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Beyond Likert Scales: Convergent Validity of an NLP-Based Future Self-Continuity Assessment from Verbal Data

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Author Note
This study was not pre-registered. All data and implementation materials to reproduce the findings are made publicly available at the Open Science Framework (OSF; Sokol, 2025) and can be accessed at https://doi.org/10.17605/OSF.IO/JC86M. This includes the study data files used in our analyses and comprehensive implementation materials including Python code for the NLP-based FSC assessment, detailed instructions for the Claude API, configuration templates and setup documentation, and a README with replication instructions. We encourage researchers interested in replicating or building upon this work to access these materials. For questions about implementation or technical details, please contact the corresponding author.

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Abstract

Psychological assessment using self-report Likert items suffers from numerous inherent biases. These biases limit our capability to assess complex psychological constructs such as Future Self-Continuity (FSC), i.e., the perceived connection between one's present and future self. However, recent advances in Natural Language Processing (NLP) and Large Language Models (LLMs) have opened new possibilities for psychological assessment. In this paper, we introduce a novel method of psychological assessment applied to measuring FSC that uses an LLM for NLP of transcripts from self-recorded audio of responses to 15 structured interview prompts developed from FSC theory and research. 164 whitelisted MTurk workers completed an online survey and interview task. Claude 3.5 Sonnet was used to process the transcripts and generate quantitative scores. The resulting FSC scores (including total score, and the similarity, vividness, and positivity components) showed significant correlations with scores on the Future Self-Continuity Questionnaire (FSCQ), a well-validated Likert item measure of FSC, supporting the new method's convergent validity. A Bland-Altman analysis indicating general agreement with standard FSCQ scores, replication using an updated Claude 3.5 Sonnet model, and the strong correlations between NLP-based FSC scores using the two models supports the new assessment method's validity and robustness. This measurement approach can inform treatment planning and interventions by providing clinicians with a more authentic FSC assessment. Beyond FSC, this NLP/LLM approach can enhance psychological assessment broadly, with significant implications for research and clinical practice.

Keywords: Future self-continuity; Natural language processing; Large language models; Validation; Verbal response analysis

Introduction

The accuracy of psychological assessment is critical to effective clinical practice and reliable psychological research. However, traditional self-report measures have significant limitations, including well-documented response biases such as social desirability, acquiescence, extreme responding, and central tendency biases (Paulhus, 1984), as well as issues with fixed response formats and interpretation variability (Schuman & Presser, 1996; Schwarz, 1999).

These limitations are particularly relevant when assessing complex psychological constructs like Future Self-Continuity (FSC). FSC, the perceived connection between one's present and future self, consists of three interrelated components: similarity (the belief that one's future self will resemble their current self), vividness (the clarity and detail with which one can imagine their future self), and positive affect (a positive assessment of one's future self) (Han et al., 2025; Sokol & Serper, 2020). High levels of FSC are associated with increased motivation, goal-directed behavior, better long-term planning and decision-making (Bartels & Urminsky, 2011; Ersner-Hershfield et al., 2009), improved self-regulation (Blouin-Hudon & Pychyl, 2015), and greater life satisfaction (Reiff et al., 2020).

The multifaceted nature of FSC, particularly the subjective assessment of components like vividness (where individuals may have vastly different internal experiences and interpretations of the concept), makes it especially vulnerable to the limitations inherent in traditional self-report measures. To overcome these assessment challenges, innovative approaches are needed.

Natural Language Processing (NLP), a branch of artificial intelligence focused on understanding and generating human language, offers a potential alternative to traditional self-report assessment (Boyd et al., 2022; Tausczik & Pennebaker, 2010). Large Language Models (LLMs), a type of

advanced deep learning model, trained on massive amounts of text data, can understand context, process natural language fluently, and identify subtle patterns in text (Alizadeh et al., 2023; Fischer & Dörpinghaus, 2024; Fischer et al., 2024). Earlier NLP methods like LIWC (Boyd et al., 2022) were limited to analyzing pre-defined linguistic features such as pronoun use and emotional tone words. In contrast, LLMs' deep learning architectures can analyze complex patterns of meaning across entire transcripts, enabling a more holistic assessment of psychological constructs.

Using LLMs and NLP may offer significant advantages over traditional written responses. Speaking is often more natural and comfortable than writing, as writing is often a more formal and less frequent activity that typically occurs in more artificial environments (Anwar & Ahmed, 2016). Thus, verbal responses can be more spontaneous, less filtered, and a more authentic reflection of thoughts and feelings. This is particularly relevant when discussing personal, sensitive topics. Additionally, verbal responses may be less susceptible to response biases.

Therefore, the current study aims to validate a novel NLP-based method of assessment derived from the analysis of verbal responses to open-ended prompts. This is the first application of LLMs to assess a psychological construct like FSC through the analysis of verbal responses elicited from a theoretically grounded structured interview. We hypothesize that the NLP-derived FSC scores will be significantly correlated with scores from a traditional, well-established FSC measure, the Future Self-Continuity Questionnaire (FSCQ; Han et al., 2025; Sokol & Serper, 2020), providing support for the convergent validity of this new NLP-based assessment.

Method

Participants

Participants (N = 164) were recruited via CloudResearch, utilizing their “whitelisted” Amazon Mechanical Turk (MTurk) worker pool. Their ages ranged from 20 to 73 years (M = 38.85, SD = 11.20), with 54.9% identifying as male and 43.9% as female, and 56.7 having a Bachelor's degree or higher. The majority of the sample was White (67.7%) and included individuals with varying levels of psychological distress. Further demographic details, including socioeconomic status and detailed ethnic breakdown, are available in the protocol paper (Sokol et al., 2025).

Measures

Future Self-Continuity Questionnaire (FSCQ). The FSCQ is a 10-item scale assessing the perceived connection between one's present and future self (Sokol & Serper, 2019). It measures three components—Similarity, Vividness, and Positive Affect—using a 6-point Likert scale.

NLP-Based FSC Assessment (NLP-FSC). This measure was derived from verbal responses to 15 open-ended prompts, developed from FSC theory and research (e.g., Sokol & Serper, 2020), and designed to elicit a structured narrative of participants' expectations, hopes, and fears for their future selves. Example prompts include: “Think about what you will be like over the next 10 years. Tell us about how you are similar and how you differ from your future self. Describe your future self as vividly as you can,” and “Describe your ideal life in 10 years. Please explain this in depth and with details.” See Sokol et al. (2025) protocol paper for the complete prompt set, detailed information on development of the prompts, and the structured interview protocol.

Procedure

This study was approved by the Institutional Review Board of [REMOVED FOR REVIEW]. Participants provided informed consent before completing the FSCQ online. They then recorded

verbal responses to the 15 prompts using Vocaroo (www.vocaroo.com), a web-based audio recording service. Participants were compensated $3.34, with a potential $2.00 bonus for high-quality audio recordings of sufficient length. The average recording duration was 15 minutes and 42 seconds (SD = 9 minutes 15 seconds), ranging from 2 minute 13 seconds to 1 hour 3 minutes 6 seconds.

Data Analysis

Audio recordings were checked for overtly identifying information (e.g., names, addresses). As none was found, no further redaction was necessary. They were then transcribed using Microsoft Word automatic transcription, after which each transcript was checked against the recording. The corrected transcripts were then analyzed using the Claude 3.5 Sonnet API (Anthropic, 2024a), selected for its demonstrated intelligence, exceeding prior models in benchmarks relevant to nuanced natural language understanding and reasoning (Anthropic, 2024a), and for its strong adherence to safety protocols (Anthropic, 2024a, 2024b). A specific prompt was engineered to assess overall FSC and its subcomponents (Similarity, Vividness, and Positive Affect) on a 1-6 scale using detailed rubrics for each dimension that were developed based on FSC theory and research (e.g. Sokol & Serper, 2020). The prompt was engineered to provide specific instructions and a standardized output format, while the rubrics were designed with detailed descriptors for each score level to enhance scoring reliability. See Appendix for the full prompt and rubrics.

Analyses were conducted using Python 3.8 with the Anthropic package (version 0.3.4) and R 4.4.1.. The prompt template was standardized (see Appendix). Default API temperature (1.0) and Top-p settings were used. Maximum token length was set to 2000. Transcripts were processed in batches using the Anthropic API's batch processing feature. The system prompt containing

scoring instructions was provided first, followed by each transcript as a user message. The API returned structured assessments following a standardized format that included analyses and numerical scores for overall FSC and each subcomponent.

The model initially used was claude-3-5-sonnet-20240620 (API cost: $0.011 per transcript; $1.77 total). To further validate the NLP-based assessment, the analysis was replicated using an updated version of the same model, claude-3-5-sonnet-20241022 (API cost: $0.009 per transcript; $1.54 total). The two versions of the NLP-FSCQ were highly correlated (see Results). All subsequent analyses utilize scores derived from the updated model.

The NLP analysis generated an overall NLP-FSCQ score and individual subscale scores. Convergent validity was assessed via Pearson correlations between the traditional FSCQ and NLP-FSCQ total scores. Correlations between corresponding subscales were also examined. A Bland-Altman plot assessed agreement between the two measures across the score range. Moderated regression analyses tested whether response length moderated the relationship between FSCQ and NLP-FSCQ scores.

Results

Table 1 presents descriptive statistics and correlations for all primary variables. Table 2 presents correlations between NLP-FSCQ scores derived from the initial June 2024 Claude 3.5 Sonnet model and the updated October 2024 version. These correlations are very high, ranging from r = .54 to r = .92 (all ps < .001). The total FSC scores from the two versions, in particular, are almost perfectly correlated (r = .91, p < .001). These very high correlations provide strong evidence for the robustness of the NLP-based assessment across different model iterations. Subsequent analyses utilize scores derived from the updated claude-3-5-sonnet-20241022 model.

The traditional FSCQ total score and the NLP-FSCQ total score were moderately correlated, $r(162) = .57$, $p < .001$, 95% CI [.45, .66]. Correlations between corresponding FSCQ and NLP-FSCQ subscales were: Similarity, $r(162) = .49$, $p < .001$, 95% CI [.36, .60]; Vividness, $r(162) = .35$, $p < .001$, 95% CI [.21, .48]; and Positive Affect, $r(162) = .62$, $p < .001$, 95% CI [.52, .71]. Moderated regression analyses showed response length did not significantly moderate convergent validity for the total FSC score (interaction $p = .959$, $\Delta R^2 = .000$) or its subscales (all interaction ps > .05, all $\Delta R^2 < .013$). In addition, the Bland-Altman analysis (mean difference: -0.73; 95% limits of agreement: -2.85, 1.39) revealed no significant proportional bias ($r = -.053$, $p = .497$) and normally distributed differences (Shapiro-Wilk $W = 0.987$, $p = .136$), indicating acceptable agreement between measures (Figure 1).

Discussion

The study's aim was to demonstrate and validate a novel NLP-based assessment of future self-continuity (FSC) derived from verbal responses against a traditional measure of FSC. Our findings of a significant moderate positive correlation between traditionally measured FSC and the NLP-measured FSC support the new assessment method's validity. The Bland-Altman analysis supported convergent validity based on consistent agreement across the measurement range with no systematic bias. The replication of the NLP method using an updated version of the LLM model (Claude Sonnet 3.5 version 10.22) also supports the new assessment method's robustness. Finally, the lack of significant moderation by response length across total scores and subscales demonstrates that response length does not affect the NLP-FSC's convergent validity and supports its validity and use without requiring standardizing response duration.

Although the moderate correlation between these measures of FSC provides evidence of convergent validity, the medium effect size suggests that while the NLP measure is tapping into the same construct, the richness and spontaneity of verbal responses, and LLM's ability to respond to subtle patterns in language may enable this method to capture unique aspects of FSC not fully captured by traditional self-report measures. This can be seen in the varying strengths of the relationships, with positive affect being the highest, which people explicitly recognize about themselves, and a self-report may have an easier time assessing, while vividness was lower. It may be that the vividness of one's future self is inherently different when speaking it out loud versus rating it on a scale. People may not easily be able to accurately assess if their future is vivid without a clear internal comparison group, but when they describe their future, its vividness is apparent in the clarity and detail. Therefore, the LLM picks up on those nuances of language that the FSCQ might miss. If this is correct, the lower correlation may paradoxically reinforce the importance of the novel assessment method.

This is the first application of LLMs in the psychological assessment of future self-continuity using verbal responses elicited from a theoretically based structured interview. This approach may have potential for use in multiple domains of psychological assessment, including other forms of identity, such as self-esteem, but also mood, personality, and mental health. It has significant potential advantages over traditional self-report measures due to the spontaneity, reduced susceptibility to Likert item response biases, greater ecological validity in its use of natural language, and potential to capture the nuances of the underlying psychological constructs.

However, there are significant limitations to this study. The use of an online MTurk sample that was also predominantly White, USA-based, and English-speaking limits generalizability. The findings would be strengthened with cross-validations in diverse populations. In addition, while

recording verbal responses may reduce certain response biases like central tendency, they may introduce others, such as performance anxiety or social desirability. Finally, current technology and understanding of NLP and LLMs are limited, with LLMs acting as "black boxes" where it is challenging to know precisely what the model is picking up on in its assessment of the construct. Furthermore, while the method was robust against the update in the model, future models may yield varying results.

Future research should seek to refine the NLP method, including experimenting with different prompts and LLMs, and exploring the integration of other modalities, such as video, in addition to audio. This should be combined with investigating how ongoing advancements in LLM technology, particularly in the areas of nuanced language understanding and bias mitigation, might further enhance the accuracy and reliability of this assessment method. In addition, future studies should attempt to apply this NLP-based assessment method to other psychological constructs, such as personality traits, mood, and mental health. It can also be applied to the prediction of future states and mental health outcomes. Preliminary evidence from our ongoing longitudinal study (N=164 at Time 1, N=100 at Time 2 [15-month follow-up]) suggests NLP-derived FSC scores predict future suicidal ideation severity, planning, and hospitalization.

In conclusion, this study demonstrates the convergent validity and robustness of a novel NLP-based assessment of Future Self-Continuity. By capturing subtle patterns in verbal expression overlooked by traditional self-reports, this method has the potential to significantly enhance research and clinical practice. For example, low NLP-derived FSC vividness could signal the need for interventions like guided imagery or narrative therapy to improve their motivation and long-term well-being. More broadly, this work supports using NLP and LLMs to enhance psychological assessment and, thereby, to better understand and support mental health.

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Table 1: Descriptive Statistics and Correlations

Variable	M	SD	1	2	3	4	5	6	7
1. FSCQ Total	3.79	0.85	—						
2. FSCQ Similarity	4.01	1.05	.78***	—					
3. FSCQ Vividness	3.45	1.08	.84***	.47***	—				
4. FSCQ Positive Affect	3.83	1.08	.75***	.28***	.60***	—			
5. NLP-Based FSC Total	4.52	0.89	.57***	.40***	.50***	.46***	—		
6. NLP-Based FSC Similarity	4.70	0.81	.49***	.49***	.39***	.27***	.80***	—	
7. NLP-Based FSC Vividness	4.52	0.89	.35***	.07	.35***	.47***	.60***	.29***	—
8. NLP-Based FSC Positive Affect	4.06	1.11	.38***	-.02	.38***	.62***	.56***	.19*	.60***

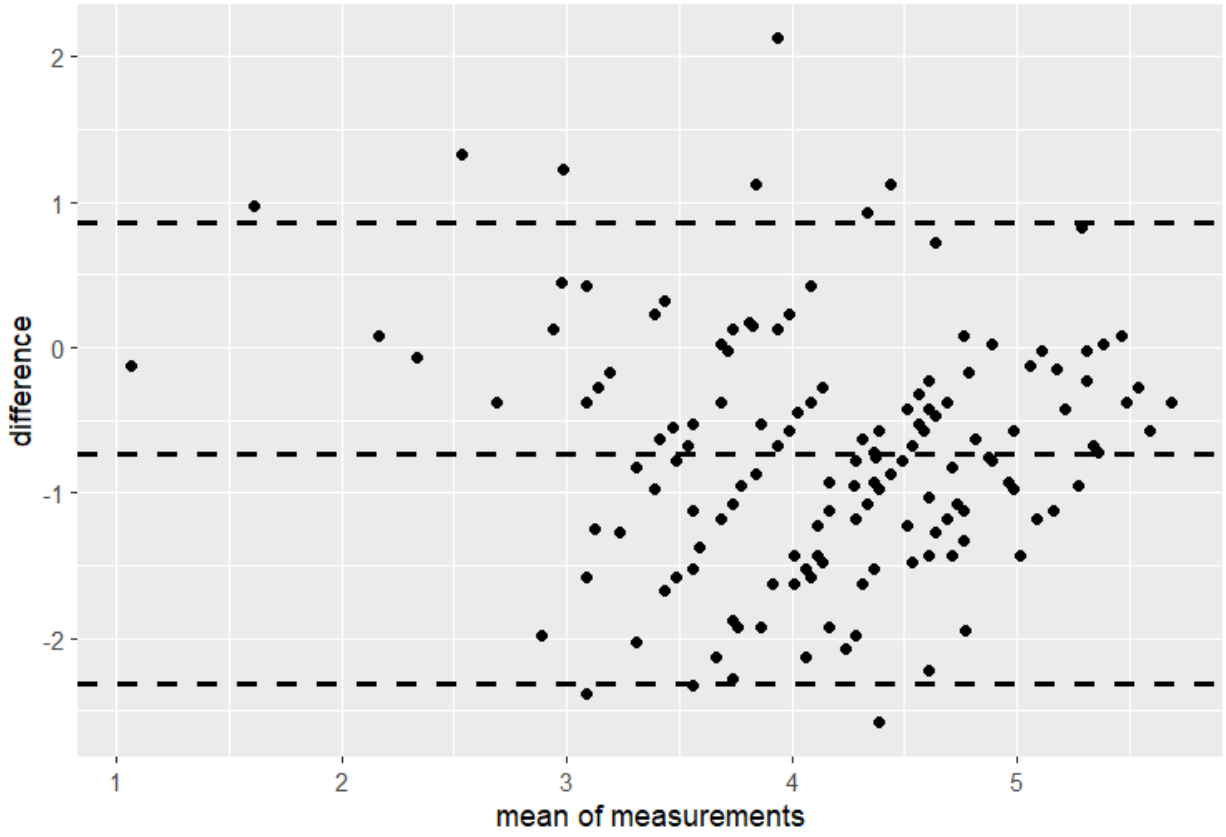
Note: * $p < .05$, ** $p < .01$, *** $p < .001$.
NLP-FSC is the NLP-derived scores on FSC

Table 2: Robustness of NLP-Based FSC Scores: Correlations Between Scores from June and October 2024 Model Versions

Variable	1	2	3	4	5	6	7	8
1. NLP-FSC Total (Jun)	—							
2. NLP-FSC Sim (Jun)	.85***	—						
3. NLP-FSC Vivid (Jun)	.66***	.44***	—					
4. NLP-FSC Pos (Jun)	.59***	.27***	.68***	—				
5. NLP-FSC Total (Oct)	.91***	.78***	.61***	.55***	—			
6. NLP-FSC Sim (Oct)	.72***	.83***	.29***	.21**	.80***	—		
7. NLP-FSC Vivid (Oct)	.54***	.35***	.78***	.55***	.60***	.29***	—	
8. NLP-FSC Pos (Oct)	.55***	.24**	.62***	.92***	.56***	.19*	.60***	—

Note: * $p < .05$. ** $p < .01$. *** $p < .001$. NLP-FSC = Natural Language Processing-based Future Self-Continuity assessment; Total = overall FSC score; Sim = Similarity FSC component; Vivid = Vividness FSC component; Pos = Positive Affect FSC component; Jun = scores from Claude 3.5 Sonnet model version released June 2024; Oct = scores from version released October 2024.

Figure 1. Bland-Altman plot assessing agreement between the traditional FSCQ and NLP-FSCQ total scores



Note: The center line represents the mean difference (-0.73), while the upper and lower dashed lines indicate 95% limits of agreement (-2.85 to 1.39). Points falling within these limits suggest acceptable agreement between measures.

Appendix: LLM Prompt and Scoring Rubrics for Future Self-Continuity Assessment

<background>

Future self-continuity (FSC) refers to the psychological connectedness people have with their future selves—the sense of persistence of selfhood from the present to the future. It represents the degree to which a person identifies their future self as being the same person as their current self.

FSC has three subcomponents:

1. Similarity to the future self: How similar one's current self is to their future self in terms of beliefs, values, personality, and other aspects of identity.

2. Vividness of the future self: How vividly an individual can imagine their future self and project themselves into the future.

3. Positive affect (positivity) toward the future self: Emotional attitudes and feelings toward one's future self, including liking, caring, and positive expectations.

</background>

<instructions>

You are an expert in assessing future self-continuity. Your task is to analyze a transcript of recorded answers to prompts related to future self-continuity and estimate the individual's FSC and its subcomponents on a scale of 1-6 based on the provided rubrics.

1. Carefully analyze the provided transcript to assess the individual's FSC and its subcomponents.

2. Assign a score between 1 and 6 for the overall FSC and each subcomponent (Similarity, Vividness, and Positivity). Scores can include up to 3 decimal places (e.g., 3.425) for precision.

3. If the transcript contains ambiguous or contradictory information, use your best judgment to interpret the overall sentiment and provide scores accordingly.

4. For each score, follow this process:

   a. Review the transcript as it relates to the construct and rubric

   b. Think step-by-step to develop an assessment

   c. Provide the numerical assessment

5. Use the rubrics provided below to guide your scoring.

</instructions>

<rubrics>

Future Self-Continuity (FSC) Rubric:

1: Little to no sense of connection or continuity with the future self. Sees the future self as a completely different person.

2: Minimal sense of connection or continuity. May see a few similarities but views the future self as largely different.

3: Moderate sense of FSC. Expects some continuity in core aspects of identity but anticipates significant changes as well.

4: Considerable FSC. Envisions notable similarity and continuity between current and future selves, with some expected changes.

5: Strong FSC. Clearly envisions the future self as an extension of the current self with high continuity. Expects core identity, beliefs and values to remain consistent.

6: Very strong FSC. Views the future self as essentially the same person, with a strong sense of persistence of selfhood over time. Anticipates very high continuity in nearly all aspects of identity.

Similarity to Future Self Rubric:

1: Expects very little similarity between current and future self.

2: Anticipates a few similarities in minor aspects, but expects core identity to change.

3: Expects moderate similarity, with some core aspects remaining consistent and others changing.

4: Envisions considerable similarity, with most key aspects of identity remaining continuous.

5: Anticipates high similarity, with beliefs, values, personality and identity largely unchanged.

6: Expects very high similarity bordering on sameness between current and future self.

Vividness of Future Self Rubric:

1: Has little to no ability to imagine or envision the future self. Future seems abstract and unreal.

2: Can imagine the future self to a minimal degree, but the image is vague, hazy and lacks detail.

3: Has a moderately vivid image of the future self. Can envision some details but much is still unclear.

4: Can envision the future self with considerable vividness and clarity. Has a fairly detailed picture.

5: Has a highly vivid and clear mental image of the future self. Can imagine many specific details.

6: Can picture the future self with extraordinary vividness and detail, almost like a mental time travel.

Positivity Toward Future Self Rubric:

1: Has strongly negative feelings toward future self. Actively dislikes or fears future self.

2: Feels somewhat negative toward future self. Has doubts, concerns, and expects to dislike future self.

3: Has mixed or ambivalent feelings. Feels somewhat positive and somewhat negative toward future self.

4: Feels largely positive toward future self. Cares about, has good expectations and wants good for future self.

5: Has strongly positive affect toward future self, with feelings of liking, caring and warm regard.

6: Has extremely positive feelings toward future self, with deep fondness, concern and sense of kinship.

</rubrics>

<output_format>

For each assessment, provide:

1. A brief analysis of the transcript related to the construct

2. Your step-by-step reasoning

3. The numerical score (1-6, up to 3 decimal places)

Present your assessments in this order:

1. Overall Future Self-Continuity (FSC)

2. Similarity to Future Self

3. Vividness of Future Self

4. Positivity Toward Future Self

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