Tracking the dynamic nature of learner individual differences: 
Initial results from a longitudinal study

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Abstract
Individual differences (IDs) have long been considered one of the most important factors explaining variable rates and outcomes in second language acquisition (Dewaele, 2013). While traditional operationalizations of IDs have, explicitly or implicitly, assumed that IDs are static traits that are stable through time, more recent research inspired by complex dynamic systems theory (Larsen-Freeman, 1997, 2020) demonstrates that many IDs are dynamic and variable through time and across contexts, a theme echoed throughout the current issue. This study reports the initial semester of a diachronic project investigating the dynamicity of four learner IDs: motivation, personality, learning and cognitive styles, and working memory. In the initial semester, data from 323 participants in their first year of university-level Spanish were collected and analyzed to determine what type of variability may be present across learners with respect to the four IDs studied at one time point and to discern possible learner profiles in the data or patterns via which the data may be otherwise meaningfully described. The results revealed four types of learner profiles present in the dataset.

Keywords: individual differences; longitudinal; cluster analysis; dynamicity; Spanish

1. Introduction
Second language (L2) development is characterized as an inherently dynamic process. Although it is commonly accepted that L2 learners pass through largely predictable stages in the acquisition of a given structure (Brown, 1973; Dulay & Burt, 1973), variability across individuals in both the outcome and the rate of acquisition has been readily observed (Van Patten & Williams, 2015, p. 10). Learner individual differences (IDs) have been posited to be one of the most important factors in accounting for this variability (Dewaele, 2009, 2013; Dörnyei, 2005, 2006; Dörnyei & Ryan, 2015). ID research concerns the identification of the parameters along which people vary and attempts to describe the manner in which IDs relate to observed differences in L2 development. As the papers in this special issue attest, there is growing awareness of the dynamic nature of IDs, absent in more traditional operationalizations (Dörnyei, 2005, 2009; Dörnyei & Ryan, 2015; Dörnyei, MacIntyre, & Henry, 2015), which calls into question the stability of IDs over time (Dewaele, 2013). This updated conceptualization considers IDs as dynamic and complex, with multiple IDs interacting with each
other and with the learning context during L2 development (Dewaele, 2013; Dörnyei, 2009; Dörnyei & Ushioda, 2009; Gurzynski-Weiss, 2020a). This update, as seen throughout this collection, is consistent with the “dynamic turn” (de Bot, 2015a) in research on L2 development, which emphasizes the dynamic nature of the L2 system (Larsen-Freeman, 2006, 2011, 2020; Larsen-Freeman & Cameron, 2008).

While there is shared conceptual agreement that IDs may best be considered on a continuum of dynamicity (see the editorial introduction to this issue), there is much research to be done to uncover the dynamic nature of each ID and how IDs interact with each other and with the larger L2 developmental system over time. For example, some IDs, such as anxiety, can be characterized as both state (highly variable, e.g., MacIntyre & Serroul, 2015) and trait (less variable, e.g., Horwitz, Horwitz, & Cope, 1986) IDs, depending on the scope of the research question (see Gregersen, this issue). Recent work has shown that several IDs, including anxiety, motivation, enjoyment, and willingness to communicate, interact over the course of a single task (e.g., Boudreau, MacIntyre, & Dewaele, 2018; Gregersen, MacIntyre, & Meza, 2014), suggesting that IDs influence one another even in the short term. Serafini (2017) has also provided evidence of longer-term interactions over the course of a semester between aptitude, working memory, and motivation. Thus, IDs may show variation and inter-influence over both shorter and longer time periods.

Despite these recent advancements demonstrating the dynamic and interactive nature of IDs, the fact remains that decades of previous research have shown IDs, when conceptualized and measured as more or less static, to be remarkably consistent predictors of L2 developmental outcomes. For example, at the level of individual studies, IDs such as motivation and language aptitude regularly yield correlations above .50 with language outcome measures (Dörnyei, 2006; Dörnyei & Skehan, 2003; Sawyer & Ranta, 2001). At the meta-analytic level, the correlations between IDs and L2 outcomes may be lower; for example, Li (2016) examined the relationship between language aptitude and language achievement and concluded that, based on 109 studies involving 13,035 participants, there was a medium-sized correlation ($r = .49$) that supported the role of language aptitude in L2 development. In an earlier meta-analysis, Masgoret and Gardner (2003) found that the correlation between motivation and language outcomes were .37 based on 75 studies involving 10,489 participants. Even at the meta-analytic level, however, IDs demonstrate a consistent, positive relationship with L2 development. Specifically, the IDs in this study, regardless of the particular operationalization used, have all been linked to L2 development (i.e., motivation: Masgoret & Gardner, 2003; learning styles: Johnson, Prior, & Artuso, 2000; personality: Hanafiyyeh & Afghari, 2017; working memory: Linck, Osthus, Koeth, & Bunting, 2014). Thus, there is work to be done to reconcile: (a) the theoretical idea
that IDs are more dynamic with (b) the empirical work that has found links between these IDs, measured on a single occasion and assuming them to be stable, and L2 development. This project, both the first semester worth of data presented in this special issue, as well as the longitudinal component underway, seeks to address this need by examining these IDs using the traditional, time-tested instruments that have been shown to be reliable and to relate the IDs measured to L2 development, and collecting data longitudinally (once per semester over 2 years) with the goal of examining if and how these learner IDs change over time.

Understanding how IDs relate to each other has practical motivations as well. For example, existing research finds that IDs may interact with instructional treatment, meaning that certain learners benefit more from a given task on the basis of their IDs such as motivation (Dörnyei, 2002) or aptitude (e.g., Yilmaz & Granena, 2016). However, this research largely considers only a single ID at a time. As Skehan (1986) noted, “it is possible that patterns or configurations of different abilities are important for language learning success” (p. 82, our emphasis). Thus, understanding multiple IDs of L2 learners in a given language department or unit may provide crucial information to program coordinators and curriculum designers. In other words, if certain profiles of L2 learners (for example, highly analytical, motivated learners) consistently outperform other groups of learners, or if only a certain subset of learners (e.g., integratively motivated leaners with high levels of extraversion) go on to advanced language classes as majors or minors while learners with other IDs do not, identifying these IDs may provide language programs with concrete ways to deliver more well-rounded instruction and with crucial information for creating better recruitment and retention strategies. This focus is also consistent with recent proposals to consider L2 development at the curriculum level, rather than at the level of task, treatment, or lesson plan (Byrnes, 2018).

The current paper reports on data from the initial semester of a longitudinal study designed to contribute to uncovering the dynamic nature of four learner IDs: motivation, personality, learning/cognitive styles, and working memory. For the longitudinal project, we are interested in understanding (a) the dynamicity of each ID over the first two years of language study; (b) whether and to what extent these IDs interact with one another, and (c) the relationship between these IDs (separately and/or together) and language learning decisions and behaviors such as

1 The current context can be considered a “foreign” language classroom context, where learners primarily learn and use the target language in the classroom with limited opportunities to use it in the outside community. An L2 classroom context on the other hand typically entails a range of learning contexts and opportunities to use the target language to communicate in everyday life (Dörnyei, 1990). Note that we do not consider Spanish to be a foreign language within the United States; we are simply using this term (admittedly problematically) to clarify that there are minimal opportunities for use outside of the classroom.
(dis)continuing language study, the amount of time using the target language outside of the classroom, and choosing to study abroad. In the current paper, we report on the patterns of IDs present in the data collected during the first semester and on the process of identifying potential learner profiles in the first semester.

2. Literature review

2.1. Dynamic systems in L2 development

A growing body of research in L2 development is conceptualized within the framework of complex dynamic systems theory (CDST; Larsen-Freeman, 2015, 2020). As outlined by Larsen-Freeman (2015, p. 228), complex systems are characterized as open (i.e., they interact with the environment and are shaped by it), adaptive (i.e., they respond to changes in the environment), and nonlinear (i.e., effects are not necessarily proportionate to the cause). This conceptualization is largely incompatible with the traditional view of IDs as concrete, modular, context-independent traits, and with the tendency to study them in isolation from each other (Segalowitz & Trofimovich, 2012). Instead, recent research has begun to adopt a more holistic approach, more in line with CDST, that examines multiple IDs in relation to one another (Dörnyei, 2009, 2010; Dörnyei & Ryan, 2015; Geeslin, 2020; Gurzynski-Weiss, 2020b; Lantolf, 2020; Larsen-Freeman, 1997, 2015, 2020).

In particular, some recent scholarship has conceptualized IDs as learner resources, which presumably change over the course of L2 learning and exert influence over other resources in the system. Learner resources, such as IDs, are limited in nature (van Geert, 1995), and they may demonstrate supportive (mutual development of resources because of support), competitive (mutual development because of competition between resources), conditional (a cause-effect relationship, in which one resource causes change in another), or even compensatory (a low level in one resource is compensated for by higher levels in another) relationships (de Bot, 2008; Verspoor, de Bot, & Lowie, 2011). Within these relationships, certain IDs may act as attractors or stabilizers in the L2 system, pulling the system into certain configurations. About the effects of this role of certain IDs, Dörnyei (2010, p. 260) states: “A relatively wide range of starting points will eventually converge on a much smaller set of states because the process unfolds in the direction of the attractor.” This may be the reason that static operationalizations continuously emerge as such strong predictors of L2 development, as certain IDs such as motivation or cognitive ability pull the system toward particular developmental paths, regardless of variability.

CDST is a promising analytical framework for understanding IDs because it posits that patterns of interaction between resources can vary across different
timescales (micro, e.g., a task, and macro, e.g., a university semester) and can also be different for individual learners (de Bot, 2008, 2015b). Given the longitudinal nature of this project and our interest in the dynamic, mutually influencing nature of IDs, we adopt a CDST perspective to identify relationships between four IDs (i.e., motivation, personality, learning/cognitive styles, and working memory) and, ultimately, to examine changes in these IDs over time.

2.2. Motivation

Motivation is one of the most studied IDs in L2 development research. We adhere to Dörnyei and Ushioda’s (2011) assertion that motivation “concerns the direction and magnitude of human behaviour” (p. 4, emphasis original) related to the choice of, persistence in, and effort expended on a particular action (Ushioda, 2008). Specifically, to conceptualize motivation, we adopt Dörnyei’s L2 motivational self system model (L2MSS, Dörnyei, 2005, 2009; Dörnyei & Ryan, 2015). The L2MSS is comprised of three main dimensions: the ideal L2 self (i.e., the collection of desirable qualities one would like to possess), the ought-to L2 self (i.e., the attributes one believes others want them to possess), and the L2 learning experience (i.e., the present learning environment the learner finds themselves in; Dörnyei, 2005, 2009). Based in Higgins’ (1987) self-discrepancy theory, the L2MSS model posits that motivated behavior arises from the need to reduce the distance between one’s possible selves (the deal and ought-to L2 selves) and one’s current self. The L2MSS brings the study of L2 motivation more in line with parallel strands of research in motivational psychology (Dörnyei, 2005, 2009; Dörnyei & Ushioda, 2011), and has been applied to L2 research across a number of different contexts, including English as a foreign language in Japan (Ryan, 2009; Yashima, 2009), China (Taguchi, Magid, & Papi, 2009), Iran (Taguchi et al., 2009), and Hungary (Csizér & Kormos, 2009), and the learning of languages other than English in the United States (Thompson, 2017a, 2017b).

When considering the relationship between motivation and L2 development, many researchers attempt to link motivation to language outcomes, positing a direct influence on language development. For example, outcome measures common in the literature are scales of self-perceived proficiency (e.g., MacIntyre, MacKinnon, & Clément, 2009), objective measurements of language ability (e.g., Lyons, 2009), and course grades (e.g., Gardner & MacIntyre, 1993). Motivation tends to correlate with these measures: MacIntyre et al. (2009), for example, showed that stronger L2 selves correlated positively ($r = .76$) with perceived L2 proficiency in a sample of 135 female first language (L1) English high school learners of foreign languages. A recent meta-analysis of research on the L2MSS (Al-Hoorie, 2018) found that the correlation between the ideal L2 self...
and language outcomes was .20, a small effect size (Plonsky & Oswald, 2014). Others attempt to link motivation to language learning behaviors that support L2 development, such as language use. For example, Hernández (2010) investigated the role of motivation in predicting language use both at-home (N = 24) and abroad (N = 20); for both groups, motivation significantly predicted L2 use outside of the classroom and improvements in oral proficiency.

Motivation as an ID variable has also been investigated longitudinally. De Bot (2015b) notes that change occurs across many interacting timescales, and Dörnyei (2003) states that “many of the controversies and disagreements in L2 motivation research go back to an insufficient temporal awareness” (p. 18), indicating the need for more research into motivation across different timescales. Motivation has been considered longitudinally across years, university semesters, weeks, and tasks. In terms of years, Chan, Dörnyei, and Henry (2015) qualitatively tracked how motivation changed over the course of study through retrospective interviews with an L1 Cantonese learner of English and Taiwanese, finding that his motivation steadily increased over the course of his schooling. At the semester level, Piniel and Csizér (2014) observed that motivation showed quantitative variability during a composition course in Hungary, although the ought-to L2 self exhibited more change than the ideal L2 self. At the level of weeks, Willis Allen and Herron (2003) found no quantitative changes in integrative motivation (using the Attitude/Motivation Test Battery; Gardner, 1985) during a six-week study abroad program in France, although Willis Allen (2010) did find qualitative changes in a subset of learners’ goals for language study. Finally, at the level of the task, MacIntyre and Serroul (2015) found that learners reported fluctuating levels of motivation as they completed eight speaking tasks in L2 French. Thus, we can conclude from this body of research that motivation shows variation across different timescales. It should be noted, however, that at the largest timescale, years, research has only been conducted retrospectively (i.e., asking participants to reflect on their change in motivation; Chan et al., 2015). Longitudinal, quantitative research over timespans longer than a year is needed to better understand the dynamics of motivation and the relationship between motivation and the process of L2 development (e.g., its relationship to continuing or discontinuing L2 study).

2.3. Personality

Personality has been defined as the set of characteristics that a person possesses which “account for consistent patterns of feeling, thinking, and behaving” (Pervin & John, 2001, p. 4). It has been analyzed from a variety of perspectives in the field of psychology, with the predominant model being that of the Big Five (Costa & McCrae, 1992). This model, also referred to as the five-factor model (FFM) is comprised of the
following personality dimensions: (1) extraversion-introversion, (2) neuroticism-emotional stability, (3) conscientiousness, (4) agreeableness, and (5) openness to experience. Many personality tests used in psychology (e.g., the Neuroticism-Extraversion-Openness Five-Factor Inventory, or NEO-FFI; Costa & McCrae, 1989) follow this model. More recently, researchers have situated the five dimensions within a sociocultural context to provide a more dynamic, integrative framework, as is proposed, for example, in the New Big Five (McAdams & Pals, 2006). Additional personality inventories have adopted supplementary dimensions to complement those of the Big Five, such as HEXACO (Ashton & Lee, 2009), which adds the dimension of honesty-humility.

In this study, we adopt the HEXACO model to conceptualize personality, as it expands upon but remains aligned with the dimensions of the Big Five, which is the model that has traditionally been used in L2 research on personality (e.g., Verhoeven & Vermeer, 2002). An overview of the six dimensions of the HEXACO model, their respective sub-dimensions, and their definitions is provided in Table 1.

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<th>HEXACO dimensions with definitions (adapted from Ashton &amp; Lee, 2009)</th>
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<td><strong>Honesty-Humility</strong></td>
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<td>Sincerity</td>
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<td>Fairness</td>
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<td>Greed avoidance</td>
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<td>Modesty</td>
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<td><strong>Emotionality</strong></td>
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<td>Fearfulness</td>
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<td>Anxiety</td>
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<td>Dependence</td>
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<td>Sentimentality</td>
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<td>Liveliness</td>
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<td>Diligence</td>
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<td>Perfectionism</td>
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<td><strong>Openness to experience</strong></td>
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<td>Aesthetic appreciation</td>
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<td>Inquisitiveness</td>
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<td>Unconventionality</td>
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<th>Definition</th>
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<td>High scorers avoid manipulating others for their own benefit, are not interested in wealth or luxuries, do not feel entitled to higher social status, and are not often tempted to break rules.</td>
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<td>High scorers are characterized by higher levels of anxiety, a greater fear of physical danger, a greater need for emotional support from others, and tend to be more empathetic and form deeper sentimental attachments to others.</td>
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<td>High scorers feel more positively about themselves, enjoy being around others in social settings, are confident when leading or addressing a group, and experience positive energy and enthusiasm.</td>
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<td>High scorers are more forgiving, more lenient regarding the actions of others, more cooperative and flexible, and have little trouble controlling their temper.</td>
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<td>High scorers are disciplined, organize their time well, have a greater tendency toward accuracy and perfection in their work, and take care in making decisions.</td>
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<tr>
<td>High scorers are curious about a wide range of subjects, have a greater appreciation for art and nature, use their imagination, and are interested in unusual people or ideas.</td>
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Given the importance of social interaction in L2 development (e.g., Cohen, 2012; Duff & Talmy, 2011; Firth & Wagner, 1997; Long, 1996; van Compernolle, 2014), it is reasonable to posit that learners’ personality may play an important role in L2 learning as it likely mediates their opportunities for L2 interaction both within and outside of the classroom context. Nevertheless, the role of personality in L2 learning has not been robustly addressed in the literature (Dewaele, 2012). The few studies that do exist have investigated a potential link between L2 learning and certain dimensions of personality, the most researched being the introversion-extraversion dimension. Dewaele (2004), for example, found that extraverted learners (as determined by the Eysenck Personality Inventory; Eysenck & Eysenck, 1984) used a higher proportion of colloquial words than more introverted learners. In the case of high achieving language learners, Ehrman (2008) found that those who had more introverted personalities (as measured by the Myers-Briggs Type Indicator [MBTI]) more frequently achieved an oral proficiency rating of 4/5 on the Interagency Language Roundtable proficiency test. Finally, MacIntyre, Clément, and Noels (2007) explored the potential interaction between learning conditions (i.e., very familiar vs. somewhat familiar vs. unfamiliar) and personality types and observed trends indicating that introverted learners of Canadian French scored higher on vocabulary tests in the very familiar condition than extroverted learners, whereas extroverted learners performed better than introverted learners in the somewhat familiar condition; there were no differences in scores by personality type in the unfamiliar condition.

Beyond introversion-extraversion, few studies examine other dimensions of personality. Verhoeven and Vermeer (2002) investigated the potential relationship between the Big Five personality dimensions and communicative competence of L2 Dutch learners and their L1 Dutch peers. For L2 learners, they found that openness to experience positively correlated with strategic (making effective use of one’s abilities to complete a task), organizational (grammatical and textual knowledge), and pragmatic (sociolinguistic and functional knowledge) competence, that extraversion correlated positively with strategic competence, and that conscientiousness correlated positively with organizational competence. Oz (2014) analyzed willingness to communicate and found it to be positively correlated with extraversion, openness to experience, and agreeableness in 168 learners in Turkey. Taken together, these findings suggest that, although there may be a link between L2 learning and certain personality dimensions, the nature of the relationship may vary depending on the situational context or the aspect of communicative competence under investigation.

Given the inconclusive findings for personality in the L2 literature outlined above, there is a need for investigation into how different personality dimensions may interact with other IDs and/or potentially change over time. Long (1996)
posited that personality may indirectly influence acquisition through consistent relationships with other variables, such as a preference for group learning, which would facilitate more interaction in the target language, affording more opportunities for negotiation and feedback. Investigating the relationship between personality and other IDs is a primary contribution of this project. Additionally, although there is some evidence that personality may change while studying abroad (Dwyer & Peters, 2004; Nash, 1976; Tracy-Ventura, Dewaele, Köylü, & McManus, 2016), to the best of our knowledge there is no research that considers if personality changes during at-home language study, although evidence suggests that multilinguals show significant differences in personality profiles in comparison to their monolingual counterparts (Dewaele & Stavans, 2014; Dewaele & van Oudenhoven, 2009). Additionally, Moody (1988) found that, when compared to a general sample of college students, students registered in university language courses showed significant differences in personality types (as measured by the MBTI test), which suggests that certain types of personalities may gravitate towards language study over other subjects. The present paper stands to contribute information about the personality profiles of learners who elect to study (and continue studying) Spanish at the university level.

2.4. Cognitive and learning styles

Learning styles refer to “an individual’s natural, habitual, and preferred way(s) of absorbing, processing, and retaining new information and skills” (Reid, 1995, p. viii). Cognitive styles can be defined as “an individual’s preferred and habitual modes of perceiving, remembering, organizing, processing, and representing information” (Dörnyei & Ryan, 2015, p. 112). The overlap in these definitions underscores the proposal by some (e.g., Nel, 2008) that the concepts and terms are interchangeable. Following Ellis (2008) and Dörnyei and Ryan (2015), we conceptualize learning and cognitive styles as two related constructs, with cognitive styles forming the core of learning styles. That is, if cognitive style refers to how individuals process information (Kinsella, 1995), learning style subsumes cognitive style and refers to “consistent ways of responding to and using stimuli in the context of learning” (Kinsella, 1995, p. 181). This conceptualization is in line with earlier research into cognitive and learning styles in general education, which proposed that learning style is a multi-layered construct (Curry, 1983, 1991). Curry conceptualized cognitive and learning styles to be layered like an onion; the first layer is comprised of environmental preferences, the second layer refers to information processing preferences, and the third layer refers to personality dimensions.

It is important to note that the theoretical basis on which cognitive and learning styles are built is fraught with conceptual difficulties. Riding (2000b) enumerates
issues related to wide-ranging labels for different styles, questionable assessment
techniques, and lack of clear distinctions between styles and other constructs (e.g.,
personality, strategies). Additionally, research findings that examine the relation-
ship between styles and learning outcomes have been mixed. For example, Tucker,
Hamayan, and Genesee (1976) found that cognitive style, operationalized as field
dependence/independence, failed to correlate with learning measures, while Seli-
ger (1977) found that it did. Conflicting findings and a lack of theoretical agreement
has led some to call for the abandonment of learning and cognitive styles research
(Griffiths & Sheen, 1992). Although scholars are increasingly critical of the scientific
foundation of styles (Coffield, 2005; Riding, 2000a, 2000b), language teachers con-
tinue to defend the construct based on their experience (Dörnyei & Ryan, 2015, p.
107). Additionally, Griffiths (2012) suggests that it is worth investigating cognitive
and learning styles due to their potential practical applications in the classroom:
“Understanding [learning styles] has the potential to greatly enhance learning and
to make learning more enjoyable and successful” (p. 151).

Early research into cognitive styles correlated performance on the Group Em-
bedded Figures Test (Witkin, Oltman, Raskin, & Karp, 1971), which measures learn-
ers’ ability to discern patterns within a complex figure, with language achievement
(Abraham, 1983; Alptekin & Atakan, 1990; Carter, 1988; Chappelle & Roberts,
1986; Elliott, 1995; Genesee & Hamayan, 1980; Hansen, 1984; Hansen & Stansfield,
1981, 1982; Hansen-Strain, 1987; Jamieson, 1992). These studies have reported sig-
nificant correlations between cognitive styles and learners’ performance in differ-
ent language tests and settings. For example, Chapelle and Roberts (1986) found
that field independence was linked to all components of the Test of English as a
Foreign Language, as well as performance on a grammar test, a diction test, and
an oral communication test. Likewise, Genesee and Hamayan (1980) found a pos-
itive correlation between field independence and achievement in French lan-
guage arts and listening comprehension. Nevertheless, Johnson et al. (2000), in
their study of 29 English learners, found field dependence to significantly and pos-
itively relate to teacher ratings of student performance and complexity (opera-
tionalized as the number of T-units produced during a 2-minute conversation sam-
ple). For learning styles, empirical evidence has been provided mainly by studies
that seek to understand the effect of matches or mismatches between learners’
preferred style and instructional design, focusing on vocabulary (Hatami, 2018;
Kassaian, 2007; Tight, 2010; Yeh & Wang, 2003). For example, Tight (2010) exam-
ined the effect of matching learning and instruction styles in a group of 128 learn-
ers of Spanish and found that, although style matching promoted better retention
of vocabulary items than mismatching, it was mixed-modality instruction that
promoted greater retention of vocabulary items overall, regardless of learner
style preference.
The dynamic turn in ID research has the potential to address some recurrent issues in style research. Specifically, CDST provides a theoretical framework through which to empirically examine whether and to what degree cognitive and learning styles interact with other IDs such as learning strategies (e.g., Cohen, 2003) or personality (e.g., Zhang, Sternberg, & Rayner, 2012). Additionally, as with the conceptualization of other IDs, recent perspectives argue for the incorporation of a dynamic view of cognitive and learning styles. Specifically, many early definitions defined both as stable, fixed variables that do not change (e.g., Reinert, 1976). However, Little and Singleton (1990) suggest that learning styles are malleable and that learners can learn to adopt and apply new styles through experience and training. Similarly, Wong and Nunan (2011) suggest that by expanding or “stretching” their teaching styles, instructors will be able to cater to a wider range of types of learners, and allow learners to expand or “stretch” their own learning styles. Additionally, as Dörnyei and Chan (2013) point out, many instruments do not force choices between different styles, but rather ask learners to indicate preferences, which implicitly allows for the idea of change over time. Nevertheless, current evidence does not provide a clear picture of the extent of dynamicity of styles. Chen (2009), for example, found that sensory preferences differed by grade level in Taiwanese junior high students, although it was not clear if learners change their preference as they advance in education or if the groups simply happened to have different preferences. The dynamicity of style and the role of learning and cognitive styles in L2 development remain open empirical questions.

2.5. Working memory

Working memory (WM) has been defined as a “mental workspace” (Lee, Ning, & Goh, 2013, p. 73) used for storing and manipulating information assumed to be necessary for a range of complex cognitive activities (Baddeley, 2003). Included in these cognitive activities are comprehending and producing an L2, which necessitates storing, selecting, and successively integrating information from a stream of discourse (Miyake & Friedman, 1998). Among the various proposed models of the structure of WM, Baddeley’s (1986) multicomponent model has received the most attention in L2 research. His model divides WM into a storage system responsible for the active maintenance of information and an executive/processing system, responsible for controlling attention and linking stored information to long-term memory.

As detailed in Jackson (this issue), WM has received considerable attention in L2 research given that many scholars (e.g., Ellis, 1996; Mackey, Philp, Egi, Fujii, & Tatsumi, 2002) view it as a robust window into the cognitive underpinnings of L2 learning. Empirical support for the role of WM in L2 learning has
been evidenced in a recent meta-analysis by Linck et al. (2014), spanning 79 studies and 3,707 participants. Results showed a positive relationship between WM and L2 outcomes, specifically production ($\rho = .27$)\(^2\) based on 42 studies involving 1,712 participants, and comprehension ($\rho = .24$) based on 43 studies involving 2,411 participants. In addition, executive components of WM predicted L2 outcomes to a greater extent than storage components. Thus, differences among learners in terms of executive control (e.g., maintaining access to information, managing potentially competing representations in the L1 and L2, and inhibiting irrelevant information in order to process language) may play an important role in the variation in L2 outcomes.

Regarding specific linguistic outcomes, a positive relationship has been found between WM and vocabulary learning (e.g., Speciale, Ellis, & Bywater, 2004); sentence processing (e.g., Dai, 2015); L2 fluency (e.g., O’Brien, Segalowitz, Collentine, & Freed, 2006); lexical comprehension (e.g., Sunderman & Kroll, 2009); self-correction of errors (e.g., Ahmadian, 2015); the ability to incorporate information learned from corrective feedback to facilitate L2 acquisition of various morphosyntactic structures (e.g., Goo, 2012; Li, 2015; Mackey et al., 2002; Sagarra, 2007; Trofimovich, Ammar, & Gatbonton, 2007; Yilmaz, 2013); and the production of modified output (e.g., Mackey, Adams, Stafford, & Winke, 2010; Sagarra, 2007), which has been empirically linked to L2 learning (e.g., Loewen, 2005; McDonough, 2005).

Of note, WM has also been examined from longitudinal and dynamic perspectives. For example, Serafini and Sanz (2016) examined the role of WM in morphosyntactic development among beginning, intermediate, and advanced adult L2 learners of Spanish during and after a semester of instruction. Results revealed a positive relationship between WM capacity and L2 development at lower levels of L2 proficiency, but minimal positive effects for WM as proficiency increased. The observed WM effect at the lower levels also varied over time: It was stronger at the beginning of instruction and after one month of no instruction, and weaker at the end of instruction, indicating that classroom exposure to Spanish may have neutralized the benefits of a higher WM capacity, whereas a break in exposure may lead to heavier reliance on WM. Serafini (2017) further illustrates the dynamic nature of WM, finding evidence that WM interacts with motivation at different proficiency levels. Specifically, Serafini found that stronger motivational intensity or effort and a stronger ought-to L2 self were associated with a smaller WM among advanced L2 learners of Spanish. These studies that examine WM from a dynamic perspective open the question of which other IDs might interact with WM and how these relationships may change over time as L2 proficiency and experience increase.

\(^2\rho = \text{estimated population effect size. Please see Linck et al. (2014) for further discussion.}\)
To measure WM, scholars have employed simple spans (e.g., digit span, non-word recognition/repetition) to measure the storage component of WM as well as complex spans (e.g., reading, counting, operation span) to measure both the storage and executive components. A commonly used measure of WM is the operation span (OSPA, Turner & Engle, 1989), which requires participants to process the correctness of mathematical operations and then recall previously seen material (e.g., integers, letters, or words) in their correct serial position. The OSPAN is the most robust measurement of WM for several reasons. First, it measures the executive attention control component of WM, which, as mentioned previously, is argued to be most relevant for L2 learning (Wen, 2012). Second, it allows for the measurement of both storage and processing components of WM, which is appropriate given the argument that the relative importance of these components may change over time (Juffs & Harrington, 2011) as well as the notion that bilingualism can shape executive attention across the lifespan (see Bialystok, 2018, for discussion). Finally, the OSPAN’s reliability has been repeatedly established (Conway et al., 2005; Engle, Tuholski, Laughlin, & Conway, 1999; Klein & Fiss, 1999), and the measurement tool has been employed in several L2 studies (e.g., Baralt, 2015; Goo, 2012; Yilmaz, 2013).

Research is warranted that explores whether WM also relates to L2 development in the context of a foreign language department and that seeks to understand the range of learner WM present in such a context so as to maximize learning opportunities across different WM capacities. In fact, if we conceive of the relationship between WM and L2 development as contextually and instructionally dependent (Jackson, this issue), WM may be particularly associated with outcomes in foreign language classroom context given that foreign language contexts often entail language as the object of study and use grammar-based pedagogy more so than L2 contexts (Shehadeh & Coombe, 2012) and may draw on explicit learning processes, which have been argued to be associated more with WM (Tagarelli, Ruiz, Vega, & Rebuschat, 2016).

3. The present study

The dynamic turn in L2 research necessitates the examination of multiple factors over the course of L2 learning. Examining IDs from a dynamic perspective has been described as “the logical next step of conceptualizing IDs” (Dörnyei, 2010, p. 260). The longitudinal project described here seeks to address the dynamic nature of four IDs: motivation, personality, learning and cognitive styles, and working

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3 More research has been called for that examines the bidirectional influences of bilingual development and changes in WM functions (e.g., Jackson, this issue).
memory. We follow the same group of students at a large, public, Mid-western university in the United States and measure their IDs at four time points over the course of two years of language study, with the goal of identifying and tracking relationships between the four learner IDs. Furthermore, following Serafini (2017), the study will investigate how these relationships change over time at a macro-level. Here, we present findings from the initial semester of data collection; subsequent analyses of the following semesters will be conducted in the future to understand the evolution of the IDs under study. This initial examination of the data is guided by two research questions:

1. How can first-semester learners’ IDs be described and what variation exists in IDs among the learners?
2. What relationships exist between the studied IDs and how can learner ID profiles be characterized?

3.1. Method

3.1.1. Participants

Participants were recruited from either a second semester Spanish course or an accelerated, semester-long course that covered the first year of content (and therefore encompassed the previously mentioned Spanish semester course) during the Fall of 2018 at a large, public research university in the United States. Of the 625 initial respondents, 325 provided complete data for motivation, personality, and cognitive and learning styles, and WM. Participants who did not provide complete data for motivation, personality, cognitive and learning styles, or WM were excluded. Additionally, two participants were excluded as outliers due to the low score on the processing component of the WM portion, resulting in 323 participants. Of the 323 respondents, 223 (69%) were in their first year of university study, 74 (23%) were in their second year, 20 (6%) were in their third year, 5 (2%) were in their fourth year, and 1 (<1%) was in their fifth year. The average age of the overall sample was 18.7 years (SD = 1.14, range = 17-26). On average, participants took 1.9 years of Spanish classes in primary school (SD = 2.50, range 0-11) and 2.7 years (SD = .93, range = 0-4) in secondary school. Fourteen (4.3%) reported experience abroad.

3.1.2. Instruments

Motivation: The motivation questionnaire was adapted from existing questionnaires designed to measure the L2MSS. The core of the instrument was adapted
from Taguchi et al. (2009), who performed a large-scale survey of learners in Japan, China, and Iran, and replicated the basic factor structure across all three contexts with minimal variation. Given the location of the present study’s university in a predominantly politically conservative state, an additional scale, fear of assimilation, was adopted from Ryan (2009). A pilot study of the current instrument at the same institution also replicated the same factor structure. The original instrument was a 70-item questionnaire with a 6-point Likert scale anchored on the left by strongly agree (1) and on the right by strongly disagree (6). Following the pilot study and initial validation, a shortened version of the questionnaire was created through an item-analysis, removing questions that did not significantly affect the overall reliability of the scale. The final instrument consisted of 47 items and measured effort towards L2 learning (8 items, alpha = .904), the ideal L2 self (6 items, alpha = .928), the ought-to L2 self (6 items, alpha = .862), family influence (4 items, alpha = .809), promotion orientation (5 items, alpha = .808), prevention orientation (6 items, alpha = .783), attitudes towards the L2 community (4 items, alpha = .834), attitudes towards the learning situation (4 items, alpha = .910), and fear of assimilation (4 items, alpha = .712). Since the L2MSS model predicts that motivated behavior comes from the drive to reduce the distance between future self-guides and the current self (Dörnyei, 2005; Higgins, 1987), only the scales representing the ideal L2 self and the ought-to L2 self were included in the analysis presented here. A sample item for each scale is provided in Table 2. The full instrument can be downloaded from the IRIS (www.iris-database.org).

Table 2 Sample items for the present study’s L2MSS questionnaire

<table>
<thead>
<tr>
<th>Scale</th>
<th># of items</th>
<th>Sample item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effort towards L2 learning</td>
<td>8</td>
<td>I would like to study Spanish even if I were not required.</td>
</tr>
<tr>
<td>Ideal self</td>
<td>6</td>
<td>I imagine myself as someone who is able to speak Spanish.</td>
</tr>
<tr>
<td>Ought-to self</td>
<td>6</td>
<td>Learning Spanish is necessary because people surrounding me expect me to do so.</td>
</tr>
<tr>
<td>Familial influence</td>
<td>4</td>
<td>My parents encourage me to study Spanish in my free time.</td>
</tr>
<tr>
<td>Promotion orientation</td>
<td>5</td>
<td>Studying Spanish is important because with a high level of Spanish proficiency I will be able to make a lot of money.</td>
</tr>
<tr>
<td>Prevention orientation</td>
<td>6</td>
<td>I have to learn Spanish because I don’t want to fail my Spanish class.</td>
</tr>
<tr>
<td>Attitudes towards the L2 community</td>
<td>4</td>
<td>I would like to know more about people from Spanish-speaking countries.</td>
</tr>
<tr>
<td>Attitudes towards the learning situation</td>
<td>4</td>
<td>I always look forward to Spanish classes.</td>
</tr>
<tr>
<td>Fear of assimilation</td>
<td>4</td>
<td>Using Spanish in front of people makes me think I will be thought of as less American.</td>
</tr>
</tbody>
</table>

Personality: We adopted the 60-item HEXACO-PI-R (Ashton & Lee, 2009) to measure learner personality. Although there is also a 100-item instrument, the logistics of data collection in our context necessitated use of the shorter
version of the questionnaire, which has been statistically shown to have internal-consistency reliability (Ashton & Lee, 2009). This instrument is comprised of 6 domain levels and 24 sub-traits. We address the six main dimensions in the present analysis: honesty-humility (10 items, alpha = .658), emotionality (10 items, alpha = .798), extraversion (10 items, alpha = .828), agreeableness (10 items, alpha = .775), conscientiousness (10 items, alpha = .774), and openness to experience (10 items, alpha = .778). Participants rated each item on a 5-point Likert scale, ranging from strongly agree (5) to strongly disagree (1). Table 3 provides a sample item from the HEXACO-PI-R. A full version of this instrument can be found at http://hexaco.org/.

Table 3 Sample items for the HEXACO-PI-R

<table>
<thead>
<tr>
<th>Scale</th>
<th># of items</th>
<th>Sample Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Honesty-humility</td>
<td>10</td>
<td>Having a lot of money is not especially important to me.</td>
</tr>
<tr>
<td>Emotionality</td>
<td>10</td>
<td>I would feel afraid if I had to travel in bad weather conditions.</td>
</tr>
<tr>
<td>Extraversion</td>
<td>10</td>
<td>The first thing that I always do in a new place is to make friends.</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>10</td>
<td>Most people tend to get angry more quickly than I do.</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>10</td>
<td>I always try to be accurate in my work, even at the expense of time.</td>
</tr>
<tr>
<td>Openness to experience</td>
<td>10</td>
<td>I like people who have unconventional views.</td>
</tr>
</tbody>
</table>

Learning and cognitive styles: Based on the research described in the literature review, learning and cognitive style is operationalized here as a construct that has two dimensions: (a) cognitive style, based on the idea of field (in)dependence, and (b) learning style, considering sensory and social preferences. With this operationalization in mind, learners responded to 40 statements using a 5-point Likert scale ranging from strongly agree (1) to strongly disagree (5), adapted from the Perceptual Learning Style Preference Questionnaire (PLSPQ; Reid, 1995) for learning styles, and the Style Analysis Survey (SAS; Oxford, 1993) for cognitive styles. There were five questions for each of the following cognitive and learning styles: field dependence (5 items, alpha = .530), field independence (5 items, alpha = .223), visual (5 items, alpha = .520), auditory (5 items, alpha = .667), kinesthetic (5 items, alpha = .724), tactile (5 items, alpha = .783), group learning (5 items, alpha = .878), and individual learning (5 items, alpha = .856). A summary of these scales with examples is presented in Table 4. A full version of this instrument can be downloaded from IRIS (www.IRIS-database.org).

Working memory: An adapted version of the OSPAN (Stone & Towse, 2015) was used to measure participants’ WM. The task presented participants with an integer (ranging from 10-99) displayed on the screen for two seconds (storage component). This was followed by a mathematical operation with a given answer that participants had to indicate as correct or incorrect (processing component). After a series of integer-operation pairs, participants were prompted to recall each integer
seen in its correct serial position (i.e., a span). The span length increased as the task proceeded, increasing incrementally from two integers to seven. Each span had three trials yielding a total of 18 trials and 81 integers to be recalled. The reader is referred to Stone and Towse (2015) for further details of the task. Participants completed the task on a computer and worked at their own pace. An Excel file containing the response data was generated for each participant. From that data file, each participant received a recall score (percentage of integers recalled correctly) and a processing score (percentage of mathematical operations solved correctly).

Table 4  Sample items for learning and cognitive styles

<table>
<thead>
<tr>
<th>Scale</th>
<th>Subscale</th>
<th># of items</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field (in)dependence</td>
<td>Field dependent</td>
<td>5</td>
<td>When I learn something new, it is easy for me to see the overall plan rather than small details.</td>
</tr>
<tr>
<td></td>
<td>Field independent</td>
<td>5</td>
<td>I focus on the details rather than on the big picture.</td>
</tr>
<tr>
<td>Sensory preferences</td>
<td>Visual</td>
<td>5</td>
<td>I learn better when there is visual support, such as PowerPoint presentations or videos.</td>
</tr>
<tr>
<td></td>
<td>Auditory</td>
<td>5</td>
<td>Listening to someone explaining something is one of the most effective ways of learning for me.</td>
</tr>
<tr>
<td></td>
<td>Kinesthetic</td>
<td>5</td>
<td>I prefer to learn by doing something that keeps me physically active while I learn.</td>
</tr>
<tr>
<td></td>
<td>Tactile</td>
<td>5</td>
<td>When I build something, I remember what I have learned better.</td>
</tr>
<tr>
<td>Social preferences</td>
<td>Group learning</td>
<td>5</td>
<td>I learn best when I work with others.</td>
</tr>
<tr>
<td></td>
<td>Individual learning</td>
<td>5</td>
<td>I learn better when I work alone.</td>
</tr>
</tbody>
</table>

3.1.3. Procedure

Participants completed all tasks in a single, 50-minute class period during their normally scheduled Spanish class. All questionnaires were administered through Qualtrics in the following order: demographic information, motivation, personality, and learning and cognitive styles. Instructions for individual instruments were presented, and items within each instrument were randomized by Qualtrics to avoid response bias. The OSPAN, which was completed last, was loaded to the individual computers. After completing the OSPAN, learners uploaded their data file to the survey for the research team.

3.1.4. Data analysis

The first research question asks how to best describe the ID variables of the present learners in the first semester of language study as well as the variability present in the sample. To answer this question, composite (mean) values were

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4 We use ID to refer to the construct, and ID variables to refer to the concrete subscales under investigation.
calculated for all scales of interest of the IDs under investigation, along with ranges and standard deviations. The descriptive statistics serve as a way to measure the variability of each ID found in the data set and further contextualize the sample. Violin plots are used for data visualization. These show the distribution of the data in a similar way to boxplots, with the addition of a density curve on both sides of the boxplot, therefore providing a clearer image of how the data is distributed. The wider the density band is, the more scores cluster at this value.

To explore the best ways of meaningfully characterizing learner IDs, and given the previous research demonstrating the potential interrelatedness of IDs, we first employed Pearson correlations between ID variables in SPSS 24 (version 24.0). Correlations are interpreted based on both the Pearson coefficient, which can be interpreted as an effect size indicator (Cohen, 1988) and on their significance level. Plonsky and Oswald (2014) have suggested that, in applied linguistics, effect sizes can be interpreted as small ($r = .25$), medium ($r = .40$), or large ($r = .60$). Afterwards, we performed a k-means cluster analysis, which has been used in previous L2 studies to identify learner profiles (e.g., Skehan, 1986). As Skehan (1986) points out, there is no straightforward approach to determining the number of clusters. The Bayes Information Criterion (BIC, Mooi & Sarstedt, 2011), generated by SPSS, can be used by examining where discontinuities occur, indicating that clusters are being “forced” together because they are the remaining clusters in the analysis, not because they are alike (Skehan, 1986).

4. Results

The first research question asked about the distribution of ID dimensions in the sample as well as the variability in ID dimensions among the learner participants. First, we present the motivation data. The descriptive statistics of the ideal and ought-to L2 selves are presented in Table 5 and Figure 1. Overall, students at this level report a weaker ideal than ought-to L2 self (3.8 versus 2.5, respectively, with integers closer to 1 indicating a stronger self), indicating that they are more motivated by external pressures than their own desires to become L2 speakers. However, a visual inspection presented in Figure 1 shows a wide distribution of ideal L2 self values, indicating considerably variability among participants. In comparison to the ideal L2 self, the ought-to L2 self shows much less variability, demonstrated by a wider band of learners clustered around 2.5. This suggests that, for these learners, the ought-to L2 self is more fully developed than the ideal L2 self.
Table 5 Descriptive statistics for the ideal and ought-to L2 selves

<table>
<thead>
<tr>
<th>Scale</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ideal L2 self</td>
<td>3.8</td>
<td>1</td>
<td>6</td>
<td>1.2</td>
</tr>
<tr>
<td>Ought-to L2 self</td>
<td>2.5</td>
<td>1</td>
<td>6</td>
<td>.9</td>
</tr>
</tbody>
</table>

Figure 1 Violin plots of ideal and ought-to L2 self scores

For personality, the results of the six scales are presented in Table 6. Given that the scale is a 5-point Likert scale, the results for all six scales cluster around the midpoint. An examination of the minimum and maximum values, however, indicates that learners responded using the entire scale. A visual inspection of the violin plots of these six variables in Figure 2 corroborates the fact that, while responses across the spectrum are found in the data, the majority of responses cluster around the middle of the scales.

Table 6 Descriptive statistics for personality

<table>
<thead>
<tr>
<th>Scale</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Honesty-humility</td>
<td>2.6</td>
<td>1.0</td>
<td>4.5</td>
<td>.6</td>
</tr>
<tr>
<td>Emotionality</td>
<td>2.7</td>
<td>1.0</td>
<td>4.8</td>
<td>.7</td>
</tr>
<tr>
<td>Extraversion-introversion</td>
<td>2.6</td>
<td>1.0</td>
<td>5.0</td>
<td>.7</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>2.8</td>
<td>1.3</td>
<td>4.4</td>
<td>.6</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>2.4</td>
<td>1.0</td>
<td>4.3</td>
<td>.6</td>
</tr>
<tr>
<td>Openness</td>
<td>2.7</td>
<td>1.1</td>
<td>4.6</td>
<td>.7</td>
</tr>
</tbody>
</table>
Figure 2 Violin plots for personality

Table 7 Descriptive statistics for field (in)dependence

<table>
<thead>
<tr>
<th>Scale</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field dependence</td>
<td>2.7</td>
<td>1.0</td>
<td>4.1</td>
<td>.6</td>
</tr>
<tr>
<td>Field independence</td>
<td>2.6</td>
<td>1.2</td>
<td>3.8</td>
<td>.5</td>
</tr>
</tbody>
</table>

Figure 3 Violin plots for field (in)dependence
The results for cognitive and learning styles are presented in three parts. First, we consider the results for field (in)dependence; we then consider the results of the different sensory preferences and, finally, the results for social preferences. As can be seen in Table 7, the mean values for both field dependence and field independence are very close, with similar minimum and maximum values, suggesting no strong differences according to cognitive style. This is confirmed with a visual inspection of Figure 3, which shows that, while there is a wide range of responses in the data, the means and density bands cluster around the middle of the scale.

The results for sensory preferences are presented in Table 8. The means for visual, auditory, and kinesthetic preferences all cluster around 2.4, while the tactile preference is slightly weaker, at 2.7, although all means are similar. The wider bands around the lower ranges of the visual preference (see Figure 4) indicate that participants mostly cluster around the lower values, which indicates a stronger overall preference.

Table 8 Descriptive statistics for sensory preferences

<table>
<thead>
<tr>
<th>Scale</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual</td>
<td>2.4</td>
<td>1.0</td>
<td>4.4</td>
<td>.5</td>
</tr>
<tr>
<td>Auditory</td>
<td>2.5</td>
<td>1.0</td>
<td>4.8</td>
<td>.6</td>
</tr>
<tr>
<td>Kinesthetic</td>
<td>2.5</td>
<td>1.0</td>
<td>4.4</td>
<td>.7</td>
</tr>
<tr>
<td>Tactile</td>
<td>2.7</td>
<td>1.0</td>
<td>5.0</td>
<td>.8</td>
</tr>
</tbody>
</table>

Figure 4 Violin plots for sensory preferences
Finally, the results for social preferences are presented in Table 9 and Figure 5. Although both scales feature the same range and similar standard deviations, the average for individual learning is lower, indicating a preference for individual over group learning. An inspection of the violin plot (see Figure 5) reveals that, for group learning, learners cluster around 3 (neutral) and seem to be distributed evenly above and below that value. Regarding individual learning, two main clusters can be observed: one around 3 (neutral) and one around 2 (agree).

**Table 9 Descriptive statistics for social preferences**

<table>
<thead>
<tr>
<th>Scale</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group learning</td>
<td>2.9</td>
<td>1.0</td>
<td>5.0</td>
<td>.9</td>
</tr>
<tr>
<td>Individual learning</td>
<td>2.5</td>
<td>1.0</td>
<td>5.0</td>
<td>.8</td>
</tr>
</tbody>
</table>

**Figure 5 Violin plots for social preferences**

Finally, the descriptive statistics for WM are presented in Table 10 and in Figure 6. With respect to the recall score, the average was 42.3 (calculated as the percentage of integers recalled correctly out of 81), with a standard deviation of 13.9. A visual inspection of the data in Figure 6 shows a wide range of scores, with most learners \(N = 242\) between 30 and 60. This suggests that the
OSPAN task is capable of distinguishing a wide range of WM abilities. The processing score, presented in Figure 6, shows much less variability, as is to be expected, given that the processing score is based on the classification of the math equations as correct or incorrect. The high average score ($M = 91.7$) indicates that learners were, overall, accurately engaged with the processing component of the task.

### Table 10 Descriptive statistics for working memory

<table>
<thead>
<tr>
<th>Scale</th>
<th>Average %</th>
<th>Minimum %</th>
<th>Maximum %</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recall</td>
<td>42.3</td>
<td>2.5</td>
<td>88.9</td>
<td>13.9</td>
</tr>
<tr>
<td>Processing</td>
<td>91.7</td>
<td>51.8</td>
<td>100</td>
<td>7.8</td>
</tr>
</tbody>
</table>

![Figure 6 Violin plots for working memory](image)

The second research question focuses on the potential relationships between IDs. Following Serafini (2017), who examined long-term interactions among ID factors at different proficiency levels, correlations were run between all ID variables to examine the degree to which they are related in the current data set. Correlograms are used to visually present the correlation and make the interpretation easier. The larger the symbol in the box, the stronger the correlation is, while the color indicates the direction of effect: blue indicates a positive correlation, while red indicates a negative one. Figure 7 presents the correlations within the data set.

For the motivational variables, the ideal and ought-to L2 selves correlate moderately with each other, while they correlate negatively with tactile and kinesthetic learning styles. The ideal L2 self has a negative correlation with extraversion and openness to experience. For learning styles, some weak correlations
emerge among the cognitive and learning style variables. For the personality variables, extraversion has a positive relationship with kinesthetic and group learning styles, while conscientiousness has a positive relationship with honesty/humility and a negative relationship with group learning and field dependence.

**Figure 7** Correlogram between ID variables

**Table 11** Results of auto-clustering

<table>
<thead>
<tr>
<th>Number of clusters</th>
<th>Bayesian Criterion (BIC)</th>
<th>BIC Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4228.946</td>
<td>-11.783</td>
</tr>
<tr>
<td>2</td>
<td>4217.163</td>
<td>34.804</td>
</tr>
<tr>
<td>3</td>
<td>4251.967</td>
<td>91.961</td>
</tr>
<tr>
<td>4</td>
<td>4343.928</td>
<td>114.831</td>
</tr>
<tr>
<td>5</td>
<td>4458.759</td>
<td>125.362</td>
</tr>
<tr>
<td>6</td>
<td>4584.121</td>
<td>134.508</td>
</tr>
<tr>
<td>7</td>
<td>4718.628</td>
<td>142.264</td>
</tr>
<tr>
<td>8</td>
<td>4860.892</td>
<td>148.070</td>
</tr>
<tr>
<td>9</td>
<td>5008.962</td>
<td>151.903</td>
</tr>
<tr>
<td>10</td>
<td>5160.864</td>
<td>160.036</td>
</tr>
<tr>
<td>11</td>
<td>5320.901</td>
<td>160.488</td>
</tr>
<tr>
<td>12</td>
<td>5481.389</td>
<td>161.116</td>
</tr>
<tr>
<td>13</td>
<td>5642.505</td>
<td>162.025</td>
</tr>
<tr>
<td>14</td>
<td>5804.530</td>
<td>165.471</td>
</tr>
<tr>
<td>15</td>
<td>5970.001</td>
<td>168.318</td>
</tr>
</tbody>
</table>
In order to explore possible learner profiles in the dataset, a k-means cluster analysis was performed. The first step was to autogenerate clusters in SPSS to obtain a list of possible clusters and their BIC. By examining the BIC change, presented in Table 11, we identified a four-cluster solution by observing the large discontinuity between five and four cluster solutions (Ledger, Ersozlu, & Fischetti, 2019). The first cluster contained 38 participants, the second 94, the third 155, and the fourth 36. Descriptive statistics on the four ID variables (distinguished in italics) and their subcomponents are presented for each cluster in Table 12.

### Table 12 Descriptive statistics by cluster

<table>
<thead>
<tr>
<th>ID variable</th>
<th>Sample</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>M</td>
<td>M</td>
<td>SD</td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>L2MSS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ideal L2 self</td>
<td>3.8</td>
<td>3.4</td>
<td>1.3</td>
<td>4.0</td>
<td>1.1</td>
</tr>
<tr>
<td>Ought-to L2 self</td>
<td>2.5</td>
<td>2.2</td>
<td>0.8</td>
<td>2.4</td>
<td>0.9</td>
</tr>
<tr>
<td>Styles</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Visual</td>
<td>2.4</td>
<td>2.5</td>
<td>0.5</td>
<td>2.4</td>
<td>0.5</td>
</tr>
<tr>
<td>Auditory</td>
<td>2.5</td>
<td>2.5</td>
<td>0.6</td>
<td>2.6</td>
<td>0.6</td>
</tr>
<tr>
<td>Tactile</td>
<td>2.5</td>
<td>2.7</td>
<td>0.8</td>
<td>2.8</td>
<td>0.8</td>
</tr>
<tr>
<td>Kinesthetic</td>
<td>2.7</td>
<td>2.5</td>
<td>0.7</td>
<td>2.5</td>
<td>0.7</td>
</tr>
<tr>
<td>Group learning</td>
<td>2.9</td>
<td>2.8</td>
<td>0.9</td>
<td>3.1</td>
<td>0.8</td>
</tr>
<tr>
<td>Individual learning</td>
<td>2.5</td>
<td>2.6</td>
<td>0.8</td>
<td>2.4</td>
<td>0.8</td>
</tr>
<tr>
<td>Field dependent</td>
<td>2.7</td>
<td>2.7</td>
<td>0.5</td>
<td>2.7</td>
<td>0.5</td>
</tr>
<tr>
<td>Field independent</td>
<td>2.6</td>
<td>2.6</td>
<td>0.4</td>
<td>2.7</td>
<td>0.5</td>
</tr>
<tr>
<td>Personality</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Honesty-humility</td>
<td>2.6</td>
<td>2.5</td>
<td>0.3</td>
<td>2.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Emotionality</td>
<td>2.7</td>
<td>2.4</td>
<td>0.6</td>
<td>2.9</td>
<td>0.7</td>
</tr>
<tr>
<td>Extraversion</td>
<td>2.6</td>
<td>2.7</td>
<td>0.7</td>
<td>2.5</td>
<td>0.7</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>2.8</td>
<td>2.8</td>
<td>0.5</td>
<td>2.7</td>
<td>0.6</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>2.4</td>
<td>2.4</td>
<td>0.5</td>
<td>2.5</td>
<td>0.6</td>
</tr>
<tr>
<td>Openness to experience</td>
<td>2.7</td>
<td>3.0</td>
<td>0.7</td>
<td>2.7</td>
<td>0.6</td>
</tr>
<tr>
<td>Working memory</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WM recall</td>
<td>42.3</td>
<td>20.4</td>
<td>8.5</td>
<td>58.0</td>
<td>8.1</td>
</tr>
<tr>
<td>WM processing</td>
<td>91.7</td>
<td>90.3</td>
<td>7.3</td>
<td>94.4</td>
<td>4.7</td>
</tr>
</tbody>
</table>

An examination of the descriptive statistics of each cluster reveals that, for most of the variables used in the analysis, there are slight differences within each. Following Skehan (1986), we present thumbnail descriptions of the four main clusters. These descriptions are reductionist, given the large number of variables, and represent an attempt to distinguish the clusters by referencing the mean values found in the sample, where appropriate, and comparing the values between the clusters. Above average in this section is a reference to the mean in the current sample, while superlatives are references to values between clusters. Field dependence and field independence show little variability between clusters and are not commented on. A summary of the thumbnail descriptions is presented in Table 13.
The first cluster is characterized by the strongest ought-to L2 self of all four clusters. Learners in this cluster have above average preferences for visual and tactile learning styles, as well as above average preferences for individual learning preferences. With respect to personality, learners in this cluster are more extraverted than the overall sample, and more open to experiences. Their scores on both recall and processing components are below average.

The second cluster is characterized by the strongest ideal L2 self. Learners in this second cluster have the highest preference for auditory, tactile, and group learning. For personality, they score highest on emotionality and have below average agreeableness scores; their WM scores are above average.

The third cluster is characterized by below average scores for both the ideal and ought-to self. Learners in this third cluster are above average on their preference for tactile learning, and they have above average preference for individual learning. Their personality results are characterized by the highest scores on extraversion. For WM, they are below average on recall measures and above average on processing.

Finally, the fourth cluster is characterized by below average score for the ideal L2 self, and an above average score for the ought-to L2 self, similar to cluster 3. Learners in this fourth cluster have the strongest preference for visual learning. In terms of personality, they have the highest score on agreeableness. For WM, they are below average on both processing and recall scores, with the lowest score on the processing measure of all four clusters.

5. Discussion

This article reports on the first semester of data from a longitudinal study designed to examine the potentially dynamic and interrelated nature of four learner individual differences.
IDs. While the larger study will examine the same cohort as they move through a language program over the course of two years, allowing an examination and characterization of different ID profiles found in the program and their relation to different activities (such as continued language study), the aim of the current paper was to explore the patterns present in the initial semester of data.

The first research question investigated the distribution of the four IDs under study: motivation, personality, learning and cognitive styles, and working memory. Overall, we observed a wide range of ID variation in our learners. We can characterize the overall student population in our dataset as having more strongly developed ought-to L2 selves, a range of personality types, as well as a range of learning and cognitive styles (despite evidence of a subgroup that prefers individual learning), and a range of WM abilities. For almost all scales, learners utilized the full range of values present, indicating that the full range of possibilities of each ID is available in the dataset.

The range of scores observed in our study for the four IDs and their subcomponents has both empirical and pedagogical implications, most particularly for our current context and longitudinal design. Despite research that has found language learners of the same language to pattern similarly in comparison to other groups (Moody, 1988), our study did not find a homogenous pattern, meaning that, empirically, it is a rich population in which to study the potential dynamic nature of IDs. As the participants advance in language study, we expect their IDs to change and to influence each other; we next aim to explore whether and how these influences can be modeled statistically and in meaningful ways. Pedagogically, variation observed among learners with respect to their IDs speaks to the importance of this language department taking into account the full range of IDs in both task and curriculum design. This is particularly relevant as previous research has found the IDs in this project to be significantly related to L2 achievement (Griffiths, 2012; Hanafiye & Afghari, 2017, Linck et al., 2014; Masgoret & Gardner, 2003). Additionally, L2 learners from this level often serve as participants in research studies, many of which do not explicitly address or account for the IDs of their participants. Any sample of this population is likely to include a wide range in scores for the ID dimensions explored. Since these IDs can all be linked with L2 learning behaviors and may result in differences in development (Skehan, 1989), care must be taken when sampling from this and all large language programs to ensure the sample reflects the variation in IDs present in the population.

In our second research question we investigated if there were discernible learner ID profiles in the data. This research question was motivated by insights from CDST research that suggests that IDs are dynamic not only through time (Gurzynski-Weiss, 2020a; Serafini, 2017, 2020), but that they also interact within individual learners (MacIntyre & Serroul, 2015). Pearson correlations showed a
number of significant relations in the dataset. Some of these patterns are rather intuitive – extraversion was positively associated with group learning and negatively associated with individual learning, indicating that more extraverted individuals prefer to learn in groups while more introverted learners prefer to learn alone. The ideal and ought-to L2 selves were negatively associated with tactile and kinesthetic preferences meaning that, in our sample, learners with these learning preferences tended to have less developed future self-guides, although future research is needed to understand the relationship between sensorial preferences and the L2MSS. Motivational self-guides are heavily dependent upon visualization and imagery (Taylor, Pham, Rivkin, & Armor, 1998), but it is not clear how sensorial preferences in learning interacts with visualization of future guides, nor what this means for L2 development. Field independence was positively associated with a preference for visual learning, while field dependence was associated with a preference for auditory learning, which is surprising given the theoretical concepts underlying the field (in)dependence dimension. Field dependent learners are thought to be highly dependent on the visual field (i.e., unable to distinguish a part from the whole), while field independent learners are more able to distinguish the part from the whole, and this distinction is assumed to “affect an individual’s whole behavior” (Dörnyei & Ryan, 2015, p. 124). However, another possibility is that a learner with a strong tendency towards field dependence may find auditory stimuli easier to process, as opposed to following a visual presentation of information (during which distinguishing different parts may be challenging). Future research is needed to better understand the relationships between these concepts and what this means for L2 development.

A k-means cluster analysis revealed four clusters of students in the sample. Admittedly, differences between clusters were very small across most ID variables. The largest differences in the current sample are found in WM, followed by L2MSS, suggesting that these variables are largely responsible for the differences. In the dynamic turn in ID research, IDs and their subcomponents are conceived of as resources, which should (a) change through the processes of L2 learning, and (b) influence each other. Given the proposed dynamic nature of the IDs in the current study, these small differences may lead to larger differences in subsequent semesters, following observation that small differences in the initial state of complex dynamic systems may lead to large differences in their development. Initial evidence of this process was provided by Serafini (2017), who showed different patterns of influence between cognitive (aptitude, working memory) and social-psychological (integrative/instrumental motivation, L2MSS) IDs at different levels of proficiency. Serafini (2017) therefore suggests that the interaction and inter-influence between learner IDs may change other over the course of the learning process, and this project is uniquely positioned to explore this question.
CDST predicts four types of relationships between learner resources: supportive, competitive, compensatory, or conditional. Supportive relationships emerge because two variables mutually, beneficially influence each other, for example, extraversion and a propensity for group learning. Competitive relationships emerge because two variables compete for limited resources, resulting in “[development] in alternating patterns (when one goes up the other goes down) because they compete with each other” (Verspoor et al., 2011, p. 86), such as, hypothetically, group and individual learning (as a preference for group learning increases, the preference for individual learning decreases and vice-versa). Conditional relationships develop when a minimal level of one resource or variable is necessary for another resource or variable to develop, for example, high levels of WM as a prerequisite for a more field independent style. Finally, compensatory relationships are ones in which a low level in one resource is compensated by high levels in another, for example, low levels of WM may be compensated by a more conscientious approach to L2 learning opportunities. It is important to stress that these relationships presuppose that resources change and develop with time – and current empirical evidence strongly suggests a continuum of dynamicity (see Gurzynski-Weiss and other papers in this issue). While some IDs may be less dynamic, more dynamic IDs may develop in predictable patterns that conspire in L2 learning.

An important, pressing question for ID research is the dynamic nature that many IDs exhibit. Their malleability through time has important implications for theory as well as research methodology. For example, if WM is shown to change with increased proficiency in the target language, theories of WM must provide some explanation for this change, and research studies incorporating the ID must also be cognizant of its variable nature and factor this into research design, analysis, and interpretation. As of now, many approaches to studying the dynamicity of IDs is similar to our own approach in taking instruments designed to measure IDs as static constructs and measuring the IDs at multiple points (e.g., Serafini, 2017). It may, instead, be necessary to develop new research methodology to study different timescales (e.g., MacIntyre & Legatto, 2011). Additionally, analyzing multiple IDs in the same study (e.g., Piniel & Csizér, 2014) addresses calls in the literature to examine how different IDs interact with each other as well as with the learning environment (Dörnyei, 2009). A longitudinal study like the one described here has the potential to address this issue by following a cohort of language learners through their first two years of study, and examining the dynamicity of each ID individually as well as how IDs influence each other at each time point and over time.

6. Future directions

This preliminary analysis was successful in identifying possible areas for future research into how different IDs interact over the course of L2 development. Following
Serafini (2017), the macro-approach taken in this study, which will span two years of language study at the end of the project, complements the micro-approach being taken elsewhere to investigate IDs over small timescales (Serafini, this issue). de Bot (2015b) proposed that different timescales capture different aspects of the dynamics of IDs, and that timescales interact. While the research into micro-approaches will allow for a fine-grained look at the nature of dynamics, a macro-perspective allows us to identify possible points of influence between IDs as experience increases, highlighting avenues for future research between these well-known and well-researched ID variables.

In subsequent semesters, the cohort considered here were/will be followed through their progress in the language program. That is, in Spring 2019 all available sections of third semester Spanish participated in the research project, and in Fall 2019 all sections of fourth semester Spanish participated. Although some students will enter and leave the cohort every semester, a core group is present at all data collection times, which will allow for an examination of how their IDs change over time and with increased proficiency. This will allow the project at its conclusion to shed light on current, important theoretical issues in the field – how dynamic IDs are and how they influence each other over time.

7. Conclusion

This paper presents an initial semester of data that examines four learner IDs from introductory levels of Spanish. This data shows that the four IDs considered here (motivation, personality, learning and cognitive styles, and working memory) demonstrate considerable variability in the sample, and learner profiles, distinguished most strongly with respect to WM and the L2MSS, did emerge.

The larger research project allows for the continued analysis of the subset of students who complete two years of language study in the same span as the research study took place. The analysis of this group will allow for an examination of how learners’ IDs change over time and with increased proficiency in the target language, an enterprise that has great theoretical potential. The study will also explore how dynamic IDs relate to and influence each other, and how these relationships may change over time. Future research will be able to examine patterns of success and continuation in the language program, which may ultimately assist program directors and curriculum designers.

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Tracking the dynamic nature of learner individual differences: Initial results from a longitudinal study

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