Critical Reflection in Professional Development: Iterative Reflective Practice for Self-Directed Learners

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Abstract

This study examines the impact of iterative reflective practice on the depth of reflection within the context of self-directed learning for professional development. Three key research questions were explored: (1) the influence of iterative reflective practice on reflection depth, (2) the relationship between forethought and reflection depth, and (3) the relationship between learning outcomes and reflection depth. Data was collected during the Professional Learning in Organizations module at the University of Twente. Participants engaged in a nine-week, challenge-based course simulating a professional consulting environment, during which they set themselves two learning goals and iteratively performed learning activities, reflecting on their progress, culminating in a final reflection. Quantitative data on forethought, satisfaction, and progress were collected via a mobile app, while qualitative data from each participants' reflection portfolio was coded using Kember's (2008) framework for reflection depth. Analyses included linear regression models, linear mixed-effects models, paired t-tests, and Pearson correlations. Results revealed that iterative reflective practice significantly predicted increased reflection depth, with structured final reflections yielding the highest levels of depth due to their holistic nature and scaffolded prompts. However, forethought and perceived learning outcomes (satisfaction and goal progress) showed no significant correlation with reflection depth, suggesting that other factors may play a more critical role. This was also implied by the large unexplained variance observed in the models. A decline in reflection depth improvement rate over time highlighted the influence of task fatigue or a learning curve effect, although reflection depth was found to be highest for the final reflection. Several suggestions are provided on addressing this study's limitations and developing a deeper understanding of iterative reflective practice. These findings emphasize the value of iterative practice as an effective tool for enhancing self-directed learning and professional development.

Key words: *Iterative Learning, Iterative Reflective Practice, Reflection, Depth of Reflection, Self-Directed Learning, Professional Development*

Critical Reflection in Professional Development: Iterative Reflective Practice for Self-Directed Learners

As companies strive to maintain their competitive edge, the effective management of people has emerged as a critical factor for organizational success and sustainability (Marthalia, 2022). The process in question also entails supporting the professional development of human capital in dynamic, ever-changing work environments, where maintaining and updating skills has become essential for sustained employability (Shivakumar, 2019). Research shows that employees who engage in ongoing competency development enhance their employability and professional growth, thereby benefiting both themselves and their employers (Haemer, Borges-Andrade, & Cassiano, 2017).

Historically, as Boud and Garrick (1999) noted, "learning" and "work" were considered distinct domains. However, modern work environments have evolved, and learning is now recognized as an integral part of professional development, both within and beyond the workplace (Brandi & Iannone, 2020). This shift reflects broader changes in educational models, with a growing emphasis on workplace learning over traditional, classroom-based education (Illeris, 2003). The increased workloads and time constraints that professionals face further underscore the need for alternative learning modalities that are better suited to the realities of the modern workplace (Noe et al., 2014). Consequently, cultivating a deeper understanding of workplace learning is critical for both organizations and professionals as they navigate these evolving demands.

Informal Learning and Self-Directed Learning in the Workplace

Workplace learning spans a continuum from formal, structured programs to informal, naturally occurring experiences that enhance job-related knowledge and skills (Brandi & Iannone, 2020; Eraut, 2004). While formal learning includes predefined workshops and training sessions, informal learning emerges through daily activities, social interactions, and self-directed efforts (Brandi & Iannone, 2020; Eraut, 2004). Notably, informal learning constitutes approximately 75% of workplace learning, highlighting its critical role in competency development (Noe et al., 2014). Eraut's (2004) typology of informal learning categorizes it into implicit learning, reactive learning, and deliberative learning. Implicit learning occurs subconsciously without explicit awareness of what has been learned (Eraut, 2004), yet it can still enhance performance (Reber, 1993, as cited in Eraut, 2004). Reactive learning refers to immediate, unplanned responses to situations, whereas deliberative learning involves conscious reflection, intentional planning, and critical analysis of past actions and future challenges (Eraut, 2004).

A key concept closely tied to deliberative learning is self-directed learning (SDL), in which individuals take responsibility for their own learning by identifying their needs, setting goals, selecting appropriate strategies, and evaluating outcomes (Saks & Leijen, 2014). SDL encompasses both observable activities such as goal-setting and internal traits like intrinsic motivation and metacognitive awareness (Brandt, 2020). Reflection, a core principle of SDL, supports goal-setting, monitoring, and strategy adjustment, refining the learning process over time (Brandt, 2020). SDL fundamentally relies on self-regulation, a proactive process that occurs before, during, and after learning, enabling individuals to engage autonomously in their development (Zimmerman, 2000, 2002; Brandt, 2020). As deliberative learning aligns closely with SDL principles, understanding how to leverage SDL effectively is crucial for both individuals and organizations to maximize the benefits of informal learning in workplace competency development.

Critical and Deep Reflection

While a universal definition of reflection is difficult to find, and much of the literature seems to assume that it is already known, generally, it can be defined as the process of looking back or reviewing past actions (Kember, 2008). For self-directed learners, there are many advantages in improving their reflective abilities, as these allow them to assess their experiences and gain insights that enhance both immediate and future learning. Chang (2019) emphasizes that reflection enables learners to revisit what they have learned, facilitating personal development. Moreover, Anseel et al. (2009) argue that reflection enhances task performance by promoting deeper cognitive engagement with experiential data. For self-directed learners, reflection fosters the development of self-regulated learning strategies, enabling them to monitor progress, adjust their approaches, and take control of their learning processes (Dutta, 2023). Thus, the role of reflection within SDL can therefore be considered as that of a “spotlight”, which illuminates the learning process and its stages.

Reflection can be further characterized along a spectrum from simple description to transformative critical reflection, as described by Kember (2008). At its most profound level, critical reflection goes beyond recounting experiences or describing situations; it involves evaluating and synthesizing information to derive deeper insights. By connecting theoretical knowledge with real-world experiences, critical reflection facilitates a deeper understanding of both tasks and contexts.

According to Lee and Mori (2021), deeper reflection is strongly associated with improved learning outcomes, such as enhanced goal achievement and mastery of complex skills. However, achieving deep reflection poses challenges, as demonstrated by Gaupp (2018), who found that even intermediate and proficient self-regulated learners often struggle to reach levels of critical reflection, underscoring this as an important aspect to consider.

Iterative Practice for Fostering Critical Reflection and Forethought

One promising approach to enhancing reflection for self-directed learners is through iterative reflective practice. This approach not only involves revisiting and refining previous reflections over time but also allows learners to progressively deepen their insights and understanding while addressing their shortcomings (Khanam, 2015). Iterative reflection has been identified as a key component in meaning generation, enabling learners to refine their focus and comprehension through repeated engagement with their experiences (Srivastava & Hopwood, 2009). These aspects lead to a more critical level of reflection, a notion further supported by Ward (2008), who modeled critical reflection as an iterative learning process crucial for integrating past experiences and questioning insights.

In addition to enhancing reflection, iterative practice also strengthens the forethought stage of SDL. The *Cambridge Dictionary* (n.d.) defines forethought as "the good judgment to consider the near future in your present actions." Just as iterative practice deepens reflection, it similarly supports forethought by encouraging learners to revisit and refine their planning processes, ultimately leading to improved strategic planning and decision-making (Khanam, 2015). Research by Zimmerman (2000) considers forethought in terms of breaking down the learning process into specific goals and strategies, enabling learners to create structured and actionable plans. Iterative reflection facilitates this process by helping learners assess progress, adjust approaches, and develop actionable plans. In line with this, Ryan (2013) found that engaging in iterative reflection helps learners make sense of experiences and reimagine future scenarios, reinforcing the connection between past reflections and future learning outcomes.

The importance of forethought and planning in SDL is further underscored by Bonnefoy (2018), who linked failures in SDL to disorganization and procrastination, often due to weak planning. By incorporating iterative reflection, learners can systematically enhance their planning skills, reduce inefficiencies, and optimize their learning journey. As a result, iterative practice not only supports immediate learning goals but also fosters long-term self-directed learning success.

Aim and Research Gap

Despite the recognized importance of reflection in self-directed learning (SDL) and professional development, the impact of iterative reflective practice to enhance critical reflection within workplace learning contexts remains underexplored. Furthermore, there is little research on the impact of iterative practice on the relationships between reflection depth and forethought.

Research of this kind can be valuable, as it has been shown that iterative reflection could play a pivotal role in enhancing self-directed learning by helping learners revisit and refine their thoughts, strategies, and learning goals over time (Khanam, 2015). An investigation of this kind into this iterative process may also uncover insights that are otherwise overlooked.

Within this context, perceived learning outcomes and self-efficacy are also important factors to consider. According to Zimmerman (2000), self-efficacy is a strong predictor of motivation and learning. Within SDL, self-efficacy influences learners' confidence and their ability to manage their own learning. Perceived learning outcomes, which reflect an individual's perception of their learning progress and achievements, can be seen as a form of self-efficacy. Research by Elcokany et al. (2022) identify self-efficacy as a fundamental aspect of SDL, yet research on its interaction with iterative reflective practice remains limited. Examining these factors within iterative reflection may provide deeper insights into their impact on self-directed learning in professional workplace settings.

This study aims to investigate how iterative reflective practices influence the depth and quality of reflection in professional settings. Using Kember's (2008) levels of reflection as a framework, the research will explore the effect of iterative practice on the depth of reflection achieved by self-directed learners. Additionally, this study will explore whether an interaction effect exists between forethought, perceived learning outcomes, and reflection depth in the context of iterative practice, examining their potential relationships. While existing literature suggests that iterative practice influences these components individually, their specific impact on reflection depth remains unclear, as well as the presence itself of such a relationship. To achieve this, the study will be guided by the following three research questions:

1. What is the effect of iterative reflective practice on depth of reflection?
2. What is the relationship between forethought and depth of reflection?
3. What is the relationship between learning outcomes and depth of reflection?

Methods

Design

Data was collected in the previous iteration of the course Professional Learning in Organizations module at the University of Twente (2023/2024) and during this thesis trajectory. As data of the current round was not complete when writing the thesis, the analysis is based on data from the previous round. The course was challenge-based and required students to act as consultants, developing an advisory solution for real-life stakeholders acting as clients. Students were organized in teams of 4 to 5 and their work was facilitated by having ‘office days’, where the teams could work amongst themselves, collaborate, and receive guidance from teachers. There were no control or comparison groups, as all participants followed the same procedures and engaged in the same tasks. The design allowed for the examination of naturalistic data reflecting students' self-directed learning experiences within a structured educational setting, simulating a work environment in Human Resource Development.

Participants

The participants in the study were all university students enrolled in the third-year *Professional Learning in Organizations* module at the University of Twente, who participated in the study as part of their required coursework. While participation in the reflection activities was mandatory for course completion, participants could opt out of having their data used for research through informed consent. From the 38 participants; 34 consented to their data being used. Of the 34 participants, one did not complete the course, resulting in a final sample of 33 participants.

Of these 33 participants, 66.7% were female. The participants were enrolled in a variety of academic programs, with the majority (48.5%) studying social sciences. Other participants were pursuing degrees in health-related fields, business and management, engineering disciplines, and technology-focused programs. Collectively, they reported 322 learning activities throughout the duration of the module.

Demographic information was anonymized, and the researcher had no access to personal details beyond the aggregated statistics. There were no specific inclusion or exclusion criteria since the dataset was preexisting and anonymized.

Instrumentation

The study utilized two primary instruments to collect data: a mobile app, called the Twente Intervention and Interaction Machine (TIIM) App, and the Professional Development (PD) Canvas reflective portfolio. The TIIM App is a smartphone application, developed by University of Twente's BMS Lab, that allows researchers to create custom questionnaires and interventions. In this study, it was used for gathering self-reported quantitative data on participants' learning experiences, among which was the data on forethought, satisfaction, and goal progress—the elements used for investigating Research Questions 2 and 3. Forethought was assessed through items prompting participants to rate their planning and anticipation of learning activities. Satisfaction was measured on a 5-point Likert scale, reflecting participants' contentment with their learning experiences. Goal progress was quantified on a scale from 0 to 100 in increments of 5, indicating participants' perceived advancement toward their learning goals.

The PD Canvas served as a reflective portfolio, capturing detailed qualitative data from reflections on participants' learning processes. Depth of reflection was measured by analyzing these reflections using Kember's (2008) four-level framework (habitual action, understanding, reflection, critical reflection). All materials were anonymized to protect participant confidentiality.

Procedure

The module's structure and the activities that generated the data were organized on a weekly and daily basis, with participants expected to perform specific tasks during designated times.

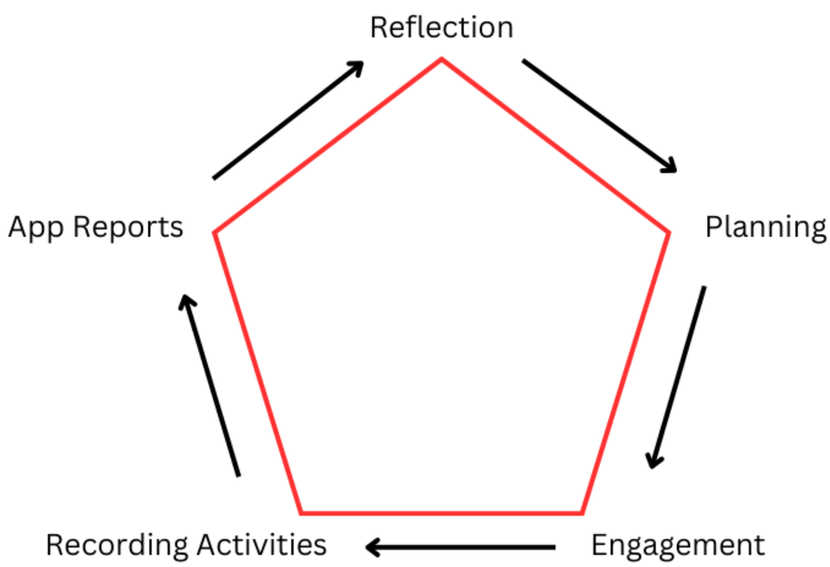
Introduction to the Module (Weeks 1–3). During the first three weeks, participants were introduced to concepts of self-directed learning and trained in using the two primary tools: the Professional Development (PD) Canvas and the mobile app called Twente Intervention and Interaction Machine (TIIM). Introduction to the module was structured as:

- **Week 1:** Participants were familiarized with the module's objectives and the significance of self-directed learning in professional development. They began exploring HRD consulting competencies to identify areas for personal growth.
- **Week 2:** Instruction focused on goal-setting using the SMART (Specific, Measurable, Achievable, Relevant, Time-bound) framework. Participants selected two professional learning goals related to HRD consulting and documented them on the PD Canvas.

- **Week 3:** Training was provided on utilizing the PD Canvas for planning and reflection and the TIIM App for logging learning activities and immediate reflections. Participants completed trial logs in the TIIM App to practice recording activities and reflections.

Iterative Learning Cycles (Weeks 3–8). From weeks 3 to 8, participants participated in weekly iterative learning cycles, with each iteration spanning one week of activities. The sequence of these activities followed the order depicted in Figure 1, which provides a visual representation of the structure of a single iterative learning cycle.

Figure 1 – *Visual representation of one iterative learning cycle*



All iterations were structured in this same way. The stages illustrated in Figure 1, as well as their sequence and the instrumentation utilized at each stage, can be described as follows:

1. **Planning (Mondays):** Participants outlined their planned learning activities for the week on the PD Canvas, ensuring alignment with their selected learning goals.
2. **Engagement:** Throughout the week, participants participated in the planned activities, which involved real-world HRD consulting tasks within their project groups.
3. **Recording Activities and Reflections:** After each activity, participants logged that activity, forethought and outcomes in the TIIM App, responding to prompts that

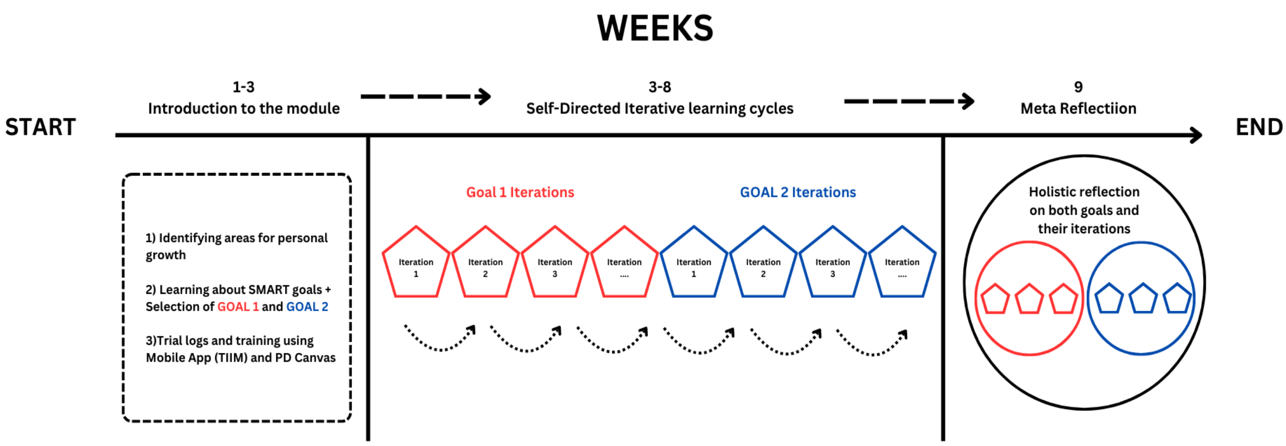
included scales, multiple-choice questions, and short answers to capture immediate insights.

4. **App Reports:** Reports were generated from the logged data before the next PD Lab session, providing visual summaries of their activities and progress.
5. **Reflection (Following Monday):** In the PD Lab sessions, participants reflected on the past week's activities using the PD Canvas. They analyzed their progress, discussed insights with peers, and planned adjustments for the next cycle.

Final Reflection (Meta-Reflection; Week 9). After completing the weekly learning cycles in the PD Lab, participants wrote a final reflection in Week 9 about their overall professional development. This reflection asked them to look back on their entire experience in the PD Lab, comparing the whole journey to the individual weeks they had focused on before. They were encouraged to draw conclusions from their experiences by adopting a broader, holistic perspective through written prompts. Participants reflected on their learning goals and the activities they took part in, discussing what they accomplished and the challenges they faced. They also evaluated how they used the mobile app and the portfolio during the PD Lab and thought about what they learned about the learning process from this experience.

The overall structure of this study, as previously described, along with the timeline of events from week 1—beginning with the module introduction—to week 9, when participants completed the meta-reflection, is presented in Figure 2.

Figure 2 – *Visual representation of the study timeline and design*



In Figure 2, the study timeline and setup are depicted from left to right. As outlined in the previous sections, the figure highlights key events occurring during the introduction stage and throughout the self-directed iterative learning cycles for both learning goals. The red shapes represent Goal 1 and its iterations, while the blue shapes correspond to Goal 2 and its iterations. Each iteration maintains a consistent structure, represented by a pentagon shape, mirroring the structure shown in Figure 1, where the five stages of an iterative cycle and the associated instrumentation are detailed.

The final section on the right illustrates the meta-reflection phase, shown as a circle encompassing both learning goals and their respective iterations. This visually signifies how participants reflected on their entire learning process during the meta-reflection in week 9.

Data Collection

Data was collected from participants' learning activities and progress ratings, recorded through the TIIM App, and documented in the PD Canvas via written reflections. Immediate reflections were logged after each activity in the TIIM App. Up to ten activities per week could be recorded in the TIIM App, and additional activities could be noted in the PD Canvas directly (which did not occur). Detailed records of planning, outcomes, and reflections were maintained in the PD Canvas throughout the module. Reminders were sent to participants daily at 17:00 to ensure they logged their activities close to their actual performance. A blank example of the PD Canvases used in the study is available in Appendix A.

The reflective material collected can be categorized into three distinct types based on their scope and focus:

Activity type: Participants made brief entries in the TIIM app to document their thoughts and perceived learning outcomes after completing a learning activity. These reflections address individual learning activities rather than the broader learning journey.

Iteration type: Participants used their experience and the TIIM app’s report to reflect on the various learning activities they completed during a given iteration, considering how these activities contributed to their learning goals (goals 1 and 2). This type of reflection provides a broader perspective than the activity type, encompassing multiple activities within a one week period.

Meta type: In the final reflection, participants reviewed their entire learning process, including aspects such as learning activities, app reports, iterations, overall progress, and their development in both goals. The meta reflection offers the most comprehensive and holistic perspective, integrating insights from both the activity and iteration types to evaluate the learning journey as a whole.

Ethical Considerations

Participants provided informed consent at the start of the third week when data collection began. They were informed that their information would be handled confidentially, and that data would be anonymized for research purposes after the module concluded.

Data Preparation

The PD Canvas reflections and TIIM App data were systematically organized and preprocessed to ensure dataset integrity and consistency before analysis. Participants who did not provide consent for research use or failed to complete the course were excluded at the outset. Further screening led to the removal of four additional participants for specific reasons. Two participants were excluded for not meeting the requirement of completing at least two iterations per learning goal. Another participant submitted incomplete reflections with missing text sections, making the data unusable. The fourth participant deviated from study guidelines by reflecting on individual learning activities rather than the defined iterations, rendering their data unsuitable for coding and analysis.

As a result, the initial sample size of 33 participants was reduced to 29 for primary analyses, ensuring adherence to the established inclusion criteria and study protocols. For analyses addressing Research Questions 2 and 3, Participant 20 was excluded due to inconsistencies caused by submitting activities for two separate goals within the same week. This overlap resulted in erroneous model outputs. However, Participant 20 was retained for Research Question 1 (iteration and reflection depth), as their inclusion did not materially affect the results. Thus, the maximum sample size for Research Questions 2 and 3 was 28 participants.

Upon further inspection, the data of the 29 participants (28 for Research Questions 2 and 3) underwent further processing on participation rate calculations at the iteration level to address the low number of reflection depth scores in later iterations of both Goal 1 and Goal 2.

The participation rate was calculated using the formula:

$$\text{Participation Rate} = \frac{Participants\ with\ a\ reflection\ for\ that\ iteration}{Total\ number\ of\ participants}$$

Table 1 presents the participation rates across goals and iterations. Participation rates for both goals were initially 1.00 for Iterations 1 and 2 but declined in later iterations. The Meta-Reflection retained a participation rate of 1.00, as it was mandatory for all participants.

Table 1 – *Participation Rates Across Goals and Iterations*

Goal / Meta	Iteration	Score Count	Total Participants	Rate
1	1	29	29	1.00
1	2	29	29	1.00
1	3	23	29	0.79
1	4	4	29	0.14
2	1	29	29	1.00
2	2	29	29	1.00
2	3	16	29	0.55
2	4	3	29	0.10
2	5	1	29	0.03
Meta	N/A	29	29	1.00

In Table 1, *Goal / Meta* denotes the goal number associated with each iteration or "meta" for the meta-reflection. *Iteration* indicates the specific iteration number for each goal. This column is not applicable to the meta-reflection, as it was not part of the iterative cycles and thus lacks an iteration number. *Score Count* refers to the number of recorded scores per iteration, while *Total Participants* represents the potential maximum scores if all participants completed the reflection. *Rate* indicates the participation percentage for each iteration.

Based on participation rate calculations, a refined dataset, referred to as **"Core Data"** was created by including only iterations where at least 50% of participants had submitted reflections. This dataset includes Iterations 1 to 3 for both Goal 1 and Goal 2, as they met the participation threshold. The term **"All Data"** refers to the complete dataset, incorporating all iterations, even those with low reflection counts. This distinction was necessary to mitigate skewing effects in the analysis of all three research questions.

Data Analysis – Present Study

Research Question 1: What is the Effect of Iterative Reflective Practice on Depth of Reflection? To address the first research question, the weekly reflections and the final meta-reflection were analyzed for depth of reflection using Kember's (2008) four-level framework.

Descriptions of the levels were added or adapted to fit the context of the study. This framework categorizes reflection depth into the following levels:

Level 1 - Habitual Action: Repetition of past actions without conscious thought. Reporting what happened without trying to reach an understanding.

Level 2 - Understanding: Basic comprehension of concepts without applying them to personal experiences. The participants' actions are attempted to be understood without being related to personal experiences/meaning or real-life applications.

Level 3 - Reflection: Active exploration of experiences, leading to new insights. Relates the experience to other past and/or future experiences and attaches personal meaning.

Level 4 - Critical Reflection: Profound examination of assumptions, resulting in a transformation of perspectives. Showing questioning of assumptions or changing perspectives as a result of their experiences.

Each reflection was assigned a numerical value from 1 (Habitual Action) to 4 (Critical Reflection) based on this framework. The coding process was conducted by scoring the reflections and recording the scores into Microsoft Excel. To ensure the reliability of the coding, inter-rater reliability was established by having a second coder independently code 15% of the reflections using the same coding scheme. The level of agreement between the two coders was assessed using Cohen's Kappa, which resulted in a score of 0.61. This score indicates a moderate to significant level of agreement (McHugh, 2012).

Descriptive statistics were calculated to summarize reflection score data, providing the frequency of occurrences for each level of reflection depth, as coded using the previously mentioned scheme. Additionally, descriptive statistics were computed to examine reflection depth scores across iterations and goals.

To investigate various relationships within the data, several statistical models were applied. Linear mixed-effects models (LMMs) were used to assess the relationship between iteration and reflection depth scores. Two separate models were run: one using the full dataset and another using the core dataset, which included only reliable iterations.

A linear regression analysis was conducted using the core dataset to compare the slopes of reflection depth scores between Goal 1 and Goal 2 across Iterations 1 to 3. Additionally, an

LMM was applied to evaluate the effect of goal type on reflection depth, examining whether significant differences existed between the two learning goals.

To analyze changes in reflection depth across consecutive iterations, paired t-tests were conducted using the core dataset. Descriptive statistics, including mean, standard deviation, and score count, were also calculated for the entire dataset to provide an overview of reflection depth trends across iterations and goals, including the meta-reflection.

To further explore the relationship between reflection scores and meta-reflection, three linear regression models were fitted at the average participant level to examine the average iteration score as a predictor of meta-reflection score, the average Goal 1 score as a predictor of meta-reflection score, and the average Goal 2 score as a predictor of meta-reflection score.

Visualizations were generated to illustrate reflection depth trends over time. Line plots displaying mean reflection scores across iterations, along with lines of best fit for both the core and full datasets, were created to highlight these trends. All statistical analyses were conducted using RStudio, with significance levels set at $p < .05$.

Research Question 2: What is the Relationship Between Forethought and Depth of Reflection? To address the second research question, the relationship between forethought and reflection depth was investigated using data from the TIIM App. Forethought scores, representing participants' self-reported levels of forethought, were matched to the corresponding iteration scores for reflection depth. Since forethought scores were provided on an activity basis and reflection depth was scored per week/iteration, all forethought scores within a specific week (iteration) were averaged to represent the participant's overall forethought level for that iterative reflective cycle. This averaging process ensured that each iteration had a single forethought value corresponding to the participant's reflective depth for that cycle.

The analyses included a Pearson correlation at the participant average level, examining the relationship between average forethought and average reflection depth using Core Data. Additionally, a linear mixed-effects model was applied to further investigate the relationship between forethought and reflection depth, also using the Core Data set.

All statistical analyses were conducted in RStudio, with statistical significance evaluated at the $p < .05$ level.

Research Question 3: What is the Relationship Between Learning Outcomes and Depth of Reflection? To address the third research question, the relationship between self-reported learning outcomes and depth of reflection was examined to examine the presence of any relationships between participants' self-perceptions of their learning, and the depth of their reflections during iterative cycles. Learning outcomes were measured using two quantitative self-reported indicators from the TIIM App:

1. **Satisfaction**: Perceived satisfaction with the outcome of the learning activity. Rated on a 5-point Likert scale (1 = Very Dissatisfied, 5 = Very Satisfied).
2. **Goal Progress**: The perceived total (cumulative) completion of a learning goal after a learning activity. Reported on a scale of 0 to 100, in increments of 5.

Based on the Goal Progress measure, a new variable called Goal Difference (GoalDif) was calculated to represent perceived improvement or decline in outcomes compared to the previous activity within the same goal. For each learning activity, the Goal Progress score from the previous activity was subtracted from the score given for the current activity, thereby establishing a perceived progress score for each learning activity. These were then summed to calculate a score for each iteration. The Satisfaction score was summed in a manner similar to the forethought measure used in the second research question.

Several analyses were conducted to explore the relationships between these variables. At the participant average level, correlations were calculated between the summed Goal Difference (GoalDif) and Average Reflection Depth, as well as between Average Satisfaction and Average Reflection Depth. At the iteration level, correlations were calculated between Goal Difference, Satisfaction, and Reflection Depth for each iteration. A linear mixed-effects model (LMM) was used to further examine the relationship between Reflection Depth (Score) and both Satisfaction and Goal Difference, with Participant included as a random effect to account for variability between individuals.

All statistical analyses were performed in RStudio, with significance evaluated at the $p < .05$ level.

Results

Research Question 1: What is the Effect of Iterative Reflective Practice on Depth of Reflection?

Descriptive Statistics – Reflection data only

In order to answer Research Question 1, Table 2 presents the descriptive statistics for participant scores across iterations and meta-reflection. The table includes the mean and standard deviation (SD) of scores, as well as the frequency counts for each level of Kember's (2008) levels of reflection, which represent distinct score values as described in the methods section.

Table 2 – *Descriptive Statistics for Reflection Data*

Category	Mean	SD	Level 1	Level 2	Level 3	Level 4	Score Count
Iterations – All Data	2.59	0.56	2	67	90	4	261
Iterations – Core Data	2.58	0.56	2	64	86	3	174
Meta-reflection	3.24	0.44	0	0	22	7	29

In Table 2, the "*Category*" column distinguishes between regular iterations from either the Core data, or the All data datasets, as well as the meta-reflection. The "*Mean*" and "*SD*" columns provide the central tendency and dispersion of scores, respectively. The columns labeled "*Level* 1" through "*Level* 4" correspond to the count of occurrences for each level of Kember's (2008) levels of reflection. Finally, the "*Score Count*" column indicates the total number of recorded scores in each category. The Meta-Reflection scores were analyzed separately, as they did not belong to the iteration-type data. These scores had the highest average, with all recorded values falling within levels 3 and 4.

Effect of Iteration on Reflection Depth Score

Two linear mixed-effects models were conducted to investigate the effect of iterations on reflection depth (Score), irrespective of goal-related factors. The models used the following formula:

$$\text{Score} \sim \text{Iteration} + (1 \mid \text{Participant})$$

The first model, using all iteration-type data, indicated that iterations significantly predicted reflection depth (b = 0.06, SE = 0.02, t(137.69) = 2.70, p = .008). The second model, using core iteration-type data, showed a slightly stronger effect of iterations on reflection depth (b = 0.07, SE = 0.02, t(127.12) = 2.96, p = .004). The effect of iterations on reflection depth remained positive and statistically significant across all models. This means that repeated iterations led to a significant increase in reflection depth, with a stronger effect observed in the core data.

Descriptive Statistics for Goal Data

Descriptive statistics for reflection depth scores were calculated for Goal 1, Goal 2, and across all iterations. The results, including mean scores (Mean), standard deviations (SD), and recorded number of scores (Score Count), are summarized in Table 3.

Table 3- *Descriptive Statistics for Reflection Depth Across Goals and Iterations*

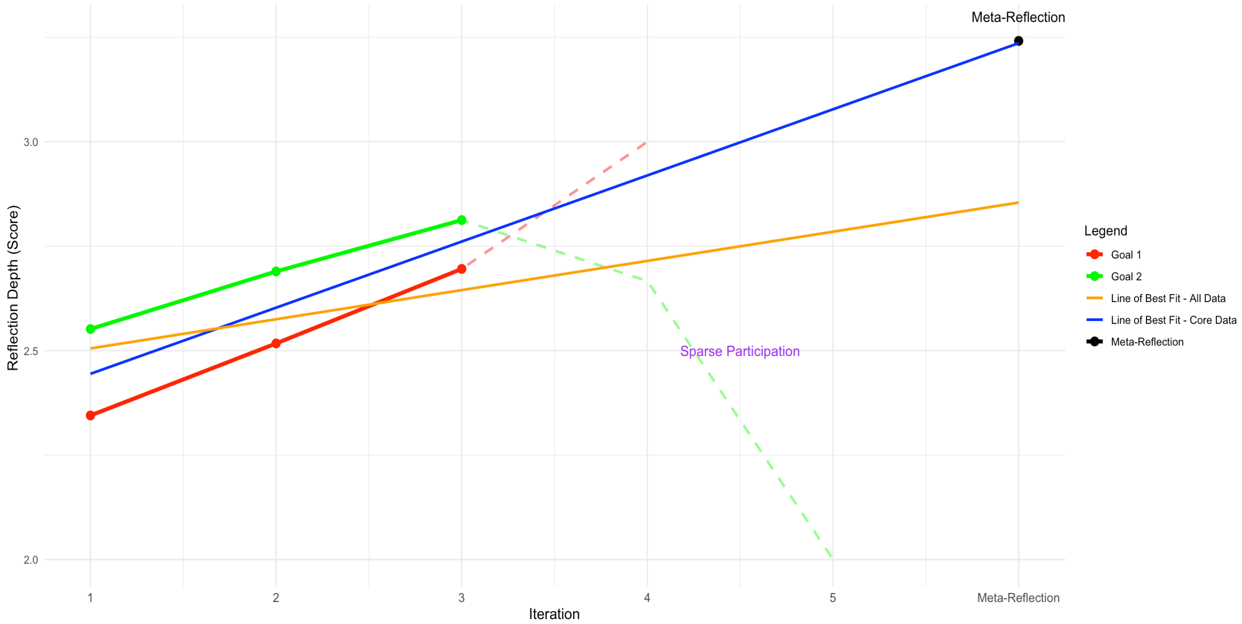
Goal	Iteration	Mean	SD	Score Count
Goal 1	1	2.34	0.55	29
Goal 1	2	2.52	0.51	29
Goal 1	3	2.70	0.47	23
Goal 1	4	3.00	0.82	4
Goal 2	1	2.55	0.51	29
Goal 2	2	2.69	0.66	29
Goal 2	3	2.81	0.54	16
Goal 2	4	2.67	0.58	3
Goal 2	5	2.00	NA	1

For Goal 1, mean reflection depth scores showed a consistent upward trend across iterations, peaking at Iteration 4 despite the significantly decreasing sample sizes. For Goal 2, scores initially increased but plateaued by Iteration 2 and slightly declined in later iterations. The final iteration for both goals had a very low Score Count, with Iteration 5 reflecting only one participant out of 29.

Linear Regression Model – Slope comparison between Goals

Linear regression models were fitted to examine trends in reflection depth scores across iterations. The Meta-Reflection scores were included only as the final point in the calculation of the lines of best fit for both the “All data” and “Core data” datasets for the purpose of comparison. These are visible in Figure 3, representing the last recorded Score values for each.

Figure 3 – *Plot of reflection depth across iterations for Goals 1 and 2.*



The slope comparison between goals was conducted using core data only, as iterations 4 and 5 had small sample sizes and low calculated participation rates that could distort the results. Linear regression models showed a positive slope for Goal 1 (b = 0.184), indicating a steady increase in reflection depth scores over time. For Goal 2, the slope was also positive (b = 0.053), though the improvement was less pronounced. The difference between the slopes was Δb = 0.131, indicating a faster rate of improvement for Goal 1 compared to Goal 2.

Linear Mixed-Effects Model

A linear mixed-effects model using the core dataset was used to examine the relationship between reflection depth scores and goals. The model formula was:

$$\text{Score} \sim \text{Goal} + (1 \mid \text{Participant})$$

The model was fit using REML, with t-tests conducted using Satterthwaite’s method. The random effect for participants showed a variance of 0.06 (SD = 0.25), indicating some variability due to individual differences, while the residual variance of 0.24 (SD = 0.49) suggests that a larger portion of the variance remains unexplained. The fixed effects analysis revealed that the baseline reflection score for Goal 1 was 2.51 (SE = 0.07, t = 34.75, p < .001).

Reflection depth for Goal 2 was higher by 0.16 (SE = 0.08, t = 1.95, p = .05), though the effect was not statistically significant at the conventional 0.05 level. The results indicate a general upward trend in reflection depth across goals, though with some uncertainty regarding the significance of differences between them.

Iteration-to-Iteration Differences

Mean differences in reflection scores between consecutive iterations were calculated for Goal 1 and Goal 2 using the core dataset. Paired t-tests were conducted to determine if these mean differences significantly differed from zero. The results, visible in Table 4, indicate that iteration-to-iteration differences were generally small and non-significant for both Goal 1 and Goal 2.

Table 4 – *Mean Differences in Reflection Scores Between Consecutive Iterations*

Goal	Iteration Pair	Mean Difference	SD	t-value	df	p-value
Goal 1	1 to 2	0.17	0.54	1.72	28	.096
Goal 1	2 to 3	0.17	0.49	1.70	22	.104
Goal 2	1 to 2	0.14	0.79	0.94	28	.355
Goal 2	2 to 3	-0.06	0.68	-0.37	15	.718

Linear Regression Analysis

A series of linear regression models using core data were conducted to examine the relationship between participants' average reflection scores across iterations and their Meta Reflection Score. The model equations were as follows:

- **Model 1:** Meta Reflection Score = $\beta_0 + \beta_1$(Average Score Across Goals 1 and 2) + ϵ
- **Model 2:** Meta Reflection Score = $\beta_0 + \beta_1$(Average Score for Goal 1) + ϵ
- **Model 3:** Meta Reflection Score = $\beta_0 + \beta_1$(Average Score for Goal 2) + ϵ

The models were fit using ordinary least squares (OLS) regression. Model 1 examined the predictive value of participants' average scores across all iterations of Goal 1 and Goal 2 on their Meta Reflection Score. The model revealed that the overall average iteration scores were not a significant predictor of Meta Reflection Score, B = 0.41 (SE = 0.24, t(26) = 1.66, p = .109). The model explained approximately 9.6% of the variance in Meta Reflection Score, R^2 = 0.10, indicating a weak association.

Model 2 investigated whether participants' average scores across Goal 1 iterations predicted Meta Reflection Score. Results indicated no significant relationship, B = 0.05 (SE = 0.21, $t(26) = 0.26$, $p = .800$). The model explained only 0.3% of the variance, $R^2 = 0.00$, suggesting that reflection levels during Goal 1 were not associated with higher Meta Reflection Scores.

Model 3 tested the predictive value of participants' average scores across Goal 2 iterations on Meta Reflection Score. The model found a significant positive relationship, B = 0.40 (SE = 0.18, $t(26) = 2.19$, $p = .038$). This model explained 15.5% of the variance in Meta Reflection Score, $R^2 = 0.16$, indicating that higher reflection scores in Goal 2 iterations were associated with improved Meta Reflection.

Overall, these findings suggest that participants' reflection depth in Goal 2 iterations was significantly related to their Meta Reflection Score, but it did not exhibit a significant relationship with reflection depth in Goal 1 and the overall per-participant average.

Research Question 2: What is the relationship Between Forethought and Depth of Reflection?

Average-Level Correlation - Forethought

To examine the relationship between participant level average forethought scores and participant level average reflection depth scores, a Pearson correlation was calculated using the core dataset. The analysis revealed a weak positive correlation, which was not statistically significant, $r = 0.14$ ($p = .505$), with a 95% confidence interval of [−0.26, 0.50]. No strong association between forethought and reflection depth across participants was found.

Linear Mixed-Effects Model – Forethought as a predictor of Score

A linear mixed-effects model using the core dataset was used to further examine the relationship between forethought and reflection depth, accounting for participant-level variability as a random effect. The model formula was:

$$\text{Score} \sim \text{Forethought} + (1 \mid \text{Participant})$$

Participant-level differences in reflection depth scores were modeled through random effects, which showed a variance of 0.09 (SD = 0.31), indicating some variability attributable to individual differences. The residual variance was 0.29 (SD = 0.53), representing the portion of variability that was not explained by the model, suggesting the presence of additional influencing factors not accounted for in the analysis. As for the fixed effects, the intercept, representing the average reflection depth across participants, was 2.73. Forethought did not significantly predict reflection depth, b = 0.00 (SE = 0.04, t = 0.05, p = .96), indicating that changes in forethought scores had no measurable effect on reflection depth. This suggests that, while the model accounted for participant-level differences, forethought did not predict reflection depth.

Research Question 3: What is the Relationship Between Learning Outcomes and Depth of Reflection?

Average-Level Correlations

Pearson's correlations were calculated to examine the relationships between reflection depth scores and learning outcomes, using activity data collected through the TIIM app. The learning outcomes included summed Goal Difference and average Satisfaction scores, calculated for each iteration based on the learning activities completed during that iteration.

The correlation between summed Goal Difference and average reflection depth on a participant level was weak and positive, $r = 0.09$, $p = .598$, with a 95% confidence interval of [−0.25, 0.41]. The correlation between average Satisfaction and reflection depth on a participant level was similarly weak and positive, $r = 0.07$, $p = .774$, with a 95% confidence interval of [−0.32, 0.44]. These results indicate no significant average-level relationships between the examined learning outcomes and reflection depth scores.

These results indicate no significant participant average-level relationships between the examined learning outcomes and reflection depth scores.

Linear Mixed-Effects Model

To explore the relationship between learning outcomes and reflection depth, a linear mixed-effects model was used, treating participants as a random effect to account for individual variability. The model formula was specified as:

$$\text{Score} \sim \text{Satisfaction} + \text{Goal Difference} + (1 \mid \text{Participant})$$

Participant-level differences in reflection depth scores were modeled through random effects, which showed a variance of 0.08 (SD = 0.28), indicating some variability attributable to individual differences. The residual variance was 0.25 (SD = 0.50), representing the portion of variability not explained by the model, suggesting the presence of additional influencing factors not accounted for in the analysis. As for the fixed effects, the intercept, representing the baseline reflection depth score, was statistically significant, b = 2.23 (SE = 0.36, t = 6.26, p <

.001). However, neither Satisfaction, b = 0.10 (SE = 0.09, t = 1.11, p = .27), nor Goal Difference, b = 0.00 (SE = 0.003, t = 0.27, p = .79), were significant predictors of reflection depth. These results indicate that neither Satisfaction nor Goal Difference predicted reflection depth scores.

Supplementary Materials

The R code used to generate these analyses and results is provided in Appendix B for transparency and reproducibility. Furthermore, a copy of a sample PD Canvas the participants used for their reflections is included.

Discussion

Building on the results, several interpretations can be drawn regarding the impact of iterative reflective practice on reflection depth in SDL. Results of the analyses of the research question, *How does iterative reflective practice affect reflection depth?*, indicate that iteration significantly impacts reflection depth scores across all analyses, regardless of goal-related factors. Furthermore, both the average reflection scores and the results from the linear mixed-effects model indicated that participants demonstrated significantly greater reflection depth in Goal 2 compared to Goal 1, with positive slopes across iterations for both goals, suggesting progressive improvement. These findings align with existing literature, which emphasizes continuous improvement through iterative reflective practice (Ward, 2008; Khanam, 2015). These results suggest that participants likely improved their reflection skills by engaging in multiple iterations during Goal 1, thereby enhancing their reflective performance in Goal 2.

Interestingly, the slope analysis using core data showed a steeper positive slope for Goal 1 compared to Goal 2, indicating a higher rate of improvement during Goal 1 iterations.
This could suggest that participants experienced some form of cognitive fatigue during Goal 2 iterations. Cognitive load theory (Sweller, 1988) supports this theory, indicating that repetitive tasks without variation may cause disengagement and lower performance (Tze, Daniels, & Klassen, 2015). Alternatively, the observed pattern may be explained by a learning curve effect, as described by Fassnacht (1974), where initial improvement in Goal 1 occurs rapidly due to participants' unfamiliarity with the structured method and prompts. As they become more proficient, the rate of improvement naturally slows in Goal 2, reflecting the diminishing returns

also commonly seen in learning processes influenced by factors such as material familiarity, hesitation, and interference.

Further analyses in the linear regression results showed a significant positive relationship between Goal 2 scores and meta-reflection scores. This suggests that reflection depth developed over time, with participant's abilities to achieve higher reflection scores in Goal 2 being associated with deeper meta-reflection scores. Another interesting finding was that paired t-tests analyzing mean differences between consecutive iterations showed small, non-significant differences for consecutive iterations in both goals. This suggests that while reflection depth improves across iterations, the incremental changes between consecutive iterations are minor. Significant improvements therefore occur over multiple iterations rather than between individual iterations.

The most prominent example of this is the last reflection, the meta-reflection, as it yielded the highest reflection depth scores, likely due to the combined influence of iterative practice and the structured guidance provided by the PD Canvas prompts. Research suggests that prompts functioned as scaffolding, guiding participants toward more critical and in-depth reflection, in line with cognitive apprenticeship models (Collins, Brown, & Newman, 1989). The meta-reflection process also encouraged participants to synthesize their learning holistically by integrating insights from multiple reflection cycles. This suggests that iterative practice itself played a significant role in enhancing reflective depth. Participants completed at least four reflective cycles before the meta-reflection, which likely reinforced their reflective processes and critical thinking. Insights gained during Goal 1 may have contributed to deeper reflection in Goal 2. Revisiting and evaluating earlier reflections helped internalize critical thinking processes, as noted by Khanam (2015) and Srivastava and Hopwood (2009). The higher meta-reflection scores hence reflect the cumulative impact of repeated reflective engagement and structured scaffolding more than other iterations. Together, these elements were observed as strengthening participants' ability to critically evaluate their experiences, resulting in deeper, more integrated insights.

For the second research question, *What is the relationship between forethought and reflection depth?*, both the correlation analysis between forethought and reflection depth scores and the linear mixed-effects model indicated that forethought, as measured by the TIIM app, was not a significant predictor of reflection depth. These findings challenge traditional self-directed learning (SDL) models, such as Garrison's (1997) framework, which emphasizes pre-planning as a key determinant of reflective depth. Similarly, Ryan (2013) highlights the role of iterative practice in shaping future choices and fostering self-awareness, suggesting a stronger link between forethought and reflection outcomes than what was observed in this study.

A possible explanation for this discrepancy is that the self-reported forethought data collected via the TIIM app may not have accurately captured participants' underlying cognitive processes, or that lower self-reported forethought scores do not necessarily indicate a diminished capacity for achieving deeper reflection. This would be in line with situated learning theory (Lave & Wenger, 1991), which states that learning is driven more by authentic, real-world contexts than by abstract pre-planning. In this regard, participants may have achieved meaningful reflective depth through engagement with the tasks themselves rather than through deliberate forethought.

Finally, the analysis for the third research question, *What is the relationship between learning outcomes and reflection depth?*, revealed weak and non-significant correlations between self-reported "satisfaction" and "goal progress" with reflection depth. These patterns, confirmed by the linear mixed-effects model, suggest that the measured learning outcomes (Satisfaction and GoalDif) did not predict participants' reflection depth in iterative practice.

A likely explanation is that participants evaluated their progress based on task completion or performance in their learning activities. As a result, no significant relationship was found between learning outcomes (satisfaction and goal progress) and reflection depth, suggesting that the depth of reflection was not influenced by how much progress participants believed they made or how satisfied they felt. Instead, their reflection depth may have been shaped by other factors unrelated to perceived progress. This aligns with research by Noe et al. (2014), who observed that individuals often prioritize tangible outcomes over deeper cognitive engagement in workplace settings

Theoretical Implications

Given the limited existing research on this specific topic, this study contributes to the literature by bridging the gap between iterative reflective practice, SDL, informal workplace learning, and the development of critical reflections. It provides valuable insights into how repeated reflective cycles enhance reflection depth over time and how these improvements relate to self-reported measures of forethought, satisfaction, and perceived goal progress. The findings from research question 1 support existing literature by Khanam (2015), Ward (2008), and Srivastava & Hopwood (2009) on iterative reflective practice as a key approach to increasing critical reflection in self-directed learning (SDL). This study adds to this body of work by demonstrating that the effectiveness of iterative reflective practice as a means of increasing reflection depth score extends to simulated work environments. This highlights the broader potential of such practices to enhance professional and skill development by improving individuals' ability to reflect critically, which was identified as an essential element of SDL.

Another implication of this study's results is that the descriptive statistics from the research question 1 analysis provide supporting evidence for Gaupp's (2018) findings that achieving critical reflection is inherently challenging, as observed throughout the iterations of both goals 1 and 2. Furthermore, the relatively high reflection depth scores observed in the meta-reflections suggest that iterative reflective practice can significantly aid in reaching deeper levels of reflection over time. This reinforces Gaupp's (2018) claim that critical reflection does not occur naturally and requires structured effort, which in the case of this study can be observed in the gradual increase in reflection depth scores from iteration 1 of goal 1, all the way to the meta-reflection.

Practical Implications

This study provides valuable insights for HRD practitioners and educators aiming to enhance reflection depth in self-directed learning (SDL) through iterative reflective practices. The significant relationship between iteration and reflection depth found in this study suggests that iterative reflection can be effectively integrated into educational and workplace training programs when deeper reflection is needed. For instance, in courses where end-of-course reflections were found to lack depth, incorporating iterative reflection throughout the learning process could enhance engagement and insight. This approach may also help address the issue of "reflective zombies" (De la Croix & Veen, 2018), where learners engage in superficial reflection without meaningful critical thinking. Structured iterative reflection, as seen in the meta-reflection phase of this study, supports more holistic and scaffolded reflection.

The observed reduction in the rate of improvement from Goal 1 to Goal 2 highlights the potential risk of cognitive fatigue with excessive iterations. Practitioners should use these findings to avoid overburdening learners with too many cycles in iterative practice designs, as diminishing returns may result (Sweller, 1988; Tze, Daniels, & Klassen, 2015). Optimizing the number of reflective cycles and adjusting task spacing could help maximize engagement and prevent fatigue, suggesting the existence of an optimal "Goldilocks zone" for iterations, in line with spaced learning theories (Smolen, Zhang, & Bern, 2016).

This study also demonstrated the critical role of meta-reflection in fostering deeper reflection. Organizations and educators can benefit from incorporating structured, holistic reflection activities—such as meta-reflection—into their programs to help learners synthesize insights across multiple cycles. Scaffolded prompts and structured guidance, as found in this study, were key in helping learners develop critical reflection skills over time. Future research should investigate how scaffolding prompts can be varied and adapted to be most effective.

Finally, caution is advised when relying on self-reported learning outcomes and forethought measures, as this study found no significant relationship between these measures and reflection depth. Practitioners should consider supplementing self-reported data with direct assessments of reflective engagement for a more accurate evaluation of learning processes.

Limitations

Despite the insightful findings, several limitations of this study should be acknowledged. First, the sample size was relatively small, and participation declined in later iterations, particularly in Iteration 4 and beyond. To address this, a core dataset of iterations completed by at least 50% of participants was used. While this approach helped ensure a more reliable analysis of core trends, the low response rates in later iterations may have introduced variability, particularly in Goal 2 scores.

Second, the assessment of reflection depth relied on only two coders. Although inter-rater reliability was found to be moderate to substantial (McHugh, 2012), expanding the number of coders or using automated text analysis tools in future studies would enhance reliability by reducing potential coder bias. Moreover, incorporating triangulation methods—such as peer review or participant validation—would provide additional checks to improve the robustness of the coding process (Birt et al. 2016). These measures could help ensure greater consistency across datasets.

Third, a notable limitation of this study is the substantial unexplained variance in the models assessing the relationship between predictor variables and reflection depth. This suggests that important factors explaining reflection depth, such as motivation, engagement, or contextual influences, for example, were not accounted for. Including variables measuring intrinsic motivation or prior experience with reflective practice could be a way to reach a more comprehensive understanding of the factors driving deeper reflection. Future research should hence explore additional predictors to improve model accuracy and explanatory power. Similarly, the non-significant effects of Forethought, Satisfaction, and Goal Difference suggest that the chosen variables may not fully capture the complexity of reflection processes, highlighting the need for alternative predictors or interaction effects.

Fourth, the study relied heavily on self-reported data for RQ2 and RQ3, which may have introduced interpretation biases. The TIIM App collected participants' perceptions of forethought, goal progress, and satisfaction, but self-reports are inherently prone to variability depending on how individuals perceive and articulate their learning experiences (Schwarz, 1999). This variability could be another factor explaining the non-significant relationships seen in RQ2 and RQ3, beyond what was previously discussed. Self-reported data can be influenced by factors such as mood, personal interpretation of prompts, or social desirability bias, which may have affected how participants rated their own planning and progress (Fischer & Katz, 2000). Future studies would hence benefit from using more objective tools to measure these variables, such as behavioral tracking or peer evaluations. More data on outcome measures could also shed more light on the relationships investigated in this paper, such as those investigated in research questions 2 and 3.

Lastly, the context study being observed being in an educational setting, as a simulated work environment, may not fully reflect the complexities of real-world workplace learning behaviors. It is likely that participants' reflections were influenced by academic requirements and motivators that differ from those typically encountered in professional environments. In real workplace contexts, factors such as job security, performance evaluations, and salary incentives play a significant role in driving learning behaviors (Andrade, 2020; Eraut, 2004; Rust, 2002). These differences could limit the external validity of the findings, as participants may have approached reflective tasks with a focus on completing coursework rather than achieving genuine professional development. Additionally, the mandatory nature of the first two iterations may have influenced participants' initial engagement, but this requirement did not extend to later cycles, which may explain the dropout observed in subsequent iterations. A lack of intrinsic motivation to sustain participation may have further contributed to the decline in engagement over time.

Conclusion

This study demonstrates that iterative reflective practice is an effective strategy for self-directed learners for fostering deeper critical reflection. Findings showed that while iteration to iteration effects were minimal, Goal 2 scores were significantly higher than Goal 1 scores, also, the final meta reflection, likely due to scaffolding through more detailed prompts and the more holistic nature of the meta reflection, showed the highest reflection depth scores, in line with the description of Kember's (2008) levels 3 and 4. However, the rate of improvement was found to diminish from Goal 1 to Goal 2, likely explained by cognitive fatigue, or the presence of a learning curve, highlighting the importance of investigating these further in order to gain more insights on how to improve the positive effect of iteration on reflection depth. Prompt scaffolding for the meta reflection should also be further investigated in order to develop an understanding of what elements or features can be leveraged to increase this effect.

Despite these positive outcomes, the models used in the analysis of the data in this study revealed a substantial amount of unexplained variance, suggesting that factors beyond those investigated in the present study influence reflection depth. This finding underscores the complexity of the reflection process and the need for further exploration into additional contributing variables. Using multiple coders, or automated text analysis tools is also encouraged, as well as the use of a larger participant sample size, who's data should be collected using additional methods beyond self-reports.

Given the observed limitations, future research should build on these findings to refine the understanding of iterative reflective practice as a means of enhancing reflection depth, and the additional factors affecting this relationship . Investigating these alternative predictors, such as intrinsic motivation, task complexity, and engagement levels, which could help explain the unexplained variance and optimize iterative reflection as a practical tool for professional development. Additionally, methodological improvements, such as employing longitudinal study designs, would provide more robust insights into how iterative practice influences long-term reflective improvement, as well as a more nuanced understanding of the process. In conclusion, this study offers valuable insights into the potential of iterative reflective practice to enhance SDL which can be used in professional education and workplace training. The promising findings provide a strong foundation for future research in these areas to explore how iterative practice can be effectively implemented to foster deeper learning, critical thinking, and sustained professional growth. By addressing current limitations and identifying other key variables to explain the unexplained variance, iterative reflective practice can become a vital component of HRD and lifelong learning strategies and helping understand the process more to help inform more effective decisions.

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Appendix A

PD Canvas structure and example

Overview of Attachments – Learning Goal 2
(e.g. outcomes of learning outcomes -raw evidence)

Attachment	Content	Description
2.A		
2.B		
2.C		
2.D		
?		

Overview of Attachments – Learning Goal 1

(e.g. outcomes of learning outcomes - raw evidence)

Attachment	Content	Description
1.A	LA1 web search	Searched on Google for information for effective communication, consulted multiple websites for tips for my situation.
1.B	LA2 consulting online doc	Tried scripting the important information I wanted to communicate in the meeting.
1.C	LA3 experimenting	Asked my team to observe and provide feedback on my application of the script in the meeting.
1.D	LA4 asking for feedback	
?	LA5 other	...

Meta-reflection on the Professional Development Trajectory

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Meta-reflection

Meaning-making:

- E.g., What is your understanding of professional development now?
- E.g., What part of your personal development process do you feel was most successful?
- E.g., What was the role of others in your professional (peers, team)?
- E.g., What tools and methods (e.g. Expert Talks, TTIM, PD Canvas) do you feel were most helpful?

Planning:

e.g., What will you do next time? What will you do the same? What will you change?

e.g., What have you learned about how you learn best? What do you need for your learning?

Questions to ask yourself as conclusion to iterations of professional development:

1) **Meaning-making:** What did you learn from this experience?
2) **Planning:** Which steps will help you in your future development?

Meta-reflection on my Two Learning Goals

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Meta-reflection

Describing:
- E.g., How successful were you in accomplishing your learning goals?
- E.g., How did the development in your learning goals contribute to the project assignment and team achievement?
- E.g., Where did you struggle? What were those struggles or obstacles?
- E.g., In what way did those obstacles or struggles impact your success?
- E.g., How did you (try) to overcome those obstacles? Where you successful in this?

Conclusion:
- E.g., What did you accomplish in your professional development? What are you proud of?
- E.g., What did you not accomplish in your professional development? What do you need to continue working on?
- E.g., What are the next steps in terms of your both learning goals and beyond?

Questions to ask yourself as conclusion to both learning goals:
1) **Describing:** What was your experience from working on your learning goals and how successful where you in achieving them?
2) **Conclusions:** What did you achieve for your professional development via both goals and what are the next steps?

Can be split up for both goals.

Meta-Reflection

Learnings from engaging in
Professional Development
In 2 Learning Goals

https://unsplash.com/photos/14BVc2mD9Bk

LEARNING GOAL 1, ITERATION X

C. Evaluating progress on your learning goal

Selected and processed evidence on my learning activities outcomes	Raw evidence (info last page)

Evaluating my progress on the learning goal & reflecting on my learnings

(Iterated) SMART learning goal	Progress

LEARNING GOAL 1, ITERATION X

A. Planning your learning activities

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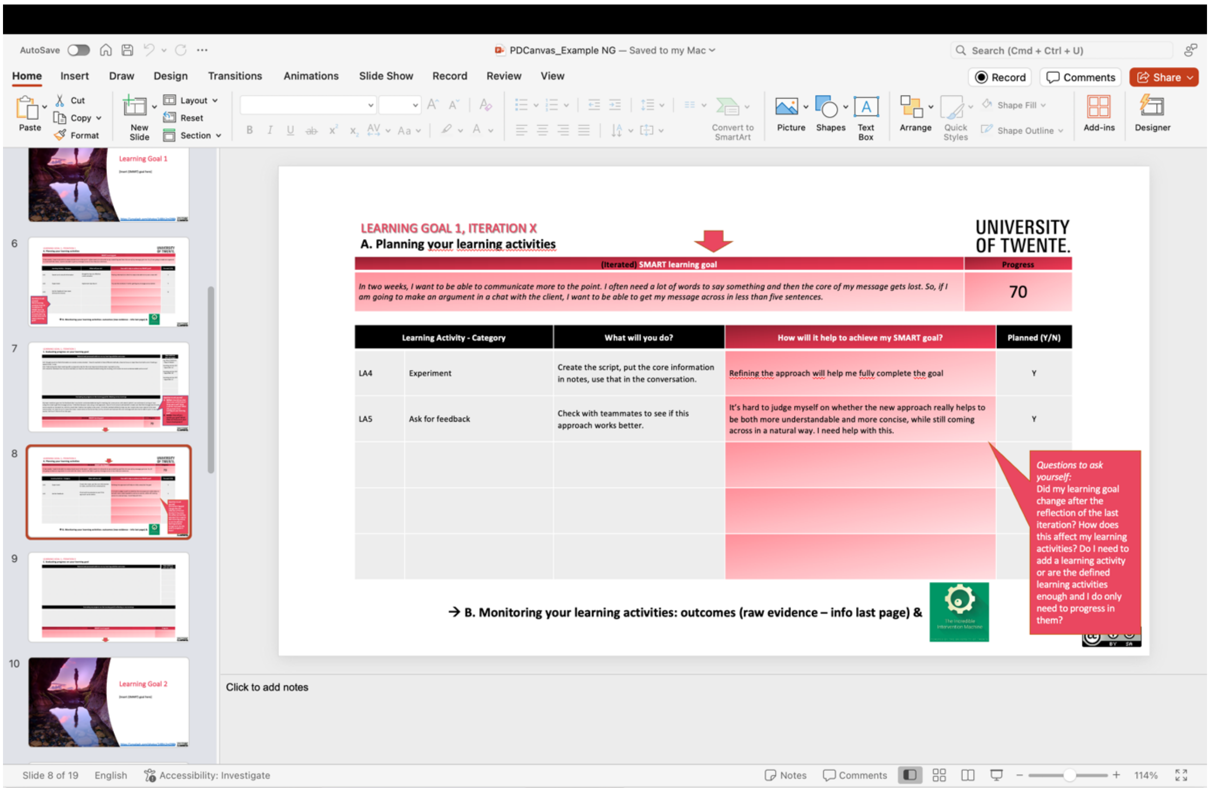
(Iterated) SMART learning goal	Progress
In two weeks, I want to be able to communicate more to the point. I often need a lot of words to say something and then the core of my message gets lost. So, if I am going to make an argument in a chat with the client, I want to be able to get my message across in less than five sentences.	70

Learning Activity - Category		What will you do?	How will it help to achieve my SMART goal?	Planned (Y/N)
LA4	Experiment	Create the script, put the core information in notes, use that in the conversation.	Refining the approach will help me fully complete the goal	Y
LA5	Ask for feedback	Check with teammates to see if this approach works better.	It's hard to judge myself on whether the new approach really helps to be both more understandable and more concise, while still coming across in a natural way. I need help with this.	Y

Questions to ask yourself:
Did my learning goal change after the reflection of the last iteration? How does this affect my learning activities? Do I need to add a learning activity or are the defined learning activities enough and I do only need to progress in them?

→ **B. Monitoring your learning activities: outcomes (raw evidence – info last page) &**

The Incredible Intervention Machine


PDCanvas_Example NG — Saved to my Mac
LEARNING GOAL 1, ITERATION X
A. Planning your learning activities
UNIVERSITY OF TWENTE.
(Iterated) SMART learning goal
Progress
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Experiment
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Click to add notes
Slide 8 of 19
English
Accessibility: Investigate


Learning Goal 1
[Insert (SMART) goal here]
https://unsplash.com/photos/14BVc2mD9Bk

Professional Development Canvas

My HRD Competence and My Learning Goals

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My HRD Competence & 2 Learning Goals				
HRD Competence		Selected Competence	Reasoning for Selection	
		(e.g. client communication)	(Relate strengths and weaknesses to opportunities and threats in team)	
Nr.	General goal	Why it is challenging and important to me?	Why is it relevant to the team and project goals?	SMART goal
1	(1. PD goal for selected HRD competence)			
2	(2. PD goal for selected HRD competence)			

Professional Development Canvas

Information, Team & Characterization

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General Information	
Student Name:	Student Number:
Study Program:	Peer coach name:

My team	
Team Name:	Assignment:
Team Goal:	

My team roles (Belbin)	
Team Role 1:	Team Role 2:

Professional Strengths to Leverage and/or Develop	Professional Weaknesses to Manage and/or Develop

cc BY SA

My Understanding of Professional Development

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Reflection
What does professional development mean? - Definition:
How does professional development work? - Procedure:
What did I do in terms of my professional development? – Previous experience:
What do I expect in the PD Lab? – Expectations:

Appendix B

R-Script used for Data Analysis

SCRIPT 1:

```
####################################################################
# STANDARD ANALYSIS WITH ALL PARTICIPANTS
####################################################################

#################################################################### LOAD REQUIRED LIBRARIES AND DATA

# Load required libraries
library(readxl)
library(dplyr)
library(tidyr)
library(ggplot2)
library(lme4)
library(Matrix)
library(lmerTest)

tiim <- read.csv("/Users/larslenard/Downloads/PD23_24Data.csv")
tiim <- select(tiim, ID.Number, Week, Goal, ActivityNum, GoalProgress, GoalDif, Satisfaction, Forethought)

tiim <- tiim %>%
  group_by(ID.Number, Week) %>%
  summarise(
    GoalDif = sum(GoalDif, na.rm = TRUE),            # Sum GoalDif per week
    Satisfaction = mean(Satisfaction, na.rm = TRUE),  # Average Satisfaction
    Forethought = mean(Forethought, na.rm = TRUE),    # Average Forethought
    .groups = 'drop'
  )

# Load dataset
data_path <- "~/Downloads/LONG_FORMAT_DATA.xlsx"  # Adjust if needed
long_data <- read_excel(data_path)

IDNumbers <- unique(long_data$Participant)

long_data <- filter(long_data, !is.na(Score))

meta_data <- long_data
for (i in IDNumbers) {
  meta_data$IT[meta_data$Participant == i] <- 1:length(which(meta_data$Participant == i))
}

long_data <- filter(long_data, Is_Meta == 0)

for (i in IDNumbers) {
  long_data$IT[long_data$Participant == i] <- 1:length(which(long_data$Participant == i))
}

model1 <- lmer(Score ~ IT + (1|Participant), data = long_data)
summary(model1)

core_data <- filter(long_data, Iteration != 4 & Iteration != 5)

model2 <- lmer(Score ~ IT + (1|Participant), data = core_data)
summary(model2)

model3 <- lmer(Score ~ IT + (1|Participant), data = meta_data)
summary(model3)

core_meta <- filter(meta_data, Iteration != 4 & Iteration != 5)

model4 <- lmer(Score ~ IT + (1|Participant), data = core_meta)
summary(model4)

######################################################################
```

```
# REUSABLE FUNCTIONS
######################################################################

# Function to calculate summary statistics
calculate_summary_stats <- function(data) {
  data %>%
    group_by(Goal, Iteration) %>%
    summarise(
      Mean = mean(Score, na.rm = TRUE),
      SD = sd(Score, na.rm = TRUE),
      Median = median(Score, na.rm = TRUE),
      Count = sum(!is.na(Score)),
      .groups = 'drop'
    )
}

# Function to calculate correlation
calculate_correlation <- function(data, goal_filter) {
  cor.test(
    data$Iteration[data$Goal == goal_filter],
    data$Score[data$Goal == goal_filter],
    use = "pairwise.complete.obs"
  )
}

# Function to calculate weights
prepare_weighted_data <- function(data) {
  data %>%
    group_by(Goal, Iteration) %>%
    summarise(
      Score_Count = sum(!is.na(Score)),
      Total_Participants = n(),
      Weight = Score_Count / Total_Participants,
      .groups = 'drop'
    )
}

# Function to calculate differences between consecutive iterations
calculate_iteration_differences <- function(data) {
  data %>%
    filter(!is.na(Score)) %>%
    arrange(Participant, Iteration) %>%
    group_by(Participant, Goal) %>%
    mutate(
      Score_Diff = Score - lag(Score),
      Iteration_Pair = paste(lag(Iteration), "to", Iteration)
    ) %>%
    filter(!is.na(Score_Diff))
}

######################################################################
# DESCRIPTIVE STATISTICS
######################################################################

# Prepare Goal Labels
goal_data <- long_data %>%
  mutate(
    Goal = case_when(
      Is_Goal1 == 1 ~ "Goal 1",
      Is_Goal2 == 1 ~ "Goal 2",
      Is_Meta == 1 ~ "Meta-Reflection",
      TRUE ~ NA_character_
    )
  )

# Exclude iterations 4 and 5 for reliability
core_goal_data <- goal_data %>%
  filter(Iteration %in% c(1, 2, 3) | Goal == "Meta-Reflection")

# Goal 1, Goal 2, and Meta-Reflection statistics
goal1_stats <- calculate_summary_stats(core_goal_data %>% filter(Is_Goal1 == 1, Is_Meta == 0))
goal2_stats <- calculate_summary_stats(core_goal_data %>% filter(Is_Goal2 == 1, Is_Meta == 0))
meta_stats <- calculate_summary_stats(core_goal_data %>% filter(Is_Meta == 1))
meta_stats$Iteration <- 6  # Place Meta-Reflection at Iteration 6
```

```
# Combine statistics
summary_stats <- bind_rows(goal1_stats, goal2_stats, meta_stats) %>%
  select(Goal, Iteration, Mean, SD, Median, Count)

# View summary statistics
print(summary_stats)

# Participant retention per iteration
goal_retention <- core_goal_data %>%
  group_by(Goal, Iteration) %>%
  summarise(
    Unique_Participants = n_distinct(Participant),
    .groups = 'drop'
  )

print("Participant Retention Across Iterations:")
print(goal_retention)


######################################################################
# TREND ANALYSIS DATA PREPARATION
######################################################################

# Prepare trend data with Meta-Reflection at Iteration 6
trend_data <- core_goal_data %>%
  filter(!is.na(Goal), !is.na(Score)) %>%
  mutate(Iteration = ifelse(Goal == "Meta-Reflection", 6, Iteration))

######################################################################
# CORRELATION ANALYSIS
######################################################################

# Goal 1 Correlation
goal1_corr <- calculate_correlation(trend_data, "Goal 1")
print(goal1_corr)

# Goal 2 Correlation
goal2_corr <- calculate_correlation(trend_data, "Goal 2")
print(goal2_corr)

# Total iterations per participant
iterations_summary <- trend_data %>%
  filter(Goal != "Meta-Reflection") %>%
  group_by(Participant) %>%
  summarise(
    Total_Iterations = sum(!is.na(Score)),
    Avg_Score = mean(Score, na.rm = TRUE),
    .groups = 'drop'
  )

# Correctly extract Meta-Reflection scores
meta_scores <- trend_data %>%
  filter(Goal == "Meta-Reflection") %>%
  group_by(Participant) %>%
  summarise(Meta_Score = mean(Score, na.rm = TRUE), .groups = 'drop')

# Combine and analyze correlation
cor_data <- left_join(iterations_summary, meta_scores, by = "Participant")
print("Combined Data for Correlation Analysis:")
print(cor_data, n = nrow(cor_data))

# Correlations
meta_corr <- cor.test(cor_data$Total_Iterations, cor_data$Meta_Score, use = "pairwise.complete.obs")
print("Correlation between Total Iterations and Meta-Reflection Score:")
print(meta_corr)

avg_meta_corr <- cor.test(cor_data$Avg_Score, cor_data$Meta_Score, use = "pairwise.complete.obs")
print("Correlation between Average Reflection Score and Meta-Reflection Score:")
print(avg_meta_corr)

# Group-level mean differences for Goal 2
goal2_group_means <- trend_data %>%
  filter(Goal == "Goal 2", Iteration %in% c(1, 2, 3)) %>%
  group_by(Iteration) %>%
  summarise(Group_Mean = mean(Score, na.rm = TRUE))
```

```
goal2_group_diffs <- diff(goal2_group_means$Group_Mean)
print("Group-Level Mean Differences for Goal 2 Iterations:")
print(goal2_group_diffs)

# Participant-level differences
goal2_diff_data <- core_goal_data %>%
  filter(Goal == "Goal 2") %>%
  calculate_iteration_differences()

# Summarize participant-level differences
goal2_diff_summary <- goal2_diff_data %>%
  group_by(Iteration_Pair) %>%
  summarise(
    Mean_Diff = mean(Score_Diff, na.rm = TRUE),
    SD_Diff = sd(Score_Diff, na.rm = TRUE),
    Count = n(),
    .groups = 'drop'
  )
print("Participant-Level Mean Differences for Goal 2:")
print(goal2_diff_summary)

# Goal 2 Correlation with sample size
goal2_corr <- calculate_correlation(trend_data, "Goal 2")
goal2_sample_size <- trend_data %>% filter(Goal == "Goal 2") %>% nrow()

print("Goal 2 Correlation:")
print(goal2_corr)
print(paste("Sample size for Goal 2 correlation:", goal2_sample_size))


##########################################################################################################
###########################
# SECTION 2: ANALYSIS USING WEIGHTED SCORES FOR RESPONSE IMBALANCE
##########################################################################################################
###########################

# Prepare weights
weights <- prepare_weighted_data(goal_data %>% filter(!is.na(Goal)))
print("Weight Distribution Across Goals and Iterations:")
print(weights)

#################################################################
# CALCULATE WEIGHTED AND NON-WEIGHTED SUMMARY STATS
#################################################################

# Function to calculate weighted and unweighted stats
calculate_weighted_stats <- function(data, weights, weighted = FALSE) {
  data %>%
    left_join(weights, by = c("Goal", "Iteration")) %>%
    group_by(Goal, Iteration) %>%
    summarise(
      Mean = if (weighted) {
        weighted.mean(Score, w = ifelse(is.na(Score), 0, Weight), na.rm = TRUE)
      } else {
        mean(Score, na.rm = TRUE)
      },
      SD = if (weighted) {
        sqrt(sum(Weight * (Score - weighted.mean(Score, w = Weight, na.rm = TRUE))^2, na.rm = TRUE) / sum(Weight, na.rm = TRUE))
      } else {
        sd(Score, na.rm = TRUE)
      },
      Median = median(Score, na.rm = TRUE),
      Count = sum(!is.na(Score)),
      .groups = 'drop'
    )
}

# Filter data to exclude Iterations 4 and 5
core_goal_data <- goal_data %>%
  filter(Iteration %in% c(1, 2, 3) | Goal == "Meta-Reflection")

# Weighted and non-weighted stats
non_weighted_stats <- calculate_weighted_stats(core_goal_data, weights, weighted = FALSE)
non_weighted_stats$Type <- "Non-Weighted"
```

```
weighted_stats <- calculate_weighted_stats(core_goal_data, weights, weighted = TRUE)
weighted_stats$Type <- "Weighted"

# Combine for comparison
comparison_stats <- bind_rows(non_weighted_stats, weighted_stats)

######################################################################
# CORE TREND PREPARATION
######################################################################

# Prepare core trend data: Only Iterations 1-3 and Meta-Reflection at Iteration 6
core_trend <- comparison_stats %>%
  filter((Goal == "Goal 1" & Iteration <= 3) |
         (Goal == "Goal 2" & Iteration <= 3) |
         Goal == "Meta-Reflection") %>%
  mutate(Iteration = ifelse(Goal == "Meta-Reflection", 6, Iteration))

######################################################################
# LINEAR MIXED-EFFECTS MODELS
######################################################################

# Regression Data Preparation: Exclude Iterations 4 and 5
core_regression_data <- goal_data %>%
  filter(!is.na(Goal), !is.na(Score)) %>%
  filter(Iteration %in% c(1, 2, 3)) %>% # Use only reliable iterations
  mutate(Iteration = ifelse(Goal == "Meta-Reflection", 6, Iteration))

# Linear Mixed-Effects Model
mixed_model <- lmer(Score ~ Goal + (1 | Participant), data = core_regression_data) # Removed Iteration * Goal interaction
print("Linear Mixed-Effects Model Summary:")
mixed_model_summary <- summary(mixed_model)
print(mixed_model_summary)

# Linear Mixed-Effects Model: Including Iteration
mixed_model_with_iteration <- lmer(Score ~ Goal * Iteration + (1 | Participant), data = core_regression_data)

print("Linear Mixed-Effects Model with Goal and Iteration:")
summary(mixed_model_with_iteration)

######################################################################
# FIXED EFFECTS SUMMARY
######################################################################

# Extract fixed effects
fixed_effects_summary <- data.frame(
  Term = rownames(mixed_model_summary$coefficients),
  Estimate = mixed_model_summary$coefficients[, "Estimate"],
  Std_Error = mixed_model_summary$coefficients[, "Std. Error"],
  t_value = mixed_model_summary$coefficients[, "t value"]
)

print("Fixed Effects for Goal-Specific Intercepts:")
print(fixed_effects_summary)

######################################################################
# ITERATION-TO-ITERATION AND LAST GOAL 2 ITERATION TO META-REFLECTION ANALYSIS
######################################################################

# Function to calculate differences between consecutive iterations
calculate_iteration_differences <- function(data) {
  data %>%
    filter(!is.na(Score)) %>%
    arrange(Participant, Iteration) %>%
    group_by(Participant, Goal) %>%
    mutate(
      Score_Diff = Score - lag(Score),
      Iteration_Pair = paste(lag(Iteration), "to", Iteration)
    ) %>%
    filter(!is.na(Score_Diff))
}

# Prepare data for Goal 1 and Goal 2 with reliable iterations
core_goal_data <- goal_data %>%
  filter(Goal %in% c("Goal 1", "Goal 2")) %>%
```

```
  filter(Iteration %in% c(1, 2, 3))

iteration_diff_data <- core_goal_data %>%
  calculate_iteration_differences()

# Summarize differences for each iteration pair
iteration_diff_summary <- iteration_diff_data %>%
  group_by(Goal, Iteration_Pair) %>%
  summarise(
    Mean_Diff = mean(Score_Diff, na.rm = TRUE),
    SD_Diff = sd(Score_Diff, na.rm = TRUE),
    Count = n(),
    .groups = 'drop'
  )

# Print iteration-to-iteration differences
print("Iteration-to-Iteration Differences:")
print(iteration_diff_summary)

# Perform paired t-tests for iteration-to-iteration differences
print("Paired t-tests for Iteration-to-Iteration Differences:")
goal_list <- unique(iteration_diff_data$Goal)

for (goal in goal_list) {
  print(paste("Results for", goal))
  pairs <- unique(iteration_diff_data$Iteration_Pair)
  for (pair in pairs) {
    subset_data <- iteration_diff_data %>% filter(Goal == goal, Iteration_Pair == pair)
    if (nrow(subset_data) >= 2) {
      test_result <- t.test(subset_data$Score_Diff, mu = 0)
      print(paste("Iteration Pair:", pair))
      print(test_result)
    } else {
      print(paste("Iteration Pair:", pair, "- Not enough data for t-test (n =", nrow(subset_data), ")"))
    }
  }
}

########################################################################
# ANALYSIS: LAST GOAL 2 ITERATION TO META-REFLECTION
########################################################################

# Function to calculate the last Goal 2 score vs Meta-Reflection
calculate_last_goal2_vs_meta <- function(data) {
  last_iteration_data <- data %>%
    filter(Goal == "Goal 2" & Iteration %in% c(1, 2, 3) & !is.na(Score)) %>%
    group_by(Participant) %>%
    filter(Iteration == max(Iteration)) %>%
    summarise(
      Last_Iteration_Score = Score,
      Goal = "Goal 2",
      .groups = 'drop'
    )

  meta_reflection_data <- data %>%
    filter(Goal == "Meta-Reflection" & !is.na(Score)) %>%
    group_by(Participant) %>%
    summarise(
      Meta_Score = mean(Score, na.rm = TRUE),
      .groups = 'drop'
    )

  combined_data <- left_join(last_iteration_data, meta_reflection_data, by = "Participant") %>%
    mutate(
      Score_Diff = Meta_Score - Last_Iteration_Score,
      Iteration_Pair = "Last Goal 2 Iteration to Meta-Reflection"
    )
  return(combined_data)
}

# Perform analysis
last_to_meta_data <- calculate_last_goal2_vs_meta(goal_data)

# Summarize results
last_to_meta_summary <- last_to_meta_data %>%
```

```
  summarise(
    Mean_Diff = mean(Score_Diff, na.rm = TRUE),
    SD_Diff = sd(Score_Diff, na.rm = TRUE),
    Count = n(),
    .groups = 'drop'
  )

print("Summary of Differences: Last Goal 2 Iteration to Meta-Reflection")
print(last_to_meta_summary)

# Paired t-test
if (nrow(last_to_meta_data) >= 2) {
  print("Paired t-test: Last Goal 2 Iteration vs Meta-Reflection")
  t_test_meta <- t.test(last_to_meta_data$Score_Diff, mu = 0)
  print(t_test_meta)
} else {
  print("Not enough data for paired t-test between Last Goal 2 Iteration and Meta-Reflection.")
}


##########################################################################################################
# GRAPHS AND PLOTS
##########################################################################################################

######################################################################
# PREPARE TREND DATA (Core and Full Trends)
######################################################################

# Full Trend Data: Mean Score across all iterations
full_trend <- long_data %>%
  mutate(
    Goal = case_when(
      Is_Goal1 == 1 ~ "Goal 1",
      Is_Goal2 == 1 ~ "Goal 2",
      Is_Meta == 1 ~ "Meta-Reflection"
    ),
    Iteration = ifelse(Is_Meta == 1, 6, Iteration)  # Move Meta-Reflection to Iteration 6
  ) %>%
  filter(!is.na(Goal), !is.na(Score)) %>%
  group_by(Goal, Iteration) %>%
  summarise(
    Mean = mean(Score, na.rm = TRUE),
    .groups = 'drop'
  )

# Core Trend Data: First 3 iterations of Goal 1, Goal 2, and Meta-Reflection
core_trend <- full_trend %>%
  filter((Goal == "Goal 1" & Iteration <= 3) |
         (Goal == "Goal 2" & Iteration <= 3) |
         Goal == "Meta-Reflection")

######################################################################
# Plot 1: Single Line of Best Fit for Reflection Depth Across Iterations (All Data)
######################################################################

ggplot(full_trend, aes(x = Iteration, y = Mean)) +
  # Group-specific lines for each Goal
  geom_line(aes(group = Goal, color = Goal), size = 1) +
  # Group-specific points for each Goal
  geom_point(aes(color = Goal), size = 3) +
  # Single line of best fit for all data
  geom_smooth(aes(color = "Line of Best Fit - All Data"), method = "lm", se = FALSE, linetype = "solid") +
  # X-axis with custom labels
  scale_x_continuous(breaks = 1:6, labels = c("1", "2", "3", "4", "5", "Meta-Reflection")) +
  # Define custom colors for Goals and line of best fit
  scale_color_manual(values = c(
    "Goal 1" = "red",            # Red for Goal 1
    "Goal 2" = "green",          # Green for Goal 2
    "Meta-Reflection" = "black",  # Black for Meta-Reflection
    "Line of Best Fit - All Data" = "orange"  # Orange for the best fit line
  )) +
  # Add labels
  labs(
    title = "All Data: Trend of Reflection Depth Across Iterations",
    x = "Iteration",
```

```
    y = "Reflection Depth (Score)",
    color = "Legend"
  ) +
  # Adjust theme for clarity
  theme_minimal() +
  theme(
    legend.position = "right",
    axis.text.x = element_text(size = 10),
    axis.title = element_text(size = 12)
  )

######################################################################
# Plot 2: Core Data - Reflection Depth Across Iterations
######################################################################

ggplot(core_trend, aes(x = Iteration, y = Mean)) +
  # Group-specific lines and points by Goal
  geom_line(aes(group = Goal, color = Goal), size = 1.5) +
  geom_point(aes(color = Goal), size = 3) +
  # Line of best fit for core data
  geom_smooth(aes(color = "Line of Best Fit - Core Data"), method = "lm", se = FALSE, linetype = "solid") +
  # X-axis with custom labels
  scale_x_continuous(breaks = 1:6, labels = c("1", "2", "3", "", "", "Meta-Reflection")) +
  # Custom color scale for Goals and line of best fit
  scale_color_manual(values = c(
    "Goal 1" = "red",                # Red for Goal 1
    "Goal 2" = "green",              # Green for Goal 2
    "Meta-Reflection" = "black",     # Black for Meta-Reflection
    "Line of Best Fit - Core Data" = "blue"  # Blue for best fit line
  )) +
  # Add labels
  labs(
    title = "Core Data: Trend of Reflection Depth Across Iterations",
    x = "Iteration",
    y = "Reflection Depth (Score)",
    color = "Legend"
  ) +
  theme_minimal() +
  theme(
    legend.position = "right",
    axis.text.x = element_text(size = 10),
    axis.title = element_text(size = 12)
  )

######################################################################
# Plot 3: Core vs Full Trend - Reflection Depth Across Iterations
######################################################################

ggplot() +
  # De-emphasize full trend (dashed lines and lower opacity)
  geom_line(data = full_trend, aes(x = Iteration, y = Mean, group = Goal, color = Goal),
            linetype = "dashed", size = 1, alpha = 0.5) +
  # Emphasize core trend (solid lines)
  geom_line(data = core_trend, aes(x = Iteration, y = Mean, group = Goal, color = Goal),
            size = 1.5) +
  # Add points for core trend
  geom_point(data = core_trend, aes(x = Iteration, y = Mean, color = Goal), size = 3) +
  # Single line of best fit for Core Trend
  geom_smooth(data = core_trend, aes(x = Iteration, y = Mean, color = "Line of Best Fit - Core Data"),
              method = "lm", se = FALSE, linetype = "solid") +
  # Single line of best fit for Full Trend
  geom_smooth(data = full_trend, aes(x = Iteration, y = Mean, color = "Line of Best Fit - All Data"),
              method = "lm", se = FALSE, linetype = "solid") +
  # X-axis with labels
  scale_x_continuous(breaks = 1:6, labels = c("1", "2", "3", "4", "5", "Meta-Reflection")) +
  # Define custom colors for Goals and lines of best fit
  scale_color_manual(values = c(
    "Goal 1" = "red",                       # Red for Goal 1
    "Goal 2" = "green",                     # Green for Goal 2
    "Meta-Reflection" = "black",            # Black for Meta-Reflection
    "Line of Best Fit - Core Data" = "blue", # Blue for Core Data best fit line
    "Line of Best Fit - All Data" = "orange" # Orange for All Data best fit line
  )) +
  # Add labels
  labs(
```

```
    title = "Core vs All Data: Reflection Depth Across Iterations",
    x = "Iteration",
    y = "Reflection Depth (Score)",
    color = "Legend"
  ) +
  # Adjust theme
  theme_minimal() +
  theme(
    legend.position = "right",
    axis.text.x = element_text(size = 10),
    axis.title = element_text(size = 12)
  ) +
  # Add annotations for sparse data and meta-reflection
  annotate("text", x = 4.5, y = 2.5, label = "Sparse Participation", color = "purple", size = 4) +
  annotate("text", x = 6, y = 3.3, label = "Meta-Reflection", color = "black", size = 4)

########################################################################
# Graph 1: Goal 1 Mean Score Data Points (All Iterations)
########################################################################

graph1 <- ggplot(full_trend %>% filter(Goal == "Goal 1"), aes(x = Iteration, y = Mean)) +
  geom_line(size = 1) +
  geom_point(size = 3) +
  labs(title = "Graph 1: Mean Score for Goal 1", x = "Iteration", y = "Mean Score") +
  theme_minimal()
print(graph1)

########################################################################
# Graph 2: Goal 2 Mean Score Data Points (All Iterations)
########################################################################

graph2 <- ggplot(full_trend %>% filter(Goal == "Goal 2"), aes(x = Iteration, y = Mean)) +
  geom_line(size = 1) +
  geom_point(size = 3) +
  labs(title = "Graph 2: Mean Score for Goal 2", x = "Iteration", y = "Mean Score") +
  theme_minimal()
print(graph2)

########################################################################
# Graph 3: Line of Best Fit for Goals 1 and 2 (All Iterations) + Slope Comparison
########################################################################

# Fit linear models for Goal 1 and Goal 2
lm_goal1 <- lm(Mean ~ Iteration, data = full_trend %>% filter(Goal == "Goal 1"))
lm_goal2 <- lm(Mean ~ Iteration, data = full_trend %>% filter(Goal == "Goal 2"))

# Extract slopes
slope_goal1 <- coef(lm_goal1)[2]
slope_goal2 <- coef(lm_goal2)[2]

# Calculate the difference in slopes
slope_difference <- slope_goal1 - slope_goal2

# Print slope values and difference
print(paste("Slope of Line of Best Fit - Goal 1:", round(slope_goal1, 4)))
print(paste("Slope of Line of Best Fit - Goal 2:", round(slope_goal2, 4)))
print(paste("Difference in Slopes (Goal 1 - Goal 2):", round(slope_difference, 4)))

# Plot Graph 3
graph3 <- ggplot(full_trend %>% filter(Goal %in% c("Goal 1", "Goal 2")),
                 aes(x = Iteration, y = Mean, color = Goal)) +
  # Points for Goal 1 and Goal 2
  geom_point(size = 3) +
  # Line of best fit for Goal 1
  geom_smooth(aes(color = "Line of Best Fit - Goal 1"),
              data = full_trend %>% filter(Goal == "Goal 1"),
              method = "lm", se = FALSE, linetype = "solid") +
  # Line of best fit for Goal 2
  geom_smooth(aes(color = "Line of Best Fit - Goal 2"),
              data = full_trend %>% filter(Goal == "Goal 2"),
              method = "lm", se = FALSE, linetype = "solid") +
  # Custom color scale for Goals and lines of best fit
  scale_color_manual(values = c(
    "Goal 1" = "red",              # Red for Goal 1
    "Goal 2" = "green",            # Green for Goal 2
```

```
    "Line of Best Fit - Goal 1" = "red",    # Red for Goal 1 line of best fit
    "Line of Best Fit - Goal 2" = "green"   # Green for Goal 2 line of best fit
  )) +
  # Labels
  labs(
    title = "Graph 3: Line of Best Fit for Score Means by Goal",
    x = "Iteration",
    y = "Mean Score",
    color = "Legend"
  ) +
  # Minimal theme for clarity
  theme_minimal() +
  theme(
    legend.position = "right",
    axis.text.x = element_text(size = 10),
    axis.title = element_text(size = 12)
  )

# Print the plot
print(graph3)


#####################################################################
# RQ2: RELATIONSHIP BETWEEN FORETHOUGHT AND REFLECTION DEPTH
#####################################################################

#####################################################################
# LOAD DATASETS AND REQUIRED LIBRARIES
#####################################################################

# Load required libraries
library(dplyr)
library(tidyr)
library(lme4)
library(lmerTest)

# Load data
long_data <- read_excel("~/Downloads/LONG_FORMAT_DATA.xlsx")
tiim_data <- read_excel("~/Downloads/TIIM_APP_DATA.xlsx")

# Remove Participant 20
tiim_data <- tiim_data %>% filter(ID.Number != 20)
long_data <- long_data %>% filter(Participant != 20)

#####################################################################
# PREPARE LONG_FORMAT_DATA FOR MAPPING
#####################################################################

# Assign meaningful iteration names based on Goal and Iteration
long_data <- long_data %>%
  mutate(
    Goal_Iteration = case_when(
      Is_Goal1 == 1 & Iteration == 1 ~ "Goal 1 - Iteration 1",
      Is_Goal1 == 1 & Iteration == 2 ~ "Goal 1 - Iteration 2",
      Is_Goal1 == 1 & Iteration == 3 ~ "Goal 1 - Iteration 3",
      Is_Goal2 == 1 & Iteration == 1 ~ "Goal 2 - Iteration 1",
      Is_Goal2 == 1 & Iteration == 2 ~ "Goal 2 - Iteration 2",
      Is_Goal2 == 1 & Iteration == 3 ~ "Goal 2 - Iteration 3",
      Is_Meta == 1                   ~ "Meta-Reflection",
      TRUE ~ NA_character_
    )
  )

long_data <- filter(long_data, !is.na(Score))
long_data <- long_data[order(long_data$Participant, long_data$Goal_Iteration, long_data$Iteration),]
long_nometa <- filter(long_data, Is_Meta == 0 & !is.na(Goal_Iteration))

tiim_data <- tiim_data %>%
  group_by(ID.Number, Week) %>%
  summarise(
    GoalDif = sum(GoalDif, na.rm = TRUE),             # Sum GoalDif per week
    Satisfaction = mean(Satisfaction, na.rm = TRUE),   # Average Satisfaction
    Forethought = mean(Forethought, na.rm = TRUE),     # Average Forethought
    .groups = 'drop'
  )
```

```
################################################################
# FILTER RELIABLE ITERATIONS
################################################################

# Filter Iterations 1–3 and Meta-Reflection
core_long_data <- long_data %>%
  filter(Iteration %in% c(1, 2, 3) | Goal_Iteration == "Meta-Reflection")

core_tiim_data <- tiim_data %>%
  filter(Week %in% c(1, 2, 3))  # Only weeks 1–3

################################################################
# AVERAGE FORETHOUGHT VS. AVERAGE REFLECTION DEPTH CORRELATION
################################################################

# Aggregate forethought to get a single value per participant
avg_forethought <- core_tiim_data %>%
  group_by(ID.Number) %>%
  summarise(Avg_Forethought = mean(Forethought, na.rm = TRUE))

avg_reflection <- core_long_data %>%
  group_by(Participant) %>%
  summarise(Avg_Reflection = mean(Score, na.rm = TRUE))

# Merge averages
avg_data <- left_join(avg_forethought, avg_reflection,
                      by = c("ID.Number" = "Participant"))

# Correlation between average forethought and average reflection depth
cor_avg <- cor.test(avg_data$Avg_Forethought, avg_data$Avg_Reflection)
print("Correlation Between Average Forethought and Average Reflection Depth:")
print(cor_avg)

################################################################
# PER-ITERATION FORETHOUGHT AND REFLECTION DEPTH CORRELATIONS
################################################################

# Match Forethought to Iteration
per_iteration_data <- core_long_data %>%
  left_join(core_tiim_data, by = c("Participant" = "ID.Number", "Iteration" = "Week")) %>%
  select(Participant, Iteration, Forethought, Score, Goal_Iteration)

# Group by Iteration and calculate correlations
iteration_correlations <- per_iteration_data %>%
  group_by(Goal_Iteration) %>%
  summarise(
    Correlation = ifelse(sd(Forethought, na.rm = TRUE) == 0 | sd(Score, na.rm = TRUE) == 0, NA,
                         cor(Forethought, Score, use = "pairwise.complete.obs")),
    n = n()
  )

print("Per-Iteration Correlations Between Forethought and Reflection Depth:")
print(iteration_correlations)

################################################################
# MIXED MODEL FOR FORETHOUGHT AND REFLECTION DEPTH
################################################################

# Mixed Model: Forethought as a Predictor (Simplified)
core_mixed_model <- lmer(Score ~ Forethought + (1 | Participant), data = per_iteration_data)

print("Mixed Model Summary: Forethought Predicting Reflection Depth")
summary(core_mixed_model)

################################################################
# META-REFLECTION ANALYSIS
################################################################

# Extract Meta-Reflection data
meta_data <- per_iteration_data %>%
  filter(Goal_Iteration == "Meta-Reflection")

# Correlation for Meta-Reflection
```

```
meta_correlation <- cor.test(meta_data$Forethought, meta_data$Score)
print("Correlation Between Forethought and Meta-Reflection Depth:")
print(meta_correlation)

###################################################################
# LMM For RQ2 and RQ3
###################################################################

# Load Required Libraries
library(readxl)
library(dplyr)
library(tidyr)
library(lme4)
library(lmerTest)

# Load Data
long_data <- read_excel("~/Downloads/LONG_FORMAT_DATA.xlsx")
tiim_data <- read_excel("~/Downloads/TIIM_APP_DATA.xlsx")

# Exclude Participant 20
long_data <- long_data %>% filter(Participant != 20)
tiim_data <- tiim_data %>% filter(ID.Number != 20)

###################################################################
# DATA PREPARATION
###################################################################

# Aggregate Activity-Level Data to Weekly/Iteration-Level
tiim_data <- tiim_data %>%
  group_by(ID.Number, Week) %>%
  summarise(
    GoalDif = sum(GoalDif, na.rm = TRUE),              # Sum GoalDif per week
    Satisfaction = mean(Satisfaction, na.rm = TRUE),   # Average Satisfaction
    Forethought = mean(Forethought, na.rm = TRUE),     # Average Forethought
    .groups = 'drop'
  )

# Filter long_data to exclude Meta-Reflection and Iterations 4 and 5
filtered_long_data <- long_data %>%
  filter(Is_Meta != 1 & Iteration %in% c(1, 2, 3))  # Exclude Meta-Reflection and unreliable iterations

# Merge Reflection Scores (excluding Meta-Reflection) with Aggregated TIIM Data
combined_data <- filtered_long_data %>%
  left_join(tiim_data, by = c("Participant" = "ID.Number", "Iteration" = "Week")) %>%
  filter(!is.na(Score))  # Remove rows with missing reflection depth scores

# Add Goal Labels to Combined Data
combined_data <- combined_data %>%
  mutate(Goal = case_when(
    Is_Goal1 == 1 ~ "Goal 1",
    Is_Goal2 == 1 ~ "Goal 2",
    TRUE ~ NA_character_
  ))

##################################################################
# Research Question 2: Relationship Between Forethought and Reflection Depth
##################################################################

# Simplified Linear Mixed Model: Forethought as a Predictor
lmm_rq2 <- lmer(Score ~ Forethought + (1 | Participant), data = combined_data)

# Print Summary of the Model
print("Research Question 2: Linear Mixed Model Summary")
summary(lmm_rq2)

##################################################################
# Research Question 3: Relationship Between Learning Outcomes and Reflection Depth
##################################################################

# Linear Mixed Model: Satisfaction, GoalDif as Predictors
lmm_rq3 <- lmer(Score ~ Satisfaction + GoalDif + (1 | Participant),
                data = combined_data)

# Print Summary of the Model
print("Research Question 3: Linear Mixed Model Summary")
```

```
summary(lmm_rq3)

####################################################################
# Model Diagnostics
####################################################################

# Residual Plots for LMM Models
par(mfrow = c(1, 2))  # Arrange plots in a grid
plot(lmm_rq2, main = "Residuals for RQ2 Model")
plot(lmm_rq3, main = "Residuals for RQ3 Model")
par(mfrow = c(1, 1))  # Reset plot layout

####################################################################
# Interpretation Notes - For better understanding
####################################################################

print("Interpretation Notes:")
print("1. Aggregation: Forethought, Satisfaction are averaged per iteration. GoalDif is summed per iteration.")
print("2. RQ2: The fixed effect of Forethought determines its relationship with reflection depth. Check p-values and coefficients.")
print("3. RQ3: Satisfaction and GoalDif are predictors of reflection depth. Examine their fixed effects.")
print("4. Random effects account for participant-specific variability.")
print("5. Models exclude Meta-Reflection and unreliable iterations (4 and 5) for reliability.")

####################################################################
# END OF ANALYSIS
####################################################################
```

SCRIPT 2:

```
#####################################################################
# STANDARD ANALYSIS WITH ALL PARTICIPANTS
#####################################################################

##################################################################### LOAD REQUIRED LIBRARIES AND DATA

# Load required libraries
library(readxl)
library(dplyr)
library(tidyr)
library(ggplot2)
library(lme4)
library(Matrix)
library(lmerTest)

# Load dataset
data_path <- "~/Downloads/LONG_FORMAT_DATA.xlsx"  # Adjust if needed
long_data <- read_excel(data_path)

#########################################################################
# REUSABLE FUNCTIONS
#########################################################################

# Function to calculate summary statistics
calculate_summary_stats <- function(data) {
  data %>%
    group_by(Goal, Iteration) %>%
    summarise(
      Mean = mean(Score, na.rm = TRUE),
      SD = sd(Score, na.rm = TRUE),
      Median = median(Score, na.rm = TRUE),
      Count = sum(!is.na(Score)),
      .groups = 'drop'
    )
}

# Function to calculate correlation
calculate_correlation <- function(data, goal_filter) {
  cor.test(
    data$Iteration[data$Goal == goal_filter],
    data$Score[data$Goal == goal_filter],
    use = "pairwise.complete.obs"
  )
}

# Function to calculate weights
prepare_weighted_data <- function(data) {
  data %>%
    group_by(Goal, Iteration) %>%
    summarise(
      Score_Count = sum(!is.na(Score)),
      Total_Participants = n(),
      Weight = Score_Count / Total_Participants,
      .groups = 'drop'
    )
}

# Function to calculate differences between consecutive iterations
calculate_iteration_differences <- function(data) {
  data %>%
    filter(!is.na(Score)) %>%
    arrange(Participant, Iteration) %>%
    group_by(Participant, Goal) %>%
    mutate(
      Score_Diff = Score - lag(Score),
      Iteration_Pair = paste(lag(Iteration), "to", Iteration)
    ) %>%
    filter(!is.na(Score_Diff))
}

#########################################################################
```

```
# DESCRIPTIVE STATISTICS
######################################################################

# Prepare Goal Labels
goal_data <- long_data %>%
  mutate(
    Goal = case_when(
      Is_Goal1 == 1 ~ "Goal 1",
      Is_Goal2 == 1 ~ "Goal 2",
      Is_Meta == 1 ~ "Meta-Reflection",
      TRUE ~ NA_character_
    )
  )

# Exclude iterations 4 and 5 for reliability
core_goal_data <- goal_data %>%
  filter(Iteration %in% c(1, 2, 3) | Goal == "Meta-Reflection")

# Goal 1, Goal 2, and Meta-Reflection statistics
goal1_stats <- calculate_summary_stats(core_goal_data %>% filter(Goal == "Goal 1"))
goal2_stats <- calculate_summary_stats(core_goal_data %>% filter(Goal == "Goal 2"))
meta_stats <- calculate_summary_stats(core_goal_data %>% filter(Goal == "Meta-Reflection"))
meta_stats$Iteration <- 6  # Place Meta-Reflection at Iteration 6

# Combine statistics
summary_stats <- bind_rows(goal1_stats, goal2_stats, meta_stats) %>%
  select(Goal, Iteration, Mean, SD, Median, Count)

# View summary statistics
print(summary_stats)

# Participant retention per iteration
goal_retention <- core_goal_data %>%
  group_by(Goal, Iteration) %>%
  summarise(
    Unique_Participants = n_distinct(Participant),
    .groups = 'drop'
  )

print("Participant Retention Across Iterations:")
print(goal_retention)

######################################################################
# TREND ANALYSIS DATA PREPARATION
######################################################################

# Prepare trend data with Meta-Reflection at Iteration 6
trend_data <- core_goal_data %>%
  filter(!is.na(Goal), !is.na(Score)) %>%
  mutate(Iteration = ifelse(Goal == "Meta-Reflection", 6, Iteration))

######################################################################
# CORRELATION ANALYSIS
######################################################################

# Goal 1 Correlation
goal1_corr <- calculate_correlation(trend_data, "Goal 1")
print(goal1_corr)

# Goal 2 Correlation
goal2_corr <- calculate_correlation(trend_data, "Goal 2")
print(goal2_corr)

# Total iterations per participant
iterations_summary <- trend_data %>%
  filter(Goal != "Meta-Reflection") %>%
  group_by(Participant, Goal) %>%
  summarise(
    Total_Iterations = sum(!is.na(Score)),
    Avg_Score = mean(Score, na.rm = TRUE),
    .groups = 'drop'
  )

# Correctly extract Meta-Reflection scores
meta_scores <- trend_data %>%
```

```
  filter(Goal == "Meta-Reflection") %>%
  group_by(Participant) %>%
  summarise(Meta_Score = mean(Score, na.rm = TRUE), .groups = 'drop')

# Combine and analyze correlation
cor_data <- left_join(iterations_summary, meta_scores, by = "Participant")
print("Combined Data for Correlation Analysis:")
print(cor_data, n = nrow(cor_data))

# Correlations
meta_corr <- cor.test(cor_data$Total_Iterations, cor_data$Meta_Score, use = "pairwise.complete.obs")
print("Correlation between Total Iterations and Meta-Reflection Score:")
print(meta_corr)

avg_meta_corr <- cor.test(cor_data$Avg_Score, cor_data$Meta_Score, use = "pairwise.complete.obs")
print("Correlation between Average Reflection Score and Meta-Reflection Score:")
print(avg_meta_corr)

########################################################################
# GROUP AND PARTICIPANT-LEVEL DIFFERENCES
########################################################################

# Group-level mean differences for Goal 1 and Goal 2
for (goal_name in c("Goal 1", "Goal 2")) {
  group_means <- trend_data %>%
    filter(Goal == goal_name, Iteration %in% c(1, 2, 3)) %>%
    group_by(Iteration) %>%
    summarise(Group_Mean = mean(Score, na.rm = TRUE))

  group_diffs <- diff(group_means$Group_Mean)
  print(paste("Group-Level Mean Differences for", goal_name, "Iterations:"))
  print(group_diffs)

  # Participant-level differences
  diff_data <- core_goal_data %>%
    filter(Goal == goal_name) %>%
    calculate_iteration_differences()

  diff_summary <- diff_data %>%
    group_by(Iteration_Pair) %>%
    summarise(
      Mean_Diff = mean(Score_Diff, na.rm = TRUE),
      SD_Diff = sd(Score_Diff, na.rm = TRUE),
      Count = n(),
      .groups = 'drop'
    )
  print(paste("Participant-Level Mean Differences for", goal_name, ":"))
  print(diff_summary)
}

########################################################################
# END OF SCRIPT
########################################################################

################################################################################################################
############################
# SECTION 2: ANALYSIS USING WEIGHTED SCORES FOR RESPONSE IMBALANCE
################################################################################################################
############################

# Prepare weights
weights <- prepare_weighted_data(goal_data %>% filter(!is.na(Goal)))
print("Weight Distribution Across Goals and Iterations:")
print(weights)

########################################################################
# CALCULATE WEIGHTED AND NON-WEIGHTED SUMMARY STATS
########################################################################

# Function to calculate weighted and unweighted stats
calculate_weighted_stats <- function(data, weights, weighted = FALSE) {
  data %>%
    left_join(weights, by = c("Goal", "Iteration")) %>%
    group_by(Goal, Iteration) %>%
    summarise(
```

```
    Mean = if (weighted) {
      weighted.mean(Score, w = ifelse(is.na(Score), 0, Weight), na.rm = TRUE)
    } else {
      mean(Score, na.rm = TRUE)
    },
    SD = if (weighted) {
      sqrt(sum(Weight * (Score - weighted.mean(Score, w = Weight, na.rm = TRUE))^2, na.rm = TRUE) / sum(Weight, na.rm = TRUE))
    } else {
      sd(Score, na.rm = TRUE)
    },
    Median = median(Score, na.rm = TRUE),
    Count = sum(!is.na(Score)),
    .groups = 'drop'
  )
}

# Filter data to exclude Iterations 4 and 5
core_goal_data <- goal_data %>%
  filter(Iteration %in% c(1, 2, 3) | Goal == "Meta-Reflection")

# Weighted and non-weighted stats
non_weighted_stats <- calculate_weighted_stats(core_goal_data, weights, weighted = FALSE)
non_weighted_stats$Type <- "Non-Weighted"

weighted_stats <- calculate_weighted_stats(core_goal_data, weights, weighted = TRUE)
weighted_stats$Type <- "Weighted"

# Combine for comparison
comparison_stats <- bind_rows(non_weighted_stats, weighted_stats)

##########################################################################
# CORE TREND PREPARATION
##########################################################################

# Prepare core trend data: Only Iterations 1-3 and Meta-Reflection at Iteration 6
core_trend <- comparison_stats %>%
  filter((Goal == "Goal 1" & Iteration <= 3) |
         (Goal == "Goal 2" & Iteration <= 3) |
         Goal == "Meta-Reflection") %>%
  mutate(Iteration = ifelse(Goal == "Meta-Reflection", 6, Iteration))

##########################################################################
# LINEAR MIXED-EFFECTS MODELS
##########################################################################

# Regression Data Preparation: Exclude Iterations 4 and 5 and Meta-Reflection goal
core_regression_data <- goal_data %>%
  filter(!is.na(Goal), !is.na(Score)) %>%
  filter(Iteration %in% c(1, 2, 3)) %>%  # Use only reliable iterations
  filter(Goal != "Meta-Reflection")     # Exclude Meta-Reflection goal

# Linear Mixed-Effects Model
mixed_model <- lmer(Score ~ Goal + (1 | Participant), data = core_regression_data)  # Removed Iteration * Goal interaction
print("Linear Mixed-Effects Model Summary:")
mixed_model_summary <- summary(mixed_model)
print(mixed_model_summary)

# Linear Mixed-Effects Model: Including Iteration
mixed_model_with_iteration <- lmer(Score ~ Goal * Iteration + (1 | Participant), data = core_regression_data)

print("Linear Mixed-Effects Model with Goal and Iteration:")
summary(mixed_model_with_iteration)

##########################################################################
# FIXED EFFECTS SUMMARY
##########################################################################

# Extract fixed effects
fixed_effects_summary <- data.frame(
  Term = rownames(mixed_model_summary$coefficients),
  Estimate = mixed_model_summary$coefficients[, "Estimate"],
  Std_Error = mixed_model_summary$coefficients[, "Std. Error"],
  t_value = mixed_model_summary$coefficients[, "t value"]
)
```

```
print("Fixed Effects for Goal-Specific Intercepts:")
print(fixed_effects_summary)

#########################################################################
# ITERATION-TO-ITERATION AND LAST GOAL 2 ITERATION TO META-REFLECTION ANALYSIS
#########################################################################

# Function to calculate differences between consecutive iterations
calculate_iteration_differences <- function(data) {
  data %>%
    filter(!is.na(Score)) %>%
    arrange(Participant, Iteration) %>%
    group_by(Participant, Goal) %>%
    mutate(
      Score_Diff = Score - lag(Score),
      Iteration_Pair = paste(lag(Iteration), "to", Iteration)
    ) %>%
    filter(!is.na(Score_Diff))
}

# Prepare data for Goal 1 and Goal 2 with reliable iterations
core_goal_data <- goal_data %>%
  filter(Goal %in% c("Goal 1", "Goal 2")) %>%
  filter(Iteration %in% c(1, 2, 3))

iteration_diff_data <- core_goal_data %>%
  calculate_iteration_differences()

# Summarize differences for each iteration pair
iteration_diff_summary <- iteration_diff_data %>%
  group_by(Goal, Iteration_Pair) %>%
  summarise(
    Mean_Diff = mean(Score_Diff, na.rm = TRUE),
    SD_Diff = sd(Score_Diff, na.rm = TRUE),
    Count = n(),
    .groups = 'drop'
  )

# Print iteration-to-iteration differences
print("Iteration-to-Iteration Differences:")
print(iteration_diff_summary)

# Perform paired t-tests for iteration-to-iteration differences
print("Paired t-tests for Iteration-to-Iteration Differences:")
goal_list <- unique(iteration_diff_data$Goal)

for (goal in goal_list) {
  print(paste("Results for", goal))
  pairs <- unique(iteration_diff_data$Iteration_Pair)
  for (pair in pairs) {
    subset_data <- iteration_diff_data %>% filter(Goal == goal, Iteration_Pair == pair)
    if (nrow(subset_data) >= 2) {
      test_result <- t.test(subset_data$Score_Diff, mu = 0)
      print(paste("Iteration Pair:", pair))
      print(test_result)
    } else {
      print(paste("Iteration Pair:", pair, "- Not enough data for t-test (n =", nrow(subset_data), ")"))
    }
  }
}

#########################################################################
# ANALYSIS: LAST GOAL 2 ITERATION TO META-REFLECTION
#########################################################################

# Function to calculate the last Goal 2 score vs Meta-Reflection
calculate_last_goal2_vs_meta <- function(data) {
  last_iteration_data <- data %>%
    filter(Goal == "Goal 2" & Iteration %in% c(1, 2, 3) & !is.na(Score)) %>%
    group_by(Participant) %>%
    filter(Iteration == max(Iteration)) %>%
    summarise(
      Last_Iteration_Score = Score,
      Goal = "Goal 2",
      .groups = 'drop'
```

```
    )

  meta_reflection_data <- data %>%
    filter(Goal == "Meta-Reflection" & !is.na(Score)) %>%
    group_by(Participant) %>%
    summarise(
      Meta_Score = mean(Score, na.rm = TRUE),
      .groups = 'drop'
    )

  combined_data <- left_join(last_iteration_data, meta_reflection_data, by = "Participant") %>%
    mutate(
      Score_Diff = Meta_Score - Last_Iteration_Score,
      Iteration_Pair = "Last Goal 2 Iteration to Meta-Reflection"
    )
  return(combined_data)
}

# Perform analysis
last_to_meta_data <- calculate_last_goal2_vs_meta(goal_data)

# Summarize results
last_to_meta_summary <- last_to_meta_data %>%
  summarise(
    Mean_Diff = mean(Score_Diff, na.rm = TRUE),
    SD_Diff = sd(Score_Diff, na.rm = TRUE),
    Count = n(),
    .groups = 'drop'
  )

print("Summary of Differences: Last Goal 2 Iteration to Meta-Reflection")
print(last_to_meta_summary)

# Paired t-test
if (nrow(last_to_meta_data) >= 2) {
  print("Paired t-test: Last Goal 2 Iteration vs Meta-Reflection")
  t_test_meta <- t.test(last_to_meta_data$Score_Diff, mu = 0)
  print(t_test_meta)
} else {
  print("Not enough data for paired t-test between Last Goal 2 Iteration and Meta-Reflection.")
}


####################################################################################################
# GRAPHS AND PLOTS
####################################################################################################

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# PREPARE TREND DATA (Core and Full Trends)
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# Full Trend Data: Mean Score across all iterations
full_trend <- long_data %>%
  mutate(
    Goal = case_when(
      Is_Goal1 == 1 ~ "Goal 1",
      Is_Goal2 == 1 ~ "Goal 2",
      Is_Meta == 1 ~ "Meta-Reflection"
    ),
    Iteration = ifelse(Is_Meta == 1, 6, Iteration)  # Move Meta-Reflection to Iteration 6
  ) %>%
  filter(!is.na(Goal), !is.na(Score)) %>%
  group_by(Goal, Iteration) %>%
  summarise(
    Mean = mean(Score, na.rm = TRUE),
    .groups = 'drop'
  )

# Core Trend Data: First 3 iterations of Goal 1, Goal 2, and Meta-Reflection
core_trend <- full_trend %>%
  filter((Goal == "Goal 1" & Iteration <= 3) |
         (Goal == "Goal 2" & Iteration <= 3) |
         Goal == "Meta-Reflection")

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# Plot 1: Single Line of Best Fit for Reflection Depth Across Iterations (All Data)
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ggplot(full_trend, aes(x = Iteration, y = Mean)) +
  # Group-specific lines for each Goal
  geom_line(aes(group = Goal, color = Goal), size = 1) +
  # Group-specific points for each Goal
  geom_point(aes(color = Goal), size = 3) +
  # Single line of best fit for all data
  geom_smooth(aes(color = "Line of Best Fit - All Data"), method = "lm", se = FALSE, linetype = "solid") +
  # X-axis with custom labels
  scale_x_continuous(breaks = 1:6, labels = c("1", "2", "3", "4", "5", "Meta-Reflection")) +
  # Define custom colors for Goals and line of best fit
  scale_color_manual(values = c(
    "Goal 1" = "red",             # Red for Goal 1
    "Goal 2" = "green",           # Green for Goal 2
    "Meta-Reflection" = "black",  # Black for Meta-Reflection
    "Line of Best Fit - All Data" = "orange"  # Orange for the best fit line
  )) +
  # Add labels
  labs(
    title = "All Data: Trend of Reflection Depth Across Iterations",
    x = "Iteration",
    y = "Reflection Depth (Score)",
    color = "Legend"
  ) +
  # Adjust theme for clarity
  theme_minimal() +
  theme(
    legend.position = "right",
    axis.text.x = element_text(size = 10),
    axis.title = element_text(size = 12)
  )

##########################################################################
# Plot 2: Core Data - Reflection Depth Across Iterations
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ggplot(core_trend, aes(x = Iteration, y = Mean)) +
  # Group-specific lines and points by Goal
  geom_line(aes(group = Goal, color = Goal), size = 1.5) +
  geom_point(aes(color = Goal), size = 3) +
  # Line of best fit for core data
  geom_smooth(aes(color = "Line of Best Fit - Core Data"), method = "lm", se = FALSE, linetype = "solid") +
  # X-axis with custom labels
  scale_x_continuous(breaks = 1:6, labels = c("1", "2", "3", "", "", "Meta-Reflection")) +
  # Custom color scale for Goals and line of best fit
  scale_color_manual(values = c(
    "Goal 1" = "red",                # Red for Goal 1
    "Goal 2" = "green",              # Green for Goal 2
    "Meta-Reflection" = "black",     # Black for Meta-Reflection
    "Line of Best Fit - Core Data" = "blue"  # Blue for best fit line
  )) +
  # Add labels
  labs(
    title = "Core Data: Trend of Reflection Depth Across Iterations",
    x = "Iteration",
    y = "Reflection Depth (Score)",
    color = "Legend"
  ) +
  theme_minimal() +
  theme(
    legend.position = "right",
    axis.text.x = element_text(size = 10),
    axis.title = element_text(size = 12)
  )

##########################################################################
# Graph 3: Line of Best Fit for Goals 1 and 2 (All Iterations) + Slope Comparison
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# Prepare the full dataset with individual measurements
full_trend_individual <- long_data %>%
  mutate(
    Goal = case_when(
```

```
      Is_Goal1 == 1 ~ "Goal 1",
      Is_Goal2 == 1 ~ "Goal 2",
      TRUE ~ NA_character_
    )
  ) %>%
  filter(!is.na(Goal), !is.na(Score))

# Mixed models for Goal 1 and Goal 2 using individual-level data
mixed_model_goal1 <- lmer(Score ~ Iteration + (1 | Participant),
                          data = full_trend_individual %>% filter(Goal == "Goal 1"))
mixed_model_goal2 <- lmer(Score ~ Iteration + (1 | Participant),
                          data = full_trend_individual %>% filter(Goal == "Goal 2"))

# Extract fixed-effect slopes for comparison
slope_goal1 <- fixef(mixed_model_goal1)["Iteration"]
slope_goal2 <- fixef(mixed_model_goal2)["Iteration"]

# Calculate the difference in slopes
slope_difference <- slope_goal1 - slope_goal2

# Print slope values and difference
print(paste("Slope of Line of Best Fit (Mixed Model) - Goal 1:", round(slope_goal1, 4)))
print(paste("Slope of Line of Best Fit (Mixed Model) - Goal 2:", round(slope_goal2, 4)))
print(paste("Difference in Slopes (Goal 1 - Goal 2):", round(slope_difference, 4)))

# Plot Graph 3 with mixed model results
graph3 <- ggplot(full_trend_individual %>% filter(Goal %in% c("Goal 1", "Goal 2")),
                 aes(x = Iteration, y = Score, color = Goal)) +
  # Line of best fit for Goal 1 (from mixed model)
  geom_smooth(aes(color = "Line of Best Fit - Goal 1"),
              data = full_trend_individual %>% filter(Goal == "Goal 1"),
              method = "lm", se = FALSE, linetype = "solid") +
  # Line of best fit for Goal 2 (from mixed model)
  geom_smooth(aes(color = "Line of Best Fit - Goal 2"),
              data = full_trend_individual %>% filter(Goal == "Goal 2"),
              method = "lm", se = FALSE, linetype = "solid") +
  # Custom color scale for Goals and lines of best fit
  scale_color_manual(values = c(
    "Goal 1" = "red",                # Red for Goal 1
    "Goal 2" = "green",              # Green for Goal 2
    "Line of Best Fit - Goal 1" = "red",    # Red for Goal 1 line of best fit
    "Line of Best Fit - Goal 2" = "green"   # Green for Goal 2 line of best fit
  )) +
  # Labels
  labs(
    title = "Graph 3: Line of Best Fit for Score Means by Goal",
    x = "Iteration",
    y = "Score",
    color = "Legend"
  ) +
  # Minimal theme for clarity
  theme_minimal() +
  theme(
    legend.position = "right",
    axis.text.x = element_text(size = 10),
    axis.title = element_text(size = 12)
  )

# Print the plot
print(graph3)



######################################################################
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######################################################################
# Prepare Data for Analyses
######################################################################

# Add a meaningful Goal label
long_data <- long_data %>%
  mutate(
    Goal = case_when(
      Is_Goal1 == 1 ~ "Goal 1",
      Is_Goal2 == 1 ~ "Goal 2",
```

```
    Is_Meta == 1 ~ "Meta-Reflection",
    TRUE ~ NA_character_
  )
 )

##################################################################
# Prepare Datasets for LMMs
##################################################################

# Core Data (Iterations 1–3) + Meta-Reflection
core_meta_data <- long_data %>%
 filter(Iteration %in% c(1, 2, 3) | Is_Meta == 1)

# Core Data (Iterations 1–3) + No Meta-Reflection
core_no_meta_data <- long_data %>%
 filter(Iteration %in% c(1, 2, 3) & Is_Meta != 1)

# All Data (All Iterations) + Meta-Reflection
all_meta_data <- long_data %>%
 filter(!is.na(Iteration) | Is_Meta == 1)

# All Data (All Iterations) + No Meta-Reflection
all_no_meta_data <- long_data %>%
 filter(!is.na(Iteration) & Is_Meta != 1)

##################################################################
# Model 1: Core Data + Meta-Reflection
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model_1 <- lmer(Score ~ Iteration + (1 | Participant), data = core_meta_data)
summary(model_1)

##################################################################
# Model 2: Core Data + No Meta-Reflection
##################################################################

model_2 <- lmer(Score ~ Iteration + (1 | Participant), data = core_no_meta_data)
summary(model_2)

##################################################################
# Model 3: All Data + Meta-Reflection
##################################################################

model_3 <- lmer(Score ~ Iteration + (1 | Participant), data = all_meta_data)
summary(model_3)

##################################################################
# Model 4: All Data + No Meta-Reflection
##################################################################

model_4 <- lmer(Score ~ Iteration + (1 | Participant), data = all_no_meta_data)
summary(model_4)

##################################################################
# Comparison of Fixed Effects Across Models
##################################################################

# Extract fixed effects from each model and compare
fixed_effects_summary <- data.frame(
 Model = c("Core + Meta", "Core + No Meta", "All + Meta", "All + No Meta"),
 Intercept = c(
  fixef(model_1)[1],
  fixef(model_2)[1],
  fixef(model_3)[1],
  fixef(model_4)[1]
 ),
 Iteration_Slope = c(
  fixef(model_1)[2],
  fixef(model_2)[2],
  fixef(model_3)[2],
  fixef(model_4)[2]
 )
)

print("Comparison of Fixed Effects Across Models:")
```

```
print(fixed_effects_summary)
###################################################################
# RQ2: RELATIONSHIP BETWEEN FORETHOUGHT AND REFLECTION DEPTH
###################################################################

###################################################################
# LOAD DATASETS AND REQUIRED LIBRARIES
###################################################################

# Load required libraries
library(dplyr)
library(tidyr)
library(lme4)
library(lmerTest)

# Load data
long_data <- read_excel("~/Downloads/LONG_FORMAT_DATA.xlsx")
tiim_data <- read_excel("~/Downloads/TIIM_APP_DATA.xlsx")

# Remove Participant 20
tiim_data <- tiim_data %>% filter(ID.Number != 20)
long_data <- long_data %>% filter(Participant != 20)

###################################################################
# PREPARE LONG_FORMAT_DATA FOR MAPPING
###################################################################

# Assign meaningful iteration names based on Goal and Iteration
long_data <- long_data %>%
  mutate(
    Goal_Iteration = case_when(
      Is_Goal1 == 1 & Iteration == 1 ~ "Goal 1 - Iteration 1",
      Is_Goal1 == 1 & Iteration == 2 ~ "Goal 1 - Iteration 2",
      Is_Goal1 == 1 & Iteration == 3 ~ "Goal 1 - Iteration 3",
      Is_Goal2 == 1 & Iteration == 1 ~ "Goal 2 - Iteration 1",
      Is_Goal2 == 1 & Iteration == 2 ~ "Goal 2 - Iteration 2",
      Is_Goal2 == 1 & Iteration == 3 ~ "Goal 2 - Iteration 3",
      Is_Meta == 1                   ~ "Meta-Reflection",
      TRUE ~ NA_character_
    )
  )

###################################################################
# FILTER RELIABLE ITERATIONS
###################################################################

# Filter Iterations 1–3 and Meta-Reflection
core_long_data <- long_data %>%
  filter(Iteration %in% c(1, 2, 3) | Goal_Iteration == "Meta-Reflection")

core_tiim_data <- tiim_data %>%
  filter(Week %in% c(1, 2, 3))  # Only weeks 1–3

###################################################################
# AVERAGE FORETHOUGHT VS. AVERAGE REFLECTION DEPTH CORRELATION
###################################################################

# Aggregate forethought to get a single value per participant
avg_forethought <- core_tiim_data %>%
  group_by(ID.Number) %>%
  summarise(Avg_Forethought = mean(Forethought, na.rm = TRUE))

avg_reflection <- core_long_data %>%
  group_by(Participant) %>%
  summarise(Avg_Reflection = mean(Score, na.rm = TRUE))

# Merge averages
avg_data <- left_join(avg_forethought, avg_reflection,
                      by = c("ID.Number" = "Participant"))

# Correlation between average forethought and average reflection depth
cor_avg <- cor.test(avg_data$Avg_Forethought, avg_data$Avg_Reflection)
print("Correlation Between Average Forethought and Average Reflection Depth:")
print(cor_avg)
```

```
####################################################################
# PER-ITERATION FORETHOUGHT AND REFLECTION DEPTH CORRELATIONS
####################################################################

# Match Forethought to Iteration
per_iteration_data <- core_long_data %>%
  left_join(core_tiim_data, by = c("Participant" = "ID.Number", "Iteration" = "Week")) %>%
  select(Participant, Iteration, Forethought, Score, Goal_Iteration)

# Group by Iteration and calculate correlations
iteration_correlations <- per_iteration_data %>%
  group_by(Goal_Iteration) %>%
  summarise(
    Correlation = ifelse(sd(Forethought, na.rm = TRUE) == 0 | sd(Score, na.rm = TRUE) == 0, NA,
                         cor(Forethought, Score, use = "pairwise.complete.obs")),
    n = n()
  )

print("Per-Iteration Correlations Between Forethought and Reflection Depth:")
print(iteration_correlations)

####################################################################
# MIXED MODEL FOR FORETHOUGHT AND REFLECTION DEPTH
####################################################################

# Mixed Model: Forethought as a Predictor (Simplified)
core_mixed_model <- lmer(Score ~ Forethought + (1 | Participant), data = per_iteration_data)

print("Mixed Model Summary: Forethought Predicting Reflection Depth")
summary(core_mixed_model)

####################################################################
# META-REFLECTION ANALYSIS
####################################################################

# Extract Meta-Reflection data
meta_data <- per_iteration_data %>%
  filter(Goal_Iteration == "Meta-Reflection")

# Correlation for Meta-Reflection
meta_correlation <- cor.test(meta_data$Forethought, meta_data$Score)
print("Correlation Between Forethought and Meta-Reflection Depth:")
print(meta_correlation)

####################################################################
# LMM For RQ2 and RQ3
####################################################################

# Load Data
long_data <- read_excel("~/Downloads/LONG_FORMAT_DATA.xlsx")
tiim_data <- read_excel("~/Downloads/TIIM_APP_DATA.xlsx")

# Exclude Participant 20
long_data <- long_data %>% filter(Participant != 20)
tiim_data <- tiim_data %>% filter(ID.Number != 20)

####################################################################
# DATA PREPARATION
####################################################################

# Aggregate Activity-Level Data to Weekly/Iteration-Level
tiim_data <- tiim_data %>%
  group_by(ID.Number, Week) %>%
  summarise(
    GoalDif = sum(GoalDif, na.rm = TRUE),            # Sum GoalDif per week
    Satisfaction = mean(Satisfaction, na.rm = TRUE),  # Average Satisfaction
    Forethought = mean(Forethought, na.rm = TRUE),    # Average Forethought
    .groups = 'drop'
  )

# Filter long_data to exclude Meta-Reflection and Iterations 4 and 5
filtered_long_data <- long_data %>%
  filter(Is_Meta != 1 & Iteration %in% c(1, 2, 3))  # Exclude Meta-Reflection and unreliable iterations

# Merge Reflection Scores (excluding Meta-Reflection) with Aggregated TIIM Data
```

```
combined_data <- filtered_long_data %>%
  left_join(tiim_data, by = c("Participant" = "ID.Number", "Iteration" = "Week")) %>%
  filter(!is.na(Score))  # Remove rows with missing reflection depth scores

# Add Goal Labels to Combined Data
combined_data <- combined_data %>%
  mutate(Goal = case_when(
    Is_Goal1 == 1 ~ "Goal 1",
    Is_Goal2 == 1 ~ "Goal 2",
    TRUE ~ NA_character_
  ))

##################################################################
# Research Question 2: Relationship Between Forethought and Reflection Depth
##################################################################

# Simplified Linear Mixed Model: Forethought as a Predictor
lmm_rq2 <- lmer(Score ~ Forethought + (1 | Participant), data = combined_data)

# Print Summary of the Model
print("Research Question 2: Linear Mixed Model Summary")
summary(lmm_rq2)

##################################################################
# Research Question 3: Relationship Between Learning Outcomes and Reflection Depth
##################################################################

# Linear Mixed Model: Satisfaction, GoalDif as Predictors
lmm_rq3 <- lmer(Score ~ Satisfaction + GoalDif + (1 | Participant),
                data = combined_data)

# Print Summary of the Model
print("Research Question 3: Linear Mixed Model Summary")
summary(lmm_rq3)


##################################################################
# Model Diagnostics
##################################################################

# Residual Plots for LMM Models
par(mfrow = c(1, 2))  # Arrange plots in a grid
plot(lmm_rq2, main = "Residuals for RQ2 Model")
plot(lmm_rq3, main = "Residuals for RQ3 Model")
par(mfrow = c(1, 1))  # Reset plot layout

##################################################################
# Interpretation Notes - For better understanding
##################################################################

print("Interpretation Notes:")
print("1. Aggregation: Forethought, Satisfaction are averaged per iteration. GoalDif is summed per iteration.")
print("2. RQ2: The fixed effect of Forethought determines its relationship with reflection depth. Check p-values and coefficients.")
print("3. RQ3: Satisfaction and GoalDif are predictors of reflection depth. Examine their fixed effects.")
print("4. Random effects account for participant-specific variability.")
print("5. Models exclude Meta-Reflection and unreliable iterations (4 and 5) for reliability.")

##################################################################
# END OF ANALYSIS
##################################################################




##################################################################
# Prepare Core Data for LMMs (Iterations 1-3 for Goal 1 and Goal 2)
##################################################################

# Filter data to include only iterations 1-3 (excluding meta-reflection)
core_no_meta_data <- long_data %>%
  filter(Iteration %in% c(1, 2, 3) & Is_Meta == 0)

# Filter meta-reflection scores (Iteration does not apply)
meta_reflection_data <- long_data %>%
  filter(Is_Meta == 1) %>%
```

```
  select(Participant, Score) %>%
  rename(Meta_Score = Score)

#####################################################################
# Calculate Average Scores per Participant
#####################################################################

# 1. Average score across all iterations (Goal 1 and Goal 2)
avg_scores_all <- core_no_meta_data %>%
  group_by(Participant) %>%
  summarise(Avg_Score_All = mean(Score, na.rm = TRUE))

# 2. Average score across Goal 1 iterations only
avg_scores_goal1 <- core_no_meta_data %>%
  filter(Is_Goal1 == 1) %>%
  group_by(Participant) %>%
  summarise(Avg_Score_Goal1 = mean(Score, na.rm = TRUE))

# 3. Average score across Goal 2 iterations only
avg_scores_goal2 <- core_no_meta_data %>%
  filter(Is_Goal2 == 1) %>%
  group_by(Participant) %>%
  summarise(Avg_Score_Goal2 = mean(Score, na.rm = TRUE))

#####################################################################
# Merge Data for Modeling
#####################################################################

# Merge average scores with meta-reflection scores
lmm_data_all <- avg_scores_all %>%
  left_join(meta_reflection_data, by = "Participant")

lmm_data_goal1 <- avg_scores_goal1 %>%
  left_join(meta_reflection_data, by = "Participant")

lmm_data_goal2 <- avg_scores_goal2 %>%
  left_join(meta_reflection_data, by = "Participant")

#####################################################################
# Linear Mixed Models (LMMs)
#####################################################################

library(lme4)

# Model 1: Predict meta-reflection score using average of all iterations (Goals 1 & 2)
model_1 <- lm(Meta_Score ~ Avg_Score_All, data = lmm_data_all)
summary(model_1)

# Model 2: Predict meta-reflection score using average of Goal 1 iterations only
model_2 <- lm(Meta_Score ~ Avg_Score_Goal1, data = lmm_data_goal1)
summary(model_2)

# Model 3: Predict meta-reflection score using average of Goal 2 iterations only
model_3 <- lm(Meta_Score ~ Avg_Score_Goal2, data = lmm_data_goal2)
summary(model_3)
```