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Memory Processes Behind Leader Identity Formation and Its Effects on Soldier Development

A Machine Learning Approach

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Abstract

In the present work, we demonstrate how natural language processing can assist Army researchers in understanding soldiers' perceptions of their leadership positions over time and the implications these views may have on their leadership training and development. We use these methods to extract and classify specific memory types that research has suggested are indicative of one's mindset and willingness to develop. Our findings show how these previously unscalable memory predictor variables can be extracted from archival data using language models. We replicate foundational psychological findings in an Army sample, illustrating how these variables can predict soldiers' willingness to develop as leaders. Future work is discussed that aims to replicate and expand on the current results.

Understanding one's identity and its behavioral ramifications has been a significant research subject in the field of psychology. Social psychological literature emphasizes that autobiographical memories form aspects of one's identity over time (Chessell et al., 2014; Libby & Eibach, 2002). These memories, recalled as episodic or semantic memories, influence self-perception and later behavior (Pezdek & Salim, 2011). Episodic memories often contain vivid details, while semantic memories may be biased as they contain more generalized information (Klein & Loftus, 1993; Klein et al., 1996). Thus, how one recalls memories can affect how one might identify with certain domains and the decisions one makes within those domains. Past military research has linked autobiographical memory to leader identity and career advancement but hasn't explored how *memory type* influences identity development, particularly in leadership positions (Shaughnessy & Coats, 2018; Shaughnessy et al., 2018). This work begins to address these gaps using natural language processing (NLP) to quantitatively analyze soldiers' leadership accounts and experiences, providing new insights and methods to enhance the understanding of soldier leader development.

Autobiographical Memory and Identity

For decades, psychologists have explored what comprises identity and how individuals understand themselves. For the past few decades, it has been understood that self-knowledge derives from cultural roles, societal roles, and relationships (Wang, 2006). Autobiographical memories are central to these influences, as identity is shaped over time through long-term memory (Bluck & Alea, 2008; Proust, 2003). While it is evident that autobiographical memory significantly informs identity, the processes of recalling these memories and the types used in shaping identity remain areas of ongoing inquiry.

Episodic and Semantic Memory Recall—Applications to Leader Identity and Development

Klein and Loftus (1993) distinguished between episodic and semantic self-representations. Semantic autobiographical memories consist of general traits and social information about oneself, while episodic self-knowledge includes specific events relevant to a person's identity tied to contexts, dates, or times. Due to the different types of information these memories contain, recalling episodic and semantic memories has been suggested by the literature to impact identity formation and behavior differently. To date, research has suggested that the specificity in episodic memories allows for a more flexible, transient identity, enabling individuals to support various identities as needed (Nicholas & Mattar, 2024; Tulving, 2002). These findings can be demonstrated in adolescents who report more episodic memories when exploring aspects of their identities. This flexibility has also been linked to mental states conducive to learning and decision-making (Lalla et al., 2022; Nicholas & Mattar, 2024). Conversely, adults, when prompted with a similar paradigm, tend to report more semantic memories when reflecting on aspects of their identities (Beike et al., 2023; Klein & Loftus, 1993; Klein et al., 1996). Recalling more semantic memories indicates a fixed identity resistant to change or a more enduring sense of self, as adults often recall general identity-relevant behaviors in a semantic fashion. This rigidity has been linked to mental states that may hinder adaptability and learning (Beike et al., 2023; Haslam et al., 2011; Klein et al., 1996).

These findings suggest that the way individuals recall aspects of their identity may reveal the malleability of their mindset or mental state toward a specific aspect of one's identity and one's potential to learn new information relevant to that domain. Malleability thus has significant implications for self-perception and willingness to develop within a particular identity, such as leadership. For instance, recalling oneself as a leader using episodic memories may indicate a capacity for continued growth and development, while reliance on semantic memories may suggest a more static self-view as a leader.

Integrating Quantitative Analyses into Qualitative Data

Past leader identity research, which inspired this project, was primarily qualitative (Shaughnessy et al., 2018). This approach provided deep insights into how leaders develop within the Army through candid soldier responses. However, qualitative research has limitations such as interrater bias and the resources these methods require in terms of time and personnel (Grimmer & Stewart, 2013; Patel et al., 2012). These limitations may not pose concern with smaller research samples or research with resources allocated to train and validate human coders, but with applied research, these limitations significantly interrupt ongoing work. Not only do we need to minimize human error and potential biases, but we also need results with a much faster turnaround. Additionally, since we are working with personnel, there is simply a ceiling on how many subject-matter experts we can request to train as human coders. Thus, to generalize and scale findings to larger Army populations, a quantitative approach is needed.

This article demonstrates how researchers can utilize NLP to analyze qualitative interview data quantitatively, thereby reducing the need for extensive human coding. NLP can quantify text and tag phrases, and assess sentiment, revealing meaningful

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patterns invisible to human coders. Additionally, using readily available data with these analyses minimizes labor and time costs and offers a nonintrusive method to examine new predictors without collecting additional data from Army populations. Ultimately these methods have the potential to save cost, reduce personnel hours, and decrease soldier burden while minimizing human error. Thus, archival interview data was used to extract episodic and semantic memory predictors using NLP analyses.

Research Objectives

The present work explores whether memory variables can predict leader development. To achieve this, four research objectives were established. First, given that natural language responses might not explicitly indicate episodic or semantic memories, analyses were planned to determine if responses included appropriate proportions of episodic and semantic elements (i.e., not biased toward one type of response or the other). Second, the present effort aims to accurately classify episodic and semantic responses using a locally run NLP model, thereby ensuring the secure processing of Army data. Specifically, we sought to build a model that could classify these responses with at least 80% accuracy. Third, based on the psychological literature of Klein and Loftus (1993) that suggests adults and adolescents may recall aspects of their identities using different types of memories, we investigated whether memory system variables differ between early and late career personnel. In other words, this analysis would examine whether types of memory recall are influenced by stages of leader development. Finally, we examined the predictive power of these memory variables. Using inspiration from past work that suggests malleable mental states can be conducive to learning (Zarrinabadi et al., 2022), we wanted to examine whether episodic or semantic memories could predict individuals' willingness to continue their leader development, bolstering their leader identities. These results would help us determine if these memory system variables, previously unused as predictors in Army settings, may predict relevant Army outcomes.

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Methods

The following section discusses participants of the study, methods, predictable variable extraction, and the outcome variable coding.

Participants

The Follower Leader Identity Integration Study (FLII; Cooperative Agreement Number W911NF-15-2-0134) was utilized, which interviewed 84 individuals about their leader and follower identities. Specifically, these interviews consisted of 26 civilian employees from a large retail company, 17 DOD civilian (veterans) employees from one command[1], and 41 Army soldiers. Because the interviews inquired about both leader and follower identity, only questions that specifically tapped into leader identity were utilized (e.g., "What does leadership mean to you?", "Why do you lead?", and "Can you tell me a story that's a good example of why you lead?").

Interview data was utilized in the following manner. All retail civilian interviews were utilized to train the language model. Because the third and fourth research objectives relied on the Army soldier and DOD civilian employee data, these interviews were utilized to create the predictor and outcome variables. Each DOD civilian and Army soldier response consisted of an average of 85.66 sentences (*SD* = 37.68). Two individuals were removed for speaking significantly more than the average participant (above 2.5 standard deviations from the average), leaving the sample with 56 usable interviews for predictors and outcomes.

Predictor Variable Extraction

The language model was built in the Army Vantage Data Analytics Platform using the retail civilian interview responses from participants in addition to explicit episodic and semantic phrases not from the retail civilian interview responses. For example, an explicit semantic phrase would look like, "The Wright brothers invented the first successful airplane." An explicit episodic phrase would look like, "I went to the park yesterday afternoon to play baseball." Utilizing the retail civilian interview sentences as training data allowed the model to learn what more complex episodic and semantic memories looked like in natural language responses. Importantly, retail civilian interview responses also mirrored Army soldier and DOD civilian responses as the same questions were posed to each sample. Including explicit episodic and semantic phrases helped the model understand how to differentiate between these memory types using more simplistic examples. In total, 520 memory state-

[1] All DOD civilians interviewed were U.S. veterans.

ments were provided to train the model; episodic and semantic memories represented 272 and 248 sentences, respectively.

To complete the second research objective, multiple language model configurations were tested. These included models using larger transformers, advanced computer algorithms that help machines understand and process human language more effectively (e.g., En core_web_lg from spaCy models [spaCy, 2024]), and XGBoost (Extreme Gradient Boosting) after fine-tuning the hyperparameters, settings that control how machine learning models learn and make predictions, with GridSearch (Tran et al., 2023). XGBoost was the first model we tried as it is a powerful and scalable machine learning algorithm for supervised learning tasks, known for its efficiency, accuracy, and speed, particularly in regression and classification problems like the current task. GridSearch is helpful in creating the most accurate XGBoost model, as it finds the optimal hyperparameters for the data fed into the model to improve performance. However, even after fine-tuning hyperparameters with GridSearch, our XGBoost models with larger transformers only had an average accuracy rating of 63%. This did not meet our classification goal for the second research objective. We realized that our training data may have been too small for these more complex language models and decided to try simpler models to improve our classification accuracy. Further elaboration as to why our more complex models may have failed is available in the discussion.

Taking a simpler approach, we were able to build a language model with an accuracy rate of 83%. This satisfied our second research objective and was built in the following way. Training data were cleaned and tokenized using a smaller transformer than what we utilized in the more complex models. Specifically, we used En_core_web_sm from the spaCy models (2024). En_core_web_sm is a small English pipeline trained on written web text (blogs, news, comments), which includes vocabulary, syntax, and entities. The data is vectorized using a term frequency inverse document frequency vectorizer. This type of vectorizer transforms text into a meaningful representation of numbers, which is used to fit machine learning algorithms for prediction (Aizawa, 2003). The vectorizer accomplishes this by counting how often specific words appear in a document and checking for how unique those words are. This helps the model understand what words are important so it can summarize main ideas. Finally, to predict outcomes, a logistic regression classifier was used due to the binary nature of the outcome variables (episodic or semantic).

Once a successful model that was able to classify between memory types was built, the predictor variables were created. The model was fed each sentence of the Army soldier and DOD civilian responses, and it calculated the total number of semantic and episodic sentences from the binary output. The ratio of episodic to semantic responses for each respondent was also calculated, in addition to counting the total number of sentences per response to use as control variables. We did not want our findings to be swayed by individuals who may have simply written more than others.

Table 1
Descriptive Statistics of Predictor Variables

Variable	*N*	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Semantic Count	56	11	82	34.96	16.45	0.94	0.68
Episodic Count	56	9	100	49.82	24.90	0.38	-0.70
Total Sentences	56	24	175	84.79	38.30	0.32	-0.05
Episodic to Semantic Response Ration	56	0.41	3.08	1.51	0.63	0.60	0.20

Outcome Variable Coding

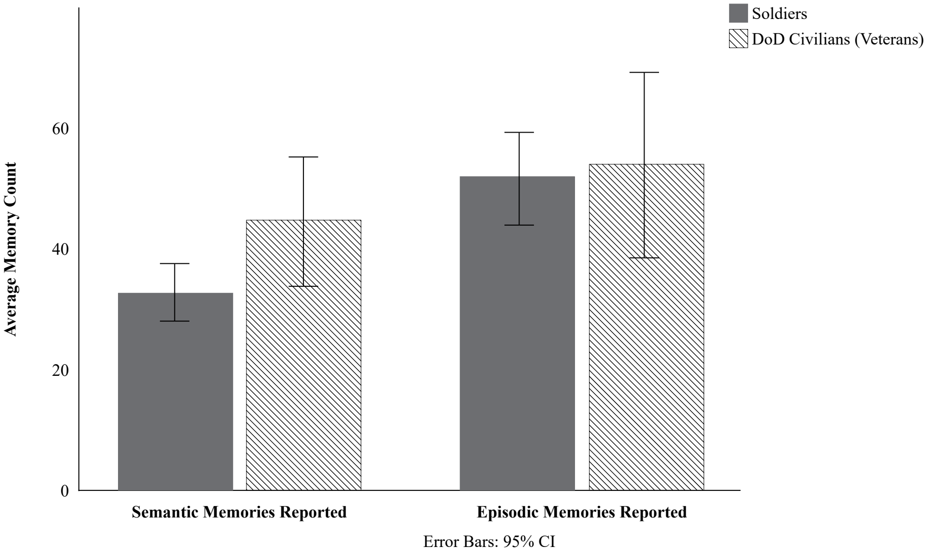
Interview responses were separated sentence by sentence into a dataset. The outcome variable of interest was coded by two raters from the final questions asked in the interview ("How did you develop into who you are as a leader?" And, "How have you changed as a leader over time?"). Specifically, raters coded for the intention to continue developing as a leader (e.g., continued reading or training courses, seeking out mentors) in a binary fashion (0, no mention; 1, mention). The sample had 30 individuals who did not mention any intention to continue developing as a leader and 26 who explicitly mentioned that they intended to continue developing as a leader. This distribution suggests that this coded variable could be used as a viable outcome as it had a relatively equal distribution. If the variable did not have an equal distribution (e.g., five individuals who mentioned they intended to continue developing as a leader and 51 individuals who did not) we would not be able to utilize the variable with confidence. Further, the interrater reliability between the two coders was calculated using Cohen's Kappa and achieved a score of .79, indicating substantial agreement between the two coders.

Results

To address the first objective, descriptive statistics across the main predictor variables were estimated. Results showed that all variables had a normal distribution indicating good variation for both episodic and semantic predictors (Semantic Memory Count: M = 34.96, SD = 16.45, Skewness = .94, Kurtosis = .68; Episodic Memory Count: M = 49.82, SD = 24.89, Skewness = .38, Kurtosis = -.69; see Table 1). This pattern was also apparent within participant responses to each specific question (not the aggregate

Figure 1

Differences in the Number of Episodic and Semantic Memories Recalled by DOD Civilians and Soldiers When Recollecting Their Leader Identities



as shown in Table 1) suggesting that each response given by participants had a normal distribution of episodic and semantic recollections. In other words, there was no specific question that prompted more episodic or semantic responses from our sample.

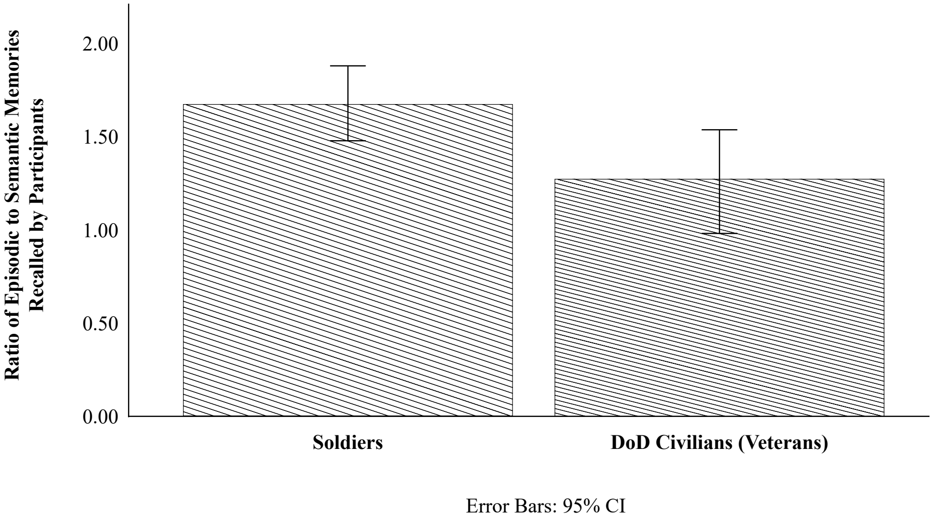
For the third objective[2], a multivariate general linear model (GLM) was run to contrast predictor variables between Army soldiers and DOD civilians. Results suggested that there were memory recall differences between the two groups consistent with past literature. DOD civilians reported higher numbers of semantic memories in comparison to Army soldiers ($F(1,54) = 6.55$, $p = .015$, $\eta^2 = .11$; see Figure 1). Further, this difference was also reflected in the ratio of episodic to semantic memories recalled by participants. Army soldiers reported a greater difference between the number of episodic to semantic memories recalled in their responses in comparison to DOD civilians ($F(1,54) = 5.56$, $p = .02$, $\eta^2 = .09$; see Figure 2). There was no difference between the number of episodic memories recalled by DOD civilian or Army soldiers ($p > .05$; see Figure 1).

Finally, we addressed research objective four. To understand the predictive nature of these memory system variables, a binary logistic regression was run to test how

[2] The second objective was addressed in the methods section with the successful building of the language model.

Figure 2

Differences in the Ratio of Episodic to Semantic Memories Recalled by Participants



Note. Higher ratio values represent greater numbers of episodic recollections in comparison to semantic recollections.

episodic and semantic memories could predict individuals' intentions to continue developing as a leader, suggesting a more malleable mindset regarding leader identity. As psychological theories would suggest, episodic memory count was a meaningful predictor of leader development intentions (B = 0.02, SE = 0.01, Wald χ^2 = 3.89, $p < .05$). The logistic regression model testing episodic memory was statistically significant, $\chi^2(1) = 4.23$, $p < .05$. The model explained 9.7% (Nagelkerke pseudo R^2) of the variance in explicitly mentioning development in a free response prompt and correctly classified 60.7% of cases. Overall, results suggest that the more episodic memories an individual recollects in their interview responses the more likely they are to spontaneously mention their leader development intentions. Semantic memory count had no effect on this outcome variable ($p > .05$).

Discussion

The present work sought to automatically extract memory system variables that indicated how soldiers and DOD civilians thought of themselves as leaders over time. Analyses utilized archival interview data in addition to a trained language model to classify these responses. Results demonstrated that natural language interview data contained normally distributed proportions of episodic and semantic responses which allowed them to be utilized as predictors. It was also possible to construct an in-house language model that classified these responses with up to 83% accuracy. Importantly, findings replicated psychological research. First, evidence was found that as leaders develop over time the memory systems used to recall leader identity may change. DOD civilian workers in their second careers recalled their leader identity using more semantic memories than Army soldiers. Second, across all DOD civilian and Army soldiers, a positive relationship was observed between the number of episodic memories recalled and the spontaneous mention of an individual's intent to continue developing as a leader.

Present results begin to tie together ways to implement predictors that were previously too obtrusive for Army use. To date, the use of episodic and semantic memories as predictors has been utilized by conducting extensive interviews and coding the outcomes using human raters (Levine et al., 2002). Although these methods are valid and reliable, they pose significant issues for the current effort due to the aforementioned challenges with human raters and would not be viable without some sort of automated assistance. Other methods include invasive neuroimaging techniques (Burianova et al., 2010). Similarly, although these methods hold great promise in the realm of basic research and academia, they are too intrusive for the applied application we are currently pursuing, which requires scalable predictors. Due to these limitations, part of the novelty of the present work utilizing archival data and NLP is that it allows these types of cognitive predictors to become accessible for Army assessment needs.

For example, memory system predictor variables may be able to provide insight into the mental state of soldiers to determine important outcomes such as the likelihood to successfully complete leadership training and development. We also would like to highlight the potential of these variables to be used in combination with other well utilized predictors. Memory system predictor variables may be used in combination with others for wholistic personnel assessments. Understanding how soldiers encode prior training, along with other knowledge, skills, abilities, and other characteristics scores, can help predict optimal future job roles for their development. For example, a soldier with weak leadership traits but high episodic encoding may be more prone to having a more flexible mental state and may embrace development opportunities more than a soldier with high semantic encoding. This differentiation may aid in determining the best job fit for soldiers to maximize their individual differences getting the right person, in the right job, at the right time.

Limitations

Although the results are promising, we want to stress that this is the first exploration of this idea of using memory variables as predictors in an Army setting, and that more work is needed. A major limitation that must be addressed is the size and distribution of the sample. This sample limited us not only in the types of models we could run but also what we could test with confidence. Our XGBoost model likely failed due to insufficient training data. XGBoost models require an appropriate amount of data given the problem at hand. Here we are asking the model to learn small differences between phrases with relatively similar sentence structures. Thus, a small training dataset likely limited the accuracy of the XGBoost model due to insufficient representation, overfitting, and limited feature discovery. In other words, with a small dataset, the model may miss important patterns, become too specialized to the training data, and fail to learn generalizable features. Increasing the size of the training dataset can provide the model with more information to learn from, thereby reducing these limitations and potentially leading to improved accuracy. In addition to greater accuracy, training a model on additional Army data would help the model better handle Army-specific acronyms and jargon, likely aiding its accuracy using a different approach.

The bias-variance tradeoff, a fundamental concept in machine learning, may have also played a role in the XGBoost model's limited accuracy. The bias-variance tradeoff refers to the balance between a model's ability to generalize well to new data (low bias) and its tendency to overfit the training data (high variance; Belkin et al., 2019; Geman et al., 1992). Bias occurs when a model is too simple and fails to capture important patterns in the data, resulting in poor performance on both training and test data. Variance occurs when a model is too complex and fits the noise in the training data, performing well on the training data but poorly on new, unseen data. In the case of the XGBoost model, it is possible that the model became too specialized to the training data (high variance) and failed to generalize well to new data, or that simplifying the model to reduce overfitting introduced bias, leading to underfitting and decreased accuracy. Finding the optimal balance between model complexity and simplicity is crucial to achieving good generalization performance and can be achieved with a larger sample size.

Because of our limited sample, we were also restricted to what types of analyses we could run. Although we were able to contrast DOD civilian and soldier memory types to replicate past work, looking across soldier rank or time in service would help bolster our initial work in addition to expanding on it. Additionally understanding how memory types may change during recollection across current enlisted soldiers may be more relevant for assisting in current Army needs.

Future Work

To address the above limitations, we are currently adding 89 archival interviews of Army soldiers that ask similar questions to the current archival data used. Adding these responses into our dataset will allow us to not only test language models that have the potential to be more accurate (i.e., XGBoost) but will also allow us to replicate and expand on current findings. For example, future work should consider testing *across* Army ranks to see how memory types may predict intentions to continue developing as a leader. This would allow us to ask whether soldiers in higher ranks recall leader identity differently than those in lower ranks and whether this may impact their future training plans.

Future work should also aim to extract other outcome variables like positive and negative leader growth (e.g., mentioning that one gained or lost positive qualities through their development) to see how that may relate to soldiers' recollections. Psychological research suggests that memory types may be able to influence how one views their identity development over time (Wilson & Ross, 2003). In other words, individuals' self-views are influenced both by what they remember about their personal past as well as how they remember these episodes and events. This would allow us to understand the predictive potential of the memory type variables so we can apply them to the best use cases as well.

Finally, future work should examine current findings not only collapsed across responses as in the present work but also within each response to each leadership question. This may allow us to focus on which responses to specific questions may be more predictive of soldier behaviors and decisions within the Army context. Together, we hope that these current and future findings assist in developing more accurate predictors of soldier behaviors and development, allowing us to develop training and experiential learning that will maximize individual soldier effectiveness and consequently, facilitate overall Army readiness.

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