Empirical guidance for developing task analyses: Do the task steps present a logical sequence?

Lucy Barnard-Brak, Ph.D.
Kagendo Mutua, Ph.D.
Amy Williamson, Ph.D.
The University of Alabama

Abstract

The current study discusses empirical guidance for developing task analyses focusing on whether steps of a particular task analysis may be considered part of a logical sequence. We utilized the task analysis steps presented by McConomy et al. (2022) as a framework for the current study. We examined and suggested how autocorrelation values may be used to help determine whether a logical sequence of steps has been developed in relation to task performance. We found that the stronger and more positive the autocorrelation value, the more likely the logical sequencing of measurable steps. The weaker and less positive (i.e., more negative) the autocorrelation value, the less likely the steps would appear to be entirely logically sequenced either by order of steps, omission of steps (therefore not a logical sequence), the understanding of steps by their content (therefore not a logical sequence to the individual), or some combination thereof for the individual.

Plain Language Summary

- Task analyses are a powerful means of teaching skills for adults with intellectual and developmental disabilities in the postsecondary education setting.
- The current study discusses guidance on how to create task analyses and we address specifically whether steps of a task analysis are in the right order.
- **What we did in this study:** We examined and suggested how certain statistical values (autocorrelation) may be used to help determine whether steps are in the right order for a task analysis. We show how to do this in Microsoft Excel.
- **Findings:** We found that the stronger and more positive the autocorrelation value, the more likely the steps are in the right order.
    - The weaker and less positive (i.e., more negative) the autocorrelation, then the steps are not in the right order.
- **Conclusion:** By creating better task analyses, we can make task analyses more effective for adults with intellectual and developmental disabilities, which was studied in the context of a

postsecondary education setting of a comprehensive transition services program.

In its most basic form, a task analysis is an identified sequence of steps to perform a task (Moyer & Dardig, 1978). Task analyses have long been noted as a particularly important tool for educators in working with students with intellectual and developmental disabilities (e.g., Chirombe, 2018 McConomy et al., 2022; Steinbrenner et al., 2020). Contemporary applications continue to demonstrate the utility of task analyses for individuals with intellectual and developmental disabilities (e.g., Baker et al., 2019; Benson et al., 2021; Randall et al., 2020). As a result, task analyses have been indicated as an empirically supported and evidence-based practice for working with individuals with disabilities (McConomy et al., 2022; Sam, 2016; Steinbrenner et al., 2020). In the context of inclusive postsecondary education, task analyses can be an equally powerful means of skill acquisition for individuals with intellectual and developmental disabilities. There has been evidence that supports the utility of task analyses for individuals with intellectual and developmental disabilities in comprehensive transition services programs within the postsecondary education setting (e.g., Baker et al., 2019; Bridges et al., 2020; Price et al., 2018; Randall et al., 2020; Walters et al., 2021) and outside of the postsecondary education setting as well (e.g., Dollar et al., 2012; Riesen & Jameson, 2018; Vascelli et al., 2021).

Guidance exists as to how task analyses can be practically employed (e.g., Carter & Kemp, 1996; McConomy et al., 2022; Sam, 2016) but less procedural guidance exists as how to develop and conduct task analyses that are related to empirically improved performance. Procedural guidance on the development of task analyses appears to be limited to general steps in designing task analyses. Overall, published studies with task analyses do tend to be successful based upon the limited guidance available (Baker et al., 2019; Benson et al., 2021; Randall et al., 2020). The development of empirically-supported procedures for task analyses appears to be a worthy endeavor to improve the performance of task analyses.

As derived from Gold (1976), McConomy et al. (2022) summarized and extended the seven general steps for developing a task analysis:

"1. Observe a task aligned to student need and record all observable behaviors.
2. Identify and logically sequence all measurable steps
3. Write each step in a format that is meaningful for the student
4. Explicitly teach students how to use the task analysis
5. Include an assessment component to record student response at the step level
6. Develop an aligned teacher task analysis to support fidelity with teaching
7. Use the task analysis in instruction and assessment," (p. 416)

However, there is a lack of empirical evidence on how to develop and conduct task analyses beyond general steps. For instance, in Step 2 (i.e., identifying a logical sequence of all measurable steps), what is the optimal number of measurable steps before a task should be further divided into separate task analyses? Alternatively, scheduled breaks may be in order if a task cannot be reasonably divided. In Step 3 (i.e., write each step in a format that is meaningful for the student), for a task analysis step as written to be meaningful requires that an individual can understand its content (i.e., difficulty or complexity). In Step 5 (i.e., include an assessment component and record), the success of any task analysis assessment would require some indication as to the duration (i.e., the number of sessions) that is associated with performance. In this way, these seven steps presented by McConomy et al. (2022) may be used as a framework for developing empirically-supported procedural guidance for task analyses. This lack of empirical-supported procedural guidance for designing task analysis is not surprising as most task analyses are considered a means to an end, with researchers and practitioners both moving on to the next goal or outcome of interest once a task has been successfully performed. As a result, task analyses can be ephemeral for both researchers and practitioners with the data discarded after a task has been successfully performed. Indeed, the lengthy iterative nature of a task analysis where steps are repeated over numerous sessions until successful performance (i.e., independence) may be one of the reasons why researchers and practitioners do not retain these data.

Number of Steps

Determining the number of steps would explicitly relate to identifying steps per the first part of the second step of McConomy et al. (2022) in developing task analyses. We could not locate any literature that has examined the optimal number of steps for a task analysis. We suggest that the optimal number of steps for a task analysis has not been explicitly examined for two reasons. First, there is literature in cognitive psychology that would support that there would be an optimal number of steps that would ostensibly transfer to the performance of task analyses. Yet, this connection has not been explicitly made prior to Barnard-Brak et al. (2023a). Second, task analyses should be individuated sufficiently so that there is not a “one size fits all” recommendation. However, the idea of an upper limit to the number of steps is reasonable, as any individual at some point would have an upper limit of the steps that they could perform without prompting when learning a novel task. If no prompting would be needed despite the ever-growing number of steps, the task analysis procedure itself is probably unnecessary altogether. Barnard-Brak et al. (2023a) indicated an optimal number of steps being 7 plus or minus two steps, which aligns well with the literature on working memory within cognitive psychology (e.g., Cowan et al., 2004; Miller, 1956; Oberauer et al., 2018).

In examining task analysis performance, Barnard-Brak et al. (2023a) found a curvilinear relationship between the number of steps and subsequent task analysis performance. This inverted-U relationship indicated an optimal number of steps at the vertex value within a 95% confidence interval resulting in the value of 7 plus or minus two steps. Therefore, a range of 5 to 9 measurable steps is recommended for task analysis. However, Barnard-Brak et al. (2023a) utilized a limited number of participants with task analyses ($n \sim 56$). Future research should expand to include more varied kinds of tasks for the task analyses as well as task analyses using different means of prompting (i.e., least to most prompting was utilized in that study). Additionally, the range of steps may have been restricted in the study as the maximum number of steps was 11 and the minimum number was five, as these task analyses were authentically developed for a transition services program. We should note that recommendations as to the optimal number of steps should not supplant the individuated needs and preferences of those individuals who will perform the task analyses.

Number of Sessions

Evaluating the number of sessions to perform is related to the seventh step of McConomy et al. (2022) in developing task analyses by using the task analysis in instruction and assessment. Additionally, the number of sessions to reach satisfactory task performance would appear to be very much individuated to the context and the individual. The definition of full satisfactory performance indeed may vary considerably based upon the individual and context as well. For instance, in Barnard-Brak et al. (2023a), satisfactory performance was defined as performing each of the consecutive steps of the task without prompting (i.e., independently) for the task of accessing public transportation by individuals with intellectual and developmental disabilities. These results indicate that approximately 11 sessions were required to achieve satisfactory performance of the task. From these analyses, we suggest that there may be a relationship between the number of task steps and the number of sessions, that as the number of steps increases, the number of sessions required to achieve satisfactory performance has to increase commensurately as well. As a result, we suggest that number of sessions be understood contextually as related to the number of steps. More task analysis individual steps will generally mean that more sessions will most likely be to be required to achieve satisfactory performance of the task. Future research should explore this relationship further as well as incorporating metrics such as the fail-safe k metric, for instance, to help determine whether more sessions may be needed (Barnard-Brak et al., 2018).

Task Difficulty/Complexity

Addressing task difficulty or complexity would be related to the third step of developing task analyses per McConomy et al. (2022) in terms of writing each step in a format that is meaningful for the student. Task difficulty or complexity also appears to interact with the number of sessions and number of steps required to achieve satisfactory performance (Barnard-Brak et al., 2023a). The same exact task steps can be expressed very differently for individuals resulting in different performance. For instance, the task step of “remove the lint from the lint tray in the dryer” in an overall task of doing laundry would be difficult if you did not first identify to the individual what is lint, where is it located, and what to do with the lint; some students might then have difficulty performing this task step. Some tasks require more contextual knowledge to their steps than others, thus increasing their task difficulty or complexity. Readability may serve as a rough approximation of whether the steps of a task analysis are difficult or sufficiently well designed using the most basic and comprehensible language to articulate the performance of the task. There are several readability measures that already exist that would provide an approximation of task difficulty. Barnard-Brak et al. (under review) found the SMOG (Simple Measure of Gobbledygook; McLaughlin, 1969) measure to perform the best in relationship to task performance. Barnard-Brak et al. (2023a) found grade levels around 7th grade to be optimal for the understanding of individuals with intellectual and developmental disabilities after being prompted “least to most” task analysis training.

IQ and Adaptive Functioning

Assessing IQ and adaptive functioning is also related to the third step of developing task analyses per McConomy et al. (2022) in terms of writing each step in a format that is meaningful for the student, with emphasis on the meaningfulness. Adaptive functioning and IQ were not strongly related to task performance among individuals with intellectual and developmental disabilities (Barnard-Brak et al., 2023c; Mutua et al., 2023), which is logical, given that students come from a variety of previous exposures and circumstances. However, the limited utility of IQ and adaptive behavior in being associated with task performance should be reiterated often in the literature. IQ and adaptive functioning scores should not be utilized as limiting or excluding factors for individuals in developing and conducting task analyses. The structure of the task analysis itself in terms of the number of steps, sessions, and complexity/difficulty of steps, for instance, should guide the development of a meaningful task analysis rather than snapshot measures of cognitive ability.

Allowing or Scheduling Breaks

Considering allowing or scheduling breaks is related to the fourth step of McConomy et al. (2022) in developing task analyses in explicitly teaching students how to use the task analysis in a way that is effective for them. Allowing or scheduling breaks would appear to be associated with better task performance, which has been corroborated more broadly by the cognitive psychology literature (e.g., Griffin et al., 2017; Osth & Farrell, 2019). With specific regard for task analyses, Barnard-Brak et al. (2023b) found evidence of primacy effects with evidence of some limited recency effects in task performance. Primacy effects would indicate better performance at the beginning steps of a task analysis. Barnard-Brak et al. (2023b) found evidence to indicate better task performance for the first or beginning steps as compared to middle steps of a task. In a study of task analyses, Barnard-Brak et al. (2023b) had indicated, "first step task performance is generally better than other latter steps, which may be a function of initial supervision being provided then faded or the novelty of task declining after the first step" (p. 229). Thus, these primacy effects may be result of initial supervision being heightened then naturally dissipating. Assuming that all steps have equivalent complexity/difficulty, this primacy effect would indicate that breaks within a task performance can be instituted to create more opportunities for a primacy effect. Barnard-Brak et al. (2023b) also found limited evidence of recency effects but that latter steps may also outperform middle steps, especially when individuals can infer that a task may be ending.

Autocorrelation

Evaluating the correlation among successive task steps, otherwise known as autocorrelation, is related to the second step of developing task analyses per McConomy et al. (2022) in terms of identifying and logically sequencing all measurable steps. If performance on the first step of a task analysis is not correlated with the second step of a task analysis, then it would indicate evidence of a lack of logical sequencing of the steps or a lack of strong or positive autocorrelation. Conversely, performance on the first step of a task analysis being well correlated with the second step and so forth would indicate evidence of a logical sequencing of steps of the task analysis or the positive and strong autocorrelation of task steps. Test-retest effects are a common indication of autocorrelation as indicative of learning from a test or measure so much that it can present a threat to internal validity to test without a multiple or parallel form (Dunbar-Jacob, 2012). Test-retest effects represent autocorrelation, and across task steps, it represents successive autocorrelation. As such, autocorrelation refers to "the degree of correlation between previous and subsequent data points that are serially dependent on each other due to repeated measurement of the dependent variable from the same individual," (Barnard-Brak et al., 2021, p. 596). Figure 1 provides a graphical representation of autocorrelation in the context of task analyses.

Figure 1:

Illustrative autocorrelation calculation example

Task Step	Performance	Lagged	Autocorrelation
1	6		-0.75
2	1	6	
3	6	1	
4	1	6	
5	1	1	
6	6	1	
7	1	6	
8	6	1	
		6	

The purpose of the current study was to examine how to determine whether a logical sequence of steps has been developed in relation to task performance using estimates of autocorrelation. We examined whether the use of autocorrelation estimates could be used to determine whether steps were logically sequenced in a task analysis assumes compliance of the individual. To reiterate, this purpose coincides with Step 2 in developing task analyses by McConomy et al. (2022) by identifying and logically sequencing all measurable steps. The stronger and more positive the autocorrelation, the more likely the logical sequencing of measurable steps. The weaker and less positive (i.e., more negative) the autocorrelation, the less likely the steps would appear to be entirely logically sequenced, either by order of steps, omission of steps (therefore not a logical sequence), the understanding of steps by their content (therefore not a logical sequence to the individual), or some combination thereof for the individual.

Method

Sample

For the current study, the sample was 23 individuals from a comprehensive transition services program for independent living skills at a local university located in the southeastern United States. All participants from the comprehensive transition services program were included in the sample, in which all had diagnoses of intellectual or developmental disabilities. The target population for the current study was adult individuals with intellectual and developmental disabilities. The mean age of participants was 21.91 years (SD = 1.65). Approximately 39% (n = 9) were female and 61% (n = 14) were male. With regard to diagnosis, approximately 65% (n = 15) of the participants were identified as having intellectual disability while other diagnoses included: Autism Spectrum Disorder; physical or orthopedic disability; traumatic brain injury; and specific learning disability. As for race/ethnicity, 61% (n = 14) were African American, 4% (n = 1) identified as Asian American, 37% (n = 9) were White, and 4% (n = 1) were Hispanic or Latinx.

Measures

The transportation task analysis measure consisted of nine steps for successfully riding a public bus to a location. Nine steps would be considered at the upper end of optimal number of steps per Barnard-Brak et al. (2023a) with a range of five to nine steps recommended. Table 1 provides the steps of the transportation task analysis. Each step of the task performance was scored along a six-point scale for different levels of prompting. A value of 1 referred to “hand over hand” prompting while at the other end of the spectrum was a value of 6 reflecting full independent performance. Independence in performance across all steps was considered the criterion for success. Least to most prompting was utilized in guiding task performance. Data were collected by mentors hired as part of the comprehensive transition services program in an inclusive postsecondary education setting on a weekly basis. Autocorrelation was not calculated in vivo or after each session as we did not want to make decisions on the development of task analyses without full data across all individuals. Higher values indicate better task performance while lower values indicate poorer task performance for individuals. The raw average number of sessions was 26.74 across individuals (SD = 8.86) to complete independence ranging from 8 to 47 sessions.

Table 1

Transportation task analysis steps

Step	Task Analysis Step
1	Chooses correct bus
2	Crosses street safely
3	Enters bus using correct door
4	Selects appropriate seating
5	Communicates appropriately with others
6	Gets off at correct stop
7	Exits using correct door
8	Use visual bus schedule to determine correct bus
9	Knows when and how to transfer buses when necessary

Analyses

To reiterate, autocorrelation refers to "the degree of correlation between previous and subsequent data points that are serially dependent on each other due to repeated measurement of the dependent variable from the same individual," (Barnard-Brak et al., 2021, p. 596). We estimated the lag 1 (or one step difference) autocorrelation for the first session of each individual. Different lags and structures of autocorrelation can be considered, but single-case designs typically estimate a lag 1 or first order autoregressive autocorrelation (Barnard-Brak et al., 2021; Harrington & Velicer, 2015; Shadish et al., 2013; Smith et al., 2012). We examined the Pearson's bivariate correlation r values between autocorrelation values and the average performance across all eight steps of the task analysis for the first session. After conducting analyses with the observed data, we simulated based upon these prior estimates or results via Monte Carlo techniques using Mplus (v. 8.1; Muthén & Muthén, 2019). Monte Carlo refers to a class of computational algorithms that use repeated random sampling to obtain numerical estimates of unknown parameters (Kroese et al., 2014). Two independent Markov chain Monte Carlo (MCMC) chains were applied to the data for 1,000 iterations. We examined the degree of parameter recovery across the 1,000 iterations, which may be considered an estimation of statistical power as well. Parameter recovery refers to the evaluation of whether a model's results can accurately estimate the true values of its parameters when applied to data generated from known parameter values (Aczel et al., 2018). Values of 0.80 and above indicate that 80% of 1,000 iterations are considered acceptable in being able to recover the observed parameter estimate (i.e., the correlation value from the sample data).

Results

The mean autocorrelation estimate was -0.051 (SD = 0.21) with values ranging from 0.625 to 0.425. The distribution of autocorrelation estimates was normal as determined by the Shapiro-Wilk test for normality, W = 0.934, p = 0.09. The mean performance across the steps for the first session was 4.61 (SD = 0.94) with values ranging from 1 to 6. The correlation between autocorrelation values and the first session task performance across all steps was r = 0.24 with a higher simulated value of r = 0.29

across 1,000 replications. In simulating the observed results, parameter recovery value of 0.82 indicated that the correlation value was recovered 82% of 1,000 replications, which also indicates acceptable level of statistical power. As the autocorrelation values increase, the average first session performance decreases. We found that the better task performance that individuals achieve on the first session, the greater the autocorrelation across the steps providing evidence that steps are logically sequenced. Conversely, the lower the autocorrelation values, the lower the performance on the first session of the task analysis. Our results found that individuals who have worse task performance, the lower the autocorrelation across the steps.

Discussion

The current study provides a means to test whether the steps of a task analysis may be considered logically sequenced as according to Step 2 of designing task analyses according to McConomy et al. (2022). We estimated the degree of autocorrelation first for each individual and then examined its association with subsequent task performance. We hypothesized that the stronger and more positive the autocorrelation, the more likely the logical sequencing of measurable steps. Conversely, we hypothesized that the weaker and less positive (i.e., more negative) the autocorrelation, the less likely the steps would appear to be entirely logically sequenced, either by order of steps, omission of steps (therefore not a logical sequence), the understanding of steps by their content (therefore not a logical sequence to the individual), or some combination thereof for the individual. The results of the current study indicate support for these hypotheses, as there was a positive correlation between autocorrelation values and subsequent average first task performance.

Researchers and practitioners can easily calculate a lag 1 autocorrelation value in a spreadsheet software program. Figure 1 provides an illustrative example as how to calculate an autocorrelation value using Microsoft Excel or any spreadsheet software program. From Figure 1, the researcher or practitioner would first enter the observed data and then copy that same data and paste it in the next column, lagged or moved one cell down. The researcher or practitioner would then correlate the two overlapping columns while omitting values without a corresponding pair (i.e., shaded in gray in Figure 1). Based upon the value achieved from the CORREL function in Microsoft Excel, researchers and practitioners can then determine whether the value is problematic.

The results of the current study are important, as by improving task analysis techniques, we can in turn increase the efficacy and effectiveness of these task analyses for individuals with intellectual and developmental disabilities in inclusive postsecondary education settings. The current study provides an illustrated example of how to determine whether a logical sequence of steps has been developed in relation to task performance using estimates of autocorrelation. These autocorrelation estimates should be used in tandem with the aforementioned guidance as to the number of steps, number of sessions, task complexity/difficulty, IQ/adaptive functioning, and the potential for permitting/scheduling breaks. It should be cautioned that all task analyses should be sufficiently individuated in order to support the learning of individuals with intellectual and developmental disabilities across settings. Thus, guidance on task analyses should not be rigidly followed over the needs of the individual. The results of the current study support the use of this task analysis guidance for adult individuals with intellectual and developmental disabilities in inclusive postsecondary education settings.

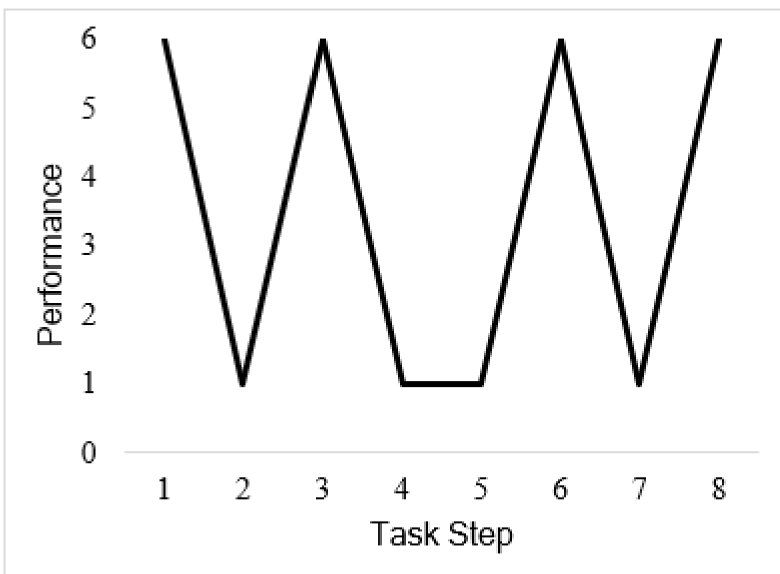
As for the interpretation of autocorrelation values, we would recommend that any negative autocorrelation values should be considered problematic as not indicating a logical sequence of steps per Step 2 of designing task analyses per McConomy et al. (2022). A larger, more positive autocorrelation value would indicate a higher likelihood of a logical sequence of steps as subsequently related to task performance across steps. Figure 2 provides a display of what a negative autocorrelation value would look like as compared to a positive autocorrelation value. From Figure 2, negative autocorrelation values illustrate a more zigzag pattern while positive autocorrelation values illustrate an overall upward trend. In Figure 2, Panel A displays a negative autocorrelation value of -0.75 while panel B displays a positive autocorrelation value of 0.46.

Figure 2

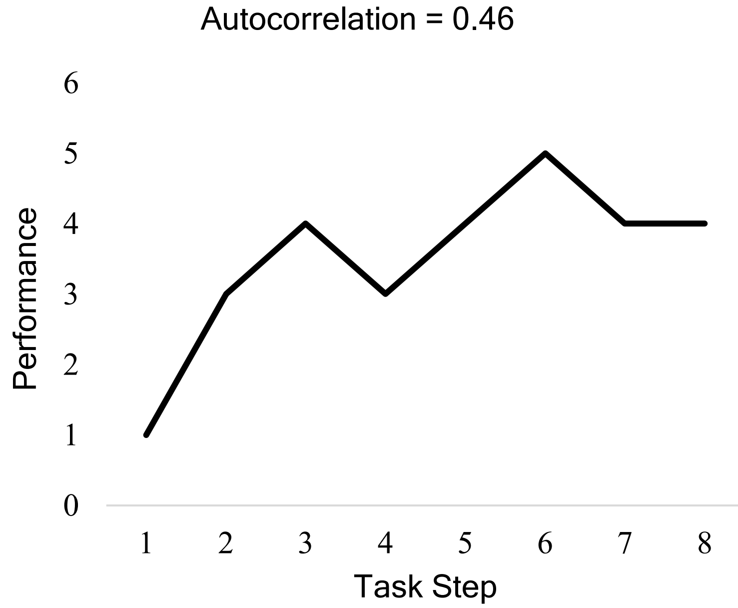
Display of Autocorrelations Graphically

Autocorrelation = -0.75

Panel A



Panel B



Limitations

Limitations emerge as part of any study and the current study is no different. First, the current study results are based upon one sample of task analysis data across 23 adult individuals with intellectual and developmental disabilities participating in a comprehensive transition services program. A wider variety of samples of task analysis data may yield different results; thus, we should further test the relationship between autocorrelation estimates and subsequent task performance indicating the presence of a logical sequence of steps.

Second, the results of the current study indicate that a negative autocorrelation estimate was not desirable both upon visual inspection (see Figure 2, Panel A) and as related to task performance and its predictive ability. However, the current study does not address the reason for this lack of a logical sequence of steps except to indicate that there is a lack of a logical sequence of steps, which would ostensibly influence its predictive ability. The lack of a logical sequence of steps can be an issue with respect to the order of steps, omission of steps (therefore not a logical sequence), or the understanding of steps by their content in terms of task complexity/difficulty. Third, we should note that the steps may be a logical sequence for one individual and not a logical sequence for another individual depending upon their IQ/adaptive functioning, for instance. The results revealed for the current study had a range of autocorrelation values across individuals. Thus, more varying samples of individuals should be examined for trends, but ultimately, decisions should be made on an individual basis given the highly individuated nature of task analyses (e.g., Chirombe, 2018 McConomy et al., 2022; Steinbrenner et al., 2020).

Future Research

Future research should expand to include more varied kinds of tasks for the task analyses as the current study only focused on public transportation. Future research should also examine task analyses using different means of prompting (i.e., least to most prompting was utilized in that study) as that may yield different results. Additionally, future research should explore incorporating metrics, such as the fail-safe k metric, for instance, to help determine whether more sessions may be needed in the context of task analyses (Barnard-Brak et al., 2018). In particular, more sessions may be needed, dependent upon the nature of the task, the individual, and the interaction thereof (e.g., number of steps, task complexity/difficulty, and IQ/adaptive functioning level). The relationship of task performance with IQ and/or adaptive functioning has been considered not strong (Barnard-Brak et al., 2023c; Mutua et al., 2023). Future research should consider a variety of samples of task analysis data to further test the relationship between autocorrelation values and subsequent task performance indicating the presence of a logical sequence of steps. The current study focuses on a sample of adult individuals with intellectual and developmental disabilities participating as part of a comprehensive transition services program in a postsecondary education setting.

Conclusion

In conclusion, we found that stronger and more positive autocorrelation estimates were associated with better subsequent task performance in the results section while weaker and less positive (i.e., negative) autocorrelation estimates were associated with poorer or weaker task performance. To summarize, the results of the current study suggest that autocorrelation estimates may be calculated easily in Microsoft Excel by using the correlation function of two arrays (CORREL). The first array would be the task performance on a task analysis and the second array would be the same task performance copied and pasted one cell down (see Figure 1). Then, a correlation between the two arrays would be performed using the CORREL function in Microsoft Excel where there were values in both arrays shaded in gray in Figure 1. In this way, this function can be used as a tool to help determine whether there is a logical sequence of task steps per Step 2 of designing task analyses per McConomy et al. (2022). The current study provides an illustrative example of how to calculate autocorrelation values via a commonly available spreadsheet software program (i.e., Microsoft Excel).

References

Aczel, B., Palfi, B., Szollosi, A., Kovacs, M., & Szabo, P. (2018). The effect of transparency on the replicability of psychological research. *Frontiers in Psychology, 9*, 1117. https://doi.org/10.3389/fpsyg.2018.01117

Baker, J. N., Rivera, C., Devine, S. M., & Mason, L. (2019). Creating a task-analysis for teaching emergent literacy skills to students with autism*. Intervention in School Clinic, 5*4(3), 166. https://doi.org/10.1177/1053451218767907

Barnard-Brak, L., Mutua, K., Mugoya, G. C., Williamson, A., & Kudesey, C. (2023a). Task analysis guidance for number of and readability of steps for individuals with intellectual disabilities. *Research in Developmental Disabilities, 133*, 104411. https://doi.org/10.1016/j.ridd.2022.104411

Barnard‐Brak, L., Mutua, K., & Williamson, A. (2023b). Primacy and recency effects in task analyses: Preliminary results. *Applied Cognitive Psychology, 37*(1), 228–231. https://doi.org/10.1002/acp.4035

Barnard-Brak, L., Richman, D. M., Little, T. D., & Yang, Z. (2018). Development of an in-vivo metric to aid visual inspection of single-case design data: Do we need to run more sessions? *Behaviour Research and Therapy, 102*, 8–15. https://doi.org/10.1016/j.brat.2017.12.003

Barnard‐Brak, L., Richman, D. M., Mutua, K., & Williamson, A. (2023c). Predictors of employment for adults with intellectual and developmental disabilities participating in a postsecondary transition program in the United States. *Journal of Applied Research in Intellectual Disabilities, 36*(1), 116–121. https://doi.org/10.1111/jar.13040

Barnard‐Brak, L., Watkins, L., & Richman, D. M. (2021). Autocorrelation and estimates of treatment effect size for single‐case experimental design data. *Behavioral Interventions, 36*(3), 595–605. https://doi.org/10.1002/bin.1783

Barnard-Brak, L., Mutua, K., & Williamson, A. (under review). The relationship between task difficulty as measured by readability and task performance among individuals with intellectual and developmental disabilities. Under review at *Research in Neurodiversity.*

Benson, V. K., Wakeman, S. Y., Wood, C. L., & Muharib, R. (2021). Using picture-based task-analytic instruction to teach students with moderate intellectual disability to email peers without disabilities. *The Journal of Special Education Apprenticeship, 10*(1), 3.

Bridges, S. A., Robinson, O. P., Stewart, E. W., Kwon, D., & Mutua, K. (2020). Augmented reality: Teaching daily living skills to adults with intellectual disabilities. *Journal of Special Education Technology, 35*(1), 3-14. https://doi.org/10.1177/0162643419836411

Carter, M., & Kemp, C. R. (1996). Strategies for task analysis in special education. *Educational Psychology, 16*(2), 155-170. https://doi.org/10.1080/0144341960160205

Chirombe, L. (2018). Task analysis: The learners' passport to successful learning. In J. Ndlovu (Ed.), *Learning to teach in an inclusive era: Methods of teaching* (p. 76-101). Future Managers.

Cowan, N., Chen, Z., & Rouder, J. N. (2004). Constant capacity in an immediate serial-recall task: A logical sequel to Miller 1956. *Psychological Science, 15*(9), 634-640. https://doi.org/10.1111/j.0956-7976.2004.00732.x
Dollar, C. A., Fredrick, L. D., Alberto, P. A., & Luke, J. K. (2012). Using simultaneous prompting to teach independent living and leisure skills to adults with severe intellectual disabilities. *Research in Developmental Disabilities, 33*(1), 189-195. https://doi.org/10.1016/j.ridd.2011.09.001
Dunbar-Jacob, J. (2012). Minimizing threats to internal validity. *Intervention Research: Designing, Conducting, Analysing, and Funding*, 91-106. https://doi.org/10.1891/9780826109583.0006
Gold, M. W. (1976). Task analysis of a complex assembly task by the retarded blind. *Exceptional Children, 43*(2), 78-84. https://doi.org/10.1177/001440297604300203
Griffin, J. W., John, S. E., Adams, J. W., Bussell, C. A., Saurman, J. L., & Gavett, B. E. (2017). The effects of age on the learning and forgetting of primacy, middle, and recency components of a multi-trial word list. *Journal of Clinical and Experimental Neuropsychology, 39*(9), 900-912. https://doi.org/10.1080/13803395.2017.1278746
Harrington, M., & Velicer, W. F. (2015). Comparing visual and statistical analysis in single-case studies using published studies. *Multivariate Behavioral Research, 50*(2), 162-183. https://doi.org/10.1080/00273171.2014.973989
Kroese, D. P., Brereton, T., Taimre, T., & Botev, Z. I. (2014). Why the Monte Carlo method is so important today. Wiley Interdisciplinary Reviews*: Computational Statistics, 6*(6), 386-392. https://doi.org/10.1002/wics.1314
McLaughlin, G. H. (1969). SMOG grading-a new readability formula. *Journal of Reading, 12*(8), 639-646. https://doi.org/10.2307/747070
McConomy, M. A., Root, J., & Wade, T. (2022). Using task analysis to support inclusion and assessment in the classroom. *TEACHING Exceptional Children, 54*(6), 414-422. https://doi.org/10.1177/00400599211025565
Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 63*(2), 81. https://doi.org/10.1037/h0043158
Moyer, J. R., & Dardig, J. C. (1978). Practical task analysis for special educators. *TEACHING Exceptional Children, 11*(1), 16-18. https://doi.org/10.1177/004005997801100105
Muthén, L., & Muthén, B. O. (2019). *Mplus user's guide* (8th ed.). Muthén & Muthén.
Mutua, K., Barnard-Brak, L., & Williamson, A. (2023). Interview skills associated with employment recommendations for individuals with intellectual and developmental disabilities. *Journal of Intellectual & Developmental Disability, 48*(1), 71-76. https://doi.org/10.3109/13668250.2022.2078799
Oberauer, K., Lewandowsky, S., Awh, E., Brown, G. D., Conway, A., Cowan, N., & Ward, G. (2018). Benchmarks for models of short-term and working memory. *Psychological Bulletin, 144*(9), 885. https://doi.org/10.1037/bul0000153
Osth, A. F., & Farrell, S. (2019). Using response time distributions and race models to characterize primacy and recency effects in free recall initiation. *Psychological Review, 126*(4), 578. https://doi.org/10.1037/rev0000149
Price, R., Marsh, A. J., & Fisher, M. H. (2018). Teaching young adults with intellectual and developmental disabilities community-based navigation skills to take public

transportation. *Behavior Analysis in Practice, 11*, 46-50. https://doi.org/10.1007/s40617-017-0202-z

Randall, K. N., Johnson, F., Adams, S. E., Kiss, C. W., & Ryan, J. B. (2020). Use of a iPhone task analysis application to increase employment-related chores for individuals with intellectual disabilities. *Journal of Special Education Technology, 35*(1), 26-36. https://doi.org/10.1177/0162643419836410

Riesen, T., & Jameson, J. M. (2018). Comparison of prompting procedures to teach work tasks to transition-aged students with disabilities. *Education and Training in Autism and Developmental Disabilities, 53*(1), 100–110. https://doi.org/10.1177/0162643419836410

Sam, A. (2016). Task analysis (TA). EBP brief packet. *National Professional Development Center on Autism Spectrum Disorders.*

Shadish, W. R., Rindskopf, D. M., Hedges, L. V., & Sullivan, K. J. (2013). Bayesian estimates of autocorrelations in single-case designs. *Behavior Research Methods, 45*, 813-821. https://doi.org/10.3758/s13428-012-0282-1

Smith, J. D., Borckardt, J. J., & Nash, M. R. (2012). Inferential precision in single-case time-series data streams: How well does the EM procedure perform when missing observations occur in autocorrelated data? *Behavior Therapy, 43*(3), 679-685. https://doi.org/10.1016/j.beth.2011.10.001

Steinbrenner, J. R., Hume, K., Odom, S. L., Morin, K. L., Nowell, S. W., Tomaszewski, B., & Savage, M. N. (2020). Evidence-based practices for children, youth, and young adults with autism. *FPG Child Development Institute*.

Vascelli, L., Iacomini, S., Artoni, V., & Cihon, T. M. (2021). Teaching self-care and domestic living skills using least-to-most prompting procedure in a semi-residential setting. *Journal of Clinical & Developmental Psychology, 3*(2), 1-16. https://doi.org/10.1007/s10882-022-09842-z

Walters, S., Stierle, J., Stockwell, D., Carlson, A., & Ryan, J. (2021). Efficacy of video prompting using mobile technology to teach employment tasks to individuals with intellectual disability. *Journal of Inclusive Postsecondary Education, 3*(1), 1-21. https://doi.org/10.13021/jipe.2021.2890