Archival Perspective on Daily Multi-Context Individual Differences Measurement

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Abstract

With the development of psychometric theories and methods, the context-dependency inherent to individual differences is receiving widespread attention. To achieve comprehensive and accurate measurement of individual differences and promote optimal development of individuals and society, researchers have increasingly emphasized measuring individual states across multiple authentic daily contexts and constructing computational models of individual differences, thereby attaining more comprehensive and objective measurement than traditional laboratory settings. Currently, technological advances epitomized by intelligent sensing and wearable devices have rendered the measurement of individual differences in daily life more convenient and efficient, driving new advances in daily multi-context individual differences research encompassing subjective reports, behavioral performance, physiological responses, and other dimensions, and giving rise to person-centered profile perspective analysis concepts and methods oriented toward high-dimensional data from daily multi-contexts. Future research should focus on integrating daily multi-context measurement with profile perspective analysis methods to promote deeper understanding of the mechanisms underlying individual differences and advance the theoretical development of individual differences.

Full Text

A Profile-Perspective on Daily-life Multi-Situational Individual Differences Assessment

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Abstract

As psychometric theories and methods continue to evolve, the situation-dependence of individual differences is receiving increasing attention. To achieve comprehensive and accurate measurement of individual differences and promote optimal development at both personal and societal levels, researchers have increasingly emphasized measuring individual states across diverse real-life daily situations and constructing computational models of individual differences. This approach aims to provide more comprehensive and objective measurement compared to traditional laboratory settings. Recent technological advances, particularly intelligent sensing and wearable devices, have made daily-life measurement of individual differences more convenient and efficient, driving new progress in multi-situational research on individual differences encompassing subjective reports, behavioral performance, and physiological responses. This has led to the development of person-centered profile-perspective analytical frameworks and methods for high-dimensional data from daily multi-situational studies. Future research should focus on integrating daily multi-situational measurement with profile-perspective analytical methods to deepen understanding of the mechanisms underlying individual differences and advance the theoretical development of individual differences research.

Keywords: Daily-life situation, multi-situation, individual difference, profile perspective, psychological assessment

Individual differences represent a classic research topic in psychological assessment, focusing on systematic distinctions among individuals across emotional experience, cognitive abilities, behavioral patterns, and other dimensions (Lubinski, 2000; Bauer, 2011), with significant applied value. At the individual level, enhanced understanding of individual differences can optimize behavioral strategies regarding emotional health and cognitive performance, thereby promoting mental health and subjective well-being (Fossati, 2013; Antoine et al., 2018). At the societal level, applications such as precise selection of occupational populations, employment recommendations and training, and mental health screening depend on comprehensive knowledge of individuals' cognitive abilities and other characteristics (Patel et al., 2023).

The classical view of individual differences measurement posits that personalized features can be described through consistent, stable patterns exhibited by individuals in social, emotional, and other domains (Allport & Odbert, 1936). Based on this perspective, personality psychologists have proposed numerous classic trait theories to quantitatively describe individual differences. For instance, Eysenck's personality theory suggests that individual differences can be abstractly summarized through three dimensions: neuroticism, extraversion, and psychoticism (Eysenck & Eysenck, 1969); MBTI theory describes people's trait types through 16 personality types constructed from four dimensions of energy allocation, cognitive style, judgment style, and lifestyle (Myers, 1962);

and the Big Five personality trait theory assesses individual differences through five dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism (Fiske, 1949; Tupes & Christal, 1961; Costa & McCrae, 1992). These theories typically employ retrospective self-report or other-report questionnaires, measuring individual differences through cross-situational aggregate ratings of individuals' performance in specific domains.

As research on individual performance across different situations has deepened, an increasing number of studies have demonstrated that performance patterns exhibit situation-dependence, challenging traditional perspectives and fueling long-standing debates about the relative dominance of person versus situation in personality psychology (Epstein & O'Brien, 1985; Hogan, 2009; Fleeson & Noftle, 2008). Notably, trait-state measurements conducted in daily-life contexts have shown that within-person variance across multiple situations for Big Five personality states is comparable to between-person variance (Fleeson, 2001; Furr & Funder, 2021), highlighting the potential importance of the richness of daily-life situations for exploring individual differences.

Over the past 30 years, research on individual differences grounded in daily-life situations has increased rapidly year by year and now comprises a growing proportion of the individual differences research field (as shown in Figure 1 [Figure 1: see original paper]), with more researchers focusing on differentiated individual performance in real-life contexts. This paper examines the developmental trends and cutting-edge developments in daily-life individual differences research, reviewing the definition, classification, and basic characteristics of daily-life situations. We synthesize progress in daily multi-situational individual differences research based on subjective reports, behavioral performance, and physiological responses, and summarize the profile-perspective concepts and methods developed for analyzing rich daily-life individual differences data.

[Figure 1: see original paper] Number and proportion of daily-life situation-related studies in individual differences (personality trait) research (Web of Science search, keywords: (personality OR trait) AND (daily OR real life))

2.1 Definition and Classification of Situations

Situations typically refer to brief and dynamic events occurring outside the individual (Rauthmann & Sherman, 2021). This ambiguous definition has led to various debates regarding situation measurement (Skimina & Cieciuch, 2020). Specifically, depending on whether situation measurement relies more on objective physical cues or subjective psychological features, measurement approaches can be divided into two major categories: objective and subjective measurement. Objective measurement approaches posit that situations are constituted by objective environmental elements, with information existing based on group consensus and independent of individual observers (Krahé, 1991). In early life-tracking studies, researchers measured situations by observing subjects' daily life trajectories, recording locations and life events such as clothing and school attendance (Barker & Wright, 1951). More recent studies have begun using wearable cameras to capture snapshots of life scenes at fixed intervals to collect information about situational changes (Brown et al., 2017), providing powerful tools for situation measurement. In contrast, subjective measurement approaches argue that situations are subjectively constructed by research participants after perceiving the environment (Yang et al., 2009; Funder, 2016), requiring integration with past experiences and existing knowledge in the perceiver's brain, and thus differ across individuals. Subjective measurement typically assesses situational information through self-reports, requiring active participation from research participants.

Once the definition of situations is clarified, situational information can be operationalized to measure situations. Rauthmann et al. (2015) propose that situational information can be divided into different levels: Cues, Characteristics, and Classes. Situational cues refer to quantifiable objective physical stimuli in the environment, describing situational-dependent environmental components such as time, location, and people (Mehl & Robbins, 2012; Saucier et al., 2007). Situational characteristics refer to internal psychological representations obtained after perceiving physical cues, which can be summarized into multiple dimensions such as duty and sociality to facilitate assessment of situational features (Rauthmann et al., 2014). These dimensions are similar to major dimensions of personality, further reflecting the intrinsic association between personality and situation concepts. Situational classes involve abstract classification of situations based on similar cues or characteristics, a process that often requires extracting relatively independent physical or psychological dimensions. For example, van Heck's (1984) ten-dimensional classification system and a motivation-based classification method (Morse et al., 2015) have considerable influence and serve as common tools for classifying situations using situational information.

Overall, these two measurement approaches have distinct features but also 各自的潜在局限. For instance, objective methods cannot ensure that subjects perceive objective cues as intended by the experiment and form corresponding psychological representations, while subjective methods require subjects to understand dimensions of situational characteristics, placing demands on participants' cognitive levels. Therefore, appropriate situational measurement methods should be selected based on practical application needs.

2.2 Definition and Classification of Daily-life Situations

Observing daily-life situations is of significant importance in individual differences research. First, not all situations can be adequately simulated in laboratory environments. The high ecological validity of daily-life research holds unique value—for example, laboratory-simulated stress situations may be far less effective than real-life stressful experiences (Wilhelm & Grossman, 2010), and emotional experiences in real-life contexts may produce peripheral physiological change patterns quite different from laboratory findings (Picard et al., 2016). Second, daily life can provide more abundant within-person longitudinal data, capturing higher ecological validity of individuals' multi-situational performance to investigate the situation-dependence of individual differences (Mõttus et al., 2017).

Although daily-life situations are complex and multifaceted, with overlapping and dynamically changing situational information (Hasson & Jalili, 2019; Huff & Papenmeier, 2017), measuring daily-life situations can still follow the hierarchical structure described in the previous section. Subjective measurement approaches assess the perception dimension of situations by evaluating individuals' psychological representations through questionnaires to obtain situational characteristics (Rauthmann et al., 2015). Common methods for measuring individual situational perception include: the "DIAMONDS" measurement, encompassing eight dimensions of duty, intellect, adversity, mating, positivity, negativity, deception, and sociality (Rauthmann et al., 2014); "CAPTION," which proposes more concise dimensions including typicality and humor (Parrigon et al., 2017); and recent research that further integrates dimensions from both "DIAMONDS" and "CAPTION" to construct a more comprehensive ten-dimensional situational perception measurement (Rauthmann et al., 2020).

Objective measurement approaches involve detecting situational cues—quantifiable physical stimuli or events in life scenes. One common strategy measures physical signals in the environment, including changes in environmental features such as light and sound. For example, driving situations have been classified based on video images (David et al., 2019), and hazardous situations have been identified using integrated information (Arriaga et al., 2017). Another strategy uses subjects' own physiological arousal as a basis for situation classification, including movement and peripheral physiological changes. For instance, classroom situations have been classified using students' movement patterns (Kotakehara et al., 2019), and daily-life situations have been segmented using physiological events that trigger changes in heart rate and movement states (Hoemann et al., 2020; van Halem et al., 2020). Overall, objective measurement of daily-life situations is increasingly adopting convenient and efficient technological means, with a growing number of environmental sensors enabling faster and more diversified acquisition of situational cues. Combined with more advanced situation classification algorithms, this facilitates automated and efficient situation measurement to serve multi-situational individual differences assessment.

2.3 Situation-Dependence of Individual Performance in Daily-life Situations

In the Cognitive-Affective Personality System (CAPS) model, personality psychologists propose that personality traits consist of different cognitive-affective units whose effects vary depending on situational changes, eliciting specific behavioral performances (Mischel & Shoda, 1995). These individual performances exhibit between-situation variability and within-situation stability (Shoda et al., 1994). In his classic research, Fleeson noted that although traditional personality trait measurement can describe average levels of individual differences, it fails to reflect situation-specific individual performance in daily life. In his subsequent Whole Trait Theory, he proposed that describing individual traits should involve measuring the distribution of personality states across different daily situations, and that explaining the causes of individual traits also requires considering environmental events and individuals' understanding of situations from a social-cognitive perspective (Fleeson, 2004).

However, despite widespread acceptance that situational factors cause dynamic within-person performance, how to measure situation-specific individual performance remains challenging. According to existing theories, only by combining multiple daily situations can the distribution of personality states be described completely and without bias, making multi-situation methods essential in individual differences research. Nevertheless, even when situation classification can be accomplished in daily-life research, the multi-variable structure introduced by multiple situations poses analytical challenges. For example, various interaction relationships between situational and individual variables can make modeling methods complex and variable (Kuper et al., 2023). Additionally, due to heterogeneity across different populations, analytical models constructed based on data from partial groups may not generalize well to other subgroups (Yin et al., 2021). Therefore, it is necessary to construct effective multi-situation analytical methods for daily-life individual differences measurement.

3 A Profile-Perspective on Multi-Situational Individual Differences Measurement

To date, most research on individual differences has employed variable-centered approaches such as correlation, regression, and factor analysis. These methods are suitable for classifying and predicting individual traits but are based on the assumption of population homogeneity—that is, the regularity of associations between variables is consistent across individuals (Yin et al., 2021). This assumption, however, limits the measurement of individual differences across different latent subgroups. To accurately measure situation-dependent individual performance, profile-perspective research is gaining attention in personality psychology (Favini et al., 2018).

The core of the profile perspective is its person-centered approach, which posits that different latent subgroups exist within a population. By observing individuals' multi-dimensional overall performance, those with similar patterns can be grouped into the same category to investigate population-level patterns of individual differences. The profile perspective views individuals as dynamic systems composed of multiple situations (Bergman & Trost, 2006; Bergman & Wångby, 2014), enabling researchers to analyze individual differences from a holistic perspective. When measuring multi-situation individual differences, based on the principle that individual performance differs between situations but remains stable within the same situation (Shoda et al., 1994), the profile perspective can incorporate multi-dimensional individual performance and their interrelationships and dependency patterns into the measurement of individual differences, achieving an effect where the whole is greater than the sum of its parts (Shaw et al., 2020).

Currently, profile-perspective research on individual differences has begun to take shape. For example, focusing on multi-situational indicators of emotional experience and cognitive ability, researchers have proposed individual psychological profiles based on behavioral and physiological dimensions (Hu X. et al., 2022; Dawes et al., 2022), which can effectively predict classic individual difference indicators such as emotional complexity and Big Five personality, demonstrating the potential of the profile perspective for understanding individual differences in human emotion and cognition. More extensive and in-depth individual difference profile research has further developed these methods in terms of situation classification approaches and individual performance measurement methods. The following sections introduce relevant research progress on multi-situational individual difference profiles from the dimensions of subjective reports, behavioral performance, and physiological responses.

[Figure 2: see original paper] Daily-life multi-situational individual differences measurement

3.1 Multi-Situational Self-Report Profiles

Self-report profiles refer to the analysis of individual differences in subjective reports from a profile perspective. Early common types of self-report profiles were personality profiles. For example, based on individuals' self-reported cognitive-affective characteristics, researchers empirically distinguished three replicable personality types: resilient, overcontrolled, and undercontrolled (Robins et al., 1996). These three personality types exhibit distinct daily performance patterns and show conceptual consistency with Big Five personality, self-recovery ability, and self-control ability. Subjective report results, including personality characteristics, are situation-dependent, with contextual situations influencing emotional experience, stress states, and other aspects (Katie et al., 2020). For instance, among occupational populations, personality influences job performance differently across various work situations (Wood et al., 2019); the Situated Five personality questionnaire, which enhances situational perception features based on the Big Five, demonstrates better performance than the Big Five in reflecting specific dimensions such as occupational engagement (Ziegler et al., 2019).

Obtaining subjective reports in daily-life situations can be traced back to diary methods and telephone interviews from the last century, which often yielded small-scale, low-frequency, fragmented information. With the promotion of intelligent terminals, collection limitations have been overcome, leading to methodological iterations. Experience sampling methods, including momentary assessment, have enabled measurement across larger populations and more daily situations (Schneider, 2008), using smartphone platforms to push brief contextualized questionnaires multiple times daily to track individual subjective reports longitudinally, showing good application potential. Specifically, the Day Reconstruction Method can obtain subjective experiences similar to experience sampling through daily retrospective reconstruction reports (Kahneman et al., 2004) and similar within-person associations of subjective variables (Han et al., 2019), further reducing intrusion into users' lives and making it suitable for diverse populations and broader life scenarios where immediate phone response is inconvenient (e.g., production line workers, students in class).

Although subjective reports remain the primary means of assessing individual psychological states, multiple limitations must be noted. First are situational constraints: not all daily scenes are suitable for subjective report measurement. For example, requiring research participants to complete questionnaires in situations where distraction is difficult (work, meetings, classrooms) is often impractical (though the Day Reconstruction Method can partially alleviate this problem). Second are population constraints: participants' cognitive levels significantly affect questionnaire results; groups such as young children or elderly individuals with cognitive impairments may not correctly understand and complete questionnaire content. Finally, there are application direction constraints: subjective report results are influenced by social desirability factors, which may be particularly pronounced in contexts involving occupational selection and social evaluation (Caputo, 2017). To overcome these limitations and achieve broad individual differences measurement, it is necessary to incorporate richer objective data dimensions to construct individual difference profiles.

3.2 Multi-Situational Behavioral Profiles

Behavioral profiles originated from multi-task measurement in laboratories and have a long history. Researchers measure systematic individual behavioral differences by conducting behavioral tests, encoding experimental tasks, and recording participants' task performance (Baker et al., 1969; Boogert et al., 2018). As behavioral testing has developed and improved, experimental paradigms have expanded from single tasks to comprehensive multi-task measurements. For example, multi-task methods have gradually replaced single tasks in distinguishing individual cognitive styles (Roehr-Brackin et al., 2021). Compared to single tasks that only cover single dimensions such as memory and visual attention (Adolphe et al., 2022), multi-task methods can be combined to cover multiple aspects including auditory, language, and logical reasoning (Steyvers & Schafer, 2020; Soreq et al., 2021). This multi-task combination approach (test battery) for measuring domain-specific individual differences has been continuously validated in many fields such as child cognitive development and cognitive aging, ultimately forming profile-based measurement methods and constructing "behavioral profiles" that reflect individual cognitive abilities.

This trend toward laboratory-based multi-task measurement can be considered a compromise and simplification of daily multi-situations or multi-scenes. As previously mentioned, laboratory and real-life scenes have numerous differences, making daily measurement critically important. Therefore, some behavioral profile research in recent years has begun selecting more naturalistic settings, such as completing cognitive measurement through gamified behavioral tasks (Landers et al., 2022; Leutner et al., 2022).

Observing online behavior is an important approach for studying daily behavioral profiles that has gained considerable attention recently. By tracking over 70,000 subjects' liking behaviors toward different targets on social software, researchers found they could significantly predict individual differences including Big Five personality, with average accuracy (r = 0.56) exceeding ratings made by friends (Wu et al., 2015). Subsequent meta-analyses confirmed that digital footprints from social media have personality prediction efficacy comparable to daily behavioral performance (Azucar et al., 2018), representing a reliable information source for predicting individual personality traits. Additionally, by analyzing aggregated large-sample data, online behavior can accurately predict a series of specific individual attributes such as sexual orientation, intelligence, and well-being (Kosinski et al., 2013). Overall, online behavioral data offer advantages of large scale, wide distribution, and easy acquisition, while demonstrating high individual prediction efficacy, making them an effective means of observing daily behavioral profiles.

3.3 Multi-Situational Physiological Profiles

Physiological profiles analyze physiological changes across different situations to measure individual differences. Compared to other measurement methods, physiological measurement is less susceptible to subjective interference from measurement objects, yielding more objective results. Physiological measurement requires low participant cooperation and engagement, making continuous long-term monitoring of individual states more practically feasible. The decreasing cost of wearable devices is facilitating the scaling of physiological data collection and computation, giving physiological profiles unique advantages in large-sample longitudinal tracking in daily life. Furthermore, physiological measurement does not depend on participants' cognitive levels, showing better applicability for groups such as children and elderly individuals. Therefore, constructing daily multi-situational physiological response profiles can compensate for limitations of existing subjective and behavioral profiles and better leverage the advantages of daily measurement. In this context, the trend of daily multi-situational physiological profile research is gradually emerging.

Physiological profiles can be traced back to individual differences measurement in resting-state physiological responses. For example, resting-state peripheral physiological system activity can reflect individual difference attributes such as gender and physical condition, with latent profile analysis showing that subjects can be classified into five independent physiological profile categories (Kupper et al., 2021; Liu et al., 2021). The Adolescent Brain Cognitive Development (ABCD) study, a large-scale dataset of 10-year resting-state brain imaging tracking of 12,000 U.S. adolescents, provides a landmark reference for exploring neuro-mechanisms of individualized cognitive development (Karcher & Barch, 2021; Lisdahl et al., 2018).

As research has progressed, physiological profile studies have increasingly focused on task-based physiological responses. For example, peripheral physiological responses under stress tasks can effectively reflect individual physical and mental health levels (Cohen & Hamrick, 2003); personality assessment methods based on emotional EEG responses can objectively and effectively reflect real individual differences in Big Five personality (Li et al., 2020; Li et al., 2022); and individual physiological differences in sensitivity to light intensity across different environments are closely related to individual performance such as sleep and circadian rhythms (Spitschan & Santhi, 2022). However, traditional studies typically adopt single situations during experiments, such as watching videos, reading text, or playing games (Hu X., Wang, et al., 2022; Li et al., 2020). Multi-situation approaches are expected to further improve the accuracy and robustness of individual differences measurement (Ahmet et al., 2017; Mehta et al., 2020), advancing relevant individual measurement research toward application.

In recent years, daily-life physiological measurement research has continuously developed, with relevant physiological datasets being established (Shui et al., 2021), and methods for measuring individual differences based on daily physiological responses receiving more attention. Researchers have found that in various daily situations such as video learning and visual games, subjects' physiological signals including heart rate and skin conductance are associated with multiple personality dimensions including extraversion and agreeableness (Chun-Hsiung et al., 2022; Darzi et al., 2019), demonstrating the feasibility of individual differences measurement in daily-life situations. Further research has preliminarily explored applications of daily multi-situational individual measurement in student populations with fixed daily schedules. By using these students' fixed schedules for situation classification and extracting heart rate features from different situations to construct multi-situational prediction models, the study found that individual heart rate features could effectively reflect personality traits across multiple dimensions including extraversion and neuroticism, while no significant associations between single-situation heart rate features and personality were found (Shui et al., 2023). This finding provides positive empirical support for constructing multi-situational physiological profiles in daily-life contexts.

Additionally, physical activity intensity represents a physiological dimension with measurement convenience and analytical value in this domain. Activity intensity shows numerous associations with individual difference variables; for example, significant positive correlations exist between walking exercise intensity and emotional health and well-being (Hallam et al., 2018; Zhu et al., 2020). Using accelerometers to measure daily circadian rhythms, research has found that fragmentation and irregularity of activity rhythms are associated with worsening indicators of depressive symptoms (Smagula et al., 2022). Particularly, identifying depression-related physiological response markers in individuals' daily-life situations is of great significance, as it can provide more interpretable intermediate evidence for clinical and subclinical diagnosis and treatment of mental disorders (Friend et al., 2023), thereby offering an important clinical demand-driven direction for the development of individual difference physiological profiles (Leuchter et al., 2014; Leventhal et al., 2008).

Overall, individual differences measurement based on physiological profiles has unique advantages. The multi-situation approach under the profile perspective, compared to traditional single-task/single-situation methods, can portray more complete distributions of individual states to achieve more accurate individual differences measurement, thereby providing effective individual information in fields such as occupational selection, mental health, and mental disorder screening with broad application value. Meanwhile, questions such as how to model and interpret high-dimensional physiological features from multiple physiological systems and how to understand the potentially many-to-many complex mapping relationships between profile data and psychological traits require researchers to explore appropriate analytical methods to objectively and comprehensively identify intrinsic associations between physiological profiles and individual variables.

4 Analytical Methods for Daily-life Individual Differences from a Profile Perspective

At the operational level, conducting individual differences analysis in daily-life contexts requires appropriate modeling methods. Compared to traditional approaches, profile-perspective assessment methods often involve significant shifts in analytical thinking, brought about by the transition from variable-centered to person-centered perspectives. In contrast, traditional analytical methods typically extract individuals' feature variables empirically, using variables or inter-variable relationships as metrics of individual differences. However, such methods struggle to explain relationships among three or more interacting variables and cannot effectively model high-dimensional inter-variable relationships including neurophysiological signals (Lanza et al., 2003; Merz & Roesch, 2011). To address these issues, current mainstream individual profile analytical methods include structural equation models, representational similarity methods, and machine learning approaches, which are introduced below.

4.1 Structural Equation Modeling Family

To describe complex interactions among multiple daily-life variables, researchers can use structural equation models (SEM) and their derivatives to model and interpret daily data. SEM is a multivariate analysis method based on variable covariance matrices. Unlike traditional regression analysis, SEM can handle multiple dependent variables within models and evaluate theoretical model relationships such as moderation and mediation among variables, making it more applicable to the multi-variable structure formed by daily multi-situation measurement. Additionally, in daily-life situation measurement, besides directly observable variables, there may be individual characteristics that are difficult to measure directly, such as living standards and diversity of daily experiences. SEM can address this by setting latent variables for modeling and quantification. In latent variable models, researchers can specify particular factor structures for computational testing, giving this method higher scalability compared to traditional exploratory factor analysis. As a classic variable relationship model, SEM has had extensive influence in social psychology. For example, Rauthmann (2021) constructed a general Person-Environment Relations Model (PERM), summarizing how to examine the influence of situational factors on individual behavior under different data structures. When studying personality-situation interactions, personality psychologists have proposed various interaction models under variable conditions to describe potential dependency relationships between personality and situations, with basic model structures changing as relationships among personality, environment, and state variables change (Kuper et al., 2023).

For the person-centered profile research perspective, SEM also has scalable practical value. For example, the profile perspective holds that individual differences arise from differences in holistic-level features, influenced jointly by subcomponents such as behavior and physiology across different situations. In SEM, latent variables and observed variables also have one-to-many influence relationships, with the former being abstract summaries of the latter in statistical models. This similarity makes it practical to use latent variable relationship models to describe intrinsic connections among subgroups in profile-perspective research, and complete statistical tools have already been developed. Specifically, depending on whether observed and latent variables are categorical or continuous, different statistical methods have been derived, including Latent Class Analysis (LCA) and Latent Profile Analysis (LPA) (温忠麟 et al., 2023). LCA explains associations among categorical observed variables through the number of latent categories, classifying latent categories based on individuals' response patterns across different items to achieve local independence through between-group heterogeneity and within-group homogeneity. LPA is an extension of LCA to continuous observed variables (侯艳天 et al., 2022). These statistical methods are widely used in individual profile research in daily-life situations, covering occupational behavior, mental health, anxiety levels, and many other aspects (Petersen et al., 2019; Liu et al., 2022; Spurk et al., 2020).

It should be noted that daily-life measurement data typically contain rich longitudinal structures; for example, dynamic characteristics such as emotional inertia and emotional variability are also important indicators reflecting individual differences (Kuppens & Verduyn, 2017). Although basic SEM can handle complex multi-variable modeling, it is not inherently adept at 挖掘纵向测量数据中隐含的动态信息. To examine temporal variation patterns in daily data, researchers can use different SEM variants to analyze and interpret patterns in the data. One such method is multilevel structural equation modeling, which combines SEM with multilevel models to capture dynamic relationships between repeated measurement data and time variables (Hox, 2013). Multilevel models can separate multiple levels of variable information including between-person and within-person variation, and have broad applications in analyzing longitudinal data. One survey found that nearly half of studies investigating within-person variability in personality traits over recent decades used multilevel modeling (Ness et al., 2021). In recent years, multilevel SEM has gradually gained attention in individual assessment, educational research, and cultural studies, with its good generalizability promoting widespread use (Hall & Malmberg, 2020; Neubauer et al., 2023).

Additionally, dynamic structural equation models can analyze temporal dynamic patterns of individual states (Asparouhov et al., 2018). Currently, dynamic SEM-based analytical methods are receiving increasing attention when assessing dynamic patterns of individual difference variables such as anxiety and depression levels (Brose et al., 2022; Bond & Wickham, 2023). These models are variants combining SEM with time series models. By incorporating time variables as factors influencing individual state changes, they enable quantitative analysis of interaction effects across time points, such as the influence of previous moments on subsequent states (e.g., emotional inertia mentioned earlier). Long-term measurement based on daily life precisely brings more complete data structures with temporal significance (date, weekday, time of day, etc.), giving this method broad application space when facing data structures obtained from daily measurement.

4.2 Representational Similarity Methods

Traditional methods for computing daily-life individual differences typically rely on empirical indicator systems that require pre-assumed relationships among factors or latent variables. Consequently, when facing complex variable conditions, more complex network models must be constructed, greatly increasing modeling and model validation complexity. In recent years, emerging multivariate analysis methods such as Representational Similarity Analysis (RSA) can partially avoid complex model limitations by refocusing attention on association patterns among multiple variables. RSA was formally proposed by neuroscience researchers to measure within-person associations among multidimensional variables (Kriegeskorte et al., 2008), and was further developed for individual differences research into Inter-Subject Representation Similarity Analysis (IS-RSA). IS-RSA combines features of inter-subject consistency analysis (Hasson et al., 2004) and RSA. Specifically, it quantifies between-person distances or similarities in behavioral or neurophysiological dimensions based on inter-subject consistency to form between-person distance matrices under single dimensions, then calculates second-order similarity between distance matrices from different dimensions.

Due to these characteristics, RSA has attracted attention in psychological research. In cognitive studies, researchers have used RSA to investigate individual differences in language-level representations in bilinguals' brains (Nichols et al., 2021). In emotion research, researchers have used this method to explore the degree of similarity in brain response patterns among individuals with similar sociosexual orientation and self-control preferences when watching movie clips (Chen et al., 2020). Emotion profile research has further calculated correlations between behavioral indicator inter-subject distances and EEG analysis indicator inter-subject distances, using RSA to analyze behavior-physiology correlation patterns to interpret neural mechanisms of individual differences in emotion (Hu X. et al., 2022).

Overall, the inter-subject RSA method has advantages in analyzing complex data. It can 挖掘个体表现模式 in high-dimensional feature spaces with relatively lightweight model loads (Finn et al., 2020). Individual daily multi-situation measurement data typically have complex high-dimensional structures, and physiological measurement data including neural signals are usually multi-channel high-dimensional data. Therefore, RSA is suitable for discovering individual difference patterns in daily data. Another advantage of RSA is its compatibility across analytical levels—the method is not limited to neuroscience research but can be flexibly used between any data modalities. Thus, in daily-life individual differences measurement, this method can be used to analyze inter-subject distances across multiple situations to form individual profiles in different dimensions, and can also explore more patterns among multi-dimensional individual profiles through second-order associations between profiles.

4.3 Machine Learning Recognition Methods

The above methods are primarily grounded in psychological theory and serve the exploration of individual difference theoretical mechanisms. However, apart from pursuing interpretability, machine learning is receiving increasing attention from the perspective of individual differences measurement performance, giving rise to emerging fields such as personality computing (Phan & Rauthmann, 2021). When facing complex relationships among daily multi-situation variables and high-dimensional features brought by different data dimensions, machine learning methods can efficiently and adaptively identify potential connections among variables to complete recognition and classification of individual difference features without relying on additional theoretical assumptions (Alexander et al., 2020). Current research in personality computing has begun to extensively focus on individual states obtained from portable devices, including diverse data sources such as handwritten text, smartphone usage, nonverbal behavior, language patterns, and gaming behavior (Ilmini & Fernando, 2017; Stachl et al., 2020a, 2020b; Vinciarelli & Mohammadi, 2014). Related research primarily proceeds from application, using machine learning methods to 挖掘隐藏的个体差异模式 in collected data to achieve quantitative assessment of individual variables, such as prediction models built for individual trait recognition in autism screening and mental health (侯婷婷 et al., 2022; Lyu et al., 2024). Additionally, feature weights or contributions in machine learning models can also support understanding of profile mechanisms. For example, a personality computing study based on natural text explored stable key features across datasets by ablating a certain proportion of input features each time (Berggren et al., 2024). This method is expected to promote in-depth analysis of high-dimensional features of individual profiles and provide important support for building generalizable models.

Current machine learning methods used in individual differences measurement need to consider characteristics such as sample size, feature dimensions, and requirements for model interpretability. Low-dimensional machine learning algorithms have simple model structures, high generalizability and interpretability, and are suitable for situations with small sample sizes or low feature dimensions. For example, when computing personality traits based on task-state EEG features, ridge regression can identify associations between high-dimensional physiological features and psychological traits (Li et al., 2020; Li et al., 2022). In analyzing social software online behavior and personality computing, researchers have used logistic regression to predict Big Five personality and other individual indicators such as life satisfaction (Wu et al., 2015). High-dimensional models including neural networks are suitable for finding association patterns in large-sample, high-dimensional feature datasets. For example, in research on the child cognitive development brain imaging dataset ABCD, researchers used neural network models to conduct targeted analysis of the data's high-dimensional structure to achieve effective prediction of individual differences such as gender (Bi et al., 2022). Neural network models have also made a series of advances in dynamic modeling of individual traits, learning personality features from social interactions and natural language corpora to predict subsequent behavior patterns (Gonzalez-Heydrich et al., 1993; Read et al., 2010; Adorni, 2023).

Overall, machine learning algorithms have been widely used in personality computing and other fields. Although the "black box" structure and end-to-end training methods of neural network models make model interpretability controversial (Zhang et al., 2021; Kar et al., 2022), as researchers continue to develop original model structures, including interpretable neural network models (Sheu, 2020), machine learning methods have considerable application potential in individual differences measurement.

5 Research Trends and Future Directions in Daily-life Individual Differences

Reviewing individual differences measurement methods, daily multi-situation assessment approaches have unique value and potential. Overall, as theoretical discoveries in individual differences gradually deepen, cutting-edge research demonstrates two major characteristics: first, the shift from laboratory scenes to daily life, which has gradually developed a relatively complete set of research methods. This trend aims not only to better study the dynamics of individual differences across multiple situations but also represents the source and development direction of individual differences research. Second, to adapt to the characteristics of daily measurement, measurement methods strive to reduce additional burden on experimental subjects (e.g., shortening questionnaire length, streamlining assessment procedures) and gradually shift toward daily measurement methods with advantages in long-term, low-burden measurement. These two research directions jointly point to one goal: constructing daily assessment of individual differences should be combined with low-cost, high-efficiency daily measurement methods.

Multi-situational individual difference profiles can also be used simultaneously and complement each other. Individual differences are typically manifested across multiple dimensions including subjective experience, behavioral performance, and physiological responses. To comprehensively reflect individual differences, profiles from different dimensions can be combined. For example, emotion individual difference profiles can measure not only self-reported emotional experience but also be constructed based on physiological response profiles. Multi-dimensional measurement expands the description of individual emotion profiles (Hu X. et al., 2022). Meanwhile, within the same dimension, multi-dimensional integration can also be performed. For example, physiological profile research uses combinations of multiple physiological signal modalities to describe individual differences in physiological changes (Fu et al., 2022). This internal integration can also expand the measurement dimensions of individual differences, enabling different individual profiles to be measured synchronously and cooperate with each other, integrating their respective measurement advantages into a more holistic individual profile to serve the goal of accurate and comprehensive individual differences measurement.

Although the individual differences research field is expected to achieve new breakthroughs on broader, more comprehensive, and more daily scales through technological and methodological advances, several issues warrant consideration by future researchers.

5.1 Mechanisms Underlying Daily-life Individual Differences

What internal factors produce daily-life individual differences, and how they are influenced by situations, remain important questions of interest to researchers. In social-cognitive models, personality psychologists believe that the situation-dependence of individual differences encompasses multiple social-cognitive processes: interpretation processes representing cognition and information processing, motivational processes driving individuals, and stable induction processes guiding typical trait expression (Fleeson & Jayawickreme, 2015). These processes originate from environmental or internal events and ultimately cause stable individual difference performance. From a social-cognitive process perspective, factors such as emotion and cognition may exert potential influences. Emotional states have motivational properties and, influenced by social-cognitive factors, show situation-dependence, affecting behavioral performance and physiological responses. Cognitive processes representing neuronal information processing are closely related to individual differences in subjective and neurophysiological activities (Dubois et al., 2018). However, existing daily research typically makes simple comparisons of individual trait-level differences across different daily environments (Hopwood et al., 2021), with relatively few attempts to explore the mechanisms generating individual differences (Shanahan et al., 2013; Roberts & Yoon, 2022).

Exploring the mechanisms of individual differences in daily-life contexts can be achieved by manipulating environmental events that individuals encounter. For example, increased contact with natural environments produces beneficial effects on physical and mental health and social well-being (Shanahan et al., 2016; Yang et al., 2021), with restorative effects becoming effective means for dealing with urban life stress and emotional problems. Empirical studies have shown that watching natural scenery videos daily continuously improves subjective well-being among occupational populations (Hu C. et al., 2022), and similar nudge methods can provide feasible approaches for mechanism research on daily-life individual differences. Additionally, mechanisms can be explored through active intervention in individuals' internal states. This approach already has precedents from animal research: optogenetic stimulation-induced heart rate changes in mice revealed that heart rate has a causal influence on individual emotional behavior (Hsueh et al., 2023). In human research, daily thinking patterns and internal concepts can be changed through cognitive training (Davidson, 2007), or individual physiological arousal in daily life can be increased through exercise training for intervention and regulation (Hallam et al., 2018). In the future, with the development of physiological measurement and active regulation technologies, researchers will have more diverse means to design daily-life experiments to explore mechanistic connections of individual differences.

5.2 Complexity of Daily-life Situation Classification Methods

With technological advances and the popularization of intelligent terminals, researchers' efficiency in obtaining situational information through subjective or objective methods has greatly improved (Mehl & Conner, 2011). Nevertheless, difficulties remain in classifying situations in daily-life research, primarily due to the complexity and instability of situational variables in daily life, making situations difficult to accurately control and compare across individuals. On one hand, people of different occupations, regions, and socioeconomic statuses naturally have vastly different lifestyles, and individual differences caused by the diversity of daily experiences cannot be summarized by the same model (Heller et al., 2020; McIntyre & Graziano, 2019). On the other hand, daily situations experienced by individuals change dynamically; for example, life scene changes such as graduation or job transitions directly affect the basic characteristics of daily situations, posing higher demands for cross-situational individual differences measurement.

Multiple paths may solve this problem. One is identifying key situations more closely related to individual differences. If relatively complete individual differences can be reconstructed from partial situational experiences, it will improve the generalizability of the method itself across different populations and bring broad application scenarios to daily multi-situation individual differences assessment methods. Additionally, more effective situational measurement methods can be sought. Advances in sensing technology have promoted the development of context-aware technologies and algorithms, and situation recognition based on daily data has begun to make progress (Chiba & Higashinaka, 2023; Khowaja et al., 2020). With the assistance of intelligent sensing devices and machine learning algorithms, it is expected to efficiently and automatically complete situation identification and classification from life events, solving many research difficulties caused by the complexity and variability of daily situations.

5.3 Application Prospects for Physiological Individual Differences Construction

Mental disorders may be accompanied by considerable physical comorbidities. A multinational collaborative survey of over 80,000 mental disorder patients in the United States, United Kingdom, and Australia found that deteriorating metabolic and other physical health conditions are significantly associated with mental disorders, and that regular monitoring and maintenance of physical health in daily life helps reduce adverse effects of physical complications on patients (Tian et al., 2023). If the advantages of low burden and high ecological validity of wearable physiological measurement are leveraged, efficient daily state detection for mental disorder patients can be completed, providing early warnings for potential disease courses and facilitating timely diagnosis and treatment.

Physiological assessment can also serve mental health monitoring for subclinical and general populations. Emotional health in daily life is closely related to mental health (Fusar-Poli et al., 2020). In addition to traditional emotional indicators, the dynamic properties of emotion are of considerable importance; for example, emotional inertia is significantly associated with mental disorders such as depression and borderline personality disorder (Nelson et al., 2020; Houben et al., 2015), while observation of emotional dynamics requires tracking individuals' emotional states over continuous periods. Compared to traditional experience sampling methods, physiological measurement and computation can achieve continuous tracking of individual states without being limited by subjective report frequency. "Unobtrusive" physiological measurement also makes emotional state assessment immune to subjective willingness interference. Particularly, many commercial-grade wearable devices already have physiological measurement interfaces and affective computing applications with large user bases, making mental health monitoring based on wearable devices highly feasible. Therefore, wearable physiological measurement has unique advantages in mental health detection and other fields.

Furthermore, individual differences assessment based on physiological measurement can help individuals make career choices. The importance of choosing the right professional position is self-evident; however, questionnaire-based personal matching assessments are also susceptible to subjective expectations. Physiological assessment can leverage its objective advantages to achieve accurate evaluation of occupation-related individual traits (Lopez et al., 2023), providing reference information for career selection and personal development.

5.4 Ethics of Individual Differences Assessment from a Physiological Perspective

As intelligent sensing devices advance and individual health-related human-computer interaction methods gradually mature and move toward commercialization, potential ethical issues they may bring have gradually attracted attention. For example, poor management of sensor data such as movement and location may pose risks of individual identity leakage. Compared to relatively simple and rudimentary recording methods in past daily measurements, data collected by intelligent sensing devices have characteristics of large scale, high precision, and long duration, and the risks and consequences of information leakage in this context may become increasingly severe. Several well-known scholars in neuroengineering and AI published a commentary in *Nature* in 2017 (Yuste et al., 2017), pointing out that privacy protection and bias avoidance need to be emphasized in the use of physiological measurement technologies. In commercial applications, necessary de-labeling and encryption of raw data are required for related data extraction and analysis. To this end, both the European Union and the United States have established clear data protection regulations to prevent problems such as individual identity leakage (Scheibner et al., 2020; Bieker, 2022). Overall, a key issue for future research development is properly managing and using large-scale individual physiological data, protecting privacy while making it available to researchers, with permission management for feedback information requiring careful consideration.

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Note: Figure translations are in progress. See original paper for figures.