defined as the number of events, and intensity can be the mean expression intensity of each event. These definitions have been used in a laboratory studies of facial expressivity which use the FACES expression coding system (Kring & Sloan, 2007), and by defining events can be extended into coding systems based on the FACS, such as the information provided by FaceReader analyses. Each of these operationalizations were calculated for happy expressions, as well as a composite of all negative valence expressions that FaceReader calculates, including sad, scared, angry, disgusted, and contempt expressions. These negative composites were operationalized as the mean across these facial expressions[2].

[2] In the course of analyses, it was noticed that the mean of negative frequency events was very low. A new composite defined as the sum across negative expression frequency categories was created, however this variable

While there are clear connections for intensity, frequency, and duration, range of expression remains somewhat more difficult to quantify. In clinical measures range to refer to a display of a diversity of expressions (e.g. happy, and sad, and so on), and is measured on ordinal scales, largely based on clinical intuition and observation. More nuanced quantification of range therefore becomes a difficult issue, and one without much past exploration in the literature. Taking the definition as “how diverse are this person’s expressions”, one possibility is to use the degree to which different facial expressions are present in the same video. FaceReader can provide the intensity of several discrete emotional expressions, such as happy, sad, angry, disgusted, and scared. To identify the extent to which each pair of emotions is present in the same video, one can calculate the “coactivation,” or the absolute value of the arctan of the two values, translated from radians into degrees, minus 45 degrees. This gives the absolute value of the deviation from perfect coactivation. As such, higher values equal more unbalanced activation of the two emotions, or less coactivation. The average of all coactivations is the range. Thus, using FaceReader, one can create operationalized and quantifiable metrics for many of the most crucial components of definitions of blunted affect, which heretofore have relied mostly on clinical intuition or self-report.

Statistical Analysis

All analyses were conducted in R (Skiendziel et al., 2019), version 4.1.1. Primary packages include lavaan (Rosseel, 2012), lme4 (Bates et al., 2015), and psych (Revelle, 2020) with most data manipulation done in dplyr (Wickham et al., 2021) and data visualization from psych (Revelle, 2020) and tidySEM (van Lissa, 2022).

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largely did not show a different pattern of results than the negative expression frequency mean, and so these results are not reported.

Descriptive Statistics. Descriptive statistics for the sample include mean and standard deviation of age, GPA, BSI and SPQ-BR scores, as well as the number of participants from each gender and ethnic or racial category sampled. From the ambulatory assessment data, means and standard deviations of relevant study variables, including frequency, intensity, and duration of positive and negative expressions, self-reported expressivity, social motivation, and online cognitive resources, were calculated. See Table 1 for these descriptive statistics. A visual depiction of the distribution of SQP-BR negative schizotypy and blunted affect scores is provided for clarity (see Figure 1).

Pearson's correlations were computed for facial expression variables, to see how they are inter-connected (see Figure 2). To identify confounds, correlations between BSI scores, negative schizotypy scores, and facial expression variables were computed, as well as ANOVAs analyzing negative schizotypy score differences between gender and ethnic groups. Correlations were computed based on the values obtained after data cleaning and assumption verification.

Data Cleaning and Assumption Verification. Several filters were applied to the data. First, surveys submitted within 5 minutes the previous survey were removed (k = 438), leaving 3243 assessments. Only surveys with a free-speech video were retained (k = 2708). Ambulatory assessment responses with no variation between self-report sliders were removed as invalid (k = 15). Then only surveys where at least 10% frames were analyzeable were retained, as per preliminary recommendations in the field of ambulatory video assessment (Cowan, Cohen, et al., 2022), leaving k = 2594. As had been found in previous literature (Cowan, Cohen, et al., 2022), Black participants were less likely than White participants to have their videos retained, based on a multilevel logistic regression nested by participants (B(SE) = -2.07(0.45), p < .001).

Missing Data. Subsequent to these filters being applied, there was baseline survey data from 216 individuals. Three participants did not provide information on their gender. One person elected not to provide information on one item of the SPQ-BR – this item was on the negative schizotypy scale but was not required to make the constricted affect subscale, and it was ignored in creating the mean negative schizotypy score for that person. Of these 216, there was sufficient data for all variables used in linear modeling. These same 216 participants provided the data for the MSEM analyses. A total of 2594 surveys had a facial expressivity video. Of these, 444 were missing data on at least one social motivation slider, though only 153 were missing data on all three sliders. In total, 86 surveys were missing a verbal fluency assessment score. A total of k = 2087 surveys had complete data for all MSEM moderator variables.

Assumptions for Linear Models. Variables used for linear modeling were scaled. For variables used in both linear modeling and structural equation modeling, values more than 3.5 *SD* from the mean were replaced with values at 3.5 *SD* from the mean. For linear models, predictor variables (expressivity variables) were checked for linearity of relationship with the outcome variable (negative schizotypy) using visual inspection of a scatterplot; normality of residuals was checked using a Q-Q plot; homoscedasticity was checked using a Scale-Location plot; multicollinearity was checked using the VIF (threshold <10; actually, all VIF scores were <5). These data checks did not reveal any significant problems.

Assumptions for Structural Equation Models. For the structural equation model, the first data check was for relative equality of variances among relevant variables (expressivity variables, social motivation variables, verbal fluency scores, and negative schizotypy). There were substantial differences, so variables were rescaled as follows: positive expression duration was divided by 1000; negative expression duration was divided by 100 and the social motivation

composite was divided by 10; positive expression frequency, negative expression frequency, range, and negative schizotypy were all multiplied by ten; negative expression frequency, positive expression intensity, and negative expression intensity were all multiplied by 100. Collinearity was assessed by correlations (see Figure 2). Missing data was automatically handled by lavaan through listwise deletion (Rosseel, 2012). Outliers more than 3.5 standard deviations from the mean were replaced with values 3.5 standard deviations from the mean for each variable. Normality of variables (after scaling and removing outliers) were assessed based on skew and kurtosis. For all variables aside from positive expression duration, skew was <2 and kurtosis was <5. For positive expression duration, skew was 2.72 and kurtosis was 10.15 suggesting a possible limitation to normality, but on the whole the data met the assumptions required for structural equation modeling.

Analysis 1. Multilevel models are commonly used to analyze ambulatory data as they account for the nested nature of the repeated assessments (i.e. assessments nested within individuals). However, multilevel models require that "Level 1" data is predicted by "Level 2" data, or cluster level data. In this study, trait measures, such as schizotypy scores, are "Level 2" data, and cannot be modeled by "Level 1" data, such as facial expression features. Therefore, each facial expression feature will be averaged within a participant to create "Level 2" data. A single linear model predicting negative schizotypy scores from range and intensity, frequency, and duration of positive and negative expressions averaged within individual was used to test the first hypothesis, that high negative schizotypy was related to diminished facial expressivity features.

Exploratory Analysis 1a. The same predictors were added to a model where the outcome variable was self-reported blunted affect to test whether this self-report metric was related to objective measures of expressivity.

Exploratory Analysis 1b. SPQ-BR Negative schizotypy scores were binarized into individuals who scored an average of 3.0 ("Agree") or above (n = 11), and a logistic regression predicting these scores by the facial expressivity variables was computed.

Analysis 2. Multilevel structural equation modelling (MSEM) with random intercepts was used to create the proposed pathways (Preacher et al., 2010) using lavaan (Rosseel, 2012). Maximum likelihood estimation was used for all models. Online cognitive resources and social motivation were predicted to mediate the relation between the negative schizotypy composite and blunted affect, where blunted affect is a latent variable composed of all facial expressivity features, and social motivation is a latent variable composed of all three social motivation questions. This model is a 2-1-1 MSEM model with random intercepts (Preacher et al., 2010). Per best practice guidelines (Kline, 2016), models were created iteratively. At each step, evaluation proceeded from assessing for Heywood cases, to local fit testing and exploring covariance residuals and residuals, to global fit testing, using the model χ^2, Root Mean Squared Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Square Root Mean Square Residual (SRMSR). The first models tested were unnested measurement models to assess the structure of the proposed latent variables. When a model was deemed possible (e.g. no Heywood cases), the subsequent test was to create a nested version of that same model. As necessary, models were simplified to create a possible model. Four iterative sets of models are presented: the two measurement models for the latent variables, the partially latent proposed model, and then two exploratory models which use only observed variables. Models which were deemed an

acceptable fit to the data were compared using the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC), and the model with the lower AIC and BIC was retained. If there were to have been a difference in retention based on these two information criteria, the BIC would be preferred as it takes sample size more directly into account (Kline, 2016).

A Priori Power Analysis

This power analysis was created before the collection of the data, based on the initial plan of a multilevel model for analysis one. Power analyses for multilevel models, even simple multilevel regression models, are difficult to estimate given the number of parameters to account for. This problem is magnified in structural equation modelling (SEM), where even modelling single level models can be problematic (Kline, 2016). For multilevel models, an accepted way to assess power is based on simulation data (Snijders, 2005). Much like other effect size calculations, a predicted effect size and a given sample size and sample rate are added to a hypothetical model. Then this hypothetical model is run a thousand times to see what percent of those cases find significant effects. This percentage is the power. Using R package paramtest (Hughes, 2017) and assuming 80% adherence for 42 possible survey times (the level at which participants would receive full compensation or 34 assessments per person), and small effect sizes (*beta* = 0.1), 100 participants is predicted to provide a power of 0.74, 120 participants gives a power of 0.82, and 150 participants gives a power of 0.89.

Following accepted heuristics for sufficient sample size in SEM, or the N:q rule stating there should be 20 cases per parameter, given the seven model parameters in each of the originally proposed SEM models, 140 cases were necessary (Kline, 2016). For these 140 cases, there would be approximately 4480 samples, again assuming 80% adherence. Given the relatively similar sample size recommended by the multilevel linear model simulations and the

heuristics for single level SEM (not accounting for the number of overall samples), then a proposed sample size of 140 was suggested as sufficient. The data collection exceeded the proposed number of participants, but with fewer assessments per participant.

Results

Correlations and Descriptive Statistics

On average, the participants completed relatively few surveys with facial analysis videos, just over one quarter of the proposed number of survey opportunities**.** Notably, not every participant received every proposed survey due to technical difficulties. Overall schizotypy, as well as negative schizotypy, and blunted affect, were all relatively low, averaging between "disagree" and "neutral," suggesting that the sample largely did not perceive themselves as having these traits (see Figure 1). Psychological symptoms, depression, and interpersonal sensitivity were also relatively low, averaging quite close to "A little bit." On average, this sample reported moderate positive emotional experience in the moment, just over halfway on the provided scale, and relatively low negative emotional experience, closer to 20% of the provided scale. Participants also reported relatively moderate in-the-moment cognitive functioning and social motivation. Reliability scores for ambulatory measures ranged from moderate (negative expression duration, positive expression duration) to excellent (positive and emotional experience, cognitive functioning, and social motivation)(Koo & Li, 2016). All self-report siders had excellent reliability, while objective metrics had lower, though still acceptable, reliability.

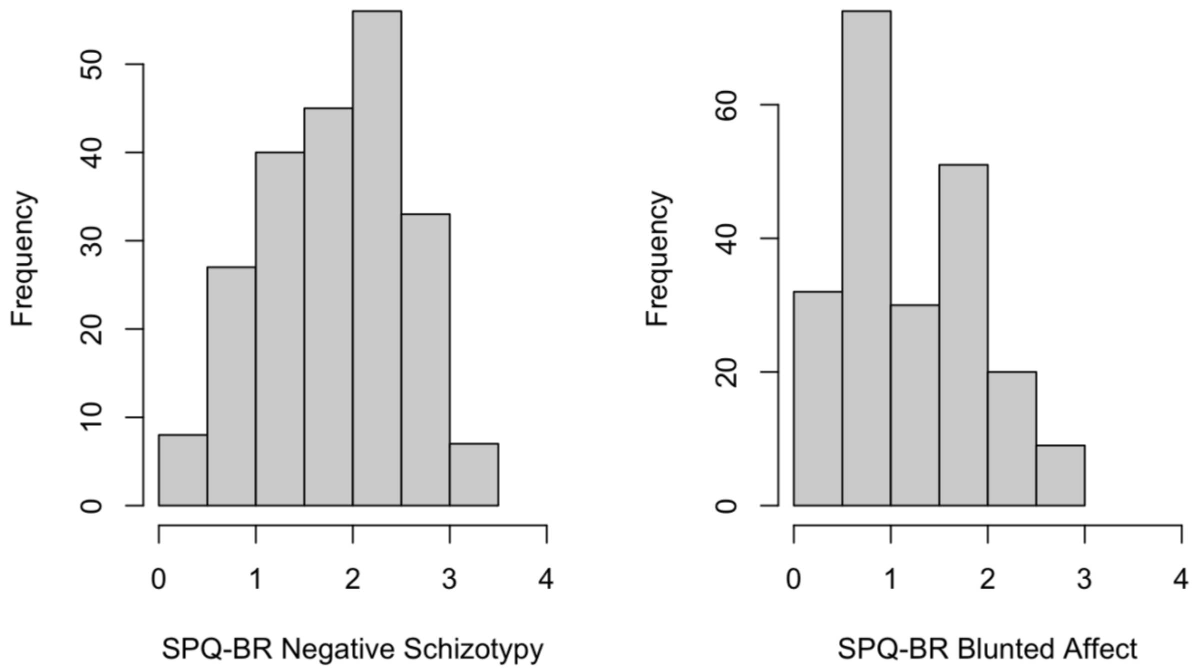

Figure 1. Distributions of *N* = 216 average scores on the SPQ-BR Negative Schizotypy scale, and of the SPQ-BR blunted affect subscale. Range for each is 0-4.

Correlations are presented in Figure 2. Positive expressivity metrics were correlated with social motivation measures, and positive expression duration was correlated with objective cognition and self-reported blunted affect. Negative expressivity metrics were significantly, though modestly, correlated with objective cognitive functioning (with the exception of negative expression duration), and weakly correlated with social motivation, if at all. Negative expression frequency was correlated with metrics of negative schizotypy and blunted affect, and negative expression intensity was correlated with negative schizotypy. Expressive range was not correlated with most other variables, though it did correlate with some other metrics of expressivity. Metrics of social motivation were negatively related to metrics of schizotypy, but

not to objective cognitive functioning. Objective cognitive functioning was also not related to metrics of schizotypy.

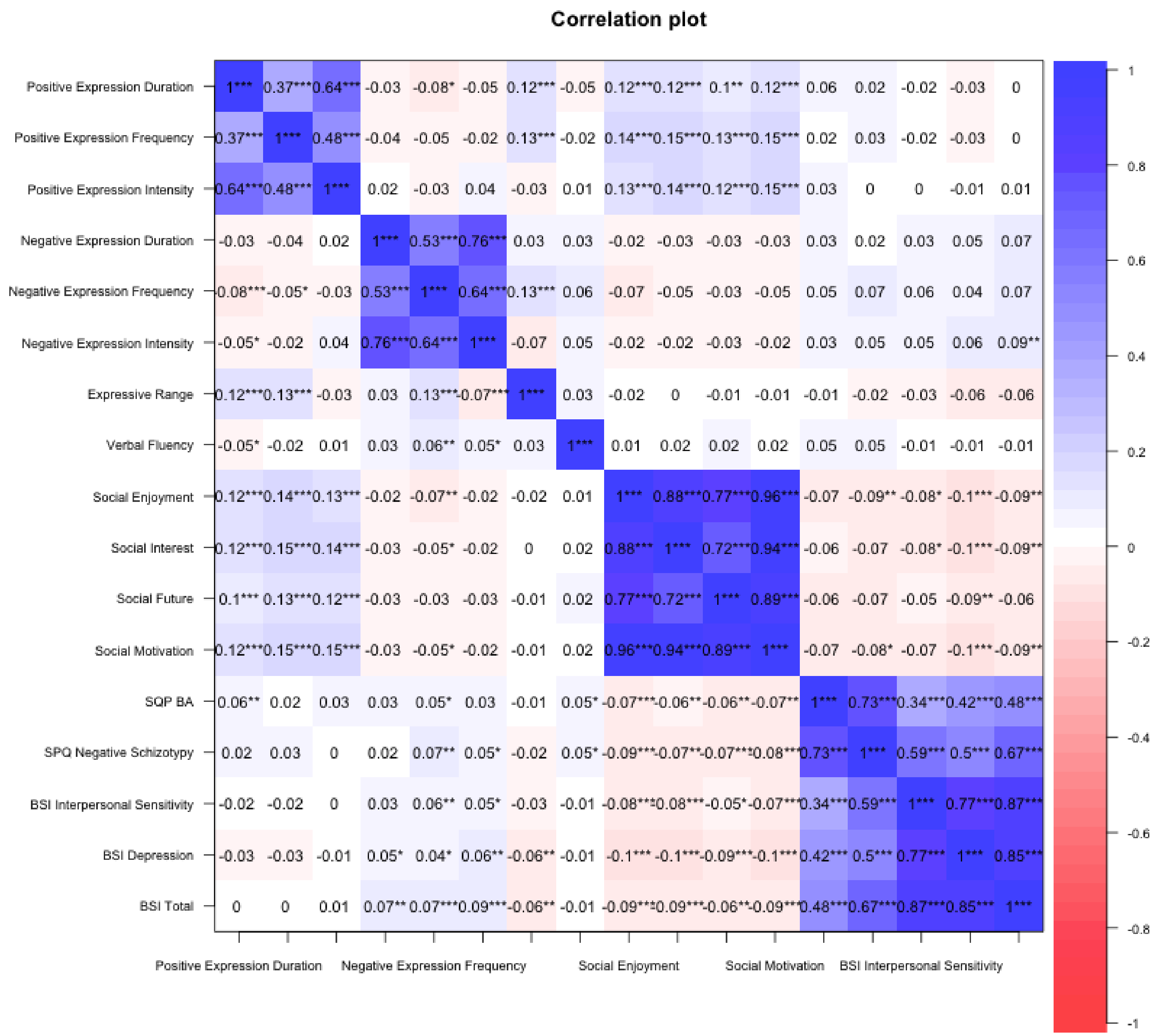

Figure 2. Correlations between facial expressivity variables, proposed mechanisms, metrics of schizotypy, and the BSI, *k* = 2087. Positive correlations are depicted in blue, negative correlations are depicted in red. The deeper the saturation of the square, the stronger the correlation. * = p <.05; ** = p <.01; *** = p <.001

Identifying Confounds.

Race/ethnicity was not significantly related to negative schizotypy or blunted affect. Gender was significantly related to negative schizotypy ($F(3,209) = 3.85$, $p = 0.01$) but not to blunted affect. Gender was also significantly related to range ($F(3, 191.81) = 4.34$, $p = .006$), but not any of the other facial expressivity variables, suggesting that it has the potential to be a confounding variable in analyses heavily dependent on range. The psychological symptoms, depression, and interpersonal sensitivity were all significantly correlated with negative schizotypy and the blunted affect subscale (r_{216} range = 0.40 – 0.70, all p's < 0.001). Regarding independent variables, psychological symptoms, depression, and interpersonal sensitivity correlated weakly with negative expression intensity and frequency; range of expressivity, and ambulatory social motivation; overall psychological symptoms also correlated with negative expression duration (r_{2508} range = -0.09 – 0.07, all p's < 0.05, see Figure 2). Given the pattern of the magnitude of these correlations, and the likelihood of finding spurious significant correlations with sample sizes this large, it seems more probable that psychological symptoms and gender are not true confounds, but instead share variance only with the outcome variables.

Correlations between facial expressivity variables (see Figure 2).

Positive facial expressivity features were significantly positively inter-related (r_{2087}'s range = 0.37-0.64 all p's < 0.001). Positive expression frequency and duration were both significantly related to negative expression duration, and positive expression frequency was significantly related to negative expression frequency (r_{2087}'s range = -0.08 – -0.05 all p's < 0.05). Negative facial expressivity features were significantly positively inter-related (r_{2087}'s range = 0.53–0.76 all p's < 0.001). Range was significantly related to positive expression

duration (r_{2087}= 0.12 <.001) and frequency (r_{2087}= 0.13, p <.001), but not intensity, and negative expression frequency (r_{2087} = 0.13 p <.001) and intensity (r_{2087} = -0.07 p <.001).

Analysis 1. Is negative schizotypy related to diminished facial expressivity features?

The overall model predicting negative schizotypy from facial expressivity features was not significant ($F(7, 208) = 0.77$, $p = 0.61$, $R^2 = 0.03$). None of the individual predictors were significant, either. See Table 3 for details on the individual predictors.

Table 3. Predictor Level Results of Analysis 1 and Exploratory Analysis 1.

	SPQ-BR Negative Schizotypy			**SPQ-BR Blunted Affect**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	0.06	-0.07 – 0.20	0.364	0.08	-0.05 – 0.22	0.225
Positive Expression Duration	0.32	-0.15 – 0.79	0.187	0.26	-0.20 – 0.73	0.269
Positive Expression Frequency	0.17	-0.13 – 0.46	0.274	0.06	-0.23 – 0.35	0.687
Positive Expression Intensity	-0.25	-0.66 – 0.16	0.236	-0.08	-0.48 – 0.33	0.713
Negative Expression Duration	-0.14	-0.74 – 0.47	0.653	0.12	-0.48 – 0.72	0.698
Negative Expression Frequency	-0.08	-0.42 – 0.27	0.667	0.02	-0.32 – 0.36	0.919
Negative Expression Intensity	0.25	-0.26 – 0.75	0.337	-0.01	-0.51 – 0.48	0.953
Range	-0.16	-0.43 – 0.11	0.256	-0.12	-0.38 – 0.15	0.392
Observations	216			216		
R^2 / R^2 adjusted	0.025 / -0.007			0.014 / -0.019		

Exploratory analysis 1a. Is self-reported blunted affect related to diminished facial expressivity features?

Similarly, the overall model predicting blunted affect from facial expressivity features was not significant ($F(7, 208) = 0.44$, $p = 0.88$, $R^2 = 0.01$). As well, none of the individual predictors were significant (see Table 3).

Exploratory analysis 1b. Do facial expressivity features predict categorial schizotypy scores?

The overall model predicting binarized negative schizotypy was not significant ($\mathrm{X}^2(7, N = 216) = 12.43, p = 0.09$), however positive expression duration was significant (*B(SE)* = 1.85 (0.85), 95% CI = [0.29, 3.71], OR = 6.37), such that for every standard deviation increase in average positive expression duration, the odds of self-reporting as high negative schizotypy increased by a factor of 6.37.

Analysis 2. Do Social Motivation and Cognitive Resources Mediate Negative Schizotypy and Blunted Affect?

Blunted Affect Measurement Models.

The first model tested an unnested confirmatory factor analysis (CFA) predicting that positive and negative duration, frequency, and intensity of expression, as well as range, would all cohere into a single blunted affect factor. The unnested model failed to converge. The nested version of this model converged with 35 parameters, and $k = 2594$. However, the variance-covariance matrix was not positive definite and there were negative variances (Heywood cases). The negative variances were in level 2.

A second unnested measurement model was created removing both positive and negative durations of expressions, as these variables most significantly overlap conceptually with the

other expressivity variables (particularly frequency). This model was estimable but had a Heywood case (negative variance of the latent variable of blunted affect). A third unnested model was tested removing range, which is conceptually the least coherent with the other variables. This model was estimable and had no Heywood cases. It had poor local fit statistics, with no significant predictors of the latent variable. Kline (2016) suggests correlational residuals > 0.1 suggest a poor fit to the data, and one correlation residual (between positive expression frequency and intensity) was 0.49. Global fit statistics were poor ($\mathrm{X}^2(2, N = 2594) = 725.69, p < 0.0001; \mathrm{RMSEA} = 0.37, 90\%\mathrm{CI} = [0.35, 0.40], p < .0001; \mathrm{CFI} = 0.67; \mathrm{SRMSR} = 0.16$). The nested version of this model had a Heywood case (negative variance on positive expression frequency in level 2), however was estimable. This model was considered to be the best and most parsimonious representation of the latent variable of blunted affect, however, it was clear that this construct as currently operationalized did not fit the data well. As such, while the full model including a latent blunted affect variable will be presented, exploratory analyses with the construct of blunted affect represented by single indicators selected based on theory and the results of analysis 1 will also be included.

Social Motivation Measurement Models.

The unnested CFA model of social motivation as represented by self-reported interest in a social interaction (interest), enjoyment from a social interaction (enjoyment), and desire for future social interactions (future) was just identified. Models which are just identified have a single, unique solution and therefore perfectly reproduce the data -as such, these models cannot test the fit of the model to the data (Kline, 2016). The unnested model converged with 6 parameters, and k = 2150. Local fit statistics were good, with all indicators significantly relating to the latent factor in the same (positive) direction. Given that the model was just identified, it was not

possible to test global fit statistics. The nested model had a Heywood case in level 2 – negative variance on the enjoyment indicator (-0.035).

Analysis 2 Full Model.

The full proposed model used positive and negative expression frequency and intensity to represent the latent variable of blunted affect, and enjoyment, interest, and pleasure to represent social motivation. In the proposed model, at level one, social motivation and verbal fluency predicted blunted affect; at level two, negative schizotypy predicted social motivation and verbal fluency, and each of these, as well as negative schizotypy, predicted blunted affect (see Figure 3). This model had a Heywood case (negative variance in positive expression intensity in level 2). This model is represented in Figure 3, though given the Heywood cases, this representation is for visualization purposes primarily.

Exploratory Analysis 2a: A social motivation mediation model.

Given the Heywood case in the proposed model, a simplified model was created which tested the mediational effect of social motivation as a latent variable composed of social enjoyment, interest, and future desire, in the pathway between negative schizotypy and blunted affect (as a latent variable represented by positive and negative frequency and intensity of expressions). This model had a Heywood case (negative variance in social enjoyment in level 2).

Exploratory Analysis 2b: A cognitive resources mediation model.

A simplified model was created which tested the mediational effect of cognitive resources in the pathway between negative schizotypy and blunted affect (as a latent variable represented by positive and negative frequency and intensity of expressions). This model had a Heywood case (negative variance in positive expression frequency in level 2).

Exploratory Analysis 2c: Representing Blunted Affect with Negative Expression Frequency.

Given that the measurement models suggested there would be significant convergence difficulties with using the latent variables for blunted affect and social motivation in nested models, two exploratory models were created. In these models, social motivation was represented by a composite reflecting the sum of the three social motivation self-report sliders, and blunted affect was represented by a single expressivity feature. In the first model, blunted affect was represented by negative expression frequency, as this feature in the measurement models seemed to be the indicator which best represented the latent construct. See Figure 4 for a representation of this model. This model converged with 16 parameters and 2508 observations from 215 individuals and did not have any Heywood cases. Local fit indicators suggested that at level 1, cognitive resources were not related to negative expression frequency (*B*(SE) = 0.25(0.22), $p > .05$) but social motivation was (*B*(SE) = -0.55 (0.20), $p = .005$). At level 2, cognitive resources were not predicted by negative schizotypy (*B*(SE) = 0.003(0.04), $p > 0.05$) but they did predict negative expression frequency (*B*(SE) = 2.50 (1.10), $p = 0.02$). At level 2, social motivation was predicted by negative schizotypy (*B*(SE) = -0.14(0.60), $p = 0.02$), but neither social motivation (*B*(SE) = -0.35(0.70), $p > 0.05$) nor negative schizotypy (*B*(SE) = 0.29(0.49), $p > 0.05$) predicted negative expression frequency. All correlation residuals were <0.1, suggesting a good fit to the data. This good fit was corroborated by global fit statistics ($\mathrm{X}^2(1, N = 2508) = 0.07, p = 0.79; \mathrm{RMSEA} = 0.000, 90\%\mathrm{CI} = [0.000, 0.034], p = 0.99; \mathrm{CFI} = 1.00; \mathrm{SRMRwithin} = 0.002; \mathrm{SRMRbetween} = 0.01$).

Exploratory Analysis 2d: Representing Blunted Affect with Positive Expression Duration.

In the second model, blunted affect was represented by positive expression duration, as this feature was what emerged in exploratory analysis 1b as a predictor of negative schizotypy

scores. See Figure 5 for a representation of this model. This model converged with 16 parameters and 2508 observations from 215 individuals and did not have any Heywood cases. Local fit indicators suggested a slightly different pattern of results than when blunted affect is represented by negative expression frequency. At level 1, both cognitive resources (*B*(SE) = -0.01(0.005), *p* = .003) and social motivation (*B*(SE) = 0.02 (0.004), *p* <.001) were related to positive expression duration. At level 2, social motivation was predicted by negative schizotypy (*B*(SE) = -0.14(0.06), *p* = 0.02), but no other predictors were significant. Cognitive resources were not predicted by negative schizotypy (*B*(SE) = 0.01(0.04), *p* > 0.05) nor did they predict positive expression duration(*B*(SE) = -0.01 (0.02), *p* >.05), nor did social motivation (*B*(SE) = 0.001 (0.01), *p* > .05) or negative schizotypy (*B*(SE) = 0.01(0.01), *p* > 0.05) predicted positive expression duration. All correlation residuals were <0.1, suggesting a good fit to the data. This good fit was corroborated by global fit statistics ($\mathrm{X}^2(1, N = 2508) = 0.07, p = 0.80; \mathrm{RMSEA} = 0.000, 90\%\mathrm{CI} = [0.000, 0.034], p = 0.991; \mathrm{CFI} = 1.00; \mathrm{SRMRwithin} = 0.002; \mathrm{SRMRbetween} = 0.01$).

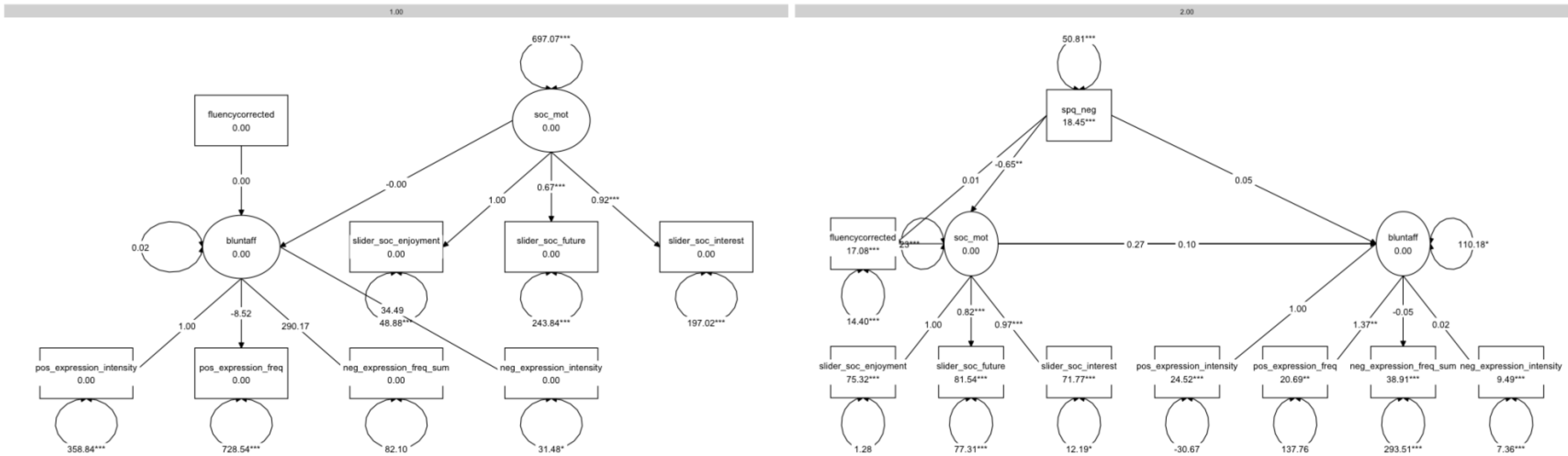

Figure 3. A visual representation of the model under study in Analysis 2. Note that this model has Heywood cases. The panel identified with a 1.00 is the first (within cluster) level of the model. The panel identified 2.00 is the second (between cluster) level of the model. “soc_mot” = social motivation; “fluencycorrected” = verbal fluency scores corrected with the reliable change index; “bluntaff” = blunted affect; “spq_neg” = negative schizotypy; “slider_soc_enjoyment” = social enjoyment ; “slider_soc_future” = future social desire ; slider_soc_interest = social interest; “pos_expression_intensity” = positive expression intensity; “pos_expression_freq” = positive expression frequency; “neg_expression_freq” = negative expression frequency; “neg_expression_intensity” = negative expression intensity.

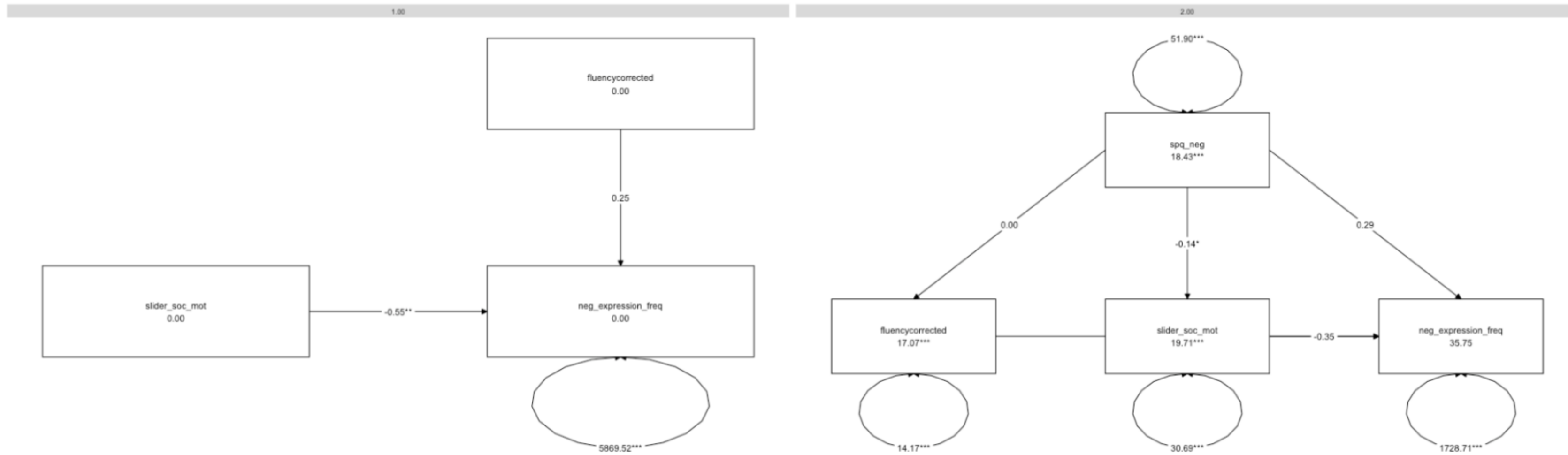

Figure 4. A visual representation of the model under study in Exploratory Analysis 2c. The panel identified with a 1.00 is the first (within cluster) level of the model. The panel identified 2.00 is the second (between cluster) level of the model. Within individuals, social motivation is significantly and negatively related to negative expression frequency. Between individuals, this pathway disappears, but there is a significant relation between negative schizotypy and social motivation. “slider_soc_mot” = social motivation composite; “fluencycorrected” = verbal fluency scores corrected with the reliable change index; “spq_neg” = negative schizotypy; “neg_expression_freq” = negative expression frequency.

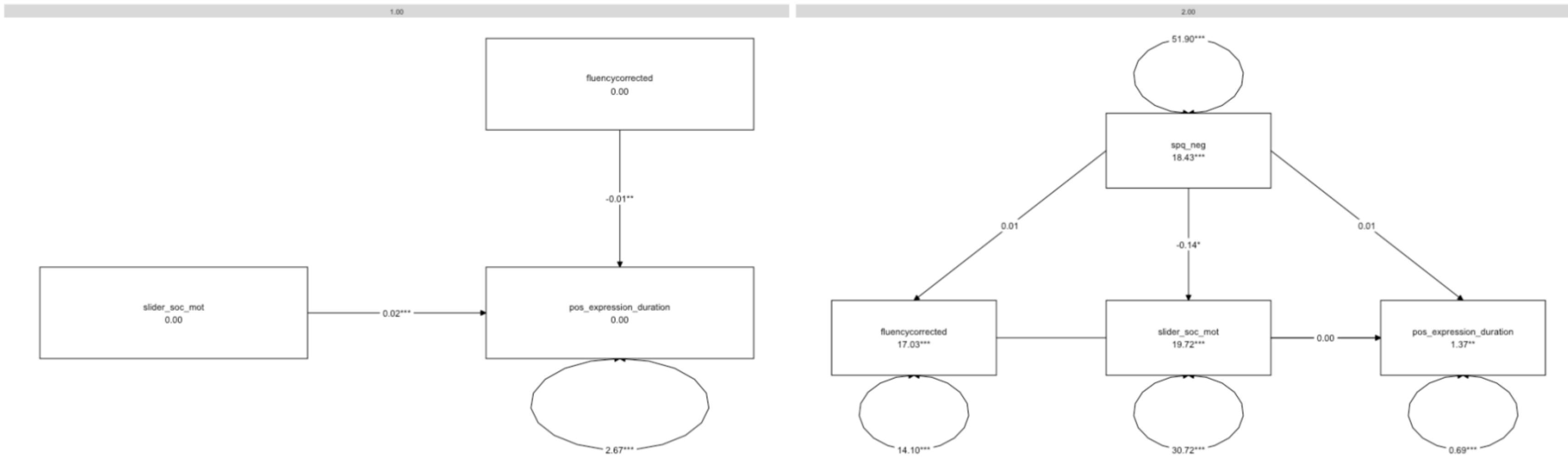

Figure 5. A visual representation of the model under study in Exploratory Analysis 2d. The panel identified with a 1.00 is the first (within cluster) level of the model. The panel identified 2.00 is the second (between cluster) level of the model. Within individuals, both cognitive resources and social motivation are significantly related to positive expression duration, though in opposite directions. Between individuals, these pathways disappears, but there is a significant relation between negative schizotypy and online cognitive resources. “slider_soc_mot” = social motivation composite; “fluencycorrected” = verbal fluency scores corrected with the reliable change index; “spq_neg” = negative schizotypy; “pos_expression_duration” = positive expression duration.

Exploratory Analysis 2e. Comparing the two best fitting models.

The AIC (46691) and BIC (46785) of the model where blunted affect was represented by positive expression duration were lower than the AIC (66016) and the BIC (66109) of the model where it was represented by negative expression frequency, suggesting that the model where blunted affect is represented by positive expression duration is a better fit to the data.

Discussion

General Study Findings: support (or lack thereof) for hypotheses, and attainment of aims

In the broader literature, blunted affect is found across the schizotypy spectrum. That is, amongst individuals who have schizotypy, their duration, intensity, and frequency of facial expressions appears to be less than individuals without, and this is true for individuals with both more and less intense manifestations of schizotypy. Preliminary evidence also linked diminished expressivity to cognitive resource limitations, or diminished social motivation. This project aimed to explore these relations further in the lives of individuals on the schizotypy spectrum, using multimodal ambulatory assessments including self-filmed videos, a verbal fluency task, and self-reports.

The first prediction was that higher negative schizotypy would be related to lower range, frequency, duration, and intensity of both positive and negative expressions. Contrary to expectations, this relation was not found. In fact, when aggregated across assessments, there was no relation between negative schizotypy and range, frequency, or intensity of expressions. However, individuals with longer positive expressions, on average, were more likely to self-report in a manner that suggested the presence of high negative schizotypy. This finding contradicts the hypotheses, in which longer positive expressions should be associated with lower negative schizotypy, based on other studies of blunted affect in individuals with serious mental illness (Cowan, Masucci, et al., 2022). However, it is worth noting that the overall model for this analysis was not significant, so this finding must be interpreted with caution. The first hypothesis was contradicted in a limited fashion, but the results of these analyses have interesting implications for operationalization of blunted affect, which will be discussed below.

The finding that ambulatory and objective metrics of expressivity are, at best, related to psychometric schizotypy in a limited and unexpected fashion was corroborated in the second analyses. The second analysis was primarily exploring whether social motivation and cognitive resources mediate the relationship between negative schizotypy and blunted affect, with the hypothesis that they do. However, it is notable that none of the nested models (which were mathematically possible) had either a direct or even indirect pathway between negative schizotypy and any variable representing blunted affect. As such, the hypotheses that social motivation or cognitive resources mediated the relation between negative schizotypy and blunted affect were not supported. However, the models explored within the framework of analysis two did suggest interesting and useful information about the constructs of blunted affect and social motivation, and the relations between expressivity, social motivation, and cognitive resources. Some of these inquiries were embedded as assumptions in the proposed model, and merit separate consideration. These results will be explored before the findings from this study are contextualized in the larger expressivity and blunted affect literature, which will be followed by an identification of the limitations of this project, and how they might inform future research directions.

Assumptions and Their Unexpected Information

What is blunted affect? Inherent in the original models proposed for this study were two significant assumptions. First, that the proposed metrics of expressivity would cohere into a meaningful unitary construct, namely, blunted affect, and secondly, that this latent unitary construct functions similarly within and across individuals. The results of this study challenged both assumptions, which will be explored in sequence. Notably, none of the nested models were a good fit to the data, or even mathematically possible. One unnested model could be estimated

and was mathematically possible but was a poor fit to the data. The tempered success of this unnested model is doubly suspect, because it may be capitalizing on intra-individual shared variance across sessions which would increase correlations (Kline, 2016, p. 237), as some of the correlations between expressivity features are quite low, or even simply on the much greater number of assessments relative to clusters/participants.

Interpreting a null finding is difficult, but the failure to find a measurement model of blunted affect which appropriately represented the nested data structure does suggest that, at least in this sample, these expressivity features do not cohere into a single latent variable. Not all these expressivity features are influenced by the same underlying construct. While this finding may be driven by the limitations of the study, which will be discussed in further detail below, it may also suggest that expressivity features are meaningfully different, or work in substantially different ways. It certainly suggests that blunted affect is not an overall reduction in expressivity, across positive and negative expressions or across duration, frequency, intensity, or range of expressions.

Similar findings have emerged in other samples. In a sample of individuals with serious mental illness broadly (Cowan, Masucci, et al., 2022), clinician rated blunted affect was related to a reduction in duration of positive expressions - though while significant the effect was small. There were also small to moderate contributions of increased duration or frequency of negative expressions to clinician rated blunted affect in this sample, but the most consistent finding was actually that clinician rated blunted affect was closely connected to reductions in expressions of surprise (Cowan, Masucci, et al., 2022). The connection between clinician rated blunted affect and increases in negative expressions has been found in several other studies across several modalities of inquiry (e.g. computerized facial analyses, manual coding of expressions, or

electromyography; Alvino et al., 2007; Bishay et al., 2019; Kohler et al., 2008; Lotzin et al., 2013; Varcin et al., 2010, 2019), Similarly, other studies have identified decreases in positive expressions associated with blunted affect (Gupta et al., 2019; Kring et al., 2013). Largely, however, these studies have not identified a coherent pattern of increase or decrease across valence, supporting the possibility that different kinds of emotional expressions, and even different aspects of these expressions, work in different or potentially interactive ways in order to create facial expressivity which is perceived as blunted.

One potential framework which has been suggested (Cowan, Masucci, et al., 2022; Rümke, 1941; Sullivan, 1962) is that what is perceived as blunted affect is, in fact, a reduction in socially connected facial expressions, or a failure to produce expressions which are socially engaging, which may be a component of why the model which predicted coherence between all variations of expressivity was not a good fit to the data. Inherent in this model is a cultural assumption about which expressions are, or are not, socially engaging. *Decreases* in expressions which communicate affiliation or interest, such as positive expressions or surprise, are impediments for social engagement, while *increases* in negative expressions are also considered an impediment. This model is likely to be culturally limited, but that is a testable empirical assertion. Negative expressions contain just as much socially relevant information as positive expressions, but they may create a sense of distance between the viewer and the producer which results in the perception of affective disconnection or affective flattening.

The second major assumption in these nested models is that blunted affect would cohere in a similar fashion both within and across individuals, or that the same latent variable definition could be used at level one and level two. This assumption is more difficult to test in the current study, given that the original proposed definition was such a poor fit in the unnested model.

Again, this model had a Heywood case in the nested version, particularly in level two, suggesting that the unnested version is capitalizing on the unnested, and inappropriate, structure of the data. However, this could also be an indication that these facial expressivity features function not only differently within features, but also across individuals, or that there is not cross-level invariance (Jak, 2019). For example, for one person, the latent construct of blunted affect may be primarily represented by decreases in durations of positive expressions, while in another person it may be primarily represented by increases in frequency of very short duration negative expressions. While it may be possible to partially test this hypothesis using random slopes in an MSEM model, which was not possible given software constraints in this current project, even then it would require including all possible permutations of interactions of facial expressivity features, which would far exceed the scope and power of the current study. Finally, it is possible that there was not sufficient variance represented at the between individual level to estimate the factor structure there, however given the moderate ICC values for these metrics, that explanation seems less likely (Jak, 2019; Kline, 2011). Kline (2016) recommends a minimum of 10% between individual variability, which each of these ICCs suggest is more than sufficiently cleared.

What is social motivation? Like assumptions made about blunted affect, inherent in the conceptualization of social motivation is that it is a unitary construct composed of in the moment social pleasure or seeking social pleasure; in the moment social interest or interest in socialization; and a future prediction of social pleasure. This conceptualization drew on understandings of hedonic experience more broadly, which have separated affective experiences of pleasure (a.k.a. consummatory pleasure) from motivation or conscious desire or future/anticipatory pleasure (Berridge & Robinson, 2003; Gard et al., 2006). Further, definitions of social anhedonia frequently include concepts of both disinterest and a lack of pleasure in

social interactions as well as a temporal component of anticipatory as well as consummatory social pleasure (Barkus & Badcock, 2019). In the current study, all three indicators appeared to represent the latent construct of social motivation well, but only in the unnested model. When the multilevel model was created, it became mathematically impossible. Again, this failure to estimate this model may represent cross-level invariance (Jak, 2019) though there is no theoretical rationale for that concern, and given the high ICC of the composite of the indicators of this factor, insufficient between individual is also unlikely to be a concern (Kline, 2011).

The other major assumption regarding social motivation in the proposed models is that it is predicted by negative schizotypy. There is substantial theoretical reason to predict this path, including that for some theories of negative schizotypy, it is essentially trait social anhedonia, or a lack of social motivation (Blanchard et al., 2011; Horan et al., 2007; Meehl, 1962). As predicted, in both models which were estimable, increased social motivation was predicted by lower negative schizotypy.

Facial Expressivity and Social Motivation

Social motivation was predicted to be negatively related to blunted affect, such that more social motivation would result in less blunted affect, or increased expressivity. However, somewhat contradictory results were found regarding these relations. Increases in in the moment or within individual social motivation were related to *decreases* in negative expression frequency and *increases* in positive expression duration. If blunted affect is assumed to be uniform decreases in all aspects of expressivity, these results are hard to interpret. However, as reviewed above, some research suggests that blunted affect can reflect *increases* in negative expressions (Alvino et al., 2007; Bishay et al., 2019; Cowan, Masucci, et al., 2022; Kohler et al., 2008;

Lotzin et al., 2013; Varcin et al., 2010, 2019). With this framework, intra-individual increases in social motivation reflected intra-individual decreases in blunted affect.

Recent research has explored the role of social motivation in expressivity among individuals with schizophrenia (Cowan, Strauss, et al., 2022), and found that, among this group, diminished expressivity may actually represent a failure to *demonstrate* social motivation, rather than a lack of experienced social motivation or a lack of general expressivity. This research suggests one reason for why decreases in positive facial expressions, which are highly socially relevant and communicate affiliation, may be commonly seen in individuals with blunted affect. However, the findings from the current study contradict other aspects of Cowan, Strauss, and colleagues (2022), which had found that between individual deviations in affective experience were more impactful in predicting expressivity than within individual deviations. In contrast, in the current study, the predictive power of social motivation on expressivity features was only observed within individuals. Significantly, that may reflect the difference in population. The current participants were individuals largely without diagnoses of schizophrenia or schizophrenia spectrum illnesses, and largely they scored relatively low on measures of schizotypy and blunted affect, where Cowan, Strauss, and colleagues (2022) explored the relations between expressivity and social motivation in individuals with schizophrenia compared to controls. Greater inter-individual variability in both expressivity and social motivation may have been found in this group which includes both individuals with and without schizophrenia, which is already a highly heterogeneous diagnostic category.

Facial Expressivity and Online Cognitive Resources

Like social motivation, cognitive resources had opposing effects on positive and negative expressions. More cognitive resources were associated with more frequent negative expressions,

and shorter positive expressions. However, these findings are not in line with the more nuanced framework on blunted affect advanced above which suggests that blunted affect is particularly connected to the lack of socially concordant messages communicated to the interaction partner. If that framework was supported by these results, one would expect that more cognitive resources would be associated with *fewer* negative expressions and *longer* positive expressions. As the results currently emerged, however, it seems that *more* cognitive resources were associated with expressivity features which would be in line with blunted affect, which contradicts the predictions of this study.

Further, unlike social motivation, which had effects on expressivity which were consistently at the within individual level, cognitive resources had different effects on expressivity at different levels. Between individual variation in cognitive resources predicted between individual variability in negative expression frequency, while within individual variation in cognitive resources predicted within individual variability in positive expression duration. This somewhat conflicting pattern of results suggests a tenuous connection between cognitive resources and expressivity.

One possible explanation for that is that the cognitive task did not appropriately tap variability in cognition. However, there are two arguments against this explanation. First, the ICC value for the uncorrected verbal fluency score was “good,” not excellent, suggesting that there was some variance from session to session. As well, this objective metric of cognition cohered with subjective reports of cognitive functioning, though notably it did not cohere with negative schizotypy in the way that would be expected.

Of the domains of cognition in which schizotypy shows deficits, the strongest support is for working memory and language (Chun et al., 2013; Siddi et al., 2017). Working memory and

language skills are particularly required for semantic verbal fluency, especially in individuals with schizophrenia (Ojeda et al., 2010; Whiteside et al., 2016). However, these associations between schizotypy and deficits in working memory and language are not necessarily true for individuals who are high in *negative* schizotypy, as relevant meta-analyses have collapsed across domains of schizotypy (Chun et al., 2013; Siddi et al., 2017). Regardless, in experimental conditions, individuals with high negative schizotypy have shown that when visual and verbal working memory are taxed at the same time, then acoustic properties of speech demonstrate reduced expressivity (Cohen et al., 2012). However, that study had slightly greater proximity between the domain of working memory being taxed and the channel of expressivity being assessed. It is possible that this coherence between taxation and expressivity is required to see a dampening effect of limited cognitive resources, or simply that much stricter experimental control is necessary.

Model Retention

Globally, the best fitting model represents expressivity with duration of positive expressions and social motivation with the pre-calculated composite of the three indicators. It had few theory congruent paths, suggesting that the hypotheses were largely unsupported. As detailed above, the original hypotheses of social motivation and/or cognitive resources mediating between negative schizotypy and blunted affect were not supported as there was no relation between negative schizotypy and blunted affect. However, the gestalt of the retained model also suggests that, in all, the hypotheses were a poor fit to the data. Relative to the model which was not retained, there were several overlapping significant paths (social motivation predicted expressivity at level 1; at level 2, social motivation was predicted by negative schizotypy, both in

explainable directions). The substantial difference is the level at which cognitive resources predicted expressivity, and what indicator represented expressivity. In the model which is the best fit to the data, the only significant predictors of expressivity (positive expression duration) are at level 1, suggesting that the processes which connect social motivation and cognitive resources to expressivity are largely within person.

This finding is particularly notable because it is so rarely explored in the broader blunted affect literature, which largely has relied on between individual comparisons. However, even inquiries which have explored within individual effects, they have been less notable than between individual differences (Cowan, Strauss, et al., 2022). Within the expressivity literature in the general population, there have been inquiries into individual differences in kinds of positive expressions (Cohn et al., 2002; Gunnery et al., 2013; Schmidt & Cohn, 2001). Notably, longitudinal work has suggested that (at least at the time-scale of a year, and in response to an evocative situation), these inter-individual differences are stable, suggesting an expressivity "signature" (Schmidt & Cohn, 2001). However, the currently retained model suggests more intra-individual variation in the influence of social motivation and cognitive resources on positive expressions, rather than between individual differences. These findings highlight the need for more ambulatory assessment of expressivity, as it is only with repeated assessments that intra-individual variability can be explored.

Potential Explanations: The Subjective-Objective Discrepancy

The results of this study join a broader literature pointing to a potential contradiction within schizotypy – the subjective-objective discrepancy. The subjective-objective discrepancy is found in many aspects of schizotypy research, and refers to the fact that individuals with

schizotypy report subjective deficits akin to individuals with schizophrenia, several standard deviations below controls, but then on objective metrics appear to be much more similar to controls, showing mild deficits, if any (Cohen et al., 2017). This discrepancy has been found in numerous domains, including both affective experience and expression (Cohen et al., 2017; Li et al., 2019). Analogous to this discrepancy is the relative difficulty in finding clear and consistent objective decreases in facial expressivity, even in individuals who are perceived, by clinicians, to have blunted affect (e.g. Alvino et al., 2007; Bishay et al., 2019; Cowan, Masucci, et al., 2022; Kohler et al., 2008; Lotzin et al., 2013; Varcin et al., 2010, 2019). Across the schizotypy spectrum, there seems to be a disconnect between how individuals perceive themselves, or are perceived by others, compared to the objective evidence. This discrepancy may explain the failure to support the first hypothesis – that individuals higher in negative schizotypy would show decreases in metrics of expressivity. Essentially, this explanation would suggest that there would be minimal objective deficits in expressivity, and as such, the effects of cognitive resources and social motivation on expressivity would hold true regardless of schizotypy levels – that these are mechanisms for expressivity, rather than for blunted expressivity, and that they function the same in individuals without schizotypy, but may be particularly activated in certain individuals with high schizotypy. Largely, this coheres with the findings from the multilevel structural equation modeling, where schizotypy was unconnected to blunted affect or expressivity.

Potential Explanations: Resolution

One important consideration when exploring the subjective-objective disjunction and the relation between negative schizotypy and expressivity more broadly, is the question of

resolution. With advances in ambulatory assessment have come new challenges in how to understand and integrate that data with more traditional forms of assessment. For example, the SPQ-BR asks respondents to report how they are generally, in their whole life, regardless of contextual factors. In contrast, the questions asked about social motivation in the current ambulatory assessment were specific to how someone was feeling at that particular moment and are highly contextual. Essentially, these two kinds of assessments work with different "resolutions" or specificity of information (Cohen, Schwartz, et al., 2020). The ambulatory assessment metrics, both subjective (e.g. self-reported social motivation) and objective (e.g. expressivity features) have the same resolution. That proximity of resolution may explain why social motivation, which again, is a critical component of negative schizotypy, was associated with expressivity features, even though negative schizotypy more generally was not. How someone perceives themselves, generally, may not have a strong influence on how they express themselves in any given moment, because that expression is so contextually dependent. However, the social motivation component of schizotypy, when activated in the moment, does have the effect of increasing expressivity. Notably, the issue of resolution may be less impactful when there is proximity in other aspects of measurement – for example, the general assessment of negative schizotypy did predict ambulatory ratings of social motivation. However, these assessments share modality (self-report), and this shared method variance may compensate for the difference in resolution.

Implications for Treating Blunted Affect

The results of this study suggest tentative directions for new treatments for blunted affect. Unfortunately, to date, there have been no specific inquiries into treatments for blunted affect. Generally, clinical trials will examine negative symptoms of schizophrenia as a unitary construct

(Correll & Schooler, 2020; Elis et al., 2013; Fusar-Poli et al., 2015; Remington et al., 2016). There have been mixed results for these treatments, with many pharmacological interventions showing statistically significant, but not necessarily clinically meaningful effects (Fusar-Poli et al., 2015). Psychological treatments, particularly cognitive behavioral therapy and social skills training, show efficacy for general negative symptoms, and in some trials that efficacy is maintained at follow-up (Elis et al., 2013). Social skills training is founded on behavioral principles, using modelling and repeated practice to help individuals improve their ability to function within social interactions, and explicitly includes practice and instruction in socially communicative expressions and when to use them (Bellack, 2004). This kind of treatment may be more useful if a lack of cognitive resources was the driving mechanism behind expressive deficits, by reducing the cognitive load of expressivity. However, the results of this inquiry do not suggest cognitive resource limitations to be the primary mechanism. Instead, therapies which target increasing social motivation, potentially by identifying values around social connection (e.g. acceptance and commitment therapy; Hayes et al., 2006) or by managing interfering cognitions (e.g. cognitive behavioral therapy, Elis et al., 2013; Turkington et al., 2004) may be more effective.

One caveat to these treatment implications is that, as of yet, objective measures of expressivity are not associated with thresholds for clinical significance. While these results suggest that declines in social motivation are associated with declines in affiliative expressivity, it is not clear whether there is a specific necessary level of social motivation required for "normative" expression, or, perhaps more crucially, even what normative expression is or would be, when accounting for a myriad of contextual factors. In comparison to clinical ratings which are typically made on ordinal scales which indicate the severity (e.g. Kirkpatrick et al., 2011;

Kring et al., 2013), it is unclear exactly at what level, and in what contexts, objectively operationalized diminished expressivity becomes impairing to social functioning. Given that there is a normal human variation in expressivity, both within and across cultures (Camras et al., 2006; McDuff et al., 2017), most individuals who present with diminished expressivity relative to some norm are likely to not need treatment or intervention, even individuals high in schizotypy or with a diagnosis of schizophrenia. In fact, in some circumstances or cultural contexts, diminished expressivity relative to other contexts or cultures may be expected or preferred (Matsumoto et al., 2008). It is critical not to inherently pathologize diminished expressivity but to recognize that at extremes, or given contextual demands, it may at times become an impediment to smooth social functioning.

Limitations and Future Directions

The results of this study are best interpreted in light of several notable limitations. First and foremost, there were significant technical difficulties in administering the surveys to the participants which resulted in many surveys not being delivered on schedule. There were three kinds of ways that surveys could not be delivered on schedule – surveys could be delivered at the wrong time, they could fail to be delivered entirely, or the wrong survey could be delivered, as there was a specific schedule for each different verbal fluency task administered. The original plan was that each verbal fluency would only be administered every other day, and never at the same time of day, to minimize the likelihood of participants practicing or preparing for the task, and that each participant would receive 42 surveys. After the technical issues were discovered, some participants had their participation window extended so they could receive full credit. As such, it is difficult to interpret the relatively low completion rates. However, the completion rates for video entries are relatively similar to other studies of participants with schizophrenia who

were not compensated specifically for the video (but were compensated for the survey they provided; Cowan, Cohen, et al., 2022), so it is also conceivable that even without technical difficulties, completion rates would have been similar. However, it is unclear exactly what percent of surveys were improperly delivered and in what ways, and so it is unclear whether participants were presented with verbal fluency tasks in a way that may have impacted their performance (e.g. being delivered the same prompt two surveys in a row). Aside from impacting verbal fluency performance, these technical difficulties resulted in missing data, above and beyond the missing data described here, though that data would not have had a systematic pattern to why it was missing, and would be equally missing across all participants, and so may be considered missing at random.

Another significant limitation to the findings of this study is also related to the verbal fluency data, and particularly to the fact that the verbal fluency task appeared to perform differently in different ethnic groups. One possibility, as discussed, is that there were difficulties in the automatic speech recognition software in parsing Black Southern accents, as there is well documented bias against Black individuals in automatic speech recognition (Koenecke et al., 2020; Mengesha et al., 2021). It is also possible that these errors were less likely to be corrected by the investigator, who is a White woman not raised in the southern USA, and therefore may have been less likely to recognize culturally meaningful idioms, synonyms, or homophones when attempting to correct for the automatic speech recognition errors in classifying the responses as correct or not. However, even laboratory based administrations of verbal fluency assessments have found differential performance in Black and White participants (Werry et al., 2019). Racial biases are also well known in facial recognition technologies, and the software used in the current study has been documented to be less effective at analyzing video frames provided by

Black participants (Cowan, Cohen, et al., 2022). In the current study, this resulted in Black participants' videos being more likely to be removed for having insufficient analyzeable frames, which may have introduced irrelevant variance in the expressivity variables. As technology (hopefully) becomes less biased against Black people, replicating these findings would be beneficial. Further, it would be useful to replicate this study in different geographic regions, to investigate the effect of accent on the verbal fluency task.

These technological racial biases are compounded by the demographic composition of the sample, which was primarily White women, which limits the possibility of an intersectional inquiry into potential biases in this study. The sample sizes when accounting for intersectional identities (i.e. different combinations of racial/ethnic/gender identities) are simply too small to allow for meaningful comparisons, or explorations of whether these findings are different within different groups. It is conceivable that different social presentation rules for expressivity for people with different identities (e.g. Black men versus Black women, Black women versus White women) (Fischer & LaFrance, 2015; Wingfield, 2010) could be impacting the results found in this study. Notably, there was a significant effect of gender on one expressive metric, but largely, race and gender did not appear to be confounds in this study. However, again, these analyses did not explore potential intersectional effects. Replicating these findings with a more diverse and larger sample would permit these explorations.

Finally, it is worth noting that this sample had somewhat restricted range in terms of both overall negative schizotypy and self-reported blunted affect. This pattern is not surprising given that schizotypy is present in approximately 10% of the population (Blanchard et al., 2000; Lenzenweger & Korfine, 1992; Verdoux & van Os, 2002), and the sample was not specifically selected for schizotypy traits. This restricted range may have been part of why negative

schizotypy was not associated with expressivity metrics. However, samples specifically selected for high schizotypy have also not demonstrated a relation between negative schizotypy and facial expressivity metrics (Cohen, Morrison, et al., 2013). It may be necessary to extend this study into a sample of individuals selected not just for schizotypy or even diagnoses of schizophrenia, but specifically participants who either self-report or are deemed by a clinician to have significant blunted affect. Notably, as reviewed above, even in samples of individuals with schizophrenia, clinician rated blunted affect shows a fairly nuanced relation with objective metrics of expressivity (Cowan, Masucci, et al., 2022), indicating that the disjunction between objective and subjective/perceived expressivity still requires significant exploration.

Summary and Conclusions

Across the schizotypy spectrum, blunted affect is a cardinal aspect of negative symptomatology. However, it remains poorly understood. This project represents a foray into the potential mechanisms for blunted affect, particularly in exploring the contributions of cognitive resources and social motivation. There were two primary hypotheses in this study. First, that high negative schizotypy would relate to diminished range, frequency, duration, and intensity of positive and negative expressions overall, and that the relation between negative schizotypy and blunted affect would be mediated by cognitive resources and social motivation. Neither of these hypotheses were supported. Negative schizotypy was not related to blunted affect, or to metrics of expressivity, and as such this relation could not be mediated. However, it does appear that, within individuals, in the moment decreases in social motivation are related to a pattern of expressivity which may reflect blunted affect. Surprisingly, in the moment cognitive resources were related to the opposite pattern of expressivity, and without a consistent within or between person effect. These results must be interpreted in light of significant limitations, but suggest

future research into the effect of social motivation on different timescales (e.g. resolution) and of cognitive resources *in situ*, rather than in controlled laboratory experiments.

Appendix A. IRB Approval and Relevant Questionnaires

LSU | Office of **Research & Economic Development**

TO:	Cohen, Alex S LSUAM	Col of HSS	Psychology
FROM:	Paul Mooney Associate Chair, Institutional Review Board
DATE:	10-Dec-2020
RE:	IRBAM-20-0713
TITLE:	Facial expression and personality
SUBMISSION TYPE:	Initial Application
Review Type:	Expedited Review
Risk Factor:	Minimal
Review Date:	10-Dec-2020
Status:	Approved
Approval Date:	10-Dec-2020
Approval Expiration Date:	09-Dec-2021
Re-review frequency:	Annually
Number of subjects approved:	200
LSU Proposal Number:	
By:	Paul Mooney, Associate Chair

Continuing approval is CONDITIONAL on:

1. Adherence to the approved protocol, familiarity with, and adherence to the ethical standards of the Belmont Report, and LSU's Assurance of Compliance with DHHS regulations for the protection of human subjects*
2. Prior approval of a change in protocol, including revision of the consent documents or an increase in the number of subjects over that approved.
3. Obtaining renewed approval (or submittal of a termination report), prior to the approval expiration date, upon request by the IRB office (irrespective of when the project actually begins); notification of project termination.
4. Retention of documentation of informed consent and study records for at least 3 years after the study ends.
5. Continuing attention to the physical and psychological well-being and informed consent of the individual participants, including notification of new information that might affect consent.
6. A prompt report to the IRB of any adverse event affecting a participant potentially arising from the study.
7. Notification of the IRB of a serious compliance failure.
8. **SPECIAL NOTE: When emailing more than one recipient, make sure you use bcc. Approvals will automatically be closed by the IRB on the expiration date unless the PI requests a continuation.**

** All investigators and support staff have access to copies of the Belmont Report, LSU's Assurance with DHHS, DHHS (45 CFR 46) and FDA regulations governing use of human subjects, and other relevant documents in print in this office or on our World Wide Web site at http://www.lsu.edu/research*

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Baton Rouge, LA 70803

O 225-578-5833
F 225-578-5983
http://www.lsu.edu/research

Demographic Questions

Age:

Sex:

- Female
- Male
- Intersex
- Not listed/Prefer not to answer

Gender

Race:
Select all that apply

- Asian/Pacific Islander American
- White
- Black/African American
- Not listed/Write in below
- Indigenous/Native/American Indian

Race not listed: write in below

Do you identify as Hispanic or Latino?

- Yes, Hispanic or Latino
- No, not Hispanic or Latino

Do you identify as Middle Eastern or North African?

- Yes, Middle Eastern or North African
- No, not Middle Eastern or North African

What is your approximate GPA?

Have you, or your family ever. . . ? (Check all that apply)

	Myself	Biological Parents	Biological Brother/Sister	Other Biological Family Member
. . . received psychological treatment for a psychological or psychiatric concern (e.g., talk or behavior therapy)?	☐	☐	☐	☐
. . . received psychiatric treatment for a psychological or psychiatric concern (e.g., medications, psycho-surgery, Electro-convulsive therapy)?	☐	☐	☐	☐
. . . been admitted to an inpatient psychiatric hospital (where you stayed overnight)?	☐	☐	☐	☐
. . . been diagnosed or treated for depression?	☐	☐	☐	☐
. . . been diagnosed or treated for anxiety?	☐	☐	☐	☐
. . . been diagnosed or treated for schizophrenia, a serious mental illness characterized by hallucinations and delusions?	☐	☐	☐	☐
. . . been diagnosed or treated for another psychotic spectrum disorder beside schizophrenia (e.g. schizoaffective disorder, a psychotic episode)?	☐	☐	☐	☐
. . . been diagnosed or treated for ADHD or other academic problem?	☐	☐	☐	☐
. . . been diagnosed or treated for mania?	☐	☐	☐	☐
. . . been diagnosed or treated for epilepsy?	☐	☐	☐	☐

What medications do you take regularly?

Schizotypal Personality Questionnaire - Brief Revised

Instructions:

Please read the following statements and answer them as honestly as possible, giving only your own opinion of yourself. Do not skip any items and answer them as honestly as possible, giving only your own opinion of yourself. When thinking about yourself and your experiences, do not count as important those attitudes, feelings, or experiences you might have had only while under the influence of alcohol or other drugs (e.g., marijuana, LSD, cocaine).

Response Format:

0	1	2	3	4
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

SPQ-BR Items (with corresponding SPQ items)

1	SA2	I sometimes avoid going to places where there will be many people because I will get anxious.
2	EB5	Other people see me as slightly eccentric (odd).
3	MT12	Do you believe in telepathy (mind-reading)?
4	EB14	People sometimes comment on my unusual mannerisms and habits.
5	OS16	I sometimes jump quickly from one topic to another when speaking.
6	CA17	I am not good at expressing my true feelings by the way I talk and look.
7	UP22	When you look at a person or yourself in a mirror, have you ever seen the face change right before your eyes?
8	OS25	I sometimes forget what I am trying to say.
9	CA26	I rarely laugh and smile.
10	S27	Do you sometimes get concerned that friends or co-workers are not really loyal or trustworthy?
11	SA29	I get anxious when meeting people for the first time.
12	MT30	Do you believe in clairvoyance (psychic forces, fortune telling) ?
13	UP31	I often hear a voice speaking my thoughts aloud.
14	CF33	I find it hard to be emotionally close to other people
15	OS34	I often ramble on too much when speaking.
16	SA38	Do you often feel nervous when you are in a group of unfamiliar people?
17	CF41	Do you feel that there is no one you are really close to outside of your immediate family, or people you can confide in or talk to about personal problems?

(table con't'd.)

Response Format:

0	1	2	3	4
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

18	IR45	When shopping do you get the feeling that other people are taking notice of you?
19	SA46	I feel very uncomfortable in social situations involving unfamiliar people.
20	MT47	Have you had experiences with astrology, seeing the future, UFO's, ESP, or a sixth sense?
21	UP48	Do everyday things seem unusually large or small?
22	MT55	Have you ever felt that you are communicating with another person telepathically (by mind-reading)?
23	OS58	Do you tend to wander off the topic when having a conversation?
24	S59	I often feel that others have it in for me.
25	IR60	Do you sometimes feel that other people are watching you?
26	IR63	Do you sometimes feel that people are talking about you?
27	UP64	Are your thoughts sometimes so strong that you can almost hear them?
28	S65	Do you often have to keep an eye out to stop people from taking advantage of you?
29	CF66	Do you feel that you cannot get "close" to people.
30	EB67	I am an odd, unusual person.
31	EB70	I have some eccentric (odd) habits.
32	CA73	I tend to keep my feelings to myself.

Brief Symptom Inventory (BSI)
By Leonard R. Derogatis, PhD

The following is a list of problems that people sometimes have. Please read each one carefully, and choose the response that best describes **how much that particular problem has distressed or bothered you during the last seven days, including today**. Choose only one response per item, rating your feelings from ‘Not At All’ to ‘Extremely.’ Please do not skip any items.

How much were you distressed by:

1. Nervousness or shakiness inside
2. Faintness or dizziness
3. The idea that someone else can control your thoughts
4. Feeling others are to blame for most of your troubles
5. Trouble remembering things
6. Feeling easily annoyed or irritated
7. Pains in heart or chest
8. Feeling afraid in open spaces or on the streets
9. Thoughts of ending your life
10. Feeling that most people cannot be trusted
11. Poor appetite
12. Being suddenly scared for no reason
13. Temper outbursts that you could not control
14. Feeling lonely even when you are with people
15. Feeling blocked in getting things done
16. Feeling lonely
17. Feeling blue
18. Feeling no interest in things
19. Feeling fearful
20. Your feelings being easily hurt
21. Feeling that people are unfriendly or dislike you
22. Feeling inferior to others
23. Nausea or upset stomach
24. Feeling that you are watched or talked about by others
25. Trouble falling asleep
26. Having to check and double-check what you do
27. Difficulty making decisions
28. Feeling afraid to travel on buses, subways, or trains
29. Trouble getting your breath
30. Hot or cold spells

31. Avoiding certain things, places, or activities because they frighten you
32. Your mind going blank
33. Numbness or tingling in parts of your body
34. The idea that you should be punished for your sins
35. Feeling hopeless about the future
36. Trouble concentrating
37. Feeling weak in parts of your body
38. Feeling tense or keyed up
39. Thoughts of death or dying
40. Having urges to beat, injure, or harm someone
41. Having urges to break or smash things
42. Feeling very self-conscious with others
43. Feeling uneasy in crowds, such as shopping or at a movie
44. Never feeling close to another person
45. Spells of terror or panic
46. Getting into frequent arguments
47. Feeling nervous when you are left alone
48. Others not giving you proper credit for your achievements
49. Feeling so restless you couldn’t sit still
50. Feelings of worthlessness
51. Feeling that people will take advantage of you if you let them
52. Feelings of guilt
53. The idea that something is wrong with your mind

Appendix B. R Code

```
library(pacman)

p_load(readr, zoo, plyr, Hmisc, ggplot2, psych, reshape, effects, VIF, reghel
per, ez, car, fBasics, matrixStats, dplyr, lavaanPlot,semPlot, tidySEM, sjmis
c, sjlabelled, sjstats, rmarkdown, lme4, kableExtra, glmnet, caret, jtools, g
gstance, huxtable, tidyr, tibble, ggcorrplot, rcompanion,  cvblocker, ICC, bo
ot,brms, gmodels, interactions,snakecase, ggpubr, naniar, egg,rstatix, mboost
,lmerTest, stringr, irr, lavaan,install = TRUE, update = TRUE, character.only
= FALSE)

cat("\f")
rm(list=ls(all=TRUE))
if(!is.null(dev.list())) dev.off()

vardd <- c("/Users/tovah/Library/CloudStorage/Box-Box/ASAP LAB/ASAP RESEARCH
DRIVE/DATA/SUMMARY DATA/hr21lsufaces/SUMMARY DATA/")

facs <-read_csv(paste(vardd, "hr21lsufaces_facs_wide_total_May22.csv", sep=""
))%>%select(-'...1')
survey <- read_csv(paste(vardd, "hr21lsufaces_qitraq_anonymous_May22.csv", se
p=""))%>%select(-c('...1', slider_concentrate2))
qualtrics <- read_csv(paste(vardd, "hr21lsufaces_qualtrics_anonymous_May22.cs
v", sep=""))%>%select(-c('...1'))
#compiled  <- read_csv(paste(vardd, "hr21lsufaces_complied_anonymous_May22.cs
v", sep=""))%>%select(-c('...1', slider_concentrate2))
fluency <-read_csv(paste(vardd, "hr21lsufaces_vf_counts_april22.csv", sep="")
)%>%select(-c('...1'))%>%rename(file_name = filename)%>%mutate(file_name = gs
ub(".txt", "", file_name))
#codex <- read_csv(paste(vardd, "hr21lsufaces_codex_May22.csv", sep=""))%>%mu
tate(file_name = gsub(".MOV", "", file_name))
codex <- read_csv(paste(vardd, "hr21lsufaces_codex_May22.csv", sep=""))%>%sel
ect(-'...1')
fluency <- select(fluency, file_name, video_type, wordcount, match_counts)%>%
rename(file= file_name)%>%join(.,codex, by=c("file", "video_type"))

variables_identifiers <- c("id_lsu", "study", "id_biobeh", "surveyname", "tim
e", "instance", "wkday", "studyday", "framerate", "time_total", "perc_valid",
"frames")

variables_facs <- facs%>%select(-file)%>%colnames()
variables_qualtrics <- qualtrics%>%select(-c("id_lsu","study", "id_biobeh", "
Progress", "Duration", "Finished", "ExternalRef", "Dist", "Language" ))%>%col
names()
variables_survey<- survey%>%select(-c("id_lsu", "study", "id_biobeh", "survey
name", "time", "instance", "wkday", "studyday"))%>%colnames()
```

```
#set identifiers to factors
facs<- join(facs, codex)
facs <- mutate(facs, across(.cols =c("id_lsu", "study", "id_biobeh", "instanc
e", "wkday"), .fns = factor))
survey <-  mutate(survey, across(.cols =c("id_lsu", "study", "id_biobeh", "su
rveyname", "instance", "wkday", "video_type"), .fns = factor))
#compiled <-  mutate(compiled, across(.cols =c("id_lsu", "study", "id_biobeh"
, "surveyname", "instance", "wkday"), .fns = factor))


#identify the three people with antipsychotics
qualtrics<- qualtrics%>% mutate(antipsychotics = ifelse(str_detect(medication
s, "Vraylar"), 1,ifelse(str_detect(medications,"Lamictal"), 1, 0)))

#build a dissertation specific database. This used to be done off of the comp
iled database, but because it has so many rows with duplicate or no data, I'm
going to build it from scratch

#this shrinks the file so that you don't have a duplicated row for each type
of video
survey <- select(survey, -video_type)%>%distinct

variables_facs<- c("summ_mean.neutral", "summ_mean.happy", "summ_mean.sad", "
summ_mean.scared", "summ_mean.angry", "summ_mean.disgusted", "summ_mean.surpr
ised", "summ_mean.contempt", "event_lengthm.neutral", "event_lengthm.happy",
"event_lengthm.sad", "event_lengthm.scared", "event_lengthm.angry", "event_le
ngthm.disgusted", "event_length.surprised", "event_length.contempt", "event
_n.neutral", "event_n.happy", "event_n.sad", "event_n.scared", "event_n.angry
", "event_n.disgusted", "event_n.surprised", "event_n.contempt","event_mean.n
eutral", "event_mean.happy", "event_mean.sad", "event_mean.scared", "event_me
an.angry", "event_mean.disgusted", "event_mean.surprised", "event_mean.contem
pt")

facs<- select(facs, file, frames, framerate, time_total, perc_valid, variable
s_facs)

#this condenses the FACS data where there were duplicating rows
facs <- facs%>%group_by(file)%>%summarize(across(.cols = c(perc_valid, frames
,framerate, time_total, variables_facs), .fns= mean, na.rm= TRUE))

#when merging, there were some nonduplicated rows with the same id, wkday, an
d instance. Try only merging on file - obviously that doesn't work, because t
hey have different file names for fluency and nonfluency videos....
subfluency <- select(fluency, id_lsu, instance, wkday, studyday,time,  wordco
unt, match_counts, video_type)

wkdb <- join(codex, facs, by ="file")

wkdb<- join(wkdb, subfluency)
```

```
#reformat such that the wkdb contains one line with the FACS data from the vi
deo_describe plus the fluency data from the other video
wkdbunsplit <- wkdb

wkdbdescribe <- filter(wkdb, video_type == "video_describe")%>%select(-c(matc
h_counts, wordcount, video_type))%>%ungroup()
wkdbfluency <- filter(wkdb, video_type != "video_describe")%>%select(id_lsu,
instance, wkday, studyday,time, match_counts, wordcount, video_type)%>%ungrou
p()

#this works, gives you 3243 observations with numeric data in fluency values-
all Facereader data is from the describe video, all wordcount data is from th
e other video for this survey. the file is the describe video file
wkdb <- join(wkdbdescribe, wkdbfluency)


wkdb<- wkdb%>% relocate(file)%>%relocate(c(wordcount, match_counts, video_typ
e), .after = studyday)


#add ambulatory survey info in
surveymerge <- survey %>% mutate(across(.cols = c(id_lsu, instance), .fns =as
.character)) %>% mutate(across(.cols = c(id_lsu, instance), .fns = as.numeric
))%>%select(-study, -id_biobeh)%>% mutate(wkday = as.character(wkday))
wkdb <- join(wkdb, surveymerge, by = c("id_lsu", "time", "instance", "wkday",
"studyday"))


#this line keeps only surveys where there was a video - drops from 3243 to 27
08
wkdb<- wkdb%>% filter(!is.na(frames))


#remove data from qualtrics according to who provided appropriate facs data -
217 people retained

qualtrics <- filter(qualtrics, id_lsu%in%wkdb$id_lsu)

#Assign numerical identifiers to all self-reports
qualtrics <- qualtrics%>%mutate(across(.cols = starts_with("SPQ"),  ~ case_wh
en(. == "Strongly Agree" ~ "4",
                       . == "Agree" ~ "3",
                       . == "Neutral" ~ "2",
                       . == "Disagree" ~ "1",
                       . == "Strongly Disagree" ~ "0"))) %>%mutate(across(.co
ls = starts_with("BSI"),  ~ case_when(. == "Extremely" ~ "5",
                       . == "Quite A bit" ~ "4",
                       . == "Moderately" ~ "3",
                       . == "A Little Bit" ~ "2",
                       . == "Not At All" ~ "1")))  %>% mutate(across(.cols =
```

```
starts_with("IPASE"),  ~ case_when(. == "Strongly Agree" ~ "5",
                       . == "Agree" ~ "4",
                       . == "Neither Agree nor Disagree" ~ "3",
                       . == "Disagree" ~ "2",
                       . == "Strongly Disagree" ~ "1")))%>% mutate(across(.co
ls = starts_with("SPQ"), as.numeric))%>% mutate(across(.cols = starts_with("B
SI"), as.numeric))%>% mutate(across(.cols = starts_with("IPASE"), as.numeric)
)

#create SPQ blunted affect and negative schizotypy composites - NB - one pers
on (116) is missin some SPQ data... but only one item which would go on the n
eg sztypy, and none on BA
qualtrics <- qualtrics%>% mutate(spq_BA = rowMeans(select(qualtrics, c(SPQBR_
6,SPQBR_9,SPQBR_32))))%>% mutate(spq_neg = rowMeans(select(qualtrics, c(SPQBR
_1,SPQBR_11,SPQBR_16,SPQBR_19,SPQBR_6,SPQBR_9,SPQBR_32, SPQBR_14,SPQBR_17,SPQ
BR_29)), na.rm = TRUE))
#qualtrics%>%select(starts_with("SPQ"))%>%filter(is.na(spq_neg))

#create composite variables for positive and negative affect
wkdb <- mutate(wkdb, slider_pos_affect = rowMeans(select(wkdb,c(slider_amused
, slider_content, slider_happy, slider_loving)), na.rm = TRUE), slider_neg_af
fect = rowMeans(select(wkdb,c(slider_angry, slider_sad, slider_scared, slider
_ashamed)), na.rm = TRUE), slider_cog = rowMeans(select(wkdb,c(slider_clearhe
aded, slider_concentrate)), na.rm = TRUE))



#create the negative expression composites for duration, intensity, and frequ
ency
wkdb <- mutate(wkdb, neg_expression_duration = rowMeans(select(wkdb,c(event_l
engthm.sad, event_lengthm.scared, event_lengthm.angry, event_lengthm.disguste
d, event_lengthm.contempt)), na.rm = TRUE), neg_expression_intensity = rowMea
ns(select(wkdb,c(event_mean.sad, event_mean.scared, event_mean.angry, event_m
ean.disgusted,  event_mean.contempt)), na.rm = TRUE), neg_expression_freq = r
owMeans(select(wkdb,c(event_n.sad, event_n.scared, event_n.angry, event_n.dis
gusted, event_n.contempt,)), na.rm = TRUE), neg_expression_freq_sum = rowSums
(select(wkdb,c(event_n.sad, event_n.scared, event_n.angry, event_n.disgusted,
event_n.contempt,)), na.rm = TRUE))


#create the coactivation variable - created by video, rather than second by s
econd, because this isn't about overlap, but overall quantity of expression p
resent
#average all of the coactivations


coactivation <- wkdb
coactivation$coac_h_a <-  ifelse(coactivation$summ_mean.happy == 0 |coactivat
ion$summ_mean.angry== 0, 0, abs((atan2(coactivation$summ_mean.happy, coactiva
tion$summ_mean.angry)*180/pi)-45))
```

```
coactivation$coac_h_sa <- ifelse(coactivation$summ_mean.happy == 0 |coactivat
ion$summ_mean.sad== 0, 0, abs((atan2(coactivation$summ_mean.happy, coactivati
on$summ_mean.sad)*180/pi)-45))
coactivation$coac_h_sc <- ifelse(coactivation$summ_mean.happy == 0 |coactivat
ion$summ_mean.scared== 0, 0, abs((atan2(coactivation$summ_mean.happy, coactiv
ation$summ_mean.scared)*180/pi)-45))
coactivation$coac_h_d <- ifelse(coactivation$summ_mean.happy == 0 |coactivati
on$summ_mean.disgusted== 0, 0, abs((atan2(coactivation$summ_mean.happy, coact
ivation$summ_mean.disgusted)*180/pi)-45))
coactivation$coac_a_sa <- ifelse(coactivation$summ_mean.angry == 0 |coactivat
ion$summ_mean.sad== 0, 0, abs((atan2(coactivation$summ_mean.angry, coactivati
on$summ_mean.sad)*180/pi)-45))
coactivation$coac_a_sc <- ifelse(coactivation$summ_mean.angry == 0 |coactivat
ion$summ_mean.scared== 0, 0, abs((atan2(coactivation$summ_mean.angry, coactiv
ation$summ_mean.scared)*180/pi)-45))
coactivation$coac_a_d <- ifelse(coactivation$summ_mean.angry == 0 |coactivati
on$summ_mean.disgusted== 0, 0, abs((atan2(coactivation$summ_mean.angry, coact
ivation$summ_mean.disgusted)*180/pi)-45))
coactivation$coac_sa_sc <- ifelse(coactivation$summ_mean.sad == 0 |coactivati
on$summ_mean.scared== 0, 0, abs((atan2(coactivation$summ_mean.sad, coactivati
on$summ_mean.scared)*180/pi)-45))
coactivation$coac_sa_d <- ifelse(coactivation$summ_mean.sad == 0 |coactivatio
n$summ_mean.disgusted== 0, 0, abs((atan2(coactivation$summ_mean.sad, coactiva
tion$summ_mean.disgusted)*180/pi)-45))
coactivation$coac_sc_d <- ifelse(coactivation$summ_mean.scared == 0 |coactiva
tion$summ_mean.disgusted== 0, 0, abs((atan2(coactivation$summ_mean.scared, co
activation$summ_mean.disgusted)*180/pi)-45))


coactivation$coac_c_a <-  ifelse(coactivation$summ_mean.contempt == 0 |coacti
vation$summ_mean.angry== 0, 0, abs((atan2(coactivation$summ_mean.contempt, co
activation$summ_mean.angry)*180/pi)-45))
coactivation$coac_c_sa <- ifelse(coactivation$summ_mean.contempt == 0 |coacti
vation$summ_mean.sad== 0, 0, abs((atan2(coactivation$summ_mean.contempt, coac
tivation$summ_mean.sad)*180/pi)-45))
coactivation$coac_c_sc <- ifelse(coactivation$summ_mean.contempt == 0 |coacti
vation$summ_mean.scared== 0, 0, abs((atan2(coactivation$summ_mean.contempt, c
oactivation$summ_mean.scared)*180/pi)-45))
coactivation$coac_c_d <- ifelse(coactivation$summ_mean.contempt == 0 |coactiv
ation$summ_mean.disgusted== 0, 0, abs((atan2(coactivation$summ_mean.contempt,
coactivation$summ_mean.disgusted)*180/pi)-45))

coactivation$range <- rowMeans(coactivation[,c("coac_h_a", "coac_h_sa", "coac
_h_sc", "coac_h_d", "coac_a_sa", "coac_a_sc", "coac_a_d", "coac_sa_sc", "coac
_sa_d", "coac_sc_d", "coac_c_a", "coac_c_sa", "coac_c_sc", "coac_c_d")])

coactivation <- ungroup(coactivation)%>%select(id_lsu, surveyname, time, inst
ance, wkday, studyday, range)
```

```
wkdb<- left_join(wkdb, coactivation, by = c("id_lsu", "surveyname", "time", "
instance", "wkday", "studyday"))


#rename positive expressions for ease of compairison
wkdb <- rename(wkdb, pos_expression_duration = event_lengthm.happy, pos_expre
ssion_intensity = event_mean.happy, pos_expression_freq = event_n.happy)


#add summaries of qualtrics data to the wkdb
negative <- qualtrics%>%select(id_lsu, spq_BA, spq_neg)
wkdb <- join(wkdb, negative)
wkdbunsplit <- join(wkdbunsplit, negative)

#manage the multiselections within the ema data

#first, get rid of the spaces
wkdb<- wkdb%>%mutate(soc_context = gsub("Significant other", "SigOth", soc_co
ntext))%>%mutate(soc_context = gsub("No one\\\\\\/Alone", "Alone", soc_contex
t))%>%mutate(interaction_type = gsub("Written electronic interaction \\(text
social media  etc\\.\\)", "messaging", interaction_type))%>%mutate(interactio
n_type = gsub("In person", "InPerson", interaction_type))%>%mutate(interactio
n_type = gsub("Phone call", "Phone", interaction_type))%>%mutate(interaction_
type = gsub("Social video call", "SocialVideo", interaction_type))%>%mutate(i
nteraction_type = gsub("School\\\\\\/work video call", "SchoolWorkVideo", int
eraction_type)) %>%mutate(interaction_type = gsub("Not interacting with anyon
e", "NoInteraction", interaction_type))

#then, create a new column for each option, and give a 1 if true, 0 if false
wkdb <- wkdb %>% mutate(soc_context_alone = ifelse(str_detect(soc_context, "A
lone"), 1,0))%>%mutate(soc_context_sigoth = ifelse(str_detect(soc_context, "S
igOth"), 1,0))%>%mutate(soc_context_familyroommates = ifelse(str_detect(soc_c
ontext, "Family\\\\\\/roommates"), 1,0))%>%mutate(soc_context_strangers = ife
lse(str_detect(soc_context, "Strangers"), 1,0)) %>%mutate(soc_context_doctors
= ifelse(str_detect(soc_context, "Doctor\\\\\\/therapist"), 1,0))%>%mutate(so
c_context_friend= ifelse(str_detect(soc_context, "Friends"), 1,0))%>%mutate(s
oc_context_colleagues = ifelse(str_detect(soc_context, "Coworkers\\\\\\/class
mates"), 1,0))%>%mutate(ix_type_noix = ifelse(str_detect(interaction_type, "N
oInteraction"), 1,0))%>%mutate(ix_type_phone = ifelse(str_detect(interaction_
type, "Phone"), 1,0))%>%mutate(ix_type_socvid = ifelse(str_detect(interaction
_type, "SocialVideo"), 1,0))%>%mutate(ix_type_schoolworkvid = ifelse(str_dete
ct(interaction_type, "SchoolWorkVideo"), 1,0))%>%mutate(ix_type_person = ifel
se(str_detect(interaction_type, "InPerson"), 1,0))%>%mutate(ix_type_messaging
= ifelse(str_detect(interaction_type, "messaging"), 1,0))



#remove data with insufficient variability within sliders - goes from 2708 to
2693
wkdb <-wkdb%>% mutate(diff = (abs(abs(abs(abs(abs(abs(abs(abs(abs(abs(abs(abs
```

```
(abs(abs(abs(slider_amused -slider_content) - slider_happy)- slider_loving) -
slider_angry) -slider_sad) -slider_scared)-slider_ashamed)-slider_concentrate
)-slider_clearheaded)-slider_stranger)-slider_imagining)-slider_partofworld)-
slider_soc_interest)-slider_soc_enjoyment)-slider_soc_future)))%>%filter(is.n
a(diff)| diff >0)%>% select(-diff)

#remove nas on slider composites - drops to 4882, but is this relevant? none
of these are study variables... Maybe run on social motivation instead

#wkdb<- filter(wkdb, !is.na(slider_pos_affect) & !is.na(slider_neg_affect) &
!is.na(slider_cog))


#refilter qualtrics data - still 217

qualtrics <- filter(qualtrics, id_lsu%in%wkdb$id_lsu)


#project data
cleaned <- wkdb


wkdb<-wkdb%>% select(id_lsu, surveyname, time, instance, wkday, studyday, per
c_valid, frames, slider_pos_affect, slider_neg_affect, slider_cog, slider_soc
_interest, slider_soc_enjoyment, slider_soc_future, video_type, wordcount, ma
tch_counts, pos_expression_duration, pos_expression_freq, pos_expression_inte
nsity,neg_expression_duration, neg_expression_freq,neg_expression_freq_sum, n
eg_expression_intensity, range, soc_context_alone, soc_context_colleagues, so
c_context_doctors, soc_context_familyroommates, soc_context_friend, soc_conte
xt_sigoth, soc_context_strangers, ix_type_noix, ix_type_phone,  ix_type_socvi
d, ix_type_schoolworkvid, ix_type_messaging, ix_type_person, spq_BA, spq_neg)



#qualtrics data management

#manage gender categories

qualtrics <- qualtrics%>% mutate(gender = tolower(gender))%>%mutate(gender_ca
tegorized = ifelse(str_detect(gender, "female|woman"), "woman", ifelse(str_de
tect(gender, "\\bmale|\\smale|\\bman"), "man", ifelse(str_detect(gender, "non
"), "nonbinary", "other"))))
qualtrics <- mutate(qualtrics, gender_categorized= factor(gender_categorized)
)

#manage racial categories

qualtrics <- qualtrics %>%mutate(race_white = ifelse(str_detect(race, "White"
), 1, 0), race_black = ifelse(str_detect(race, "Black"), 1, 0), race_asian =
ifelse(str_detect(race, "Asian"), 1, 0), race_indigenous = ifelse(str_detect(
```

```
race, "Native"), 1, 0), latinx = ifelse(str_detect(latinx, "Yes"), 1, 0), MEN
A = ifelse(str_detect(MENA, "Yes"), 1, 0))

qualtrics <- qualtrics%>% mutate(race_multi =ifelse(rowSums(select(., race_wh
ite, race_black, race_asian, race_indigenous, latinx, MENA)) >1, "multiracial
", race))

qualtrics <- qualtrics%>% mutate(race_multi = if_else(str_detect(race_multi,
"Not listed/Write in below") & latinx ==1, "latinx", race_multi))%>%mutate(ra
ce_multi = if_else(is.na(race_multi) & latinx ==1, "latinx", race_multi))%>%m
utate(race_multi = factor(race_multi))

#create spq total
spq <- colnames(qualtrics)%>%str_subset("SPQBR_\\d")
qualtrics <- qualtrics %>%mutate(spq_total = rowMeans(select(qualtrics, all_o
f(spq)), na.rm = TRUE))

#create BSI subscales - NOTE THAT THE QUESTIONS WERE NOT GIVEN IN THE ORIGINA
L ORDER SO THE SUBSCALES ARE MADE UP OF THE SAME ITEMS BUT DIFFERENTLY NUMBER
ED
#rename bsi validity 27 abd 42
qualtrics <- qualtrics %>% rename(BSI_validity_1 = BSI_27 ,  BSI_Validity_2=B
SI_42 )

bsi <- colnames(qualtrics)%>%str_subset("BSI_\\d")
qualtrics <- qualtrics %>%mutate(bsi_total = rowMeans(select(qualtrics, all_o
f(bsi)), na.rm = TRUE))
qualtrics <- qualtrics %>%mutate(bsi_depression = rowMeans(select(qualtrics,
BSI_9, BSI_23, BSI_24, BSI_25, BSI_36, BSI_52), na.rm = TRUE), bsi_is = rowMe
ans(select(qualtrics, BSI_10, BSI_11, BSI_12, BSI_44), na.rm = TRUE))

#Calculate number of videos, summarize
nvideos = wkdb%>% group_by(id_lsu) %>% summarize(n= n())%>%summarize(m = mean
(n), sd = sd(n))

#how many VF videos? - this is without any processing
wkdbfluency%>% group_by(id_lsu) %>% summarize(n= n())%>%summarize(m = mean(n)
, sd = sd(n))
wkdbfluency %>% mutate(id_lsu = factor(id_lsu)) %>%summarize(n= nlevels(id_ls
u))
#social motivation - sum of interest, enjoyment, future

wkdb<- mutate(wkdb, slider_soc_mot = rowSums(select(wkdb, slider_soc_interest
, slider_soc_enjoyment, slider_soc_future), na.rm= TRUE))

#not going filter based on missing social motivation data - SEM will do this
naturally, and it's not relevant for the first analysis


#how many rows do you lose if you remove VF videos with no data
```

```
#decide to keep these in - all have at least one word in them, and up to 30 w
ords, just not target relevant - suggests possible actual variance. Plus it's
only 53 rows.

wkdbunsplit %>%filter(video_type != "video_describe" &match_counts<1)

#test how many removed if  match count is NA - 74 videos THESE ARE NOT REMOVE
D BECAUSE IT DOESN'T AFFECT ANALYSIS 1

wkdb%>% filter((is.na(match_counts)))%>%summarize(n = n())


#identify the max number of times each category was completed - 6 is the max
across categories excluding video_describe

df <-wkdb %>%select(id_lsu, video_type, studyday, instance)%>%group_by(id_lsu
, video_type) %>%count()%>%ungroup(id_lsu)%>%summarize(max = max(n))


#add race and gender to wkdb

genderrace<- qualtrics%>% select(id_lsu, gender_categorized, race_multi)

wkdb<-join(wkdb, genderrace)

wkdbunsplit<- join(wkdbunsplit, genderrace)

#add bsi to wkdb

bsi<- qualtrics%>% select(id_lsu, bsi_total, bsi_depression, bsi_is)

wkdb<-join(wkdb, bsi)

wkdbunsplit<- join(wkdbunsplit, bsi)

#filter for at least 90% of frames, which drops from 2693 to 2594
wkdb <- wkdb%>%filter(perc_valid >10)

qualtrics <- filter(qualtrics, id_lsu%in%wkdb$id_lsu)#216

####### Validation of VF #########
validationset <- read_csv("/Users/tovah/Library/CloudStorage/Box-Box/ASAP LAB
/ASAP RESEARCH DRIVE/DATA/SUMMARY DATA/hr21lsufaces/SUMMARY DATA/hr21lsufaces
_vf_validation.csv")%>%select(file = file_name, count)


validationset<- join(validationset, fluency)%>%select(file,video_type, count,
match_counts)
#tests convergence with handscored subsample
psych::ICC(select(validationset, count, match_counts))
```

```
#there is a significant difference in that the ASR version is statistically h
igher
t.test(validationset$count, validationset$match_counts, paired = TRUE)
describe(validationset)

#
####preliminary investigations into fluency data#####

  #question 1: are there differences between the catgories in terms of respon
ses - you get the same results as an MLM or LM- relative to animals, everythi
ng except colors is less, colors, NS different.

  fluencyonly  <- wkdb%>% select(id_lsu, video_type, match_counts, slider_cog
, spq_BA, spq_neg,  gender_categorized, race_multi) %>% mutate_at(vars( match
_counts, slider_cog, spq_BA, spq_neg), list(scale))


fluencyonly[, c("match_counts", "slider_cog", "spq_BA", "spq_neg")][fluencyon
ly[, c("match_counts", "slider_cog", "spq_BA", "spq_neg")] >= 3.5] <- 3.5; fl
uencyonly[, c("match_counts", "slider_cog", "spq_BA", "spq_neg")][fluencyonly
[, c("match_counts", "slider_cog", "spq_BA", "spq_neg")] <= -3.5] <- -3.5



varint <- c("match_counts   ~1")
varrando <- c("match_counts ~  (1|id_lsu)")
varmlm1 <- c("match_counts  ~ video_type+  (1|id_lsu)")

intercept   <- glm(varint,  data=fluencyonly,   na.action=na.exclude)
rando.intercept <-lmer(varrando, data=fluencyonly,  REML=FALSE, na.action=na.
exclude)
lme1 <- lmer(varmlm1, data=fluencyonly, REML=FALSE, na.action=na.exclude)

print(summary(lme1))



#question 2: does it vary with schizotypy: interestingly, the model with the
interaction is significant relative to the simpler model, but schizotypy does
n't predict, nor does any of the interaction terms. #with the simpler data se
t, you can't compare models, but sztypy is still not significant.

cor(fluencyonly$spq_neg, fluencyonly$match_counts, use= "complete.obs")

varint <- c("match_counts   ~1")
varrando <- c("match_counts ~  (1|id_lsu)")
varmlm1 <- c("match_counts  ~ video_type+  spq_neg+ (1|id_lsu)")
varmlm2 <- c("match_counts  ~ video_type+  spq_neg+ spq_neg:video_type+(1|id_
lsu)")
```

```
intercept   <- glm(varint,  data=fluencyonly,   na.action=na.exclude)
rando.intercept <-lmer(varrando, data=fluencyonly,  REML=FALSE, na.action=na.
exclude)
lme1 <- lmer(varmlm1, data=fluencyonly, REML=FALSE, na.action=na.exclude)
lme2 <- lmer(varmlm2, data=fluencyonly, REML=FALSE, na.action=na.exclude)

print(summary(lme1))
print(summary(lme2))
## rerun with just spq_neg
varint <- c("match_counts   ~1")
varrando <- c("match_counts ~  (1|id_lsu)")
varmlm1 <- c("match_counts  ~  spq_neg+ (1|id_lsu)")

intercept   <- glm(varint,  data=fluencyonly,   na.action=na.exclude)
rando.intercept <-lmer(varrando, data=fluencyonly,  REML=FALSE, na.action=na.
exclude)
lme1 <- lmer(varmlm1, data=fluencyonly, REML=FALSE, na.action=na.exclude)

anova <- anova( lme1, rando.intercept, test="F")
print(anova)
print(summary(lme1))


#question 3: does it connect to subjective cognition - yes but not if you int
eract with video type


cor(fluencyonly$match_counts, fluencyonly$slider_cog, use = "complete.obs")

varint <- c("match_counts   ~1")
varrando <- c("match_counts ~  (1|id_lsu)")
varmlm1 <- c("match_counts  ~ video_type+  slider_cog+ (1|id_lsu)")
varmlm2 <- c("match_counts  ~ video_type+  slider_cog+ slider_cog:video_type+
(1|id_lsu)")


intercept   <- glm(varint,  data=fluencyonly,   na.action=na.exclude)
rando.intercept <-lmer(varrando, data=fluencyonly,  REML=FALSE, na.action=na.
exclude)
lme1 <- lmer(varmlm1, data=fluencyonly, REML=FALSE, na.action=na.exclude)
lme2 <- lmer(varmlm2, data=fluencyonly, REML=FALSE, na.action=na.exclude)



# ANOVA SUMMARY
#anova <- anova(lme1, rando.intercept, test="F")
#print(anova)
```

```
# MODEL ESTIMATES: "DROP1" METHOD. COMPUTES CHANGE STATS BY DROPPING ALLLOWAB
LE SINGLE TERMS FROM THE MODEL
print(summary(lme1))
print(summary(lme2))




#question 4: does it connect to race - yes, Black participants have lower sco
res  compared to White participants

fluencyonly$race_multi <-relevel(fluencyonly$race_multi, ref = "White")

varint <- c("match_counts   ~1")
varrando <- c("match_counts ~  (1|id_lsu)")
varmlm1 <- c("match_counts  ~ video_type+  race_multi+ (1|id_lsu)")
varmlm2 <- c("match_counts  ~ video_type+  race_multi+ race_multi:video_type+
(1|id_lsu)")


intercept   <- glm(varint,  data=fluencyonly,   na.action=na.exclude)
rando.intercept <-lmer(varrando, data=fluencyonly,  REML=FALSE, na.action=na.
exclude)
lme1 <- lmer(varmlm1, data=fluencyonly, REML=FALSE, na.action=na.exclude)
lme2 <- lmer(varmlm2, data=fluencyonly, REML=FALSE, na.action=na.exclude)



# ANOVA SUMMARY
anova <- anova(lme2, lme1, rando.intercept, test="F")
print(anova)


# MODEL ESTIMATES: "DROP1" METHOD. COMPUTES CHANGE STATS BY DROPPING ALLLOWAB
LE SINGLE TERMS FROM THE MODEL
print(summary(lme1))
print(summary(lme2))



#question 5: does it connect to gender - nope - maybe something interactions.
..



varint <- c("match_counts   ~1")
varrando <- c("match_counts ~  (1|id_lsu)")
varmlm1 <- c("match_counts  ~ video_type+  gender_categorized+ (1|id_lsu)")
varmlm2 <- c("match_counts  ~ video_type+  gender_categorized+ gender_categor
```

```
ized:video_type+(1|id_lsu)")


intercept   <- glm(varint,  data=fluencyonly,   na.action=na.exclude)
rando.intercept <-lmer(varrando, data=fluencyonly,  REML=FALSE, na.action=na.
exclude)
lme1 <- lmer(varmlm1, data=fluencyonly, REML=FALSE, na.action=na.exclude)
lme2 <- lmer(varmlm2, data=fluencyonly, REML=FALSE, na.action=na.exclude)



# ANOVA SUMMARY
#anova <- anova(lme1, rando.intercept, test="F")
#print(anova)


# MODEL ESTIMATES: "DROP1" METHOD. COMPUTES CHANGE STATS BY DROPPING ALLLOWAB
LE SINGLE TERMS FROM THE MODEL
print(summary(lme1))
print(summary(lme2))

describe <- describe(wkdb)

qualtricsfull <- read_csv(paste(vardd, "hr21lsufaces_qualtrics_anonymous_May2
2.csv", sep=""))%>%select(-c('...1'))

qualtrics <-filter(qualtrics, id_lsu%in%wkdb$id_lsu)
sum(is.na(qualtrics$gender_categorized))#missing gender data- 3
sum(is.na(qualtrics$SPQBR_30))#missing an SPQ item - 1
#age
qualtrics %>%filter(id_lsu %in% wkdb$id_lsu)%>%summarize(age_m = mean(na.omit
(age)), age_sd = sd(na.omit(age)), max = max(age))

#gpa
qualtrics %>%filter(id_lsu %in% wkdb$id_lsu)%>%summarize(gpa_m = mean(na.omit
(GPA)), gpa_sd = sd(na.omit(GPA)))

#gender
qualtrics %>%summarize(woman = (sum(na.omit(str_detect(gender, "female|woman"
)))/nrow(qualtrics)), nonbinary = sum(na.omit(str_detect(gender, "non")))/nro
w(qualtrics), man = sum(na.omit(str_detect(gender, "\\bmale|\\smale|\\bman"))
)/nrow(qualtrics))

#ethnicity percentages

qualtrics %>%summarize(asian = (sum(na.omit(race_asian))/nrow(qualtrics)), ra
ce_multi = sum(na.omit(str_detect(race_multi, "multiracial")))/nrow(qualtrics
), black = sum(na.omit(race_black))/nrow(qualtrics), hispanic = sum(na.omit(l
atinx))/nrow(qualtrics), sum(na.omit(race_indigenous))/nrow(qualtrics), MENA
= sum(na.omit(MENA))/nrow(qualtrics), white = sum(na.omit(race_white))/nrow(q
```

```
ualtrics))


qualtrics %>% mutate(race_multi = factor(race_multi))%>% group_by(race_multi)
%>% summarise(n= n(), p = n()/nrow(qualtrics))

#videos completed, fluency with at least one word (not necessarily category r
elevant) and frames analyzeable

wkdb%>%group_by(id_lsu)%>% summarize(n= n())%>%summarize(m = mean(n), sd = sd
(n), min  = min(n), max = max(n))
wkdbfluency%>%group_by(id_lsu)%>% filter(!is.na(wordcount))%>%summarize(n= n(
))%>%summarize(m = mean(n), sd = sd(n))


wkdb%>% summarize(mframes = mean(perc_valid), sdframes= sd(perc_valid))

#number of surveys completed
wkdb%>%group_by(id_lsu)%>% summarize(n= n())%>%summarize(m = mean(n), sd = sd
(n), max = max(n), min = min(n))


#SPQ
qualtrics%>%filter(id_lsu %in% wkdb$id_lsu)%>% summarize(spq_neg.m = mean(spq
_neg),spq_neg.sd = sd(spq_neg),  spq_BA.m = mean(spq_BA), spq_BA.sd = sd(spq_
BA),spq_total.m = mean(spq_total), spq_total.sd = sd(spq_total))

#bsi
qualtrics%>% summarize(bsi_totalm = mean(bsi_total, na.rm=TRUE),bsi_totalsd =
sd(bsi_total),  bsi_ism = mean(bsi_is), bsi_issd = sd(bsi_is),bsi_depressionm
= mean(bsi_depression), bsi_depressionsd = sd(bsi_depression))

#####ICC scores####
varrel <- c("pos_expression_duration", "pos_expression_freq",  "pos_expressio
n_intensity", "neg_expression_duration", "neg_expression_freq", "neg_expressi
on_freq_sum","neg_expression_intensity", "range", "slider_soc_mot", "slider_p
os_affect", "slider_neg_affect", "slider_cog", "match_counts")
temp <- wkdb %>%select(id= id_lsu, session = instance, varrel)
tempicc <- data.frame("feature"=NA, "scale1"=NA, "scale2"=NA, "icc"=NA, "df1"
=NA, "df2"=NA, "LCI"=NA, "UCI"=NA, "krippalpha"= NA) # ICC TABLE
    for (i in varrel) {
      al1 <- select(temp, id, session, i) %>% dplyr::rename("valuei" = i) %>%
filter(is.na(valuei) == "FALSE")
      al1 <- al1[order(al1$id, al1$session), ] %>% group_by(id) %>% mutate(ro
w_number = row_number()) %>% select(id, row_number, valuei) %>% spread(key=ro
w_number, value=valuei) %>% ungroup() %>% select(-id)
# MISSING DATA
  # EXCLUDE COLUMNS MISSING EVERYTHING PAST SESSION 2
    #al1 <- al1[ lapply( al1, function(x) sum(is.na(x)) / length(x) ) < 0.75
]
```

```
      al1 <- al1 %>%rename(col2=2)%>%filter(!is.na(col2))%>%rename("2"=col2)
      #Removes the session that only one person did
      al1 <- al1[,1:25]
  # EXCLUDE ROWS MISSING MORE THAN 75% of data
  # al1$row_del <- (rowSums(is.na(al1))/ ncol(al1)); al1 <- na.omit(al1); al1
<- filter(al1, row_del < 0.75) %>% select(-row_del)

      alicc <- psych::ICC(al1, missing=FALSE, lmer=TRUE, check.keys = FALSE)
            alicc2 <-al1%>%as.matrix()%>%t() %>%irr::kripp.alpha(method= "rat
io")

      al2 <- data.frame("feature"=i, "scale1"="none", "scale2"="none", "icc"=
alicc$results$ICC[6], "df1"=alicc$results$df1[6], "df2"=alicc$results$df2[6],
"LCI"=alicc$results$`lower bound`[6], "UCI"=alicc$results$`upper bound`[6], "
krippalpha" = alicc2$value)
      tempicc <- rbind(tempicc, al2) }
  print(tempicc %>% kable(digits = 2, format="html", caption="Table X. Intra-
class Correlation Coefficients: Average Fixed Raters . . . ") %>% kable_styli
ng(full_width=FALSE, position="left", bootstrap_options="condensed") %>%  foo
tnote(general=paste("n = ")) )


  ####histograms###
par(mfrow=c(1,2))
hist(qualtrics$spq_neg, xlab = "SPQ-BR Negative Schizotypy", main = "", xlim
= c(0,4))
hist(qualtrics$spq_BA, xlab = "SPQ-BR Blunted Affect", main = "", xlim = c(0,
4))

#do this only with the data included in the study
fluencydata <- wkdb %>%select(id_lsu, time, instance, wkday, studyday, video_
type, wordcount, match_counts)%>%filter(!is.na(video_type))
fluencydata <-fluencydata %>%group_by(id_lsu, video_type)%>% arrange(studyday
, instance, .by_group = TRUE)%>% mutate(session = row_number(id_lsu))%>%ungro
up()%>%pivot_wider(id_cols = c(id_lsu, studyday, instance, video_type), names
_from = session, names_prefix = "session" , values_from = match_counts)%>%unn
est()

means <- fluencydata%>%ungroup()%>%group_by(video_type)%>%summarize(across(.c
ols = starts_with("session"), ~ mean(.x, na.rm = TRUE)))


#then, the SD dataframe per session
sd <- select(fluencydata, id_lsu, video_type, starts_with("session"))%>%group
_by(id_lsu,video_type)%>%mutate(across(.cols=contains("session"), ~mean(.x, n
a.rm = TRUE)))%>%ungroup()%>%distinct()
sd[sapply(sd, is.nan)] <- NA
sd[,4:ncol(sd)] = sd[,4:ncol(sd)] - sd[,((4:ncol(sd)) - 1)]
sd <- sd%>%ungroup()%>% group_by(video_type)%>% select(-session1) %>%summariz
```

```
e(across(.cols = starts_with("session"), ~sd(.x, na.rm=TRUE)))


#this creates a value for the average sd, for sessions where only one person
completed it and therefore you can't caluclate an SD
animalsd <- sd%>%filter(video_type == "video_animals")%>%select(-video_type)
animalsd <-  rowMeans(animalsd, na.rm = TRUE)

birdsd <- sd%>%filter(video_type == "video_birds")%>%select(-video_type)
birdsd <-  rowMeans(birdsd, na.rm = TRUE)

colorsd <- sd%>%filter(video_type == "video_colors")%>%select(-video_type)
colorsd <-  rowMeans(colorsd, na.rm = TRUE)

collegesd <- sd%>%filter(video_type == "video_college")%>%select(-video_type)
collegesd <-  rowMeans(collegesd, na.rm = TRUE)

clothingsd <- sd%>%filter(video_type == "video_clothing")%>%select(-video_typ
e)
clothingsd <-  rowMeans(clothingsd, na.rm = TRUE)

fruitsd <- sd%>%filter(video_type == "video_fruits")%>%select(-video_type)
fruitsd <-  rowMeans(fruitsd, na.rm = TRUE)

furnituresd <- sd%>%filter(video_type == "video_furniture")%>%select(-video_t
ype)
furnituresd <-  rowMeans(furnituresd, na.rm = TRUE)

musicalsd <- sd%>%filter(video_type == "video_musical")%>%select(-video_type)
musicalsd <-  rowMeans(musicalsd, na.rm = TRUE)

sportsd <- sd%>%filter(video_type == "video_sports")%>%select(-video_type)
sportsd <-  rowMeans(sportsd, na.rm = TRUE)

vegetablesd <- sd%>%filter(video_type == "video_vegetables")%>%select(-video_
type)
vegetablesd <-  rowMeans(vegetablesd, na.rm = TRUE)

vehiclesd <- sd%>%filter(video_type == "video_vehicles")%>%select(-video_type
)
vehiclesd <-  rowMeans(vehiclesd, na.rm = TRUE)

#this uses the mean SD across all sessions to fill in any missing sds

sdanimals <-sd%>%filter(video_type == "video_animals")%>%mutate(across(starts
_with("session"), ~replace_na(.x, animalsd)))
sdbirds <-sd%>%filter(video_type == "video_birds")%>%mutate(across(starts_wit
h("session"), ~replace_na(.x, birdsd)))
sdcolors <-sd%>%filter(video_type == "video_colors")%>%mutate(across(starts_w
ith("session"), ~replace_na(.x, colorsd)))
```

```
sdcolleges <-sd%>%filter(video_type == "video_college")%>%mutate(across(start
s_with("session"), ~replace_na(.x, collegesd)))
sdclothing <-sd%>%filter(video_type == "video_clothing")%>%mutate(across(star
ts_with("session"), ~replace_na(.x, clothingsd)))
sdfruits <-sd%>%filter(video_type == "video_fruits")%>%mutate(across(starts_w
ith("session"), ~replace_na(.x, fruitsd)))
sdfurniture <-sd%>%filter(video_type == "video_furniture")%>%mutate(across(st
arts_with("session"), ~replace_na(.x, furnituresd)))
sdmusical <-sd%>%filter(video_type == "video_musical")%>%mutate(across(starts
_with("session"), ~replace_na(.x, musicalsd)))
sdsports <-sd%>%filter(video_type == "video_sports")%>%mutate(across(starts_w
ith("session"), ~replace_na(.x, sportsd)))
sdvegetables <-sd%>%filter(video_type == "video_vegetables")%>%mutate(across(
starts_with("session"), ~replace_na(.x, vegetablesd)))
sdvehicles <-sd%>%filter(video_type == "video_vehicles")%>%mutate(across(star
ts_with("session"), ~replace_na(.x, vehiclesd)))

sd<- rbind(sdanimals, sdbirds, sdcolors, sdcolleges, sdclothing, sdfruits,sdf
urniture, sdmusical, sdsports, sdvegetables, sdvehicles)

#save a version for remerging with data
fluencydataremerge <- (select(fluencydata, id_lsu, studyday, instance,video_t
ype, session1))

#this creates a dataframe which condenses all sessions into one row, and then 
replaces NAN with NA
fluencydata <- fluencydata %>% rename( first_session= session1)%>%select(-stu
dyday, -instance)%>%group_by(id_lsu, video_type)%>%mutate(across(.cols=contai
ns("session"), ~mean(.x, na.rm = TRUE)))%>%ungroup()%>%distinct()
fluencydata[sapply(fluencydata, is.nan)] <- NA

#this is the actual Reliable change index function
rcifunction <- function(df, x){
  for (i in 1:nrow(df)){
  #this identifies the category of that row, so that you can extract the prop
er data for the rest of the comparisons
    category <- df[i,"video_type"]%>%dplyr::distinct()%>%as.character()
   #this extracts the mean difference between the specified session and the o
ne previous for the proper category
    means2 <- dplyr::filter(means, video_type==category)
    #this replaces all NAN with NAs
    means2[sapply(means2, is.nan)] <- NA
  meandiff <- means2[1,x] - means2[1,which(colnames(means2)==x)-1]

   #this selects the proper category of sd
   sd2<- dplyr::filter(sd, video_type == category)

   #if there is no SD for that category/session, this replaces that category/
session with the SD for the last session
   if (sd2[1,x]==0)
```

```
   {
     sd2[1,x] = sd2[1, (which(colnames(sd2)==x)-1)]
   }
   #this adjusts the specified session according to the prior session, the me
an diff, and the sd of that session

    df[i,x]<- (df[i,x] + (((df[i,x] -df[i, (which(colnames(df)==x)-1)])-(mean
diff[1,1]))/sd2[1,x]))
  }
  return(df)
}

fluencydata<- fluencydata%>%rcifunction("session2")%>%rcifunction("session3")
%>%rcifunction("session4")%>%rcifunction("session5")%>%rcifunction("session6"
)

#then, need to scale video data within category, and then unscale it relative
to the overall. This is the "fluency corrected" value - the version that is s
caled is scaled relative to the overall

#to do this, I think it should be long again.
fluencydata <- rename(fluencydata, session1 = first_session)
fluencydata <- pivot_longer(fluencydata, cols =starts_with("session"))
fluencydata<-filter(fluencydata,!is.na(value))
m <-mean(fluencydata$value)
sd <-sd(fluencydata$value)
fluencydatascaled <- group_by(fluencydata, name)%>%mutate(value=scale(value))
fluencydataunscaled <- fluencydatascaled%>%mutate(fluencycorrected= ((value*s
d)+m))%>%select(id_lsu, video_type, session = name, fluencycorrected)
fluencydatascaled <- fluencydatascaled%>%select(id_lsu, video_type, session =
name, fluencyscaled = value)

#then, need to re-match it to overall data
fluencymerge <- wkdb %>%select(id_lsu, time, instance, wkday, studyday, video
_type, wordcount, match_counts)%>%filter(!is.na(video_type))%>%group_by(id_ls
u, video_type)%>% arrange(studyday, instance, .by_group = TRUE)%>% mutate(ses
sion = row_number(id_lsu))

fluencydataunscaled$session<- as.numeric(gsub("session", "", fluencydataunsca
led$session))
fluencydatascaled$session<- as.numeric(gsub("session", "", fluencydatascaled$
session))

fluencymerge <- join(fluencymerge, fluencydataunscaled)%>%mutate(fluencycorre
cted = as.numeric(fluencycorrected))
fluencymerge <- join(fluencymerge, fluencydatascaled)%>%mutate(fluencyscaled
= as.numeric(fluencyscaled))

#just add that data back to the main file via id, studyday, instance
fluencymerge2 <-fluencymerge%>%ungroup()%>% select( id_lsu, studyday, wkday,
```

```
instance,time, fluencycorrected, fluencyscaled)%>%filter(id_lsu %in%wkdb$id_l
su)

wkdb <- join(wkdb, fluencymerge2, by = c("id_lsu", "studyday", "time", "wkday
", "instance"))
sum(is.na(wkdb$fluencycorrected))#86 NAs

temp <- na.omit(select(wkdb, pos_expression_duration, pos_expression_freq,  p
os_expression_intensity, neg_expression_duration, neg_expression_freq,neg_exp
ression_freq_sum,  neg_expression_intensity, range, spq_BA, spq_neg))
corr <- rcorr(as.matrix(temp), type='pearson')
print(corr$r, digits = 3)
cat("\n", "CORRELATIONS: P VALUES", "\n")
print(corr$P, digits=3, scipen=0)
cat("\n", "CORRELATIONS: N VALUES", "\n")
print(corr$n)

cor.plot(temp)

temp <- na.omit(select(qualtrics,age, spq_total, spq_neg, spq_BA, bsi_total,
bsi_depression, bsi_is))
corr <- rcorr(as.matrix(temp), type='pearson')
print(corr$r, digits = 3)
cat("\n", "CORRELATIONS: P VALUES", "\n")
print(corr$P, digits=3, scipen=0)
cat("\n", "CORRELATIONS: N VALUES", "\n")
print(corr$n)

cor.plot(temp)

#you should test if bsi is related to the independent variables before using
it as a confound #this includes fluency corrected so you need to run that fir
st
temp <- na.omit(select(wkdb,pos_expression_duration, pos_expression_freq,  po
s_expression_intensity, neg_expression_duration, neg_expression_freq,neg_expr
ession_freq_sum,  neg_expression_intensity, range, slider_soc_mot,fluencycorr
ected, bsi_total, bsi_depression, bsi_is))
corr <- rcorr(as.matrix(temp), type='pearson')
print(corr$r, digits = 3)
cat("\n", "CORRELATIONS: P VALUES", "\n")
print(corr$P, digits=3, scipen=0)
cat("\n", "CORRELATIONS: N VALUES", "\n")
print(corr$n)

cor.plot(temp)
```

```
#gender and spq neg/spq BA - gender is significant for spq neg but not BA
qualtricstest <- qualtrics %>%filter(!is.na(gender_categorized ))

leveneTest(spq_neg ~ gender_categorized, data = qualtricstest)
summary(aov(spq_neg~gender_categorized, data = qualtricstest))

qualtricstest %>% group_by(gender_categorized)%>%summarize(neg_mean = mean(sp
q_neg), neg_sd = sd(spq_neg), ba_mean = mean(spq_BA), BA_sd = sd(spq_BA))

leveneTest(spq_BA ~ gender_categorized, data = qualtricstest)
summary(aov(spq_BA~gender_categorized, data = qualtricstest))


anova(lmer("pos_expression_duration ~ gender_categorized+ (1|id_lsu)", data=w
kdb, REML=FALSE, na.action=na.exclude))
anova(lmer("neg_expression_duration ~ gender_categorized+ (1|id_lsu)", data=w
kdb, REML=FALSE, na.action=na.exclude))

anova(lmer("pos_expression_freq ~ gender_categorized+ (1|id_lsu)", data=wkdb,
REML=FALSE, na.action=na.exclude))
anova(lmer("neg_expression_freq~ gender_categorized+ (1|id_lsu)", data=wkdb,
REML=FALSE, na.action=na.exclude))
anova(lmer("neg_expression_freq_sum~ gender_categorized+ (1|id_lsu)", data=wk
db, REML=FALSE, na.action=na.exclude))

anova(lmer("pos_expression_intensity ~ gender_categorized+ (1|id_lsu)", data=
wkdb, REML=FALSE, na.action=na.exclude))
anova(lmer("neg_expression_intensity ~ gender_categorized+ (1|id_lsu)", data=
wkdb, REML=FALSE, na.action=na.exclude))
anova(lmer("range ~ gender_categorized+ (1|id_lsu)", data=wkdb, REML=FALSE, n
a.action=na.exclude))
wkdb %>%group_by(gender_categorized)%>%summarize(mrange = mean(range))

#race and ethnicity - not significant
leveneTest(spq_neg ~ race_multi, data = qualtrics)
summary(aov(spq_neg~race_multi, data = qualtrics))


leveneTest(spq_BA ~ race_multi, data = qualtrics)
summary(aov(spq_BA~race_multi, data = qualtrics))


#equality of variance between categories - not preserved. this tests the high
est variance from the lowest variance provides support for rescaling data
wkdb %>% filter(video_type != "video_describe")%>%select(match_counts, video_
type)%>%group_by(video_type)%>%summarize(sd = sd(match_counts, na.rm = TRUE))
wkdb %>%filter(video_type == "video_clothing"|video_type == "video_sports")%>
% leveneTest(match_counts~video_type, data = .)
```

```
wkdbunscaled<- wkdb
covariates <- select(qualtrics, id_lsu, age, bsi_is, gender_categorized)
wkdb<- join(wkdb, covariates)
wkdbtest <- wkdb %>% mutate(binary_neg = ifelse(spq_neg > 2.9, 1, 0))%>% muta
te(binary_BA = ifelse(spq_BA > 2.9, 1, 0))%>%select(id_lsu,pos_expression_dur
ation, pos_expression_freq,  pos_expression_intensity, neg_expression_duratio
n, neg_expression_freq,neg_expression_freq_sum, neg_expression_intensity, ran
ge, slider_soc_mot, slider_cog, spq_BA, spq_neg,binary_neg,binary_BA, age, bs
i_is, gender_categorized) %>% mutate_at(vars(pos_expression_duration, pos_exp
ression_freq,  pos_expression_intensity, neg_expression_duration, neg_express
ion_freq,neg_expression_freq_sum,  neg_expression_intensity, range, slider_so
c_mot, slider_cog, spq_BA, spq_neg, age, bsi_is), list(scale))


wkdbtest[, c("pos_expression_duration", "pos_expression_freq",  "pos_expressi
on_intensity", "neg_expression_duration", "neg_expression_freq","neg_expressi
on_freq_sum", "neg_expression_intensity", "range", "slider_cog", "slider_soc_
mot", "spq_BA", "spq_neg", "age", "bsi_is")][wkdbtest[, c("pos_expression_dur
ation", "pos_expression_freq",  "pos_expression_intensity", "neg_expression_d
uration", "neg_expression_freq", "neg_expression_freq_sum", "neg_expression_i
ntensity", "range","slider_cog", "slider_soc_mot", "spq_BA", "spq_neg", "age"
, "bsi_is")] >= 3.5] <- 3.5; wkdbtest[, c("pos_expression_duration", "pos_exp
ression_freq",  "pos_expression_intensity", "neg_expression_duration", "neg_e
xpression_freq","neg_expression_freq_sum", "neg_expression_intensity", "range
", "slider_cog", "slider_soc_mot","spq_BA", "spq_neg", "age", "bsi_is")][wkdb
test[, c("pos_expression_duration", "pos_expression_freq",  "pos_expression_i
ntensity", "neg_expression_duration", "neg_expression_freq","neg_expression_f
req_sum", "neg_expression_intensity", "range", "slider_cog", "slider_soc_mot"
,"spq_BA", "spq_neg", "age", "bsi_is")] <= -3.5] <- -3.5

describe(wkdbtest)



test <- wkdbtest%>% group_by(id_lsu) %>% summarize(across(.cols = c(spq_BA,sp
q_neg,binary_neg,binary_BA, age,  bsi_is, pos_expression_duration, pos_expres
sion_freq ,pos_expression_intensity , neg_expression_duration , neg_expressio
n_freq ,neg_expression_freq_sum,  neg_expression_intensity,  range), .fns= me
an))


describe(test)

#no clear problems with either version of negative expression frequency
model <- lm(spq_neg ~  pos_expression_duration + pos_expression_freq + pos_ex
pression_intensity + neg_expression_duration + neg_expression_freq + neg_expr
ession_intensity+ range, data = test)
#linearity
```

```
linear <- select(test, spq_neg, neg_expression_duration,neg_expression_freq, neg_expression_freq_sum, neg_expression_intensity,pos_expression_duration,pos_expression_freq, pos_expression_intensity)
#they're not curvilinear with the outcome, at least
pairs(linear)

plot(model)
#normality of residuals Q-Q plot seems roughly normal

#homoscedasciticity - shows generally mixed but acceptable findings

#multicolinearity - fine
vif(model)

#bsi is so highly correlated with spq that I don't think it's a valid confound. essentially, it's just the same thing.
#this only includes video describe data
modelneg <- lm(spq_neg  ~  pos_expression_duration + pos_expression_freq + pos_expression_intensity + neg_expression_duration + neg_expression_freq + neg_expression_intensity+ range, data = test)
summary(modelneg)
anova(model)
fit <- aov(lm(spq_neg   ~  pos_expression_duration + pos_expression_freq + pos_expression_intensity + neg_expression_duration + neg_expression_freq + neg_expression_intensity+ range, data = test))
eta_sq(fit,partial =TRUE )

modelba <- lm(spq_BA    ~  pos_expression_duration + pos_expression_freq + pos_expression_intensity + neg_expression_duration + neg_expression_freq+ neg_expression_intensity+ range, data = test)
summary(modelba)
sjPlot::tab_model(modelneg,modelba, pred.labels = c("Intercept", "Positive Expression Duration", "Positive Expression Frequency", "Positive Expression Intensity", "Negative Expression Duration", "Negative Expression Frequency", "Negative Expression Intensity", "Range"), dv.labels = c("SPQ-BR Negative Schizotypy", "SPQ-BR Blunted Affect"), file = "/Users/tovah/Library/CloudStorage/Box-Box/ASAP LAB/ASAP RESEARCH DRIVE/MANUSCRIPTS/5. GRAD THESES DISS/Tovah Cowan/Dissertation_TC/table3.doc")



######exploratory 2: logistic regression #####

#how many people are above the threshold for negative schizotypy

test %>% group_by(id_lsu)%>%filter(binary_neg >0)%>%summarize(n = n())

modellogit <- glm(binary_neg    ~  pos_expression_duration + pos_expression_freq + pos_expression_intensity + neg_expression_duration + neg_expression_freq+ neg_expression_intensity+ range, data = test, family = "binomial")
```

```
summary(modellogit)

#chi squared of model vs null (intercept only)
with(modellogit, null.deviance - deviance)

#df of model vs null
with(modellogit, df.null - df.residual)

#significance of model vs null (intercept only)
with(modellogit, pchisq(null.deviance - deviance, df.null - df.residual, lowe
r.tail = FALSE))

#confidence interval
confint(modellogit)
#get odds ratio
exp(coef(modellogit))

semwkdb<-wkdb
#check for missing data in verbal fluency items - 86 assessments
sum(is.na(semwkdb$fluencycorrected))

#check relatively same scale of variance. absolutely not the case. adjusted b
elow
describe(semwkdb)

#Would need to divide both durations by 100, multiple spq neg/freq/intensity/
range by 10-100 - otherwise won't run normally
semwkdb <- semwkdb%>%mutate(pos_expression_duration = pos_expression_duration
/1000, neg_expression_duration = neg_expression_duration/100, slider_soc_mot
= slider_soc_mot/10, pos_expression_freq = pos_expression_freq*10, neg_expres
sion_freq = neg_expression_freq*100, neg_expression_freq_sum = neg_expression
_freq_sum*10,pos_expression_intensity = pos_expression_intensity*100, neg_exp
ression_intensity = neg_expression_intensity*100, range = range*10, spq_neg=s
pq_neg*10)


#here are the assumptions to test
#extreme collinearity - inspected based on correlations - the negative expres
sion metrics are pretty correlated. The social stuff is VERY highly correlate
d.

temp <- na.omit(select(semwkdb, pos_expression_freq, pos_expression_intensity
, pos_expression_duration, neg_expression_intensity, neg_expression_duration,
neg_expression_freq,neg_expression_freq_sum, slider_soc_enjoyment, slider_soc
_future, slider_soc_interest, fluencycorrected, spq_neg))
corr <- rcorr(as.matrix(temp), type='pearson')
print(corr$r, digits = 3)
cat("\n", "CORRELATIONS: P VALUES", "\n")
print(corr$P, digits=3, scipen=0)
cat("\n", "CORRELATIONS: N VALUES", "\n")
```

```
print(corr$n)

cor.plot(temp)

#normality, based on skew/kurtosis - biggest concern for durations
desc <- semwkdb %>%select( pos_expression_freq, pos_expression_intensity, pos
_expression_duration, neg_expression_intensity, neg_expression_duration, neg_
expression_freq,neg_expression_freq_sum, slider_soc_enjoyment, slider_soc_fut
ure, slider_soc_interest,slider_soc_mot, fluencycorrected, spq_neg)%>% descri
be()


#lavaan does listwise deletion for missing data

#need to look for linearity

linear <- select(semwkdb, fluencycorrected, slider_soc_enjoyment, slider_soc_
future, slider_soc_interest, neg_expression_duration,neg_expression_freq,neg_
expression_freq_sum, neg_expression_intensity, pos_expression_duration,pos_ex
pression_freq, pos_expression_intensity,range,  spq_neg, spq_BA)
#it's not really linear because there's just so much data...

pairs(linear)

#handling outliers

outlier <- describe(linear)%>%as.data.frame()
outlier <- mutate(outlier, outlier_upper= 3.5*sd+mean)%>%mutate(outlier_lower
= mean - (3.5*sd))
outlier <- as.data.frame(outlier) %>% select(outlier_upper, outlier_lower)%>%
t()%>%as.data.frame%>%rownames_to_column()%>%rename(class = rowname)
outlierupper <- filter(outlier, class == "outlier_upper")
outlierlower <- filter(outlier, class != "outlier_upper")

#the values for outliers for  soc enjoymentfuture interest, spq ba or neg are
outside the observed (and largely the possible, range)
#fluency corrected upper has outliers

columnsofinterest <- colnames(select(outlier, -class))

semwkdb$fluencycorrected<- ifelse(semwkdb[,"fluencycorrected"] > outlierupper
[1,"fluencycorrected"], outlierupper[1,"fluencycorrected"],semwkdb[,"fluencyc
orrected"])


semwkdb$pos_expression_duration<- ifelse(semwkdb[,"pos_expression_duration"]
> outlierupper[1,"pos_expression_duration"], outlierupper[1,"pos_expression_d
uration"],ifelse(semwkdb[,"pos_expression_duration"] <outlierlower[1,"pos_exp
ression_duration"], outlierlower[1,"pos_expression_duration"],semwkdb[,"pos_e
xpression_duration"]))
```

```
semwkdb$pos_expression_freq<- ifelse(semwkdb[,"pos_expression_freq"] > outlierupper[1,"pos_expression_freq"], outlierupper[1,"pos_expression_freq"],ifelse(semwkdb[,"pos_expression_freq"] <outlierlower[1,"pos_expression_freq"], outlierlower[1,"pos_expression_freq"],semwkdb[,"pos_expression_freq"]))

semwkdb$pos_expression_intensity<- ifelse(semwkdb[,"pos_expression_intensity"] > outlierupper[1,"pos_expression_intensity"], outlierupper[1,"pos_expression_intensity"],ifelse(semwkdb[,"pos_expression_intensity"] <outlierlower[1,"pos_expression_intensity"], outlierlower[1,"pos_expression_intensity"],semwkdb[,"pos_expression_intensity"]))



semwkdb$neg_expression_duration<- ifelse(semwkdb[,"neg_expression_duration"] > outlierupper[1,"neg_expression_duration"], outlierupper[1,"neg_expression_duration"],ifelse(semwkdb[,"neg_expression_duration"] <outlierlower[1,"neg_expression_duration"], outlierlower[1,"neg_expression_duration"],semwkdb[,"neg_expression_duration"]))

semwkdb$neg_expression_freq<- ifelse(semwkdb[,"neg_expression_freq"] > outlierupper[1,"neg_expression_freq"], outlierupper[1,"neg_expression_freq"],ifelse(semwkdb[,"neg_expression_freq"] <outlierlower[1,"neg_expression_freq"], outlierlower[1,"neg_expression_freq"],semwkdb[,"neg_expression_freq"]))


semwkdb$neg_expression_freq_sum<- ifelse(semwkdb[,"neg_expression_freq_sum"] > outlierupper[1,"neg_expression_freq_sum"], outlierupper[1,"neg_expression_freq_sum"],ifelse(semwkdb[,"neg_expression_freq_sum"] <outlierlower[1,"neg_expression_freq_sum"], outlierlower[1,"neg_expression_freq_sum"],semwkdb[,"neg_expression_freq_sum"]))

semwkdb$neg_expression_intensity<- ifelse(semwkdb[,"neg_expression_intensity"] > outlierupper[1,"neg_expression_intensity"], outlierupper[1,"neg_expression_intensity"],ifelse(semwkdb[,"neg_expression_intensity"] <outlierlower[1,"neg_expression_intensity"], outlierlower[1,"neg_expression_intensity"],semwkdb[,"neg_expression_intensity"]))

semwkdb$range<- ifelse(semwkdb[,"range"] > outlierupper[1,"range"], outlierupper[1,"range"],ifelse(semwkdb[,"range"] <outlierlower[1,"range"], outlierlower[1,"range"],semwkdb[,"range"]))



desc <- semwkdb %>%select( pos_expression_freq, pos_expression_intensity, pos_expression_duration, neg_expression_intensity, neg_expression_duration, neg_expression_freq,neg_expression_freq_sum, slider_soc_enjoyment, slider_soc_future, slider_soc_interest, fluencycorrected, spq_neg)%>% describe()
```

```
###SEM correlations

temp <- na.omit(select(semwkdb, pos_expression_duration, pos_expression_freq,
pos_expression_intensity, neg_expression_duration, neg_expression_freq,neg_ex
pression_freq_sum, neg_expression_intensity, range, fluencycorrected, slider_
soc_enjoyment, slider_soc_interest, slider_soc_future, slider_soc_mot, spq_BA
, spq_neg, bsi_is, bsi_depression, bsi_total))
corr <- rcorr(as.matrix(temp), type='pearson')
print(corr$r, digits = 3)
cat("\n", "CORRELATIONS: P VALUES", "\n")
print(corr$P, digits=3, scipen=0)
cat("\n", "CORRELATIONS: N VALUES", "\n")
print(corr$n)



#without negative expression sum
temp <- na.omit(select(semwkdb, pos_expression_duration, pos_expression_freq,
pos_expression_intensity, neg_expression_duration, neg_expression_freq, neg_e
xpression_intensity, range, fluencycorrected, slider_soc_enjoyment, slider_so
c_interest, slider_soc_future, slider_soc_mot, spq_BA, spq_neg, bsi_is, bsi_d
epression, bsi_total))
corr <- rcorr(as.matrix(temp), type='pearson')
print(corr$r, digits = 3)
cat("\n", "CORRELATIONS: P VALUES", "\n")
print(corr$P, digits=3, scipen=0)
cat("\n", "CORRELATIONS: N VALUES", "\n")
print(corr$n)

plot <- cor.plot(temp, labels = c("Positive Expression Duration","Positive Ex
pression Frequency", "Positive Expression Intensity","Negative Expression Dur
ation","Negative Expression Frequency", "Negative Expression Intensity", "Exp
ressive Range", "Verbal Fluency", "Social Enjoyment", "Social Interest", "Soc
ial Future", "Social Motivation", "SQP BA", "SPQ Negative Schizotypy", "BSI I
nterpersonal Sensitivity", "BSI Depression", "BSI Total"), stars =TRUE)

#corrplot::corrplot(corr$r, method= "number", type = "lower")
png('/Users/tovah/Desktop/correlations.png', height  = 800, width = 800)
cor.plot(temp, labels = c("Positive Expression Duration","Positive Expression
Frequency", "Positive Expression Intensity","Negative Expression Duration","N
egative Expression Frequency", "Negative Expression Intensity", "Expressive R
ange", "Verbal Fluency", "Social Enjoyment", "Social Interest", "Social Futur
e", "Social Motivation", "SQP BA", "SPQ Negative Schizotypy", "BSI Interperso
nal Sensitivity", "BSI Depression", "BSI Total"), stars =TRUE, cex.axis = 0.7
5, cex = 0.9)
dev.off()

#qualtrics data - of study relevant variables, only missing one person, SPQBR
30
describe(qualtrics)
```

```
#linear model database
wkdb%>% group_by(id_lsu) %>%
  summarise(no_rows = length(id_lsu))%>%filter(no_rows ==1) #this tells you h
ow many were in the total data - 216
test%>% group_by(id_lsu) %>%
  summarise(no_rows = length(id_lsu))%>%filter(no_rows ==1) #this tells you h
ow many people were included in the linear model - 216

describe(test)
#sem wkdb includes 216
semwkdb%>% group_by(id_lsu) %>%
  summarise(no_rows = length(id_lsu))
describe(semwkdb)

#for study relevant variables there is missing data in social sliders and flu
ency corrected
semwkdb%>%filter(is.na(slider_soc_future) | is.na(slider_soc_interest) | is.n
a(slider_soc_enjoyment)) #444
semwkdb%>%filter(is.na(slider_soc_future) & is.na(slider_soc_interest) & is.n
a(slider_soc_enjoyment))#153
semwkdb%>%filter(is.na(fluencycorrected))#86

semwkdb%>%filter(!is.na(slider_soc_future) & !is.na(slider_soc_interest) & !i
s.na(slider_soc_enjoyment) & !is.na(fluencycorrected))#2087

#check whether difference in missing video by race

facerace <-  read_csv(paste(vardd, "hr21lsufaces_qualtrics_anonymous_May22.cs
v", sep=""))%>%select(-c('...1'))%>%mutate(race_white = ifelse(str_detect(rac
e, "White"), 1, 0), race_black = ifelse(str_detect(race, "Black"), 1, 0), rac
e_asian = ifelse(str_detect(race, "Asian"), 1, 0), race_indigenous = ifelse(s
tr_detect(race, "Native"), 1, 0), latinx = ifelse(str_detect(latinx, "Yes"),
1, 0), MENA = ifelse(str_detect(MENA, "Yes"), 1, 0)) %>% mutate(race_multi =i
felse(rowSums(select(., race_white, race_black, race_asian, race_indigenous,
latinx, MENA)) >1, "multiracial", race))%>% mutate(race_multi = if_else(str_d
etect(race_multi, "Not listed/Write in below") & latinx ==1, "latinx", race_m
ulti))%>%mutate(race_multi = if_else(is.na(race_multi) & latinx ==1, "latinx"
, race_multi))%>%mutate(race_multi = factor(race_multi))%>%select(id_lsu, lat
inx, MENA, starts_with("race"))

facsrace <- join(facs, codex)%>%filter(video_type == "video_describe")%>%sele
ct(id_lsu, file, perc_valid)

facerace <- join(facerace, facsrace)
facerace$race_multi <-relevel(facerace$race_multi, ref = "White")

facerace<- facerace%>%mutate(retained = ifelse(perc_valid >= 10, 1, 0))
#This now has 2708 and SEM measurmeent model has 2594 - this makes sense sinc
e videos would have been removed
#Black participants have fewer frames analyzeable than white participants.
```

```
varint <- c("perc_valid ~1")
varrando <- c("perc_valid ~  (1|id_lsu)")
varmlm1 <- c("perc_valid    ~ race_multi+ (1|id_lsu)")


intercept   <- glm(varint,  data=facerace,  na.action=na.exclude)
rando.intercept <-lmer(varrando, data=facerace, REML=FALSE, na.action=na.excl
ude)
lme1 <- lmer(varmlm1, data=facerace, REML=FALSE, na.action=na.exclude)



# ANOVA SUMMARY
anova <- anova(lme1, rando.intercept, test="F")
print(anova)


# MODEL ESTIMATES: "DROP1" METHOD. COMPUTES CHANGE STATS BY DROPPING ALLLOWAB
LE SINGLE TERMS FROM THE MODEL
print(summary(lme1))



#try binary outcome see if racial bias in retention
varint <- c("retained   ~1")
varrando <- c("retained ~  (1|id_lsu)")
varmlm1 <- c("retained  ~ race_multi+ (1|id_lsu)")


intercept   <- glm(varint,  data=facerace,  na.action=na.exclude,  family = "
binomial")
rando.intercept <-glmer(varrando, data=facerace,na.action=na.exclude,  family
= "binomial")
lme1 <- glmer(varmlm1, data=facerace, na.action=na.exclude,  family = "binomi
al")



# ANOVA SUMMARY
anova <- anova(lme1, rando.intercept, test="F")
print(anova)


# MODEL ESTIMATES: "DROP1" METHOD. COMPUTES CHANGE STATS BY DROPPING ALLLOWAB
LE SINGLE TERMS FROM THE MODEL
print(summary(lme1))
#Black participants' videos are less likely to be retained
```

```
#try running a measurement model on blunted affect
cfawkdb <- select(semwkdb, range, pos_expression_duration, pos_expression_fre
q, pos_expression_intensity, neg_expression_duration, neg_expression_intensit
y, neg_expression_freq)

bluntaffcfa <- '
bluntaff =~ range+pos_expression_duration+pos_expression_freq+pos_expression_
intensity+neg_expression_duration+neg_expression_freq+neg_expression_intensit
y
'
bluntaffcfa <- cfa(model = bluntaffcfa, data = cfawkdb)
summary(bluntaffcfa)
resid(bluntaffcfa, type= "cor")
fitmeasures(bluntaffcfa)

### DOES NOT RUN
bluntaffsem <- '
level: 1
bluntaff =~ range+pos_expression_duration+pos_expression_freq+pos_expression_
intensity+neg_expression_duration+neg_expression_freq+neg_expression_intensit
y
level: 2
bluntaff =~ range+pos_expression_duration+pos_expression_freq+pos_expression_
intensity+neg_expression_duration+neg_expression_freq+neg_expression_intensit
y

bluntaff~~bluntaff
'
bluntaffsem <- sem(model = bluntaffsem, data = semwkdb,cluster="id_lsu")
summary(bluntaffsem)

#Remove durations - gives a heywood case. all except neg expression intensity
are negative.
bluntaffcfa <- '
bluntaff =~ range+pos_expression_freq+pos_expression_intensity+neg_expression
_freq+neg_expression_intensity
'
bluntaffcfa <- cfa(model = bluntaffcfa, data = semwkdb)
summary(bluntaffcfa)


#if you remove range, you don't get a heywood case, but it's also a terrible
fit for the data... but at least possible.
bluntaffcfa <- '
bluntaff =~ pos_expression_freq+pos_expression_intensity+neg_expression_inten
sity+neg_expression_freq
'
bluntaffcfa <- cfa(model = bluntaffcfa, data = semwkdb)
summary(bluntaffcfa)
resid(bluntaffcfa, type= "cor")
```

```
fitmeasures(bluntaffcfa)



#best model, clustered data
bluntaffsem<- '
level: 1
bluntaff =~ pos_expression_intensity+pos_expression_freq+neg_expression_freq_
sum+neg_expression_intensity
level: 2
bluntaff =~ pos_expression_intensity+pos_expression_freq+neg_expression_freq_
sum+neg_expression_intensity

bluntaff~~bluntaff
'
bluntaffsem<- sem(model = bluntaffsem, data = semwkdb,cluster="id_lsu")
summary(bluntaffsem)

#then do the same for social motivation
socmot <- '
socmot =~ slider_soc_interest+slider_soc_future + slider_soc_enjoyment
'
socmotcfa <- cfa(model = socmot, data = semwkdb)
summary(socmotcfa)

socmot <- '
level: 1
socmot =~ slider_soc_interest+slider_soc_future + slider_soc_enjoyment
level: 2
socmot =~ slider_soc_interest+slider_soc_future + slider_soc_enjoyment
socmot~~socmot
'
socmotsem<- sem(model = socmot, data = semwkdb, cluster="id_lsu")
summary(socmotsem)



###### run the proposed model with the definition above from blunted affect #
######
model1 <- '
#within

level: 1
#first, define all regressions
bluntaff ~ fluencycorrected
bluntaff ~ soc_mot

#then define latent variables
bluntaff =~ pos_expression_intensity+pos_expression_freq+neg_expression_freq_
sum+neg_expression_intensity
```

```
soc_mot =~ slider_soc_enjoyment + slider_soc_future + slider_soc_interest

#then set variances/covariances


#between
level: 2
#first, define all regressions
fluencycorrected~spq_neg
soc_mot~spq_neg
bluntaff ~ fluencycorrected
bluntaff ~ soc_mot
bluntaff ~spq_neg
#then define latent variables
bluntaff =~ pos_expression_intensity+pos_expression_freq+neg_expression_freq_
sum+neg_expression_intensity
soc_mot =~ slider_soc_enjoyment + slider_soc_future + slider_soc_interest

#then set variances/covariances
spq_neg ~~ spq_neg

'

#with the full data, this runs normally, but does have heywood cases.
fit <- sem(model = model1, data = semwkdb, cluster = "id_lsu")
summary(fit)
#heywood cases: negative variance
graph1 <- tidySEM::graph_sem(fit, layout_algorithm = "layout_in_circle")
png('/Users/tovah/Library/CloudStorage/Box-Box/ASAP LAB/ASAP RESEARCH DRIVE/M
ANUSCRIPTS/5. GRAD THESES DISS/Tovah Cowan/Dissertation_TC/SEMmodel1_plot.png
',  width = 2000, height = 600)
plot(graph1)
dev.off()





#mediation model soc mot
medsocmot <- '
level:1
#first define latent variables
bluntaff =~ pos_expression_intensity+pos_expression_freq+neg_expression_freq_
sum+neg_expression_intensity
socmot =~ slider_soc_interest+slider_soc_enjoyment+slider_soc_future
socmot ~ a*bluntaff

level: 2
#first define latent variables
bluntaff =~ pos_expression_intensity+pos_expression_freq+neg_expression_freq_
```

```
sum+neg_expression_intensity
socmot =~ slider_soc_interest+slider_soc_enjoyment+slider_soc_future
# direct effect
            spq_neg ~ c*bluntaff
           # mediator
             socmot ~ a*bluntaff
             spq_neg ~ b*socmot
           # indirect effect (a*b)
             ab := a*b
           # total effect
             total := c + (a*b)
spq_neg~~spq_neg
         '
medsocmot <- sem(model = medsocmot, data = semwkdb,cluster="id_lsu")
summary(medsocmot)
#Heywood case - negative variance





#mediation model cog resources
medcogresources <- '
level:1
#first define latent variables
bluntaff =~ pos_expression_intensity+pos_expression_freq+neg_expression_freq_
sum+neg_expression_intensity
fluencycorrected ~ a*bluntaff

level: 2
#first define latent variables
bluntaff =~ pos_expression_intensity+pos_expression_freq+neg_expression_freq_
sum+neg_expression_intensity
# direct effect
            spq_neg ~ c*bluntaff
           # mediator
             fluencycorrected ~ a*bluntaff
             spq_neg ~ b*fluencycorrected
           # indirect effect (a*b)
             ab := a*b
           # total effect
             total := c + (a*b)
spq_neg~~spq_neg
         '
medcogres <- sem(model = medcogresources, data = semwkdb,cluster="id_lsu")
summary(medcogres)



##### no latent variables versions of the full models ####
```

```
model4 <- '
#within

level: 1
#first, define all regressions
neg_expression_freq ~ fluencycorrected
neg_expression_freq ~ slider_soc_mot

#between
level: 2
#first, define all regressions
fluencycorrected~spq_neg
slider_soc_mot~spq_neg
neg_expression_freq ~ fluencycorrected
neg_expression_freq ~ slider_soc_mot
neg_expression_freq ~spq_neg

#then set variances/covariances
spq_neg ~~ spq_neg

'

#with the full data, this runs normally, and without issue!
fit4 <- sem(model = model4, data = semwkdb, cluster = "id_lsu")
summary(fit4)
resid(fit4, type = "cor")
fitmeasures(fit4)
graph4 <- tidySEM::graph_sem(fit4, layout_algorithm = "layout_in_circle")
png('/Users/tovah/Library/CloudStorage/Box-Box/ASAP LAB/ASAP RESEARCH DRIVE/M
ANUSCRIPTS/5. GRAD THESES DISS/Tovah Cowan/Dissertation_TC/SEMmodel2_plot.png
',  width = 2000, height = 600)
plot(graph4, cex = 2)
dev.off()


#following up form the logistic regression above, use positive expression dur
ation
model5 <- '
#within

level: 1
#first, define all regressions
pos_expression_duration ~ fluencycorrected
pos_expression_duration ~ slider_soc_mot

#between
level: 2
#first, define all regressions
fluencycorrected~spq_neg
```

```
slider_soc_mot~spq_neg
pos_expression_duration ~ fluencycorrected
pos_expression_duration ~ slider_soc_mot
pos_expression_duration ~spq_neg

#then set variances/covariances
spq_neg ~~ spq_neg

'

#with the full data, this runs normally, and without issue!
fit5 <- sem(model = model5, data = semwkdb, cluster = "id_lsu")
summary(fit5)
resid(fit5, type= "cor")
fitmeasures(fit5)
graph5 <- tidySEM::graph_sem(fit5, layout_algorithm = "layout_in_circle")
png('/Users/tovah/Library/CloudStorage/Box-Box/ASAP LAB/ASAP RESEARCH DRIVE/M
ANUSCRIPTS/5. GRAD THESES DISS/Tovah Cowan/Dissertation_TC/SEMmodel3_plot.png
',  width = 2000, height = 600)
plot(graph5)
dev.off()



###comparing these two models ####

lavTestLRT(fit4, fit5)
```

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Vita

Tovah Cowan grew up in Montréal, Québec, on the traditional and unceded territory of the Haudenosaunee Confederacy and Kanien'kehâka Nation. There, she completed her Bachelor of Science, Honours Psychology with a minor in Multidisciplinary Studies in Science, at Concordia University in 2013. During her undergraduate studies she worked in several research laboratories, and completed projects in exercise science, philosophy of science, and developmental psychology. Before beginning her graduate studies at Louisiana State University (LSU), she worked as a research assistant at the PEPP-Montréal (Prevention and Early Intervention in Psychosis Program) exploring post-traumatic growth after a first episode of psychosis, and engagement in wellbeing and in specialized early intervention services following first episode of psychosis. Tovah's research and clinical interests in serving individuals with psychosis led her to LSU in 2013, where she is currently completing her Doctor of Philosophy in Clinical Psychology under the supervision of Dr. Alex S. Cohen. Her current research interests center on social communication, motivation, and functioning in individuals with serious mental illness, and particularly psychosis, and leveraging novel assessment and intervention strategies to improve quality of live for these individuals. As well, she is focused on ensuring that these new assessments and interventions are equitable for all. Tovah is currently completing her predoctoral internship at the VA Maryland Health Care System/University of Maryland School of Medicine Consortium (Clinical High Risk for Psychosis -CHiRP track) and anticipates graduating August 2023.