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A discourse on the use of machine learning (ML) in personality psychology: Can we expect ML to predict questionnaire scores from idiographic text-based data?

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ABSTRACT

This paper explores Machine Learning's (ML) potential to predict motives and personality dispositions from text-based data, aligning with McAdams' framework on layers of personality. ML-predicted scores demonstrated no significant advantage over a baseline model that consistently predicted the median of the motives or personality dispositions. Possible factors discussed include unmet ML algorithm requirements, unsuitability of collected texts for predicting motives and dispositions, and ML's limitations in capturing contextualized and implicit aspects of personality. We discuss life narrative research and practice in relation to the nomothetic-idiographic debate and advocate for personality research to incorporate context-specificity and idiosyncrasy. From a social constructionist perspective, we envision future research – though not yet practice – on counselling processes delivered or supported by Generative AI (GenAI).

1. Introduction

Traditionally, personality psychology research views personality as a disposition persisting over time and across situations, and describes inter-individual differences by means of variable-centered, quantitative methods. But in applied settings, as well as in modern personality research, we aim to explain both inter- *and* intra-individual variation of experiences and actions within specific contexts (e.g., work, family) and the development of personality and identity over time. These approaches consider the *structure of personality* (e.g., different layers) as well as the *process of personality development* (e.g., self-growth as the interplay of individual dispositions and specific contexts) (Baumert et al., 2017; see also Mõttus et al., 2020; Quirin et al., 2020), and they oftentimes make use of person-centered, qualitative (e.g., narrative), and idiographic procedures for personality assessment (Beck & Jackson, 2020).

In this paper, we aim to explore the use of Machine Learning (ML) to predict individual motives and personality dispositions from two different text-based measures, grounding our work in McAdams' (2013; McAdams & Olson, 2010) framework of different layers of personality. Artificial Intelligence (AI) has become an increasingly prominent topic across various fields of psychology, including personality psychology (Beck & Jackson, 2022; Bleidorn & Hopwood, 2019; Fan et al., 2023; Phan & Rauthmann, 2021; Rauthmann, 2020; Renner et al., 2020), industrial and organizational psychology (Blyler & Seligman, 2023; Da Motta Veiga & Figueroa-Armijos, 2022; Hanna et al., 2024; Woo et al., 2024), and even in discussions surrounding AI's adoption of the theory of mind (Kosinski, 2024). Within personality psychology, one prominent branch of research focuses on explaining and predicting individual experiences and actions using elaborate profiling algorithms. Some data-driven studies derived from AI research, along with commercially driven products, claim that personality dispositions can be accurately inferred from text-based data if sufficient textual material is available from an individual. However, even though Moreno et al.'s (2021) metanalysis reports promising results, personality psychological research deriving from the life narrative tradition (e.g., McAdams, 1996) does not inherently support the expectation of large correlations between text-based life narratives and personality dispositions.

We will first reflect on current findings of research on automatically predicting personality dispositions from text-based data (2.1). We then

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refer to life narrative research according to McAdams (1996, 2013; McAdams & Pals, 2006) who differentiates between three layers of personality and offers suggestions for personality assessment on all these layers (2.2). Building on these theoretical foundations, we collected data through an online platform providing questionnaires and two text-based methods to assess all layers of personality, and we apply supervised ML algorithms to connect them. For both practical application and academic research, we aim to contribute to the discourse on the capabilities and limitations of ML algorithms within personality psychology, especially life narrative research and practice.

2. Background

2.1. ML as a means to predict personality dispositions from text-based data

Within personality psychology, there are various efforts to predict personality dispositions with the help of ML (Bleidorn & Hopwood, 2019; Fan et al., 2023; Gonzalez, 2021; Phan & Rauthmann, 2021; Renner et al., 2020; Stachl et al., 2021). These rely on the availability of personal data from social media (Azucar et al., 2018; Park et al., 2015; Schwartz et al., 2013; Tay et al., 2020) or on behavioral data, often assessed via smartphone sensing data (Boyd et al., 2020; Boyd & Schwartz, 2021; Harari et al., 2017; Rüegger et al., 2020; Stachl et al., 2020), or since the emergence of Generative AI (GenAI) via chatbots (Fan et al., 2023).

One promising approach is to predict a person's personality disposition from free text, for example, self-descriptions as well as stories, letters, or social media status messages that a person has written. This can be referred to as "personality computing" (Phan & Rauthmann, 2021). A distinction can be made between closed- versus open-vocabulary approaches (Park et al., 2015; Schwartz et al., 2013). Both approaches rely on word counting and co-occurrence statistics, but only the latter is considered AI-based. Closed-vocabulary approaches (e.g. Linguistic Inquiry and Word Count, LIWC; Pennebaker et al., 2015; Tausczik & Pennebaker, 2010) use lists of words that are combined into predetermined semantic and/or syntactic categories based on human experts' criteria, whereas open-vocabulary approaches such as the one introduced by IBM Watson (Biondi et al., 2017) or the myPersonality application (Kern, Eichstaedt, Schwartz, Dziurzynski, et al., 2014; Kern, Eichstaedt, Schwartz, Park, et al., 2014; Park et al., 2015; Stillwell & Kosinski, 2012) analyze texts by means of extracting semantic and/or syntactic language features from the texts itself. According to Park et al. (2015), prediction models for self-reported Big Five personality dispositions that are based on open-vocabulary approaches – "characteriz[ing] a language sample by the relative use of (a) single, uncategorized words; (b) nonword symbols (e.g., emoticons, punctuation); (c) multiword phrases; and (d) clusters of semantically related words identified through unsupervised methods, or topics" (p. 935) – perform better than approaches that are based on closed-vocabulary models. They found correlations between text-based assessments based on Facebook user status messages and self-ratings of the Big Five personality traits, ranging from $r = 0.35$ (agreeableness and neuroticism) to $r = 0.43$ (openness).

Based on their *meta*-analytic review, Moreno et al. (2021) recommend using computational models that focus on both semantic and syntactic information to predict personality from written language. The review included studies employing various ML algorithms as predictive models (i.e., logistic and multivariate regression, artificial neural networks, naïve Bayes, and support vector machines) to predict personality traits. They found combined correlation estimates between written language and self-ratings of the Big Five personality traits, ranging from $r = 0.26$ (agreeableness and neuroticism) to $r = 0.30$ (openness). Fan et al. (2023) employed the text-based interview method, commonly referred to as the AI chatbot (i.e., GenAI), and discovered that the inferred personality dispositions of the chatbot, derived from free-text responses on AI chatbot's questions such as "What are you passionate about?" or "What is your greatest talent?" collected during online interviews, demonstrate good convergent validity. They observed correlations between the chatbot inferred scores and self-rated Big Five personality domains, ranging from $r = 0.38$ (neuroticism) to $r = 0.57$ (openness). In addition to this good convergent validity, however, they indicate poor discriminant validity (too high correlations) with an average absolute intercorrelation of the chatbot inferred scores of 0.35. Fan et al. (2023) thereby underscore the importance of the discriminant validity of scores inferred by means of AI. Further, AI inferred scores derived from data-driven approaches – whether ML- or GenAI-based – are oftentimes prone to methodological (e.g., overfitting of the training data, overemphasis of small relationships due to type I errors when working with big sample sizes), psychometric (e.g., reliability, validity), and ethical (e.g., privacy breach, manipulation, intransparency) issues (Baumert et al., 2017; Bleidorn & Hopwood, 2019; Phan & Rauthmann, 2021; Renner et al., 2020).

The effectiveness of text-based personality inference seems to be similar in both AI-based systems and human assessors. Küfner et al. (2010), who analyzed fictional short stories with given words such as "plane crash" and "parlormaid" that had to be included, and Holleran and Mehl (2008), who analyzed stream of thought essays, found that word use, as well as patterns of written expression were indicative of underlying personality characteristics. Holleran and Mehl (2008) had research assistants estimate participants' personalities based on participants' stream of thought essays. They found significant correlations for all Big Five dispositions, ranging from 0.29 (openness to experience) to 0.50 (conscientiousness). Küfner et al. (2010), who had undergraduates estimate participants' personalities, found significant cues for openness (i.e., use of creative expression and positive emotions) and agreeableness (i.e., use of social orientation) in the short stories.

2.2. Life narrative research considering three layers of personality to form personality

For the last decades, personality psychology has largely focused on personality dispositions, emphasizing on describing and explaining personality structure and dispositions by means of inter-individual differences and variable-centered application of questionnaires. With reference to applied settings such as counselling, coaching or human resources development, personality psychology calls for the importance of taking a person-centered, idiographic approach and analyzing the individual person (see Allport, 1937; Beck & Jackson, 2020; Kluckhohn & Murray, 1953; McAdams & Pals, 2006; Mischel, 2009; Stern, 1911). Cervone and Little (2019) thereby speak of idiosyncrasy and suggest that contemporary researchers should not only recognize intra-individual variability with respect to nomothetic dispositional categories ("like some other person") but also individual patterns of experiences and actions that must not correspond to any nomothetic categories ("like no other person") (see also Kluckhohn & Murray, 1953; McAdams & Pals, 2006). They also call for the use of assessment methods that are "sensitive to idiosyncrasy" (Cervone & Little, 2019, p. 13; see also Baumert et al., 2017; Kelly, 1955).

McAdams (1996, 2013; McAdams & Pals, 2006) provides a framework of three different layers of personality that allows for idiographic personality assessment. First, the dispositional traits (i.e., personality dispositions) consist of broad, decontextualized individual differences in how people behave, think, and feel consistently across situations. Second, the characteristic adaptations (e.g., motives) count for "motivational, social-cognitive, and developmental variables that are contextualized in time, situations, and social roles" (McAdams & Pals, 2006, p. 212). Third, the life narratives (also identity narratives) (see Savickas, 2019, 2020, who adopted the three layers to career counselling) are "evolving life stories that reconstruct the past and imagine the future to provide a person's life with identity" (McAdams & Pals, 2006, p. 212).[1] Thereby, meaningful (life) themes (such as having difficulties in managing boundaries between own needs and expectations of the environment) are crucial to form an internalized narrative identity (McAdams, 2018, 2021; McLean et al., 2020). Life narratives and the corresponding (life) themes are contextualized in a person's social and cultural context, also serving to meaningfully connect the three layers of the personality (see also Savickas, 2011, 2019, 2020).

The narrative approach, drawing on the psychosocial construction of life stories, finds attention within both personality psychology (McAdams, 2021) and applied settings such as vocational psychology (Cardoso et al., 2021; McMahon & Abkhezr, 2024; Savickas, 2020). This approach fosters meaning-making through social interaction and storytelling "to provide a person's life with some degree of unity, purpose, and meaning" (McAdams & McLean, 2013, p. 13). This can be achieved by deconstructing challenging (life) themes and reconstructing a narrative identity in which these themes are transferred from passive suffering to active mastery (Savickas, 2019). For example, an extraverted person (dispositional trait) with strong achievement orientation (characteristic adaptation) may act with assertiveness in their working environment and highly values a corporate career with the potential (life) theme of overvaluing social expectations to climb up in the hierarchy and neglecting their own needs (i.e., passive suffering). By deconstructing this (life) theme and reconstructing a new narrative identity, the person could reinterpret this (life) theme as a meaningful opportunity for personal growth, trying to balance social expectations with their own needs, and fostering a stronger self-congruence when setting goals (i.e., active mastery).

McAdams (2007) introduced the Life Story Interview (LSI) as a research instrument to collect personal stories and assess the narrative identities (i.e., life narratives) of participants. This method invites participants to discuss key scenes, characters, and significant events in their lives, as well as how they envision their future. In crafting their personal narratives, participants not only feel their lives are meaningful, but also demonstrate it. "Narrative methods therefore allow for the *enactment* of meaning rather than a report of the *perception* of meaningfulness" (Adler et al., 2017, p. 520). Even though life narrative research largely focuses on the single individual (e.g., Adler, 2018; Nasby & Read, 1997), it has also generated numerous studies that applied established coding systems to capture core narrative elements and to develop confirmatory research hypotheses across different samples representing different populations (i.e., nomothetic research). McLean et al. (2020; see also Adler et al., 2017) established a factor structure for life narratives, identifying motivational and affective themes (e.g., agency, communion, affective tone), autobiographical reasoning (e.g., meaning-making, change connections), and structural aspects (e.g., facts, context coherence). To assess key aspects of participants' narrative identity, researchers have employed both expert coding (conducted by researchers) and narrative self-ratings (Panattoni & McLean, 2018).

Savickas (2011, 2019) developed the Career Construction Interview (CCI) as a narrative method intended for both career counselling research and practice, and designed to assess narrative identities (i.e., life narratives). CCI comprises six questions (e.g., Who did you admire when you were growing up? What is your favorite book or movie?) aimed at helping clients "perform change by engaging in new projects that advance self-making, identity-shaping, and career-constructing" (Savickas, 2020, p. 186) through the processes of construction, deconstruction, reconstruction, and co-construction. This involves reflecting on the significance of their responses to deconstruct (life) themes, dispositional traits (e.g., personality dispositions), characteristic adaptations (e.g., motives, interests), and to reconstruct their new story (i.e., narrative identity).

Chou et al. (2022; see also McAdams et al., 2004; McLean et al., 2020; Raggatt, 2006) examined the connection between life narratives assessed through the LSI (McAdams, 2007) and personality dispositions assessed through questionnaires. They searched for motivational (i.e., agency, communion), affective (i.e., contamination, redemption), and autobiographical reasoning themes (i.e., stability, change self-event connections) in the narratives and found strongest correlations between personality domains (and aspects), and life narratives for the motivational themes of agency (r = -0.23 (neuroticism) to r = 0.26 (industriousness)) and communion (r = -0.07 (withdrawal) to r = 0.26 (enthusiasm)). These small to moderate correlations are plausible, as life narratives constitute a distinct layer of personality, reflecting how individuals construct and convey meaning in their lives. Although they fulfill an integrative function by linking the three layers of personality, McAdams et al. (2004) emphasized that life narratives should not be regarded as direct proxies for the other layers. As they noted, "there is no reason to expect strong symmetry and consistency across different layers of personality description, for people's lives are typically complex and often contradictory." (p. 762). Moreover, Adler et al. (2016, 2017), in distinguishing between linguistic and narrative approaches, argue that automated linguistic methods such as LIWC (Pennebaker et al., 2015; Tausczik & Pennebaker, 2010) are unlikely to capture the richness of narrative aspects in text data. Given the complexity of life narratives, accurate coding requires deep immersion into participants' stories, taking into account not only linguistic (i.e., semantic and syntactic), but especially narrative elements such as explicit content (e.g., emotional language), implicit content (e.g., themes), and structural aspects (e.g., coherence).

3. Research question

In summarizing the background section, (1) we assert that within the context of life narrative research, exploring life narratives (both through ML inference and human assessment), it is – due to the idiographic nature and complexity of the narrative content – plausible to expect only small (0.10) to moderate (0.30) correlations between life narratives and personality dispositions. (2) However, the investigation outlined in Section 2.1, utilizing ML as a data-driven tool for extracting personality characteristics from text data while emphasizing linguistic aspects and word counts, implies a scenario wherein personality dispositions could be inferred from text data originating from the same individual, and therefore it is also plausible to expect moderate (0.30) to large (0.50) correlations (Phan & Rauthmann, 2021; see also Moreno et al., 2021). Alexander et al. (2020, p. 644; see also Rauthmann, 2020; Renner et al., 2020) call for personality psychologists building multidisciplinary teams with computer scientists in order "to shape how the big data and analytics community can more effectively and efficiently forge useful pathways towards achieving new and rapid insights about personality (habits of human attitudes, thoughts, and behaviour)".

The aim of the present study is to explore supervised ML to connect two different text-based measures with characteristic adaptations (i.e., motives) and dispositional traits (i.e., personality dispositions) according to McAdams' (2013; McAdams & Olson, 2010) framework of three different layers of personality. One of the two text-based measures

[1] Unlike McAdams and Pals (2006), who view dispositional traits as decontextualized, and who differ between characteristic adaptations and life narratives, DeYoung (2015) in his cybernetic framework considers dispositional traits as context-specific, and he sees life narratives as part of the characteristic adaptations. In the present paper, we use McAdams and Pals' (2006) framework as we consider the distinction between characteristic adaptations and life narratives useful for applied settings.

explicitly assesses the narrative identity according to life narrative research tradition (see Section 3.2). The overarching question is whether it is possible to use supervised ML to predict motives and personality dispositions based on two different text-based measures (of life narratives). Specifically, we aim to answer the following research questions:

(1) Can text-based data (of life narratives) be used to draw conclusions about questionnaire data of motives by means of supervised ML?

(2) Can text-based data (of life narratives) be used to draw conclusions about questionnaire data of personality dispositions by means of supervised ML?

4. Methods

In the following sections, we describe the study design (3.1), the questionnaire- and text-based data collection methods (3.2) and the sample used for the experiments (3.3). We then discuss the prediction tasks and their evaluation (3.4), followed by a detailed description of the supervised ML approach (3.5).

4.1. Study design

We assessed text-based measures, characteristic adaptations (i.e., motives), and dispositional traits (i.e., personality dispositions) through an online platform. Then, we applied ML algorithms to connect the different measures. The platform "Laufbahndiagnostik" [career diagnostic)] (www.laufbahndiagnostik.zhaw.ch) provides quantitative questionnaires as well as qualitative methods for counselling and coaching. Access to the platform is free of charge and the platform is mainly used by counsellors in the field of career counselling and coaching. Participants have given their explicit consent for their data to be used in anonymous form for research purposes. People are always asked if they completed the questionnaire and processed the methods honestly and seriously. We only included data from participants who affirmed this question. We set up a multidisciplinary team of authors (psychology, computational linguistics, and computer sciences) for this paper to test our research question. Data were analyzed using Python 3.9, R Statistics (Version 4.4.3), and IBM SPSS Statistics (Version 29). The study design and its analysis are exploratory and were not preregistered.

4.2. Measures

Text-based Measures were derived from two different methods, assessed through the platform "Laufbahndiagnostik":

(1) *Life Narratives:* The digitized German version of the My Career Story (MCS) (Hartung & Santilli, 2017; Savickas & Hartung, 2016) is a text-based, narrative method that transforms the CCI questions into a self-guided autobiographical workbook, designed to elicit a person's narrative identity (i.e., life narrative). In the digitized version of the MCS, participants are guided through an online process, where participants "tell" their story by means of answering to the CCI questions (part 1, construction). In part 2, participants "hear" (i.e., read) their responses to derive meaning (deconstruction). This involves reflecting on the significance of their responses to deconstruct (life) themes, characteristic adaptations (e.g., motives, interests), dispositional traits (e.g., personality dispositions, competencies), and to reconstruct their new story (i.e., narrative identity), visualized through the vocational ID card (Schreiber et al., 2020), as an outcome of the process. The vocational ID, as an outcome of the MCS, serves as an explicit measure of the participant's life narrative, encompassing (life) themes (e.g., "belonging and a sense of security"), motives (e.g., "desire to belong"), and personality dispositions (e.g., "friendly and supportive").

(2) The "resource images" (RI) method (Schreiber, 2022) consists of 80 images and guides participants through a multistep process. Each image is judged based on three categories of whether it appeals to the person or not ("doesn't appeal to me", "neutral", or "appeals to me"). Next, participants are invited to select their personal resource image and to write a story about what is going on in the image. The instructions to write the story is based on the Thematic Apperception Test (TAT; Murray, 1943)[2]: "Now please try to make up a story about what is going on in this image right now and what happened before. What are the people[3] in the image thinking and feeling and what are their intentions. Try to tell a self-contained story that has a beginning, a middle, and an end. There are no "right" or "wrong" stories. So, write the story about what first comes to mind. Spelling and grammar are unimportant. The following questions will help you write the story: What is happening? Who are the people? What happened before? What are the people thinking and feeling? What are their intentions and desires? What will happen next? Look at the image for 15–20 s and then write the story. Writing the story should take no more than 10 min." (see Section 5.5 for an example of a story). Further, clients write down their reflections on their personal resource image based on the following questions: What are your first thoughts when you look at your favorite resource image? What kind of emotions and feelings do you perceive when you look at the image? Describe what aspect of the image gives you strength? Which resources can you derive from it? (positive inner images, values, competencies, experiences, etc.) How could you currently make use of these resources for yourself? In contrast to the MCS, which is a self-guided autobiographical workbook designed to explicitly construct a participant's life narrative, the RI method (i.e., the chosen resource image, accompanying written story, and personal reflections) is a text-based measure intended to foster deeper self-reflection. However, it is neither grounded in the life narrative research tradition nor narrative in the strict sense, since – despite including some self-referential reflection questions – it is not explicitly designed to form a participant's life narrative.

In applied contexts (e.g., counselling), meaningful (life) themes, motives, and personality dispositions are deconstructed and reconstructed by individuals together with a professional and materialized into a manifest life narrative.

*Characteristic adaptations (*i.e.*, motives):* Motives were assessed with the 30-item Motive Profile following the Zurich Model (MPZM; Schönbrodt et al., 2009), assessing the Zurich model of social motivation (Bischof, 1985, 1993). The MPZM consists of the motives security, arousal, and autonomy. Autonomy is further divided into power (rank hierarchy, "to lead and take responsibility"), prestige (prestige hierarchy, "to be the center of attention"), and achievement (achievement hierarchy, "to meet one's own performance standards"). Example items are "Affiliations are very important to me (security)" and "I love thrill (arousal)", measured on a Likert scale ranging from 1 "very untypical" to 6 "very typical". Additional data were collected using the revised version of the MPZM, which has been available on the "Laufbahndiagnostik" platform since March 2023 under the acronym MPZM-R (for MPZM-Revised). The revision involved minor rewording of eight items to enhance applicability, for example, changing "It is extremely important to me to always feel safe and secure with my partner." to "It is extremely important to me to always feel safe and secure with my trusted friends.".

*Dispositional traits (*i.e.*, personality dispositions):* Personality dispositions were assessed with the IPIP-5F30F-R1 (Iller et al., 2025), a 180-item questionnaire that is based on the International Personality Item Pool (IPIP) (Goldberg et al., 2006; Treiber et al., 2013). The IPIP-5F30F-R1 measures the Big Five domains according to the NEO-PI-R (Costa & McCrae, 1992). Each domain comprises six facets (30 in total), with each

[2] Note that the "resource images" method is *not* intended to serve as a projective measure such as the TAT (Murray, 1943), the Operant Motive Test (OMT; Kuhl & Scheffer, 1999), or other implicit motive measures (see Schüler et al., 2015).

[3] If there are no people on the chosen personal resource image, the story writing instructions will omit the appropriate sentences.

facet assessed using six items: Neuroticism, extraversion, openness, agreeableness, and conscientiousness. Example items are “I have frequent mood swings (neuroticism)” and “I make friends easily (extraversion)”, measured on a Likert scale ranging from 1 “do not agree at all” to 5 “fully agree”.

4.3. Sample

The sample comprises platform participants from March 2020 to May 2025 who accessed the platform within career counselling, during educational courses, or on individual initiative. We created two datasets, (1) the motive (i.e., characteristic adaptations) dataset, supplemented with the text-based measures (i.e., MCS and RI method), and (2) the personality (i.e., dispositional traits) dataset, likewise supplemented with the text-based measures (i.e., MCS and RI method). The text-based data collected through both the MCS and the RI method were manually anonymized. Both data sets were cleaned according to the following rules: (a) keep only entries where participants reported that they completed the tasks seriously; (b) in case of multiple entries for a single participant for a text-based measure, keep the chronologically first one[4]; (c) remove texts with less than 20 words, and (d) remove texts that are not written in German.[5] The final sample for the motive dataset consists of 932 participants who completed either the MCS or the RI method, together with the motives (MPZM or MPZM-R). Of these, 169 completed the MCS, and 874 completed the RI method (see Table 1). The final sample for the personality dataset includes 624 participants who completed either the MCS or the RI method, together with the IPIP-5F30F-R1. Among them, 80 completed the MCS, and 586 completed the RI method.

65.2 % of the sample for the motives identified as female and 34.5 % as male. Mean age was 38.5 years (SD = 10.2), and 61.6 % had a bachelor’s, master’s, or doctorate degree. The average life narratives in this sample consists of 382 words (SD = 264) for the MCS and 196 words (SD = 100) for the RI method. 67.9 % of the sample for the personality dispositions identified as female and 31.9 % as male. Mean age was 37.6 years (SD = 9.7), and 65.7 % had a bachelor’s, master’s, or doctorate degree. The average narrative in this sample consists of 364 words (SD = 244) for the MCS and 198 words (SD = 112) for the RI method.

Table 1
Sample characteristics for motive and personality datasets.

	Motive dataset (i.e., MPZM & MPZM-R)	Personality dataset (i.e., IPIP-30F6F-R1)
Total	932	624
Sample with text-based measures		
MCS (i.e., life narratives)	169	80
RI	874	586
Number of words		
MCS (i.e., life narratives)	M = 382 (SD = 264)	M = 364 (SD = 244)
RI	M = 196 (SD = 100)	M = 198 (SD = 112)
Age	M = 38.5 (SD = 10.2)	M = 37.6 (SD = 9.7)
Gender		
female	608 (65.2 %)	424 (67.9 %)
male	322 (34.5 %)	199 (31.9 %)
other	2 (0.2 %)	1 (0.2 %)
Educational level		
Compulsory school or no completed formal education	16 (1.7 %)	4 (0.6 %)
Vocational education	112 (12.0 %)	61 (9.8 %)
Higher vocational education	170 (18.2 %)	107 (17.1 %)
General secondary education	39 (4.2 %)	22 (3.5 %)
Bachelor’s, Master’s, or Doctorate degree	574 (61.6 %)	410 (65.7 %)
Missing	21 (2.3 %)	20 (3.2 %)

Note. MPZM = Motive Profile following the Zurich Model. MPZM-R = Motive Profile following the Zurich Model revised. IPIP-30F6F-R1 = Questionnaire based on the International Personality Item Pool (IPIP) measuring the Big Five domains according to the NEO-PI-R. MCS = My Career Story. RI = “resource images” method.

4.4. Prediction tasks and evaluation

We formulated regression tasks for predicting questionnaire scores from text-based data. The *regression task* consists in individually predicting the numeric value of each motive and personality disposition for each participant (see also Pargent et al., 2023, who established a tutorial for best practices in supervised ML for psychologists). As an evaluation metric for regression performance, we used the mean absolute error (MAE). If n is the number of samples, y_i the predicted value of the i-th sample and x_i the corresponding true value, the MAE is defined as follows:

$$MAE(x, y) = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i|$$

Since the motives and personality dispositions have different numeric ranges, we normalized the MAEs by the mean values of the motives and personality dispositions across all participants. As a baseline (naïve model) for regression, we always predicted the median value of the motives and personality dispositions across all participants in the respective dataset.

Since we saw that the regression results were not very promising (see Sections 4.1 and 4.2 below), we introduced an additional multiclass *classification task*, which we hypothesized to be easier: the prediction of the *dominant* motive and personality disposition of each participant (see Supplementary Material).

4.5. Approach: Supervised ML

For the supervised approaches, we extracted features from the text-based data using unsupervised statistical methods and then trained supervised prediction models. These consisted of individual regression models per motive and personality disposition. We decided to use these methods rather than neural-network-based approaches due to the small amount of training data available. For the implementation of supervised ML, we took some decisions based on preliminary experiments (see Supplementary Material). For the experiments reported in this paper, we extracted two different types of features from the text-based data: ‘Term Frequency – Inverse Document Frequency’ (TF-IDF) (Section 3.5.1.) and topics based on ‘Latent Dirichlet Allocation’ (LDA) (Section 3.5.2.). We additionally used demographic features (Section 3.5.3.) and summarize the different feature groups in Section 3.5.4. The prediction algorithms are described in Section 3.5.5.

4.5.1. Term frequency – inverse document frequency (TF-IDF) features

TF-IDF is a method to assign weights to words or sequences of words (n-grams) in a text collection. It was originally developed in the context of information retrieval, i.e., the task of finding documents that are relevant to a textual query in a set of documents. TF-IDF is frequently used in Natural Language Processing (NLP) as a feature representation, especially for smaller datasets. If raw word counts are used as features,

[4] We take the chronologically first entry because we believe that only the first exposure to the platform results in an unbiased participation. For subsequent uses, we cannot exclude effects due to prior exposure for the life narrative measures.

[5] We used the cld3 package in R to identify the language of the text-based measures of the MCS and the RI method.

common words such as articles and pronouns are weighted highly, but they are not informative regarding text content. TF-IDF is a metric which gives more weight to uncommon and distinctive words by taking into account two components: (1) the term frequency (TF) is the occurrence count of a word within a document (in our case, a document corresponds to a text written by one participant), and (2) the inverse document frequency (IDF), which is the inverse of the number of documents that a word occurs in (i.e., across all text-based data). We used the following definition, where n is the total number of documents, t a term (word), d a specific document, df(t) the number of documents that contain term t, and tf(t, d) the frequency of t in d:

$$tfidf(t,d) = tf(t,d) \times log\frac{1+n}{1+df(t)} + 1.$$

TF-IDF vectors were normalized by the Euclidean norm. We extracted two different TF-IDF feature sets with the following characteristics: *TF-IDF basic* was calculated on bigrams (sequences of two consecutive words) of the entire text (lowercased), and *TF-IDF clean* was calculated on unigrams (single words) and bigrams of a cleaned version of the text, where function words and punctuation had been removed and lowercasing had been applied. The TF-IDF vectors for each document (i.e., text-based data) were of the following sizes: *TF-IDF basic* contained 40′368 features for motives on MCS, 93′701 features for motives on RI method, 20′085 features for personality dispositions on MCS, and 67′283 features for personality disposition on RI method. *TF-IDF clean* contained 38′371 features for motives on MCS, 89′709 features for motives on RI method, 18′808 features for personality dispositions on MCS, and 62′892 features for personality disposition on RI method.

4.5.2. Latent Dirichlet Allocation (LDA) topics

Topic modelling is a statistical technique which aims to extract abstract semantic structures (“topics”) from a collection of documents, and which is often used in text classification. A document can contain multiple topics, and a topic is represented by a set of words which are likely used to describe it. We applied the Latent Dirichlet Allocation (LDA) algorithm (Blei et al., 2003) to extract topics from the collection of the written texts. LDA assumes that each document is a mixture of topics, and each topic is a mixture of words. The document-topic and topic-word distributions are modelled as Dirichlet processes, whose parameters can be inferred using Expectation Maximization during topic model fitting. We first fitted a topic model on the text collection and then used it to estimate the topic probability distribution of each document. The feature vector for each document therefore consisted of the estimated topic probabilities. We used two different LDA implementations: (1) *LDA-Gensim*: This LDA implementation is from the gensim Python package (Rehurek & Sojka, 2010) and is based on Hoffman et al. (2010), and (2) *LDA-Mallet*: This is a Java-based implementation of LDA (McCallum, 2002). Both topic models were calculated on TF-IDF vectors of a cleaned version of the written texts, where function words and punctuation had been removed and lowercasing had been applied. Topic models use only single words and treat the document as a bag-of-words, that is, word sequence is not considered. Since the number of topics to be extracted must be passed to LDA as a parameter, we first identified the most appropriate number of topics using the coherence score C_V (Röder et al., 2015). We searched within a range of two to 20 topics (inclusive) and found that the highest coherence score was achieved with 15 topics for LDA-Gensim and 20 topics for LDA-Mallet.

4.5.3. Demographic features

We use three demographic features: gender, age, and educational level. Gender and education level are categorical features while age is numerical (continuous). Their distributions are given at the end of Section 3.3.

4.5.4. Feature groups

We define the following feature groups based on the feature sets described above: 1) Only demographic; 2) TF-IDF basic + demographic; 3) TF-IDF clean + demographic; 4) LDA gensim + demographic; 5) LDA Mallet + demographic; and 6) Best performing of [TF-IDF basic, TF-IDF clean, LDA genism, LDA Mallet] on its own, i.e., without demographic features.

4.5.5. Prediction models

We use the AdaBoost algorithm for regression since in our preliminary experiments, this provided better results than other approaches (see Supplemental Material). AdaBoost works by fitting a series of weak learners on the data whereby data weights are adjusted so that later learners focus increasingly on difficult samples. For regression, we used the AdaBoost.R2 algorithm (Drucker, 1997), 1997) with ten decision tree base estimators (max_depth = 3). These hyperparameters were determined in the preliminary experiments.

5. Results

5.1. Results for motive prediction

We ran 50 iterations for each feature group where the data are randomly shuffled in each iteration. For the trained prediction models, we used 5-fold cross validation in each iteration. The baseline results, in contrast, are obtained by applying an 80 %:20 % train-test split once per iteration. We compare the performance of the six different feature groups (see Section 3.5.4.) and additionally present correlations between the ML-predicted motives and personality dispositions on the one hand and the questionnaire data on the other to test convergent (i.e., average of monotrait-heteromethod correlations) and discriminant validity (i.e., average of absolute heterotrait–ML-predicted correlations) of the predicted scores. For the ML-predicted motives and personality dispositions, we always used the LDA-Gensim algorithm (see Section 3.5.2.) because it performed best on average.

5.1.1. Motive prediction results with my career story (MCS)

Tables 2 and 3 show the results for predicting the motives using MCS data (i.e., text-based, narrative data as an explicit measure of the participants life narrative). The differences between the feature group configurations are extremely small for each motive. When we compare the outcomes to the baselines, it further becomes evident that none of the methods are significantly better than the baseline model which always predicts the median of the motive across all participants (Tab. 2). In other words, the baseline MAE lies within the 95 % confidence interval (two Standard Deviations, *SD*) of each of the configurations' distribution. The low performance is evident in the small convergent correlations observed between the questionnaire scores and their corresponding ML-predicted scores (Tab. 3). Convergent validity, as reflected in the average of the monotrait-heteromethod correlations, of 0.08, highlights this constrained relationship. Only the correlation for the security motive exceeds 0.20. These modest correlations may be attributed, in part, to the lower *SD*s of the ML-predicted scores in comparison to the questionnaire scores, signaling that the algorithm generated limited between-person variance. Discriminant validity, defined as the average of the absolute heterotrait–ML-predicted correlations, yields a value of 0.14. A discriminant validity exceeding that of convergent validity suggests, at the very least, suboptimal discriminant validity, further compounding the already reported lack of convergent validity.

5.1.2. Motive prediction results with “resource images” (RI) method

Tables 4 and 5 show the results for predicting motives using RI data (i.e., text-based data *not* grounded in the life narrative research tradition). For the security motive, the MAE of the median baseline lies above the two *SD* interval of the MAE for the feature groups 1–5, indicating that text-based data obtained through the RI method slightly outperform the naïve median baseline in predicting this motive (Tab. 4). This aligns with the convergent correlations shown in Table 5, where – similar to

Table 2
Motive regression results for MCS.

	Mean MAE + 2 *SD* interval on MAE					
	1	2	3	4	5	6
Security MB = 0.131	0.134 [0.129, 0.140]	0.134 [0.127, 0.140]	0.134 [0.129, 0.139]	0.130 [0.123, 0.136]	0.134 [0.128, 0.140]	0.134 [0.129, 0.139]
Arousal MB = 0.182	0.184 [0.177, 0.192]	0.185 [0.177, 0.192]	0.189 [0.182, 0.196]	0.183 [0.176, 0.191]	0.183 [0.175, 0.191]	0.190 [0.182, 0.197]
Power MB = 0.172	0.183 [0.175, 0.192]	0.170 [0.163, 0.178]	0.170 [0.164, 0.177]	0.183 [0.172, 0.194]	0.182 [0.173, 0.191]	0.170 [0.164, 0.177]
Prestige MB = 0.190	0.203 [0.196, 0.211]	0.198 [0.191, 0.205]	0.195 [0.186, 0.204]	0.197 [0.189, 0.205]	0.203 [0.194, 0.211]	0.194 [0.186, 0.201]
Achievement MB = 0.122	0.127 [0.120, 0.134]	0.126 [0.121, 0.131]	0.126 [0.121, 0.131]	0.128 [0.122, 0.133]	0.127 [0.121, 0.134]	0.126 [0.121, 0.130]

Note. MB = MAE of Median Baseline, 1 = only demographic, 2 = TF-IDF basic + dem., 3 = TF-IDF clean + dem., 4 = LDA genism + dem., 5 = LDA Mallet + dem., 6 = Only TF-IDF clean. All median baselines are within 2 *SD*.

Table 3
Means (*M*), standard deviations (*SD*), Cronbach's alpha (α), and correlations between ML-predicted motives (LDA-Gensim) and questionnaire data (MPZM, including MPZM-R) for MCS.

	M	*SD*	α	1	2	3	4	5	6	7	8	9	10
Questionnaire													
1. Security	4.14 (4.64)	0.90 (0.67)	0.85 (0.75)	–									
2. Arousal	3.75 (3.78)	0.94 (0.82)	0.82 (0.79)	*−0.40 (−0.14)*	–								
3. Power	3.33 (3.62)	0.91 (0.70)	0.80 (0.69)	*−0.12 (0.02)*	*0.39 (0.37)*	–							
4. Prestige	3.52 (3.58)	0.86 (0.87)	0.78 (0.82)	*0.11 0.21)*	*0.42 (0.00)*	*0.50 (0.29)*	–						
5. Achievement	4.27 (4.57)	0.87 (0.60)	0.84 (0.74)	*0.06 (0.20)*	*0.37 (0.25)*	*0.46 (0.27)*	*0.38 (0.05)*	–					
ML prediction													
6. Security	4.59	0.25	–	**0.22**	−0.06	−0.17	0.01	0.03	–				
7. Arousal	3.74	0.27	–	−0.22	**0.13**	0.00	−0.11	−0.05	*−0.24*	–			
8. Power	3.49	0.24	–	−0.20	−0.02	**0.07**	0.06	0.04	*−0.12*	*0.29*	–		
9. Prestige	3.54	0.20	–	0.05	0.00	−0.07	**−0.06**	0.05	*−0.04*	*0.20*	*0.17*	–	
10. Achievement	4.48	0.23	–	0.07	−0.03	−0.02	−0.03	**−0.03**	*0.17*	*0.03*	*0.01*	*0.13*	–

Note. N_{MPZM} = 46. ($N_{\text{MPZM-R}}$ = 123). Convergent correlations are in bold; discriminant correlations are in italics.

Table 4
Motive regression results for RI.

	Mean MAE + 2 *SD* interval on MAE					
	1	2	3	4	5	6
Security MB = 0.135	0.131 [0.130, 0.132]	0.132 [0.131, 0.134]	0.132 [0.130, 0.133]	0.131 [0.130, 0.132]	0.131 [0.130, 0.132]	0.135 [0.134, 0.136]
Arousal MB = 0.190	0.189 [0.188, 0.191]	0.19 [0.189, 0.190]	0.189 [0.188, 0.190]	0.189 [0.188, 0.191]	0.190 [0.188, 0.192]	0.189 [0.188, 0.190]
Power MB = 0.174	0.174 [0.172, 0.175]	0.174 [0.173, 0.175]	0.174 [0.173, 0.175]	0.174 [0.173, 0.176]	0.174 [0.172, 0.176]	0.174 [0.173, 0.175]
Prestige MB = 0.180	0.182 [0.180, 0.183]	0.180 [0.180, 0.181]	0.180 [0.179, 0.181]	0.181 [0.180, 0.182]	0.182 [0.180, 0.183]	0.180 [0.179, 0.182]
Achievement MB = 0.124	0.126 [0.125, 0.127]	0.125 [0.124, 0.125]	0.125 [0.124, 0.125]	0.125 [0.124, 0.126]	0.126 [0.124, 0.127]	0.125 [0.124, 0.125]

Note. MB = MAE of Median Baseline, 1 = only demographic, 2 = TF-IDF basic + dem., 3 = TF-IDF clean + dem., 4 = LDA genism + dem., 5 = LDA Mallet + dem., 6 = Only TF-IDF clean. All median baselines are within 2 *SD* except for feature groups 1–5 for security, which have lower *Mean* Average Errors.

the MCS data – the only correlation exceeding 0.20 is the convergent correlation for the security motive. As with the MCS data, the ML-predicted scores exhibit lower *SD*s compared to the questionnaire scores, indicating limited between-person variance – particularly for the prestige and achievement motives. The convergent validity shows an average correlation of 0.06, whereas the discriminant validity yields a higher average absolute correlation of 0.12, again exceeding the level of convergent validity.

5.2. Results for personality prediction

5.2.1. Personality prediction results with my career story (MCS)

Tables 6 and 7 present the results for predicting personality dispositions using MCS data (i.e., text-based, narrative data as an explicit measure of the participants life narrative), incorporating the six feature groups described in Section 3.5.4. The results are largely consistent with those for the motives: the configurations all perform similarly, and rather poorly, i.e. not significantly different from the baselines. The ML-predicted scores display lower *SD*s compared to the questionnaire scores. The convergent validity shows an average correlation of 0.04, whereas the discriminant validity yields a higher average absolute correlation of 0.14, again exceeding the level of convergent validity (Tab. 7). Notably, for agreeableness, we report a correlation of r = 0.51 between ML-predicted and questionnaire scores. In contrast, ML-predicted scores for conscientiousness (r = -0.23), neuroticism (r = -0.12), and extraversion (r = -0.07) show a negative correlation with the corresponding questionnaire scores.

Table 5
Means (*M*), standard deviations (*SD*), Cronbach's alpha (α), and correlations between ML-predicted motives (LDA-Gensim) and questionnaire data (MPZM, including MPZM-R) for RI.

	M	*SD*	α	1	2	3	4	5	6	7	8	9	10
Questionnaire													
1. Security	4.29 (4.61)	0.73 (0.71)	0.70 (0.76)	–									
2. Arousal	3.78 (3.70)	0.89 (0.88)	0.82 (0.84)	*−0.18 (−0.22)*	–								
3. Power	3.51 (3.50)	0.81 (0.71)	0.77 (0.69)	*−0.15 (−0.07)*	*0.35 (0.39)*	–							
4. Prestige	3.60 (3.65)	0.77 (0.86)	0.73 (0.83)	*0.21 (0.24)*	*0.07 (0.05)*	*0.25 (0.29)*	–						
5. Achievement	4.54 (4.51)	0.71 (0.68)	0.78 (0.77)	*0.00 (0.04)*	*0.17 (0.22)*	*0.31 (0.30)*	*0.16 (0.16)*	–					
ML prediction													
6. Security	4.39	0.18	–	**0.23**	−0.06	−0.10	−0.03	0.03	–				
7. Arousal	3.71	0.10	–	−0.08	**0.07**	0.02	0.05	−0.04	*−0.26*	–			
8. Power	3.49	0.11	–	−0.11	−0.04	**−0.05**	−0.01	−0.04	*−0.39*	*0.07*	–		
9. Prestige	3.64	0.05	–	−0.02	0.03	0.00	**0.01**	0.04	*0.02*	*0.14*	*0.05*	–	
10. Achievement	4.51	0.07	–	−0.01	0.01	−0.01	0.08	**0.02**	*0.07*	*0.04*	*−0.02*	*0.14*	–

Note. $N_{\text{MPZM}} = 453$. ($N_{\text{MPZM-R}} = 421$). Convergent correlations are in bold; discriminant correlations are in italics.

Table 6
Personality regression results for MCS.

	Mean MAE + 2 *SD* interval on MAE					
	1	2	3	4	5	6
Neuroticism MB = 0.199	0.211 [0.194, 0.228]	0.219 [0.199, 0.238]	0.219 [0.201, 0.237]	0.213 [0.195, 0.231]	0.211 [0.194, 0.227]	0.221 [0.202, 0.239]
Extraversion MB = 0.121	0.134 [0.123, 0.144]	0.132 [0.121, 0.143]	0.136 [0.124, 0.147]	0.125 [0.116, 0.134]	0.133 [0.124, 0.143]	0.131 [0.121, 0.141]
Openness MB = 0.111	0.116 [0.105, 0.127]	0.115 [0.105, 0.125]	0.116 [0.106, 0.126]	0.118 [0.108, 0.129]	0.116 [0.107, 0.125]	0.115 [0.104, 0.126]
Agreeableness MB = 0.085	0.087 [0.081, 0.093]	0.087 [0.081, 0.093]	0.086 [0.079, 0.093]	0.083 [0.076, 0.090]	0.087 [0.081, 0.093]	0.091 [0.083, 0.098]
Conscientiousness MB = 0.096	0.107 [0.099, 0.115]	0.105 [0.097, 0.114]	0.106 [0.097, 0.116]	0.107 [0.099, 0.114]	0.107 [0.100, 0.115]	0.106 [0.099, 0.114]

Note. MB = MAE of Median Baseline, 1 = only demographic, 2 = TF-IDF basic + dem., 3 = TF-IDF clean + dem., 4 = LDA genism + dem., 5 = LDA Mallet + dem., 6 = Only TF-IDF basic. All median baselines are within 2 *SD*.

Table 7
Means (*M*), standard deviations (*SD*), Cronbach's alpha (α), and correlations between ML-predicted personality dispositions (LDA-Gensim) and questionnaire data (IPIP-5F30F-R1) for MCS.

	M	*SD*	α	1	2	3	4	5	6	7	8	9	10
Questionnaire													
1. Neuroticism	2.59	0.63	0.95	–									
2. Extraversion	3.47	0.51	0.91	*−0.33*	–								
3. Openness	3.49	0.48	0.90	*−0.01*	*0.30*	–							
4. Agreeabl.	3.54	0.40	0.86	*−0.05*	*0.06*	*0.33*	–						
5. Conscient.	3.73	0.45	0.91	*−0.31*	*0.24*	*0.19*	*0.28*	–					
ML prediction													
6. Neuroticism	2.60	0.32	–	**−0.12**	0.00	0.12	−0.01	0.17	–				
7. Extraversion	3.48	0.19	–	0.01	**−0.07**	−0.26	−0.17	0.09	*−0.09*	–			
8. Openness	3.50	0.28	–	0.02	−0.20	**0.13**	0.35	−0.08	*0.16*	*−0.10*	–		
9. Agreeabl.	3.57	0.25	–	0.16	−0.16	0.27	**0.51**	0.00	*0.12*	*−0.12*	*0.41*	–	
10 Conscient.	3.74	0.24	–	−0.05	−0.02	−0.21	−0.07	**−0.23**	*−0.09*	*0.10*	*−0.12*	*−0.08*	–

Note. $N_{\text{IPIP-5F30F-R1}} = 80$. Convergent correlations are in bold; discriminant correlations are in italics.

Table 8
Personality prediction results for RI.

	Mean MAE + 2 *SD* interval on MAE					
	1	2	3	4	5	6
Neuroticism MB = 0.209	0.205 [0.203, 0.208]	0.207 [0.204, 0.210]	0.208 [0.205, 0.211]	0.205 [0.202, 0.208]	0.206 [0.202, 0.209]	0.211 [0.209, 0.213]
Extraversion MB = 0.107	0.107 [0.105, 0.109]	0.107 [0.107, 0.108]	0.107 [0.106, 0.108]	0.107 [0.106, 0.108]	0.107 [0.105, 0.109]	0.107 [0.107, 0.108]
Openness MB = 0.102	0.103 [0.102, 0.104]	0.102 [0.101, 0.103]	0.102 [0.101, 0.104]	0.102 [0.101, 0.103]	0.103 [0.102, 0.105]	0.102 [0.101, 0.103]
Agreeableness MB = 0.084	0.086 [0.084, 0.087]	0.084 [0.083, 0.085]	0.084 [0.084, 0.085]	0.084 [0.083, 0.086]	0.086 [0.084, 0.087]	0.085 [0.084, 0.085]
Conscientiousness MB = 0.090	0.091 [0.089, 0.092]	0.090 [0.089, 0.091]	0.090 [0.089, 0.090]	0.090 [0.089, 0.091]	0.091 [0.089, 0.092]	0.090 [0.089, 0.090]

Note. MB = MAE of Median Baseline, 1 = only demographic, 2 = TF-IDF basic + dem., 3 = TF-IDF clean + dem., 4 = LDA genism + dem., 5 = LDA Mallet + dem., 6 = Only TF-IDF basic. All median baselines are within 2 *SD*.

5.2.2. *Personality prediction results with "resource images" (RI) method*

The results for predicting personality dispositions using RI data (i.e., text-based data not grounded in the life narrative research tradition), shown in Table 8, are consistent with the previously reported findings in the sense that all median baselines of MAE – with the exception of neuroticism for the feature model 4 (LDA genism + dem.) – lie within the two *SD* interval of each of the configurations' distribution. This aligns with the correlation between ML-predicted and questionnaire scores for neuroticism, which almost reaches a correlation of 0.20 (Tab. 9). The ML-predicted scores display lower *SD*s than the questionnaire scores, particularly for conscientiousness, extraversion, and openness. The convergent validity shows an average correlation of 0.07, whereas the discriminant validity yields a higher average absolute correlation of 0.10, again exceeding the level of convergent validity.

6. Discussion

In our exploratory study, supervised ML prediction approaches based on text-based data, whether grounded in the life narrative research tradition (i.e., MCS) or not (i.e., RI method) showed almost no significant advantage over a baseline model that predicted the median value of each motive or personality disposition. The security motive represents an exception indicating that text-based data obtained through the RI method slightly outperform the naïve baseline in predicting security. Further, discriminant validity (i.e., the average of the absolute heterotrait–ML-predicted correlations) consistently exceeded convergent validity (i.e., the average of the monotrait-heteromethod correlations) for both motives and personality dispositions. Thereby, ML-predicted scores relative to the questionnaire scores experienced restricted variance, signaling that the algorithm generated limited between-person variance. Moreover, "easier" multiclass classification tasks, which predicted participants' dominant motive or personality disposition rather than their questionnaire scores, did not markedly surpass that of regression tasks (see Supplemental Material).

In the following sections, we want to reflect on several potential reasons why ML algorithms did not outperform the baseline model. We focus on study limitations (Sections 5.1 to 5.3), methodological challenges and implications, including ML integration into life narrative research and practice (Sections 5.4 to 5.6), and ethical as well as epistemological considerations (Sections 5.7 and 5.8).

6.1. *Amount of data for the application of ML algorithms may not suffice*

ML algorithms need a sufficient amount of data: We cannot rule out the possibility that our datasets were too limited, either due to small sample sizes (especially for the MCS) and/or written texts that were too short (especially for the RI method). However, as the relationships we encountered between the ML-predicted scores and the questionnaire data was negligible, we do not believe that additional data would have revealed stronger relationships between the text-based and questionnaire data.

6.2. *Domain-level measures of personality dispositions may lack nuance*

With regard to our measure of personality dispositions, one could criticize that we used ML algorithms to predict the broad Big Five domains rather than the more nuanced facets of the IPIP-5F30F-R1 (Iller et al., 2025), as recommended by McAdams et al. (2004). However, consistent with the research cited in Sections 2.1 and 2.2, where Big Five domains have likewise been employed, we decided to focus on the domain level. In addition, Chou et al. (2022), who used the Big Five Aspect Scales (BFAS; DeYoung et al., 2007) to examine personality at the aspect level – that is, between the domain and facet levels – found very similar magnitudes of correlations (with narrative themes) across domains and aspects. Nevertheless, we cannot exclude the possibility that analyses at the facet level of personality would have yielded substantial correlations, and we therefore recommend that future research pursue this question further.

6.3. *RI method as a text-based measure may not capture motives and personality dispositions*

We used the MCS – the online version of the CCI (Savickas, 2011, 2019) – and the RI method as text-based measures, both designed for practical application. While the MCS follows the life narrative research tradition to assess participants' life narratives, the RI method – although also intended to facilitate narrative counselling – can be considered a text-based measure similar to the free texts used in other data-driven research (see Moreno et al., 2021). As our research is grounded in the life narrative research tradition, we cannot rule out that, in the case of the RI method, the stories – written in response to an image that appealed to the person and accompanied by reflection questions – may have been strongly influenced by the content of the image rather than by the participants' life narratives, including their motives and/or personality dispositions. However, with regard to the data-driven research cited in Section 2.1, we would still expect free text to be related to the personality dispositions assessed.

6.4. *Text-based data are contextualized, questionnaire data are not*

In psychology, questionnaire data is omnipresent in both research and application. As in our study, ML algorithms are often trained on questionnaire data which is used as "ground truth" (see also Pargent et al., 2023; Stachl et al., 2021). But questionnaires mostly assess dispositions that are based on the assumptions of time and situational stability of individual experiences and actions. However, considering McAdams' (2013; McAdams & Olson, 2010) three layers of personality as well as other personality psychological research (e.g., Beck &

Table 9
Means (*M*), standard deviations (*SD*), Cronbach's alpha (α), and correlations between ML-predicted personality dispositions (LDA-Gensim) and questionnaire data (IPIP-5F30F-R1) for RI.

	M	*SD*	α	1	2	3	4	5	6	7	8	9	10
Questionnaire													
1. Neuroticism	2.56	0.66	0.95	–									
2. Extraversion	3.38	0.46	0.91	*−0.38*	–								
3. Openness	3.60	0.46	0.90	*0.14*	*0.26*	–							
4. Agreeabl.	3.58	0.39	0.86	*0.06*	*−0.01*	*0.19*	–						
5. Conscient.	3.77	0.43	0.91	*−0.26*	*0.15*	*0.04*	*0.15*	–					
ML prediction													
6. Neuroticism	2.58	0.17	–	**0.19**	0.06	−0.08	−0.03	−0.07	–				
7. Extraversion	3.37	0.07	–	0.11	**0.05**	−0.04	0.02	0.00	*0.21*	–			
8. Openness	3.59	0.08	–	−0.09	−0.02	**−0.01**	0.01	0.02	*−0.20*	*−0.10*	–		
9. Agreeabl.	3.57	0.13	–	0.02	0.06	0.10	**0.12**	0.04	*−0.01*	*−0.01*	*0.16*	–	
10. Conscient.	3.75	0.06	–	−0.12	0.02	0.05	0.08	**−0.01**	*−0.13*	*−0.05*	*0.07*	*0.04*	–

Note. $N_{\text{IPIP-5F30F-R1}} = 586$. Convergent correlations are in bold; discriminant correlations are in italics.

Jackson, 2020; DeYoung, 2015), personality is considered being highly contextualized, especially at the layer of the life narratives. Deduction of motives and personality dispositions from text-based data – whether explicitly assessing life narratives (i.e., MCS) or not (i.e., RI method) – is limited without any contextual embedding, such as the individual's subjective perspective or validation through behavior across situations.

6.5. Text-based data contain implicit and explicit aspects, questionnaire data do not

Text-based data (i.e., MCS and RI method) are not only contextualized but also encompass both explicit and implicit personality characteristics – such as (life) themes, motives, personality dispositions, and their interconnections – whereas questionnaire data capture only explicit aspects. Some of these characteristics appear more obvious and explicit, as illustrated in the following RI method example story (translated into English by the authors), from which the themes of "perseverance" and "commitment to personal goals", as well as their connection to an achievement motive and to conscientiousness, may be inferred:

> *"I did it, a goal is reached, and I stand on the mountain that I have climbed. All the sweat, the leg pain has been worth it and are forgotten at this moment. The reward is the peace, the view, the warming rays of sun on my face. A light wind and a sweet scent mixed with sea air. It is an incredible feeling to stand here. It was a rocky road, but it was worth it. This is a goal I set for myself and vowed to achieve, no matter what it takes. With perseverance and will and a lot of humor, I have mastered all the hurdles up to here. But it is not only a goal achieved, it is immediately the prospect of more. It is the peace and freedom to plan next goals. So, I am proud of what I have achieved and make new plans."*

Other characteristics may extend beyond explicit deduction. For example, the expression "warming rays of sun on my face" could be interpreted as a metaphor implicitly indicating a need "to calm down" or "to be protected". Although the different layers of personality outlined by McAdams (2018; Panattoni & McLean, 2018) – and reflected in the text-based data of our study – are expressed in both implicit and explicit forms, explicit questionnaire measures fail to adequately represent implicit aspects. As a consequence, the connection between participants' questionnaire scores and the personality dispositions and motives predicted by ML may have been weakened.

6.6. The nomothetic–idiographic debate – ML algorithms may not be suitable for life narrative research and practice

Our most fundamental topic of discussion addresses the *idiographic* nature of both the construct and the measurement of life narratives, as well as the relationships between the three layers of personality. We assume that life narratives assessed through the MCS are sensitive to idiosyncrasy and therefore allow for the assessment of personality characteristics (i.e., (life) themes, motives, and personality dispositions) that are only relevant for one single person. This corresponds to Allport's (1937) view of idiographic research, which according to Bem and Allen (1974, p. 509) "emphasized that individuals differ not only in the ways in which traits are related to one another in each person but that they differ also in terms of which traits are even relevant." The ongoing debate between nomothetic and idiographic approaches, prominent in personality psychology (Beck & Jackson, 2020; Kuper et al., 2024; Modersitzki et al., 2025; Phan et al., 2024; Renner et al., 2020), provides valuable frameworks for contrasting perspectives, also in life narrative research and practice. The application of narrative methods in practical settings, such as the CCI (or MCS) within career counselling, or the LSI in case study research (e.g., Adler, 2018), is inherently idiographic, as it aims to draw inferences about a single individual (see Kuper et al., 2024). Renner et al. (2020; see also Beck & Jackson, 2022) highlight the potential of big data to revive Allport's (1937) view of idiographic research. Extensive data available on single individuals (e.g., through smartphones), potentially processed with AI-based methods, could pave the possibility to generate knowledge about individual persons (i.e., person-specific inferences).

The *nomothetic* approach as originally proposed by Windelband (1894) seeks to identify general laws applicable to *every* individual (i.e., all humans) (i.e., generalization approach). Many researchers (e.g., Beck & Jackson, 2020; Mõttus, 2022; Phan et al., 2024; Renner et al., 2020) argue that although psychology is more concerned with the individual, much research still focuses on populations through sample-level statistics such as factor analyses or correlations, yielding insights about populations or a hypothetical average individual (i.e., population approach) rather than about a single individual. This also applies to life narrative research that establishes a factor structure of life narratives (e.g., McLean et al., 2020) or examines correlations between life narratives and personality dispositions (e.g., McAdams et al., 2004). Nonetheless, nomothetic research according to the population approach provides valuable insights for both life narrative research and practice, as it enables the derivation of useful hypotheses that can inform both scientific inquiry and client-focused work.

In exploring the use of ML algorithms in life narrative research – even though incorporating the MCS as a person-centered, idiographic measure of life narratives – our study aligns with this tradition of nomothetic research (i.e., population approach): We employed ML algorithms on text-based data to predict questionnaire scores and to identify general patterns across the different layers of personality. However, unlike the small to moderate correlations between human-coded narrative themes and questionnaire scores reported by Chou et al. (2022), our study yielded neither meaningful nor substantial correlations. This may stem not only from the limitations discussed in Sections 5.1 to 5.5 but also from constraints inherent to ML algorithms: Although they can account for both semantic and syntactic features, ML algorithms may still fail to capture the implicit and contextualized aspects of life narratives. Moreover, they cannot fully account for narrative aspects in text data (see Section 2.2), nor are they sensitive to important features of human language such as irony, sarcasm, or metaphor. Consequently, ML may be insufficient for detecting the full spectrum of explicit and implicit aspects of life narratives.

6.7. Ethical considerations – Should we use ML algorithms for life narrative research and practice?

Ethical considerations in applying ML algorithms to life narrative research and practice include obtaining explicit consent, acknowledging the deeply personal nature of life narratives, ensuring confidentiality of both data and ML-generated outcomes, and maintaining robust data security. Moreover, while the efficiency and scalability of ML-generated outcomes – since ML can process large datasets and detect complex patterns very rapidly – are undeniable, these outputs often remain a "black box", lacking transparency and interpretive grounding (e.g., Phan & Rauthmann, 2021). In addition, given the potential risk of clients over-relying on AI-generated insights – a concern that, while not unique to AI, also applies to human counselling and questionnaire-based profiles (e.g., Forer, 1949) – it is questionable whether ML-predicted scores for motives or personality dispositions would be approached with sufficient caution by both counsellors and clients. Therefore, even if we had found correlations of 0.50, as reported in the literature cited in Section 2.1, we would still remain cautious about adopting ML algorithms in practice. Correlations, as outlined above, describe population-level characteristics and are not intended to support inferences about individual persons (see also Mõttus, 2022, for guidance on how (not) to use correlations to make claims about individuals). Yet, this is precisely the aim of life narrative practice, which raises serious concerns about the ecological validity of ML algorithms for client work. Moreover, the population-level focus of correlations stands in sharp contrast to the contextualized, co-constructed meaning-making that is central to life narrative work facilitated by a human researcher or counsellor – an aspect elaborated in the following section.

6.8. Epistemological considerations – Practice often aligns with social constructionism, ML does not

ML algorithms are grounded in the linear causal assumptions of positivist research, relying on large datasets (e.g., text, video, and self-reports) to detect person- or population-specific patterns. In contrast, the construction, deconstruction, reconstruction, and co-construction processes involved in shaping a story into a meaningful life narrative (i.e., narrative identity) – whether in research or in practice – do not necessarily rely on linear causalities. Rather, these processes align more closely with the epistemological stance of social constructionism (Gergen, 1985; Savickas et al., 2009; see also Pasupathi, 2001; as well as McAdams, 2021, who takes distance from a strictly social constructionist standpoint), which emphasizes meaning-making through dialogue and human engagement. From this perspective, human researchers or counsellors draw on implicit knowledge, embodied experience, and interpersonal sensitivity to engage in meaning-making through dialogue. In this thoroughly subjective and process- rather than outcome-oriented endeavor, they are not regarded as providers of objective information but as co-constructors of clients' life narratives. While the limitations of ML outlined in Section 5.6 constrain the interpretive depth of its analyses, the epistemological perspective further challenges its outcome-oriented interpretations – much like those of a human counsellor working without collaborative engagement with the client (i.e., co-construction). Accordingly, practices incorporating ML may not only fall short of capturing an individual's life narrative but, more critically, risk neglecting the individual as an individual due to their positivistic grounding.

7. Conclusion

Life narrative research and practice call for approaches that place the individual person at the center of inquiry (i.e., person-specific inferences). In line with the view that personality research should describe and explain both inter- and intra-individual variations in cognition, emotion, motivation, and behavior across time and situations (Baumert et al., 2017; Jayawickreme et al., 2021), we advocate for further life narrative research – and personality psychology research in general – that emphasizes context-specificity and idiosyncrasy (e.g., case studies). This includes a focus on (1) the *structure* of an individual's life narrative and its relation to other layers of personality, (2) the co-construction *processes* through which the individual's narrative is shaped, and (3) the *development* of the individual's life narrative over time. Future research could examine life narratives deriving from practice, for example, comparing client life narratives before and after counselling, exploring the specificity of the counsellor–client interaction, and examining the counsellor's role in narrative co-construction.

On the basis of the limitations discussed in this paper, we conclude that ML algorithms are not suitable for this kind of research or practice. However, in light of the recent developments in GenAI, we offer a forward-looking perspective and propose a potential future scenario in which GenAI supports life narrative research and its practical applications. While GenAI chatbots are also based on ML algorithms, they introduce a new dimension to this field by simulating human interaction through Large Language Models (LLMs) trained on extensive textual datasets (e.g., internet-based sources). These models generate language by probabilistically predicting the next word based on patterns of word co-occurrence. Although GenAI, like traditional ML algorithms, is trained solely on explicit data, its ability to simulate human communication introduces new possibilities. That said, we remain convinced that the co-construction of life narratives is fundamentally a human process – one that inherently relies on intuition, empathy, and interpersonal sensitivity, all of which remain beyond GenAI's current capabilities. Hence, we advocate for life narrative research (not yet practice) that critically explores the potential role of GenAI in supporting the co-construction of a person's life narrative.

Ethical statement

No ethical review was necessary under national, university or departmental rules. The study was conducted under strict observation of ethical and professional guidelines.

Open Science statement

We provide the code of our analysis (see Supplementary Material). But we cannot provide the written life narratives due to the data privacy policy of the online platform that collected the data. We provide one typical example of a text in the paper.

CRediT authorship contribution statement

Marc Schreiber: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing (Draft, Review, Editing), Supervision, Project administration, Funding acquisition. **Gregor J. Jenny:** Conceptualization, Methodology, Investigation, Writing (Draft, Review, Editing), Visualization, Supervision, Project administration, Funding acquisition. **Manuela Hürlimann:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing (Draft, Review, Editing). **Yuliya Parfenova:** Methodology, Software, Data curation, Formal Analysis. **Pius von Däniken:** Methodology, Software, Formal analysis. **Mark Cieliebak:** Methodology, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrp.2025.104666.

Data availability

The authors do not have permission to share data.

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