Managing Uncertainty in Group Work: The Role of Self-Regulation and Need for Closure

Lena Schell (s2737353)

Department of Learning, Data Analytics and Technology (BMS), University of Twente

202200364: Educational Psychology

Chandan Dasgupta

Loes Hogenkamp

Date: 25.06.2025

Word count: 7.276

Abstract

Collaborative learning often involves navigating uncertainty, as students must make decisions under uncertain conditions, negotiate differing perspectives, and respond to evolving task demands. How effectively they manage this uncertainty can influence group performance, engagement, and learning outcomes, making individual traits such as self-regulation and the need for cognitive closure particularly relevant. This study examines how distinct self-regulation components and the need for closure relate to students' use of four uncertainty management strategies during a collaborative design task. These strategies are reduce, maintain, increase, and ignore. Twenty-one university students participated in a problem-solving task using the Aladdin simulation platform. Their behaviours were coded based on Zimmerman's self-regulated learning model and Jordan and McDaniel's uncertainty management framework. Participants also completed the 15-item Need for Closure Scale. Results showed statistically significant positive correlations between the following self-regulation components: strategic planning, task strategy use, self-monitoring and uncertainty strategies, particularly maintain and increase. No significant associations were found between the need for closure and self-regulation behaviours. These findings suggest that highly self-regulated students adopt flexible and context-sensitive strategies to engage with uncertainty, rather than simply aiming to reduce it. Collaborative learning environments should support flexible uncertainty engagement by scaffolding self-regulation processes and accounting for individual differences in need for closure.

Keywords: collaborative learning, self-regulated learning, uncertainty management, need for closure, design tasks, group interaction

Introduction

Problem Statement

Whether in an educational or a professional setting, collaborative learning plays a significant role when working in a group. Collaborative learning refers to learning activities in which students actively work together toward shared goals by coordinating their thinking, exchanging ideas, and negotiating understanding (Dillenbourg, 1999; Gokhale, 1995). It is widely recognised for promoting deep learning, critical thinking, and problem-solving. However, simply placing students in groups does not automatically lead to successful learning outcomes (Gokhale, 1995). Students often encounter challenges such as unequal participation, coordination difficulties, or lack of focus, which can reduce the effectiveness of collaboration (Irzawati, 2023).

One often overlooked yet crucial factor in this context is uncertainty. In collaborative learning, uncertainty refers to moments where learners experience incomplete knowledge, unclear task instructions, or unpredictable group dynamics (Manz, 2018). These uncertain moments can either support or hinder learning. Hence, they may trigger deeper reflection and exploration when managed well, but can also lead to confusion, frustration, or disengagement if ignored (Manz, 2018; Chester et al., 2016). Thus, how students manage uncertainty during group tasks is key to determining the success of collaborative learning.

To deal with uncertainty, students need specific self-regulatory skills. Self-regulated learning (SRL) refers to a cyclical process in which learners proactively set goals, monitor their progress, and adapt their strategies and motivation (Zimmerman, 2000). Research suggests that students who can plan ahead, track their understanding, and reflect on their progress are better able to handle complex, uncertain tasks (Zimmerman & Schunk, 2011; Parker et al., 2018). However, not all students engage with uncertainty in the same way. Their behaviour is also shaped by individual traits such as the need for closure (NFC), a dispositional preference for structure, order, and clear answers, and an aversion to uncertainty (Webster & Kruglanski, 1994; Roets & Van Hiel, 2011). High-NFC individuals may prefer to eliminate uncertainty quickly, which could hinder deeper exploration or adaptation in open-ended collaborative settings.

While SRL and NFC are both linked to students' learning behaviour, we still know little about how they influence observable uncertainty management during group work. Most research treats uncertainty as something to reduce, and rarely considers how students actively decide to reduce, maintain, increase, or ignore uncertainty (Jordan & McDaniel, 2014). Moreover, SRL is often examined as a general skill, not as a set of distinct components that may relate differently to uncertainty strategies. This study addresses these gaps by investigating how individual SRL behaviours and NFC relate to four types of uncertainty strategies during a collaborative design task.

Uncertainty Management

Uncertainty management refers to strategies students use to cope with confusion and uncertainty in learning situations (Jordan & McDaniel, 2014). Jordan and McDaniel (2014) propose four key strategies for dealing with uncertainty: ignore, reduce, increase, and maintain. For example, ignoring uncertainty may involve disregarding uncertain elements deemed irrelevant, while reducing uncertainty involves clarifying expectations or establishing clear goals. Conversely, increasing uncertainty may encourage creative exploration and maintaining a manageable level of uncertainty can enhance adaptability during collaboration. These approaches provide a framework for understanding how students regulate their responses in uncertain group environments (Jordan & McDaniel, 2014). Productively managing uncertainty is not optional but essential in collaborative learning, as it allows students to navigate uncertainty without disengaging, coordinate with peers despite conflicting perspectives, and remain open to new information. Recent studies in clinical education describe productive uncertainty management as an approach that encourages learners to turn ambiguous situations into opportunities for deeper collective reflection and sense-making (Manoli et al., 2024). Rather than avoiding confusion, productive uncertainty management encourages learners to reflect, explore alternatives, and make shared decisions, skills that are central to problem-solving and group success (Jordan & McDaniel, 2014; Manz, 2018). However, poor uncertainty management can lead to negative outcomes, such as withdrawal from the learning process, reduced participation, and over-reliance on peers (Chester et al., 2016; Manz, 2018). In this context, self-regulation plays a critical role. Students with strong self-regulation skills are more likely to adopt proactive strategies to address uncertainty. This highlights the importance of self-regulation, as students must continuously monitor their understanding and adapt their behaviour to handle uncertainty in productive ways.

Self-regulation

Self-regulated learning (SRL) refers to students' ability to actively control their learning process by setting goals, selecting strategies, monitoring progress, and adjusting behaviour based on feedback. It involves the coordinated use of metacognitive, motivational, and behavioural strategies to achieve learning goals (Zimmerman, 2000). In Zimmerman's model, learners are not passive recipients of instruction but take initiative in managing their thoughts and actions throughout the learning task. It is a dynamic, cyclical process that plays a key role in how students manage uncertainty in learning contexts. According to Zimmerman's model, self-regulation progresses in three interrelated phases: forethought, performance, and self-reflection (Zimmerman, 2000). In the forethought phase, learners set goals and plan strategies before beginning a task. During the performance phase, learners apply those strategies and monitor their engagement and progress in the task. Finally, in the self-reflection phase, they evaluate their performance and adapt for the future. These phases are iterative and help learners adjust to evolving task conditions, especially in uncertain or collaborative settings (Zimmerman & Schunk, 2011). Effective self-regulation goes beyond detached behaviours and reflects a broader willingness to apply sustained effort toward meaningful goals, even in the face of challenges. It involves treating setbacks and failures as learning opportunities. Furthermore, using them to identify weaknesses, refine approaches, and develop more effective strategies over time (Crocker et al., 2006). Collaborative settings often require students to regulate their learning continuously, as they encounter uncertain tasks, evolving group dynamics, and uncertain roles. In such contexts, SRL becomes essential for maintaining focus and adapting strategies. By engaging in all three phases of the self-regulatory cycle, students are able to plan for potential uncertainties (forethought), monitor their understanding and adjust strategies in real time (performance), and reflect on which strategies worked best for future situations (self-reflection). This helps them respond to uncertainty not by avoiding it, but by actively managing it as part of the learning process (Zimmerman & Schunk, 2011).

Need for Closure

In addition to self-regulation, another individual factor that may influence uncertainty management is the need for closure (NFC). This construct reflects a person's desire for clear, definite answers and a discomfort with (Roets & Van Hiel, 2011; Webster & Kruglanski, 1994). Individuals high in need for closure tend to prefer order, predictability, and quick decision-making, often avoiding situations that require extended exploration or tolerate uncertainty. In contrast, those with a low need for closure are more open to uncertainty and more willing to engage in extended information processing (Roets & Van Hiel, 2011). In collaborative learning contexts, a high need for closure may lead students to settle on decisions too soon, while also avoiding open-ended discussions or relying on others to reduce uncertainty. Moreover, this can potentially hinder deep engagement and strategic uncertainty management in the group. To assess this trait, the Need for Closure Scale (NFCS) has been developed and validated across various domains (Webster & Kruglanski, 1994). The scale captures adjustable preferences regarding order, predictability, decisiveness, and closed-mindedness. It has been widely used to examine how individuals cope with unclear or unpredictable situations in both social and cognitive settings (Roets & Van Hiel, 2011). These tendencies may significantly shape how students communicate and make decisions in group learning environments, especially under conditions of uncertainty.

Design-Based Tasks as a Context for SRL and Uncertainty

In this study, the collaborative task takes the form of a design process, in which students work together to plan and construct an energy-efficient house. Design-based tasks are inherently uncertain and open-ended, often involving multiple phases such as problem definition, idea generation, decision-making, and evaluation (Cross, 2006). These phases require students to continuously set goals, adapt strategies, manage incomplete information, and negotiate solutions. It makes them the ideal contexts for observing self-regulated learning (SRL) and uncertainty management in action. During early design phases, students may experience uncertainty due to vague problem constraints, which require proactive planning and strategic decision-making. In design-based tasks, students often face open-ended problems with multiple possible solutions and changing constraints. As the task progresses, they must monitor their progress, adjust their collaboration strategies, and reflect on their choices, often without clear right or wrong answers. This makes continuous self-regulation particularly important to stay aligned with group goals and respond flexibly to new information. This alignment between the design process and Zimmerman's model of SRL offers a valuable opportunity to explore how individual regulation skills and need for closure influence uncertainty management during complex, collaborative problem-solving.

Research Question and Hypotheses

Therefore, this study aims to investigate the relationship between individual self-regulation skills, need for closure and uncertainty management in collaborative learning by answering the research question: *"To what extent is there a relation between student's individual self-regulation skills, need for closure, and their uncertainty management strategies during a collaborative design process?"*. Based on this research question and the reviewed literature, the following hypotheses were formulated to be answered:

H1: Students with higher self-regulation skills will demonstrate more productive uncertainty management, specifically a greater use of reduce and maintain strategies, during collaborative learning tasks.

Students with higher self-regulation skills will demonstrate more productive uncertainty management, specifically by using more reduce and maintain strategies during collaborative learning tasks. Self-regulation enables students to plan, monitor, and adapt their behaviour in response to complex tasks (Zimmerman, 2000). These skills are especially useful in uncertain settings, where learners must manage ambiguity while maintaining progress. Reduce and maintain strategies reflect this adaptive capacity and have been shown to support engagement, reflection, and collaboration (Jordan & McDaniel, 2014; Manz, 2018). Recent work conceptualises these strategies as forms of productive uncertainty management because they foster deeper exploration and sustained participation (Manoli et al., 2024).

*H2**:** Students with higher scores for self-regulation skills will engage in more productive uncertainty management strategies (reduce) compared to students with lower self-regulation skills.*

The reduce strategy involves actively seeking clarity and structure. These are behaviours that align closely with the forethought and performance phases of self-regulated learning (Zimmerman & Schunk, 2011). Students with strong self-regulation are more likely to anticipate areas of uncertainty and respond by planning, asking questions, and applying structured strategies, rather than avoiding the problem (Jordan & McDaniel, 2014). These behaviours reflect a proactive approach to managing uncertainty.

*H3**:** Students with high levels of need for closure will show reduced engagement in self-regulation skills in collaborative tasks.*

Individuals high in need for closure tend to avoid uncertainty and prefer quick, definitive answers (Kruglanski & Webster, 1996). In collaborative learning settings, this may lead to reduced engagement in exploratory or adaptive behaviours that are central to self-regulation, such as planning, monitoring, and strategy revision. Rather than persisting through uncertainty, high-NFC individuals may rely on others to direct the task or prematurely commit to solutions. This reflects reduced use of forethought and reflection-phase SRL strategies, such as goal setting and self-evaluation (Zimmerman, 2000), which limits their ability to regulate learning flexibly and independently (Roets & Van Hiel, 2011; Crocker et al., 2006).

Methodology

Research design

This study followed a mixed-methods design to examine how self-regulation (SRL), need for closure (NFC), and uncertainty management interact in collaborative learning. A convergent parallel approach was used, where qualitative and quantitative data were collected simultaneously and integrated during interpretation.

The self-regulation and uncertainty management strategies were measured through deductive behavioural coding of group interactions. Students' verbal behaviours during the task were categorised according to established theoretical frameworks (Zimmerman, 2000; Jordan & McDaniel, 2014), and the frequency of each behaviour was counted. Although the final data for these variables were expressed as numerical counts, they originated from qualitative observation and are therefore best described as quantified qualitative data. The need for closure was assessed using the 15-item Need for Closure Scale (NFCS) (Roets & Van Hiel, 2011), a validated self-report instrument. Items were rated on a 6-point Likert scale, and a total score was calculated for each participant.

Participants

The final sample consisted of 21 university students (Mage = 23.3, SD = 1.5). Thirteen participants identified as male, seven as female, and one as other. Nineteen participants reported German nationality, one participant identified as Chinese, and one as Korean. All participants were fluent in English and currently enrolled in higher education programmes. Participants were randomly assigned to groups of three, forming a total of seven teams. Hence, this group size was chosen to reflect realistic collaborative learning scenarios.

The recruitment of participants was carried out through a combination of convenience sampling, snowball sampling, and the SONA system of the University. Convenience and snowball sampling involved inviting students from the researchers' networks who met the study's inclusion criteria. Snowball sampling allowed these initial participants to refer contacts who were also eligible. These methods were particularly suitable given the limited timeframe and the need for face-to-face data collection. In addition, participants were recruited via the SONA platform, a university system for research participation. Those who participated through SONA received 1.25 course credits as compensation for their participation.

To be eligible for participation, students had to be currently enrolled in a university-level academic program, be proficient in English and be willing to engage in both the collaborative task and the accompanying survey instruments. Furthermore, participants were required to have no prior experience with the Aladdin platform or specific knowledge of the design task. Moreover, this was to ensure that all individuals approached the activity with a comparable baseline of familiarity and uncertainty, to be able to ensure that all participants encountered the activity with comparable levels of uncertainty and no prior task-specific knowledge. Individuals who did not meet these inclusion criteria were excluded from the study.

All participants provided written informed consent before taking part in the study. The study was approved by the Ethics Committee of the Faculty of Behavioural, Management and Social Sciences. The final sample represented a diverse range of academic majors and included both male and female students, although demographic composition was not used as a basis for group assignment.

Materials

Collaborative Task and Platform

The collaborative task was administered using the Aladdin web-based simulation platform, shown in Figure 1. Participants worked in groups of three in a quiet room, seated around a single laptop. One camera was positioned to record participants' facial expressions and verbal interactions (via Microsoft Teams), while screen activity was captured using the macOS screen recording tool to track real-time design decisions and interaction with the simulation environment.

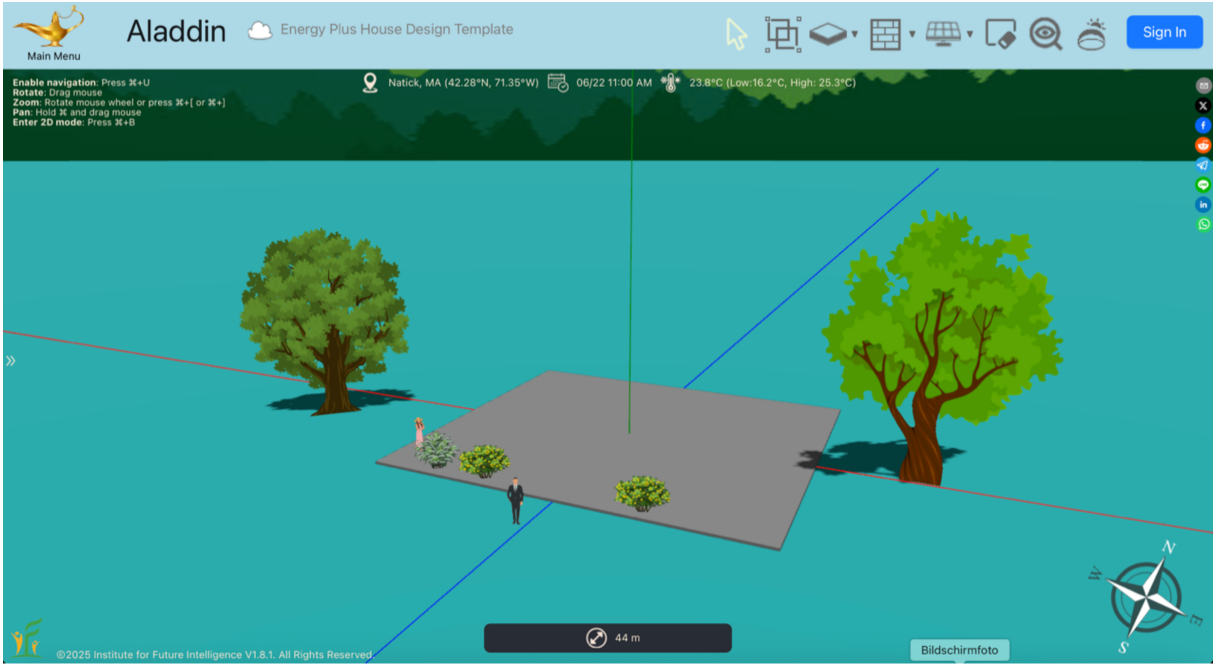

Figure 1. *Screenshot of the Aladdin platform interface used for the collaborative house design task.*

Aladdin is a simulation environment developed to teach and assess energy-efficient building design. The platform enables users to collaboratively construct a sustainable house for a fictional family of four. It presents a 3D interface where participants can add and manipulate various architectural and environmental elements, including rooms, windows, doors, trees, solar panels, and ventilation systems. What makes Aladdin especially suitable for studying self-regulated learning (SRL) and uncertainty management is its built-in energy analysis tool, which provides real-time feedback on the consequences of design choices. This feedback requires students to monitor their progress, interpret ambiguous results, and adjust their strategies based on the outcomes. In doing so, the platform not only encourages iterative decision-making but also introduces situational uncertainty, as some results may contradict group expectations or require further negotiation. By adjusting design features, participants can immediately observe the impact on energy efficiency, including metrics such as heat retention, solar gain, natural ventilation, and overall consumption.

The task is designed to elicit uncertainty by imposing multiple, and sometimes conflicting, constraints. For example, while students must minimise energy loss, they are also required to include at least three windows. This is a design choice that typically increases heat transfer. Additionally, the house must fall within a specific height range (8–10 meters), and the environment includes variable elements like tree placement, which influences shading and solar input. These competing demands require participants to make adjustments, anticipate consequences, and revise their strategies. These are core behaviours associated with SRL.

Participants were asked to design an energy-efficient house for a fictional family with the following design brief:

"Create an energy-efficient house for a family of four. Include at least one tree, a minimum of three windows, and a door. The house must be between 8 and 10 meters high, and you must place four people in the home."

This open-ended and multi-criteria design task was selected to create a high-uncertainty and problem-solving context, encouraging the use of a wide range of regulatory behaviours. It reaches from goal setting and planning to reflection, collaboration, and strategy adjustment.

Need for Closure Questionnaire

Participants provided informed consent and completed a brief demographic questionnaire (age, gender, academic major). They also filled out the 15-item version of the Short Need for Closure Scale (NFCS) (Roets & Van Hiel, 2011). It is a validated self-report instrument assessing individuals' preference for certainty and discomfort with uncertainty. Items were rated on a 6-point Likert scale from 1 (*strongly disagree*) to 6 (*strongly agree*), with negatively worded items reverse-coded. An example item is: “I dislike unpredictable situations.” (See Appendix C). Higher scores indicate a greater need for closure. In this study, the NFCS showed acceptable internal consistency (Cronbach’s $\alpha = .78$).

Behavioural Coding Scheme

To assess self-regulated learning (SRL) and uncertainty management (UM), the video- and audio-recorded group sessions were coded using deductive coding schemes. The coding followed theory-based categories drawn from Zimmerman’s (2000) cyclical model of SRL and Jordan & McDaniel’s (2014) uncertainty management framework.

Each SRL behaviour was assigned to one of the three SRL phases (forethought, performance, reflection) and included categories such as goal setting, strategic planning, self-monitoring, task strategy use, and strategy adaptation.
Uncertainty management behaviours were coded into four strategy types: reduce, maintain, increase, and ignore. Frequency counts were calculated per participant based on their contributions in the group interaction transcripts (see Appendix D for the full coding scheme).

Procedure

The study was conducted in a quiet seminar room at the researchers’ university (name anonymised for review). Each group was seated around a single laptop and recorded via webcam and screen capture. After recruitment, participants provided informed consent and completed the demographic questionnaire and pre-task measures (NFCS). Afterwards, they were assigned to groups and introduced to the collaborative task environment. Each group got five minutes to familiarise themself with the Aladdin environment and the task. During the task, they got minimal guidance to maintain an authentic collaboration setting. After that, the teams had 25 minutes to design an energy-efficient house for a family of four, incorporating the following requirements: at least one tree, minimum, and maximum height of the house. All the conversations were recorded. The researchers only assisted the groups if there were major technical issues. At the end of the experiment, a short debriefing concluded the session, which clarified the focus of the different researchers and answered possible questions.

Data Analysis

Quantitative data were analysed using descriptive statistics (means and standard deviations) for each participant's scores on the ten self-regulation components, the four uncertainty management strategies (*reduce*, *maintain*, *increase*, *ignore*), and the total Need for Closure (NFCS) score.

Behavioural data were analysed using deductive coding, based on theory-driven coding schemes. Self-regulation behaviours were coded according to Zimmerman's (2000) cyclical model of SRL, which includes ten components grouped into three phases: *Forethought* (goal setting, strategic planning), *Performance* (time management, environment structuring, help-seeking, motivation control/effort regulation, self-monitoring, task strategy use), and *Reflection* (self-evaluation, strategy adaptation).

Uncertainty management behaviours were coded using Jordan and McDaniel's (2014) framework, which defines four core strategies: *reduce*, *maintain*, *increase*, and *ignore*. Before coding, both researchers agreed on category definitions, decision rules, and coding examples for each UM component. Each transcript was read collaboratively, and speaker contributions were jointly assigned to one of the predefined categories. Discrepancies occurred infrequently and typically involved uncertain remarks that could fit more than one strategy. These cases were resolved through short discussions until a consensus was reached. Because coding was conducted jointly and iteratively, and agreement was high, no inter-rater reliability coefficient was calculated. Instead, a consensus-based approach (Guest et al., 2012) was followed.

The NFCS was measured using the 15-item short version of the Need for Closure Scale (Roets & Van Hiel, 2011), with items rated on a 6-point Likert scale (1 = *strongly disagree*, 6 = *strongly agree*). An example item is: *"I dislike unpredictable situations."* Negatively worded items were reverse-coded. Higher scores reflect a stronger need for closure. In the present study, the NFCS showed acceptable internal consistency (α = .78).

Before running correlational analyses, the main variables (SRL total score, uncertainty management strategies, NFCS scores) were tested for normality using Shapiro-Wilk tests and visual inspection. Several variables showed deviations from normality (see Appendix E), and some variable pairs included outliers. Due to these violations of parametric assumptions, Spearman's rank-order correlations were used.

Results

Table 1 presents the means, standard deviations, and score ranges for all key study variables, including each self-regulation component, the four uncertainty management strategies, and the Need for Closure (NFCS) score. These descriptive statistics provide a general overview of students' behavioural patterns and dispositional characteristics before the correlation analyses.

Table 1

Descriptive Statistics for Self-Regulation, Uncertainty Management, and NFC

Self-Regulated Learning (SRL)	**M**	**SD**	**Min**	**Max**
Forethought Phase				
Goal Setting	1.62	1.83	0.0	6.0
Strategic Planning	7.05	7.05	0.0	27.0
Performance Phase				
Time Management	1.10	1.37	0.0	4.0
Environment Structuring	1.43	2.87	0.0	10.0
Help-Seeking	5.19	4.46	0.0	16.0
Motivation Control / Effort Regulation	0.95	1.22	0.0	4.0
Self-Monitoring	7.10	6.57	0.0	22.0
Task Strategy Use	6.14	4.74	0.0	18.0
Reflection Phase				
Self-Evaluation	3.48	3.08	0.0	13.0
Strategy Adaption	1.71	1.52	0.0	4.0
SRL Total	35.76	23.38	2.0	76
Uncertainty Strategies				
Reduce	7.81	4.36	1.0	19.0
Maintain	3.33	2.81	0.0	11.0
Ignore	1.48	1.17	0.0	4.0
Increase	1.52	1.63	0.0	5.0
Need for Closure (NFCS)				
NFCS Total	60.38	7.45	46.0	74.0

Note. Values reflect individual-level data. M = mean, SD = standard deviation.

Hypothesis Testing

To examine the relationships between specific self-regulated learning (SRL) behaviours and uncertainty management strategies, a series of Spearman correlation analyses were conducted. Due to violations of the normality assumption for most SRL components, Spearman's rank-order correlations were used to examine associations between individual SRL components, uncertainty management strategies, and the NFCS. For the SRL total score, assumptions were met, so Pearson's correlation was retained (see Appendix E).

Table 2 displays the statistically significant Spearman correlations between self-regulated learning components, uncertainty strategies, and need for closure.

Table 2

Spearman's p Correlations Between SRL Components, Uncertainty Management Strategies, and Need for Closure (NFCS)

#	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Strategic Planning	-												
2	Environment Structuring		-											
3	Time Management			-										
4	Motivation Control				-									
5	Self-Monitoring					-								
6	Task Strategy Use						-							
7	Maintain	.46*	.46*					-						
8	Increase	.73**				.58*	.53*		-					
9	Ignore		.54*		.62*		.47*			-				
10	Reduce										-			
11	NFCS			.48*								-		
12	Self-Evaluation												-	
13	Strategy Adaption													-

Note. *N* = 21. Values represent Spearman's ρ. $p < .05$ = *, $p < .01$ = **.
Only significant correlations are reported; blank cells represent non-significant results.

Hypothesis 1

Hypothesis 1 stated that students with higher self-regulation skills would engage more frequently in productive uncertainty management, particularly the Reduce and Maintain strategies. The correlation results partially support this hypothesis.

Significant positive associations were observed between several SRL components and uncertainty strategies. Strategic Planning was positively correlated with both the Maintain strategy (ρ = .46, p = .037) and the Increase strategy (ρ = .73, p < .001). Similarly, Environment Structuring showed positive correlations with Maintain (ρ = .46, p = .036) and Ignore (ρ = .54, p = .012). Task Strategy Use was positively associated with Ignore (ρ = .47, p = .031) and Increase (ρ = .53, p = .014). Additionally, Self-Monitoring was significantly correlated with Increase (ρ = .58, p = .006), and Motivation Control / Effort Regulation was significantly associated with Ignore (ρ = .62, p = .003).

These results indicate that students with high levels of strategic, environmental, and metacognitive regulation are more likely to adopt a variety of uncertainty management strategies. Furthermore, including those that reflect tolerance for uncertainty and flexibility in group settings. Rather than solely aiming to reduce uncertainty, well-regulated students appeared to apply a broader, adaptive approach to managing it.

Hypothesis 2

Hypothesis 2 proposed that students with strong self-regulation skills would use the Reduce strategy more frequently. The analysis revealed a non-significant positive correlation between Strategic Planning and Reduce (ρ = .42, p = .058). No other SRL component showed a significant association with Reduce. This does not offer sufficient statistical support to confirm the hypothesis.

Hypothesis 3

Hypothesis 3 expected that students with high levels of Need for Closure (NFCS) would show lower self-regulation in collaborative tasks. However, no significant Spearman correlations were found between NFCS and any of the individual SRL components. For example, the association between Motivation Control and NFCS was negligible ($\rho = -.06$, $p = .79$), and other SRL components showed similarly weak, non-significant relationships.

This states that in this setting, the need for closure did not influence how students regulated their learning behaviours during the task.

In summary, while particularly the SRL behaviours: Strategic Planning, Task Strategy Use and Self-Monitoring showed significant associations with uncertainty strategies, the expected exclusive link to Reduce was not consistently supported. Moreover, no significant relationship was found between NFCS and any SRL behaviour, suggesting that closure may play a less direct role in this collaborative context.

Discussion

Overview of Findings

This study explored how students' self-regulation behaviours and their need for closure were associated with the use of uncertainty management strategies during a collaborative design task. The findings are interpreted in light of Zimmerman's cyclical model of SRL and the uncertainty management framework by Jordan and McDaniel (2014).

Overall, the results provide partial support for the proposed hypotheses. The following SRL components were significantly associated with different uncertainty management strategies: Strategic Planning, Task Strategy Use and Self-Monitoring. Moreover, these suggest that students' regulatory behaviours are linked to how they respond to uncertainty. Notably, these associations did not only concern strategies such as reduce or maintain but also included increase and ignore, which indicates a more distinct and context-sensitive use of uncertainty strategies among self-regulated learners.

In contrast, the expected negative relationship between the need for closure and self-regulated learning was not supported. The absence of significant associations suggests that personal preferences for clarity and closure may not strongly inhibit observable regulatory behaviours in structured collaborative tasks, or that their influence may be more subtle or context dependent.

Taken together, the findings suggest that effective self-regulation in uncertain environments may involve more than simply minimising uncertainty. Instead, students appear to draw on a range of strategies, some of which may involve tolerating, sustaining, or even increasing uncertainty depending on the demands of the task and the group context (Manz, 2018).

Hypothesis 1

Hypothesis 1 proposed that students with higher self-regulation skills would demonstrate more productive uncertainty management, defined as the use of *reduce* and *maintain* strategies. The results provided partial support for this hypothesis. Most notably, Strategic Planning was significantly correlated with both *maintain* and *increase*, with large effect sizes. Similarly, Task Strategy Use showed significant positive correlations with *maintain*, *ignore* and *increase*.

These findings reveal a more nuanced view of how SRL components relate to uncertainty management. Strategic Planning was significantly associated with both the Maintain and Increase strategies. This suggests that students who plan ahead may be comfortable navigating or even introducing uncertainty. In the context of a design task, this could mean intentionally withholding decisions to allow room for exploration or generating creative tension to stimulate group discussion. The association with Increase particularly highlights how planning can support not just problem-solving, but active engagement with uncertainty as a productive force.

Task Strategy Use showed significant associations with both Ignore and Increase strategies. This indicates that students who use diverse cognitive strategies may selectively engage or disengage with uncertainty depending on task relevance. For instance, some uncertainties may be seen as distractions and therefore ignored, while others are embraced to test new possibilities, reflecting strategic flexibility rather than avoidance.

Environment Structuring was also significantly associated with both Maintain and Ignore. Students who shape their environment (e.g., arranging materials, reducing noise) may do so to either hold space for ambiguity or sideline less relevant uncertainties. This further supports the idea that self-regulated learners are not simply seeking clarity but are managing uncertainty in a context-sensitive manner.

Finally, both Self-Monitoring and Motivation Control were associated with the Increase and Ignore strategies. These results suggest that metacognitive monitoring and emotional regulation help students to either tolerate uncertainty or actively confront it when necessary, pointing to deeper regulatory processes that support uncertainty engagement.

Taken together, these findings challenge the idea that productive uncertainty management only involves reduction. Instead, they demonstrate that self-regulated learners flexibly choose from multiple strategies, including those traditionally seen as ineffective, based on task demands and collaboration needs. The findings both align with and extend previous research. Studies such as Parker et al. (2018) and Zimmerman and Schunk (2011) have shown that strategic planning and self-monitoring support goal-directed behaviour in uncertain tasks. The current results support this but go further by showing how these SRL components relate not just to task performance, but to how uncertainty is managed. The significant association of planning and task strategy use with increase strategies echoes Manz's (2018) claim that uncertainty can be used productively to stimulate inquiry and creativity. At the same time, the link between self-regulation and ignore strategies challenges assumptions that ignoring uncertainty is always maladaptive. This suggests that uncertainty management may be more context-sensitive and flexible than previously described, and that self-regulated learners are capable of using diverse strategies to serve their task goals.

Hypothesis 2

Hypothesis 2 proposed that students with strong self-regulation skills would engage more frequently in the reduce strategy. This is commonly interpreted as a proactive way of managing uncertainty. Only Strategic Planning showed a marginal positive correlation with Reduce, suggesting a weak trend toward proactive uncertainty reduction among students with strong planning skills. However, the absence of broader significant results implies that students with high SRL may prefer to maintain or even increase uncertainty rather than reduce it immediately, especially in open-ended tasks where exploration is valued.

At first, this outcome may appear surprising. The reduce strategy, which includes actions such as clarifying goals or resolving misunderstandings, aligns conceptually with core self-regulatory processes like goal setting, monitoring, and adaptive strategy use. From this perspective, a positive association between self-regulation and reduce could seem plausible. However, the absence of significant findings suggests that students may not generally prefer to reduce uncertainty, even when they have strong self-regulatory skills.

One explanation for this could lie in the collaborative design task. Unlike tasks with fixed answers, the house design scenario was unstructured, creative, and open-ended. In such contexts, uncertainty is not necessarily an obstacle to be removed but can instead become a resource for exploration. Students may intentionally delay resolution or introduce uncertainty to foster creativity and group dialogue. This is reflected in the significant correlations between self-regulation components and the maintain and increase strategies. But, these strategies that are not traditionally labelled as “effective” may reflect adaptive uncertainty engagement depending on task demands (Jordan & McDaniel, 2014; Manz, 2018).

Furthermore, it is possible that highly self-regulated students adjust their strategy choice to the momentary needs of the group rather than defaulting to reduction. In some cases, attempting to reduce uncertainty too quickly may even hinder group processes, especially when ideas are still forming or when premature closure could limit creativity. This highlights the importance of contextual flexibility: effective uncertainty management may not be about using one strategy more than others, but about selecting the right one at the right time.

Taken together, these findings suggest that the assumption that self-regulated students will always reduce uncertainty may be too narrow. Instead, they may draw from a more diverse strategy range while reflecting situational awareness and group dynamics. While the reduce strategy remains an important aspect of managing uncertainty, its use may not be the defining component of self-regulatory competence in open-ended, collaborative settings.

Hypothesis 3

Hypothesis 3 proposed a negative relationship between students’ need for cognitive closure (NFC) and their self-regulation skills in collaborative learning contexts. The theoretical reasoning behind this hypothesis was that individuals high in NFC prefer structure, predictability, and rapid resolution of ambiguity (Webster & Kruglanski, 1994). Hence, this may conflict with the iterative, adaptive nature of self-regulated learning. In contrast, students with low NFC are thought to be more open to ongoing uncertainty and better prepared to engage in metacognitive regulation.

However, the results did not support this hypothesis. None of the SRL components showed a significant correlation with NFC scores. The observed relationships were small and inconsistent, with some being positive and others negative, but none reached statistical significance. This suggests that the tendency to seek closure did not have a strong or consistent influence on the frequency of self-regulated learning behaviours during the collaborative task.

There are several possible explanations for these findings. First, NFC is a trait-level variable, while SRL behaviours in this study were observed in a single, time-limited task. The influence of NFC may come out clearer across longer time spans or in tasks that allow for multiple regulatory cycles. In short-term settings, students may temporarily override their tendencies in response to task demands, group norms, or the pressure to contribute effectively.

Second, the collaborative nature of the task may have reduced individual-level influences. High-NFC individuals might have been influenced by their group members, adapting their behaviour to align with shared goals or dominant group strategies. Prior research suggests that group processes can moderate the impact of individual traits (Jordan & McDaniel, 2014). For example, in a highly communicative group, even students with high NFC might tolerate more uncertainty than they would individually, simply because the group expects exploration before closure (Jordan & McDaniel, 2014).

Third, it is possible that NFC does not affect the quantity, but the quality or style of self-regulation. For example, a high-NFC student may still engage in planning and monitoring but might prefer quick decisions or minimal experimentation. These qualitative aspects are not captured by frequency-based behavioural coding.

Lastly, the design task itself provided some structure (e.g., time limits, technical constraints, clearly stated objectives). This may have mitigated the discomfort typically experienced by high-NFC individuals in uncertain situations by allowing them to perform similarly to their low-NFC peers in terms of observable behaviours.

In summary, while the theoretical link between NFC and SRL remains plausible, this study did not find strong empirical support for it. The findings suggest that the relationship between dispositional need for closure and self-regulated learning may be more indirect, context-dependent, or qualitatively expressed than originally hypothesised.

Connection Between Task Context and Study Variables

These findings can be better understood in the context of the collaborative design task. The Aladdin platform presented students with multiple as well as competing design constraints (e.g., energy efficiency, mandatory windows, limited height). Moreover, this created uncertainty about how to proceed. In several groups, participants postponed early decisions and kept options open, reflecting the maintain strategy. In contrast, some students pushed for fast decisions and prioritised efficiency, which may reflect a high need for closure and lower engagement in self-regulation.

Strategic planning and self-monitoring, the two SRL components most strongly related to uncertainty strategies, appeared to play out in key moments such as comparing solar exposure versus window placement or testing different design layouts. Students who verbalised plans, monitored task progress, and coordinated actions more actively were also more likely to engage in productive uncertainty management. This supports the idea that SRL processes are especially useful in open-ended tasks that require adaptive decision-making.

Limitations

The following limitations that came up during this study should be considered when interpreting the findings. First, the small sample size (N = 21) is a significant limitation in terms of statistical power and generalizability. As Biau et al. (2008) note, small samples increase the likelihood of Type II errors, potentially inflating effect sizes or covering real effects. While several correlations were statistically significant, the results should be viewed cautiously until replicated with a larger and more diverse participant pool.

Second, the homogeneity of the sample, composed exclusively of university students with relatively similar academic backgrounds and cognitive skill levels, limits the external validity of the findings. McEwan (2020) emphasises that homogenous samples can restrict the transferability of results, as students from other educational levels or cultural contexts may exhibit different patterns of self-regulation and uncertainty engagement. Future studies should therefore consider more diverse samples to better capture variability in learning behaviours.

Third, the use of behavioural coding, while conceptually grounded in Zimmerman's and Jordan & McDaniel's frameworks, relies on observable indicators of internal processes. This approach may miss nuanced aspects of students' motivation, reasoning, or emotional regulation during group tasks. Although coding was performed collaboratively, inter-rater reliability for all categories was not statistically assessed, which limits the robustness and objectivity of the data. As Campbell et al. (2013) argue, multiple coders and formal agreement measures are essential to enhance the trustworthiness of qualitative coding in educational research.

Future Research

Building on the current findings, future research should aim to expand both the scope and depth of investigation into self-regulated learning and uncertainty management in collaborative environments. One clear direction is to increase the sample size and diversity of participants. A larger and more heterogeneous sample would allow for greater statistical power and the exploration of subgroup differences, such as variations in regulatory behaviour by academic discipline, educational background, or cultural context. This could help clarify whether the observed patterns generalise beyond the current university student population.

Methodologically, future studies could benefit from combining behavioural observation with multimodal data collection. For example, integrating think-aloud protocols, screen-capture analysis, eye-tracking, or physiological measures (e.g., heart rate variability) could reveal real-time shifts in regulation and stress in response to uncertainty. This would provide richer insight into the dynamic and situational aspects of SRL that are not fully captured by frequency-based coding schemes (Azevedo & Gašević, 2019).

In addition, researchers may consider expanding the scope to include shared and co-regulation. As many self-regulatory behaviours are influenced by social interactions, future studies could investigate how regulation is distributed across group members and how uncertainty is managed collectively. This could involve coding not only individual actions but also group-level negotiation, coordination, or scaffolding.

Finally, further research should critically examine the qualitative dimensions of strategy use. Rather than focusing solely on frequency, future work could analyse how students justify or adapt their uncertainty management approaches in different phases of collaboration. For instance, under what conditions do students switch from “reduce” to “maintain” or “increase,” and how do these transitions impact task outcomes and learning.

Practical Implications

The findings of this study have important implications for the design of collaborative learning environments in higher education, especially those involving open-ended, problem-based tasks. First, the results underscore the value of fostering specific self-regulated learning behaviours, particularly strategic planning, task strategy use, and self-evaluation, which were positively associated with the flexible and productive management of uncertainty. Educators can support the development of these behaviours through scaffolding techniques such as structured planning templates, reflective prompts, or training in goal setting and monitoring strategies (Dignath & Veenman, 2021).

Second, the study challenges the assumption that uncertainty should always be minimised in educational settings. Instead, it highlights the potential benefits of encouraging students to maintain or even increase uncertainty under certain conditions, such as when exploring design alternatives or negotiating ideas within a group. This interpretation is supported by the finding that Strategic Planning and Task Strategy Use, key self-regulated learning behaviours, were positively associated with both maintain and increase strategies. This suggests that students with stronger regulation skills may deliberately engage with uncertainty as a productive part of collaborative problem-solving. Instructional approaches that frame uncertainty as a resource rather than a barrier may help students develop a more adaptive and resilient mindset (Martin et al., 2013). This includes setting up tasks that explicitly invite exploration, experimentation, and delayed decision-making.

Moreover, collaborative tools like the Aladdin platform, which provide real-time feedback, limited trial opportunities, and ambiguous task parameters, can serve as powerful environments for both practising and studying regulation and uncertainty. Educators should be encouraged to integrate such tools not only to enhance authenticity but also to provide learners with opportunities to engage in and reflect on uncertainty management.

Finally, understanding students' dispositional characteristics, such as their need for closure, can help instructors offer differentiated support. For example, high-NFC students may benefit from clearly structured roles, time cues, or checkpoints to reduce stress and maintain engagement, while low-NFC students might thrive in more open-ended, flexible tasks. Tailoring group support based on these individual differences could improve both participation and learning outcomes.

Conclusion

This study investigated how individual differences in self-regulated learning (SRL) and need for closure (NFC) relate to the use of uncertainty management strategies in collaborative design tasks. Drawing on video-based behavioural coding and validated self-report data, the findings contribute to a deeper understanding of how students navigate uncertainty during group work.

The results showed that several SRL components, most notably strategic planning and task strategy use, were significantly associated with a variety of uncertainty management strategies. Rather than exclusively using proactive strategies like reduce, self-regulated students appeared to engage flexibly with uncertainty, sometimes maintaining or even increasing it in response to task demands. These findings suggest that adaptive uncertainty management is not about eliminating uncertainty but about engaging with it strategically and contextually.

Contrary to expectations, the need for closure was not significantly related to SRL behaviours. This suggests that students' regulatory actions may be shaped more by the learning context and task structure than by dispositional preferences. Future work could examine more nuanced dimensions of regulation, such as flexibility, metacognitive awareness, or emotional coping.

Together, these findings highlight the importance of designing collaborative learning environments that do not simply aim to minimise uncertainty but instead support students in developing the skills and mindsets needed to manage it productively. By equipping learners with strong self-regulation skills and creating space for uncertainty as part of the learning process, educators can better prepare students for collaborative learning tasks.

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Appendices

Appendix A:

Complete R Script

```
#R SCRIPT

library(tidyverse)

### getting overview of the data

glimpse(Bachelor_Thesis_Tom_Lena_May_18_2025_06_26)

head(Bachelor_Thesis_Tom_Lena_May_18_2025_06_26)

colnames(Bachelor_Thesis_Tom_Lena_May_18_2025_06_26)



###selecting the relevant data

data_nfcs <- Bachelor_Thesis_Tom_Lena_May_18_2025_06_26 %>%

  select(Q30, Q1, Q4, Q5, Q6, Q7, Q8, Q9, Q10, Q11, Q12, Q13, Q14, Q15, Q16, Q17)



###creating a likert map

likert_map <- c("Strongly disagree" = 1,

                "Disagree" = 2,

                "Somewhat disagree" = 3,

                "Somewhat agree" = 4,

                "Agree" = 5,

                "Strongly agree" = 6)
```

```
###applying the likert items

likert_items <- c("Q1", "Q4", "Q5", "Q6", "Q7", "Q8", "Q9",
                  "Q10", "Q11", "Q12", "Q13", "Q14", "Q15", "Q16", "Q17")


###apply to data

data_clean_NFCS <- data_nfcs %>%
  mutate(across(all_of(likert_items), ~recode(.x, !!!likert_map)))


### recode the first three persons missing/invalid responded data

data_clean_NFCS$Q1[2] <- 6

data_clean_NFCS$Q1[3] <- 6

data_clean_NFCS$Q1[4] <- 5

data_clean_NFCS$Q5[3] <- 4

data_clean_NFCS$Q5[4] <- 4

data_clean_NFCS$Q7[2] <- 4

data_clean_NFCS$Q8[3] <- 4

data_clean_NFCS$Q12[3] <- 4

data_clean_NFCS$Q12[4] <- 4

data_clean_NFCS$Q14[3] <- 4
```

```
data_clean_NFCS$Q15[3] <- 4

data_clean_NFCS$Q16[3] <- 4

data_clean_NFCS$Q30[2] <- 001

data_clean_NFCS$Q30[3] <- 003

data_clean_NFCS$Q30[4] <- 002


### Summed scores

data_clean_final_NFCS_Score <- data_clean_NFCS %>%

  mutate(NFCS_total = rowSums(select(., all_of(likert_items)), na.rm = TRUE))


### mean scores

data_clean_final_NFCS_Score1 <- data_clean_final_NFCS_Score %>%

  mutate(NFCS_mean = rowMeans(select(., all_of(likert_items)), na.rm = TRUE))


### Reliability testing

psych::alpha(data_clean_final_NFCS_Score1[, likert_items], check.keys = TRUE)

library(dplyr)

data_clean_final_NFCS_Score1 <- data_clean_final_NFCS_Score1 %>%

  mutate(

    Q4 = 7 - Q4,

    Q7 = 7 - Q7)
```

```
library(psych)

psych::alpha(data_clean_final_NFCS_Score1[, likert_items], check.keys = TRUE)
```

Atlas.ti research beginning now

```
library(readxl)

library(ggplot2)


# Step 3: Run correlation test

cor.test(X1_Participant_Data_with_NFCS_Scores$NFCS_total, data$Self_Regulation_Total)


# Optional: visualize the relationship

ggplot(data, aes(x = NFCS_total, y = Self_Regulation_Total)) +
  geom_point() +
  geom_smooth(method = "lm", se = TRUE) +
  labs(title = "Relationship Between Need for Closure and Self-Regulation",
       x = "NFCS Total Score",
       y = "Self-Regulation Behaviors")


colnames(X1_Participant_Data_with_NFCS_Scores)

library(readxl)

cor.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
         Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce)
```

```
Final_Participant_Dataset_with_Uncertainty_Strategies$Effective_Uncertainty_Management
<-
  Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce +
  Final_Participant_Dataset_with_Uncertainty_Strategies$Maintain

cor.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,

Final_Participant_Dataset_with_Uncertainty_Strategies$Effective_Uncertainty_Management)

cor.test(Final_Participant_Dataset_with_Uncertainty_Strategies$NFCS_total,
         Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total)

#TESTING Parametric assumptions

###Normality

shapiro.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total)
shapiro.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce)
shapiro.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Maintain)

###Linearity

plot(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
     Final_Participant_Dataset_with_Uncertainty_Strategies$Eff_UM,
     main = "Linearity Check",
     xlab = "Self-Regulation", ylab = "Effective UM")
```

```
abline(lm(Eff_UM ~ Self_Regulation_Total, data =
Final_Participant_Dataset_with_Uncertainty_Strategies), col = "red")

###Homoscedasticity

model <- lm(Eff_UM ~ Self_Regulation_Total, data =
Final_Participant_Dataset_with_Uncertainty_Strategies)
plot(model, which = 1)  # Residuals vs fitted

###No Outliers

boxplot(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
main = "SRL Outliers")
boxplot.stats(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total)
$out
```

Shapiro-Wilk Normality Test Results:

```
shapiro.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total)

	Shapiro-Wilk normality test

data:  Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total
W = 0.97665, p-value = 0.8706

> shapiro.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce)
```

```
	Shapiro-Wilk normality test

data:  Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce
W = 0.96071, p-value = 0.5305

> shapiro.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Maintain)

	Shapiro-Wilk normality test

data:  Final_Participant_Dataset_with_Uncertainty_Strategies$Maintain
W = 0.91427, p-value = 0.06672
```

#H1

Load your data (if not already loaded)

```
# df <- read_excel("Final_Participant_Dataset_with_Uncertainty_Strategies.xlsx")

# Make sure variables are numeric
Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total <-
as.numeric(as.character(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regula
tion_Total))
Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce <-
as.numeric(as.character(Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce))
Final_Participant_Dataset_with_Uncertainty_Strategies$Maintain <-
as.numeric(as.character(Final_Participant_Dataset_with_Uncertainty_Strategies$Maintain))
```

```
Final_Participant_Dataset_with_Uncertainty_Strategies$Ignore <-
as.numeric(as.character(Final_Participant_Dataset_with_Uncertainty_Strategies$Ignore))
Final_Participant_Dataset_with_Uncertainty_Strategies$Increase <-
as.numeric(as.character(Final_Participant_Dataset_with_Uncertainty_Strategies$Increase))

# Create effective uncertainty management variable
Final_Participant_Dataset_with_Uncertainty_Strategies$Eff_UM <-
Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce +
Final_Participant_Dataset_with_Uncertainty_Strategies$Maintain

# Run Pearson correlations
cor.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Eff_UM)
cor.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce)
cor.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Maintain)
cor.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Ignore)
cor.test(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Increase)

# Function to calculate r² (effect size)
r_squared <- function(r) { round(r^2, 2) }

# Calculate r and r² values
```

```
r_eff_um <-
cor(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Eff_UM, use = "complete.obs")
r_reduce <-
cor(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Reduce, use = "complete.obs")
r_maintain <-
cor(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Maintain, use = "complete.obs")
r_ignore <-
cor(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Ignore, use = "complete.obs")
r_increase <-
cor(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
Final_Participant_Dataset_with_Uncertainty_Strategies$Increase, use = "complete.obs")

# Print effect sizes
cat("Effect sizes (r²):\n")
cat("Effective UM: ", r_squared(r_eff_um), "\n")
cat("Reduce: ", r_squared(r_reduce), "\n")
cat("Maintain: ", r_squared(r_maintain), "\n")
cat("Ignore: ", r_squared(r_ignore), "\n")
cat("Increase: ", r_squared(r_increase), "\n")
```

#H2

```
# Create median split on SRL
median_srl <-
median(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total,
na.rm = TRUE)
Final_Participant_Dataset_with_Uncertainty_Strategies$SRL_Group <-
ifelse(Final_Participant_Dataset_with_Uncertainty_Strategies$Self_Regulation_Total >
median_srl, "High SRL", "Low SRL")

# View group sizes
table(Final_Participant_Dataset_with_Uncertainty_Strategies$SRL_Group)

# Compare mean use of Reduce strategy
t.test(Reduce ~ SRL_Group, data = Final_Participant_Dataset_with_Uncertainty_Strategies)

# Optional: Summary stats by group
aggregate(Reduce ~ SRL_Group, data =
Final_Participant_Dataset_with_Uncertainty_Strategies, mean)
aggregate(Reduce ~ SRL_Group, data =
Final_Participant_Dataset_with_Uncertainty_Strategies, sd)
###RESULTS

# Load required libraries
library(readxl)
library(tidyverse)

str(df)
```

```
#List of SRL variables
srl_vars <- c("Goal.Setting", "Strategic.Planning", "Time.Management",
        "Environment.Structuring", "Help.Seeking",
"Motivation.Control...Effort.Regulation",
        "Self.Monitoring", "Self.Evaluation", "Task.Strategy.Use", "Strategy.Adaption")

# List of uncertainty and closure variables
outcome_vars <- c("Reduce", "Maintain", "Ignore", "Increase", "NFCS_total")

# Run correlations
for (srl in srl_vars) {
  for (outcome in outcome_vars) {
    cat("\n--- Correlation between", srl, "and", outcome, "---\n")
    result <- try(cor.test(df[[srl]], df[[outcome]]), silent = TRUE)
    if (inherits(result, "try-error")) {
      cat("Error with", srl, "and", outcome, "\n")
    } else {
      print(result)
    }
  }
}

#Function to compute and print r and r² nicely
print_r_and_r2 <- function(r_value, label) {
  r2_value <- round(r_value^2, 2)
```

```
  cat("\n", label, "\n")
  cat("  r: ", round(r_value, 3), "\n")
  cat("  r² (effect size): ", r2_value, "\n")
}

# Significant and near-significant results
print_r_and_r2(0.6512884, "Strategic Planning & Maintain")
print_r_and_r2(0.648002,  "Strategic Planning & Increase")
print_r_and_r2(0.5258475, "Task Strategy Use & Ignore")
print_r_and_r2(0.5941995, "Task Strategy Use & Increase")
print_r_and_r2(0.4847964, "Task Strategy Use & Maintain")
print_r_and_r2(0.4579543, "Environment Structuring & Ignore")
print_r_and_r2(0.4402034, "Motivation Control & Ignore")
print_r_and_r2(0.417579,  "Strategic Planning & Ignore")
print_r_and_r2(0.4055262, "Self-Evaluation & Reduce")

#Testing ASSUMPTIONS #new

# Load required libraries
library(readxl)
library(ggplot2)
library(gridExtra)

# Load your dataset (adjust the path if needed)
df <- read_excel("Final_Participant_Dataset_with_Uncertainty_Strategies.xlsx")
```

```
# Create folder to save diagnostic plots
dir.create("diagnostic_plots", showWarnings = FALSE)

# List of variables you want to check
variables <- c("NFCS_total", "Strategic.Planning", "Task.Strategy.Use", "Self.Monitoring",
               "Maintain", "Reduce", "Increase", "Ignore")

# Function to create diagnostics per variable
create_diagnostics <- function(varname) {
  var <- df[[varname]]

  # Histogram
  p1 <- ggplot(data.frame(var), aes(x = var)) +
    geom_histogram(bins = 10, fill = "skyblue", color = "black") +
    ggtitle(paste("Histogram of", varname)) +
    theme_minimal()

  # Q-Q Plot
  p2 <- ggplot(data.frame(var), aes(sample = var)) +
    stat_qq(color = "red") +
    stat_qq_line() +
    ggtitle(paste("Q-Q Plot of", varname)) +
    theme_minimal()

  # Boxplot
  p3 <- ggplot(data.frame(var), aes(y = var)) +
```

```
    geom_boxplot(fill = "lightgreen") +
    ggtitle(paste("Boxplot of", varname)) +
    theme_minimal()

  # Combine & save
  safe_name <- gsub("[ /]", "_", varname)
  filename <- paste0("diagnostic_plots/", safe_name, "_diagnostics.png")
  fig <- grid.arrange(p1, p2, p3, ncol = 3)
  ggsave(filename, fig, width = 14, height = 5, dpi = 300)
}

# Run for all variables
for (var in variables) {
  create_diagnostics(var)
}

create_diagnostics <- function(varname) {
  var <- df[[varname]]
  var <- as.numeric(var)            # ensure it's numeric
  var <- var[!is.na(var)]           # remove NAs

  # Histogram
  p1 <- ggplot(data.frame(var), aes(x = var)) +
    geom_histogram(bins = 10, fill = "skyblue", color = "black") +
    ggtitle(paste("Histogram of", varname)) +
    theme_minimal()
```

```
  # Q-Q Plot
  p2 <- ggplot(data.frame(var), aes(sample = var)) +
    stat_qq(color = "red") +
    stat_qq_line() +
    ggtitle(paste("Q-Q Plot of", varname)) +
    theme_minimal()

  # Boxplot
  p3 <- ggplot(data.frame(var), aes(y = var)) +
    geom_boxplot(fill = "lightgreen") +
    ggtitle(paste("Boxplot of", varname)) +
    theme_minimal()

  # Save combined plot
  safe_name <- gsub("[ /]", "_", varname)
  filename <- paste0("diagnostic_plots/", safe_name, "_diagnostics.png")
  fig <- grid.arrange(p1, p2, p3, ncol = 3)
  ggsave(filename, fig, width = 14, height = 5, dpi = 300)
}

#Spearman correlation

# Load required libraries
library(readxl)
library(dplyr)
```

```
# Load your dataset
df <- read_excel("Final_Participant_Dataset_with_Uncertainty_Strategies.xlsx")

# Define variable names exactly as in the Excel file
srl_vars <- c("Goal Setting", "Strategic Planning", "Time Management", "Environment
Structuring",
              "Help-Seeking", "Motivation Control / Effort Regulation", "Self-Monitoring",
              "Self-Evaluation", "Task Strategy Use", "Strategy Adaption")

uncertainty_vars <- c("Reduce", "Maintain", "Ignore", "Increase")
nfcs_var <- "NFCS_total"

# Convert relevant columns to numeric (just to be sure)
df[srl_vars] <- lapply(df[srl_vars], as.numeric)
df[uncertainty_vars] <- lapply(df[uncertainty_vars], as.numeric)
df[[nfcs_var]] <- as.numeric(df[[nfcs_var]])

# Combine all outcomes into one list
outcome_vars <- c(uncertainty_vars, nfcs_var)

# Run Spearman correlations
results <- data.frame()

for (srl in srl_vars) {
  for (outcome in outcome_vars) {
```

```
    rho <- cor.test(df[[srl]], df[[outcome]], method = "spearman")
    results <- rbind(results, data.frame(
      SRL_Component = srl,
      Outcome_Variable = outcome,
      Spearman_rho = round(rho$estimate, 3),
      p_value = round(rho$p.value, 3)
    ))
  }
}

# View results
print(results)

# Optionally export
write.csv(results, "Spearman_Correlations.csv", row.names = FALSE)
```

Appendix B

Experimental Task Description

Study design

Welcome to our Study! We are a group of bachelor students currently writing our bachelor thesis. This experiment is part of our thesis and will help us find valuable insights into group work. In the following, you will find a Task that we ask you to complete with your group. You are encouraged to talk and discuss during the following, so please do so! If you have any further questions you can always ask the researchers. Below you can also find a user manual for the program you will be using Aladdin. Please indicate your participation numbers below. Thank you for your participation and have fun!:)

Participation number:

Participation number:

Participation number:

Participation number:

Task:

Create an energy-efficient house with your teammates for a family of 4 (include the family in the home by adding four people) using one tree, at least three windows, and a door. The house must also be between 8 and 10 meters high. You will have 5 minutes to familiarise yourself with the program and then 25 minutes to complete your task.

User-manual for Aladdin:

- On the top right bar, all the tools for building your house can be found
- On the top left you can find the main menu here it is possible to change the direction of the house and find additional information about various topics, furthermore here you can also find the sticky note accessory
- You can use the Analysis tools under the main menu to find how much your energy your house is using

Additional help:

- Check the direction of the sun in relation to where the house is standing
- What about trees? Are they in the way?
- Did you do everything possible to be as energy efficient as you can be ;)?
- Is there any additional help the program gives you that you did not use?
- Take a look in the main menu under the tap tutorials
- Have a look at the analysis tab

Appendix C

Need for Closure Scale

The NFCS
short version

The NFCS short version (15 items) was developed by Webster and Kruglanski (1994), and was further revised by Pierro (2005 unpublished). Below is the updated version of the short NFCS published by Roets and Van Hiel (2011)**. When reporting results the two published scales should be referenced**.

Webster, D. M., & Kruglanski, A. W. (1994). Individual differences in need for cognitive closure. *Journal of Personality and Social Psychology, 67*(6), 1049–1062.

Pierro, A., & Kruglanski, A.W. (2005). *Revised need for cognitive closure scale.* (Unpublished manuscript). Università di Roma, "La Sapienza", Rome.

Roets, A., & Van Hiel, A. (2011). Item selection and validation of a brief, 15-item version of the Need for Closure Scale. *Personality and Individual Differences*, *50*(1), 90-94.

Read each of the following statements and decide how much you agree with each according to your beliefs and experiences. Please respond according to the following scale:

1 = Strongly disagree	4 = Slightly agree
2 = Moderately disagree	5 = Moderately agree
3 = Slightly disagree	6 = Strongly agree

1	I don't like situations that are uncertain.	1	2	3	4	5	6
2	I dislike questions which could be answered in many different ways.	1	2	3	4	5	6
3	I find that a well ordered life with regular hours suits my temperament.	1	2	3	4	5	6
4	I feel uncomfortable when I don't understand the reason why an event occurred in my life.	1	2	3	4	5	6
5	I feel irritated when one person disagrees with what everyone else in a group believes.	1	2	3	4	5	6
6	I don't like to go into a situation without knowing what I can expect from it.	1	2	3	4	5	6
7	When I have made a decision, I feel relieved	1	2	3	4	5	6
8	When I am confronted with a problem, I'm dying to reach a solution very quickly.	1	2	3	4	5	6
9	I would quickly become impatient and irritated if I would not find a solution to a problem immediately.	1	2	3	4	5	6
10	I don't like to be with people who are capable of unexpected actions.	1	2	3	4	5	6
11	I dislike it when a person's statement could mean many different things.	1	2	3	4	5	6
12	I find that establishing a consistent routine enables me to enjoy life more.	1	2	3	4	5	6
13	I enjoy having a clear and structured mode of life.	1	2	3	4	5	6
14	I do not usually consult many different opinions before forming my own view.	1	2	3	4	5	6
15	I dislike unpredictable situations.	1	2	3	4	5	6

Scoring Note
Scores up to 30 mean low NFC. Scores between 75-90 mean high NFC.

For support, please contact Dr. Erica Molinario (molie@umd.edu)

Appendix D

Coding Schemes

Uncertainty Types

Code Name	Definition	Example Phrase
Task Uncertainty	Uncertainty or lack of clarity regarding goals, requirements, or expected outcomes of the task.	"What exactly should the outcome be?"
Social Uncertainty	Uncertainty about roles, responsibilities, expectations, or interpersonal dynamics within the group.	"Who is supposed to take which role here?"
Procedural Uncertainty	Uncertainty related to methods, steps, or procedures needed to complete the task.	"How should we best start planning this?"

Uncertainty Management Strategies

Code Name	Definition	Example Phrase
Ignore	The participant disregards or avoids addressing uncertainty in the task or interaction.	"It doesn't matter now, let's just move on."
Reduce	The participant attempts to decrease uncertainty by seeking clarification or additional information.	"Can we double-check if this window placement is correct?"
Increase	The participant deliberately maintains or increases uncertainty to explore alternatives or ideas.	"Maybe we should consider other options as well."
Maintain	The participant consciously keeps uncertainty unresolved, allowing flexibility in approach.	"We're not sure yet how to proceed; let's keep it open."

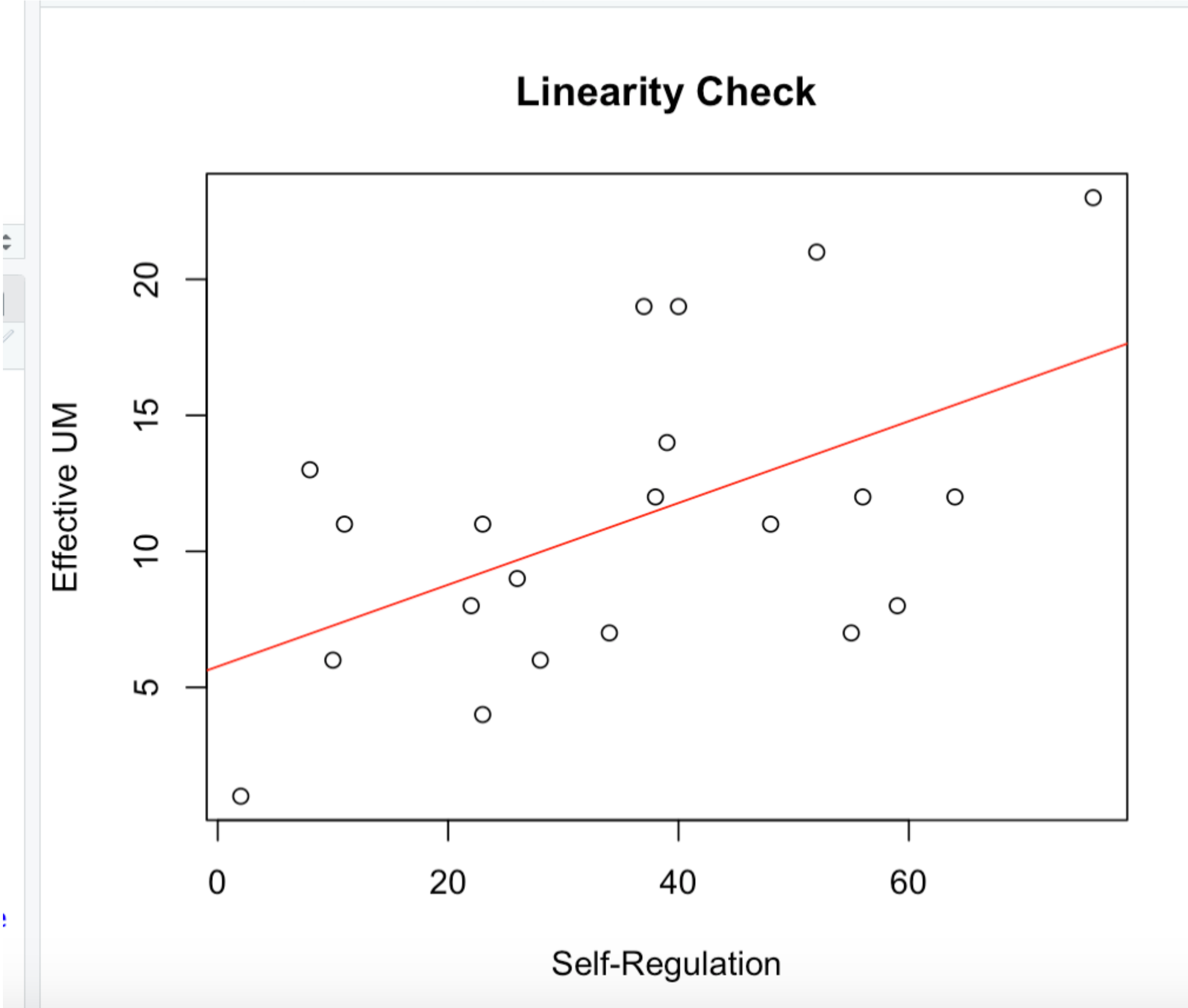
Self-regulation

Code Name	Code Description (Use as Definition / Memo in ATLAS.ti)
Goal Setting (Forethought Phase)	Setting specific objectives to be achieved during the task. This includes statements about desired outcomes, intentions, or targets for the group.
Strategic Planning (Forethought Phase)	Outlining or discussing specific strategies or procedures to reach a goal. This includes assigning roles, prioritizing actions, or scheduling work steps.
Environment Structuring (Performance Phase)	Modifying or organizing the physical or digital environment to support learning or task completion (e.g., minimizing distractions, rearranging tools).
Help-Seeking (Performance Phase)	Actively requesting assistance or clarification from peers or external sources to overcome obstacles or uncertainty.
Motivation Control / Effort Regulation (Performance Phase)	Statements or actions reflecting persistence, encouragement, or control of motivation in response to setbacks or challenges.
Self-Monitoring (Performance Phase)	Ongoing evaluation of one's own or the group's task performance, including identifying mistakes, tracking progress, or checking understanding.

Code Name	**Code Description (Use as Definition / Memo in ATLAS.ti)**
Task Strategy Use (Performance Phase)	Applying specific cognitive or procedural strategies to work on the task (e.g., trial-and-error, hypothesis testing, sketching a plan)
Time Management (Performance Phase)	Allocating or monitoring the use of time effectively during task execution, including references to pacing or deadlines.
Self-Evaluation (Reflection Phase)	Assessing the quality or success of one's own or the group's performance, usually after completing a task phase or at a turning point.
Strategy Adaption (Reflection Phase)	Changing or refining the current approach based on feedback or perceived inefficiency; includes reflecting on what is not working and proposing alternatives.

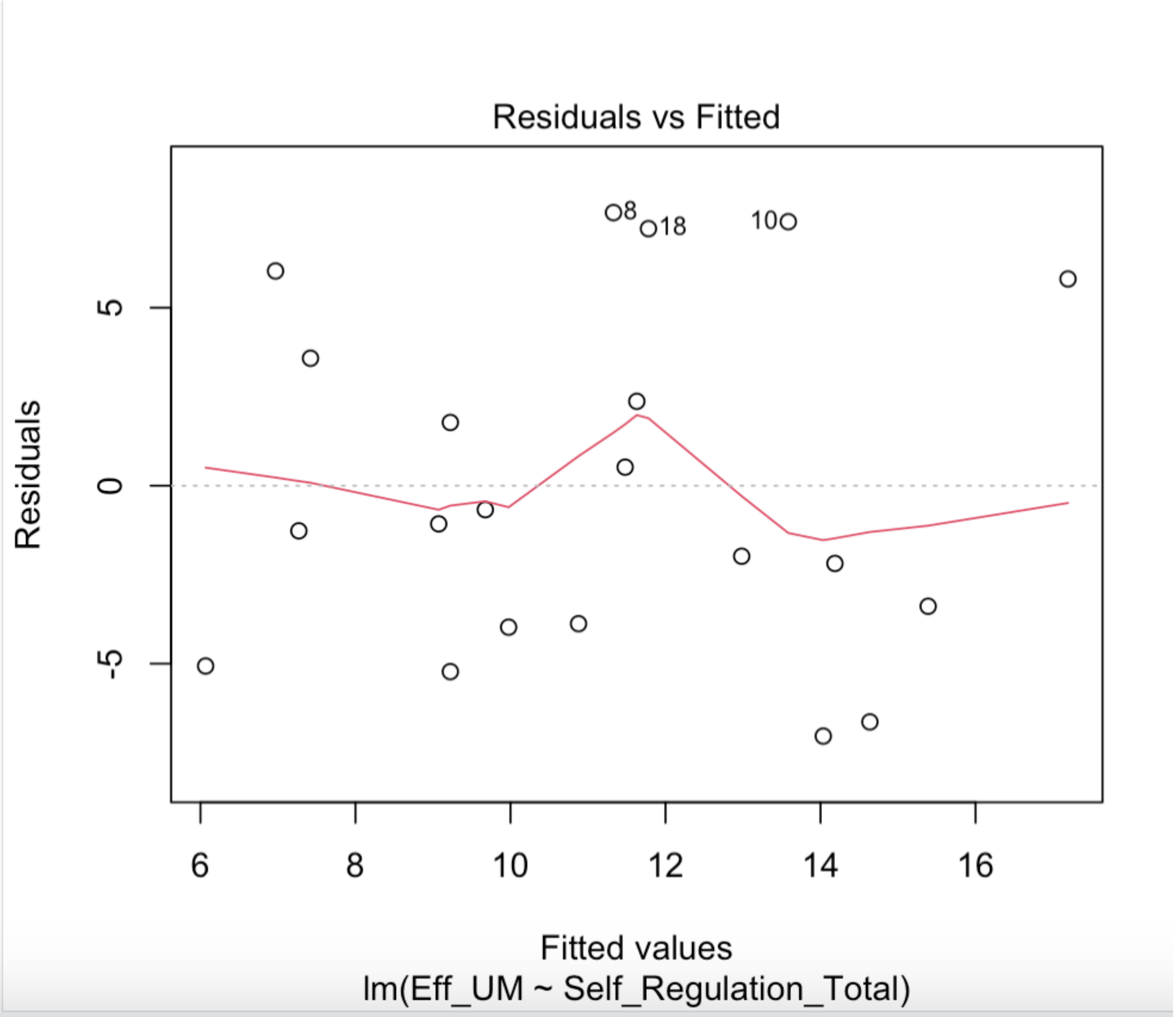
Appendix E
Diagnostic Plots for Parametric Assumptions

Figure E1



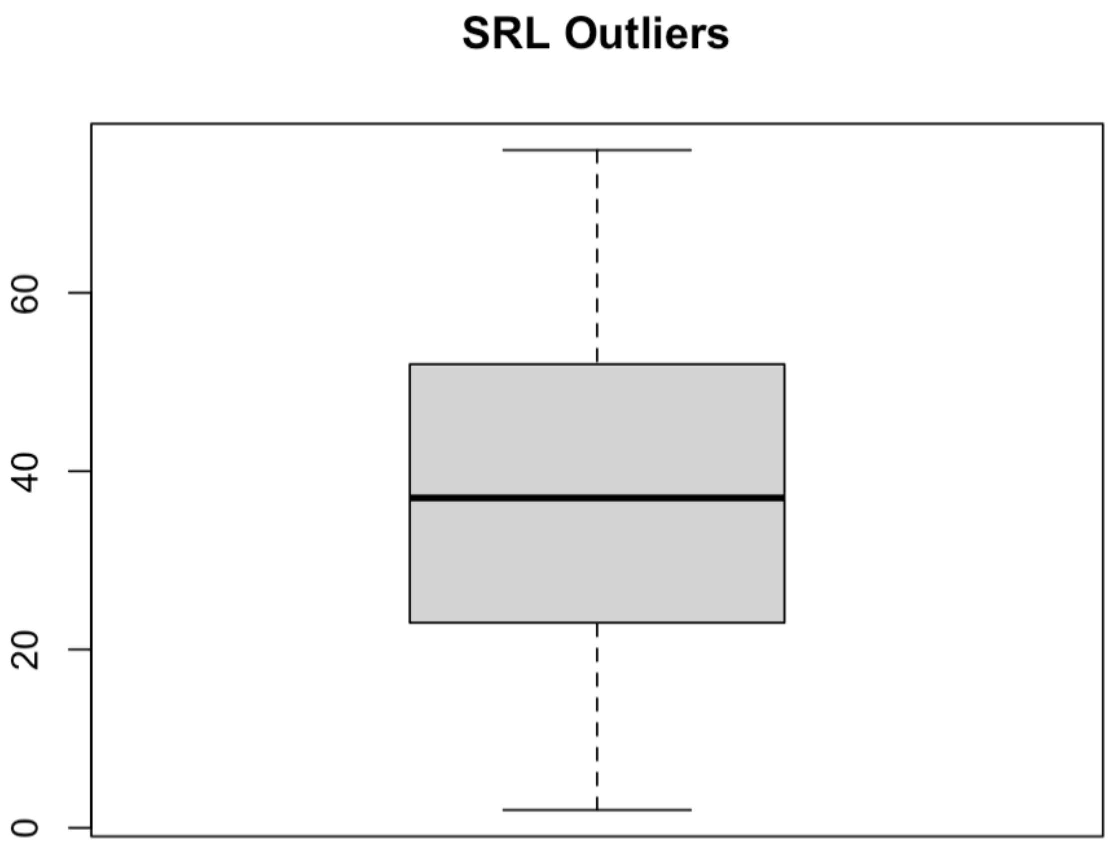
Scatterplot for Linearity

Figure E2



Residuals vs Fitted Plot

Figure E3



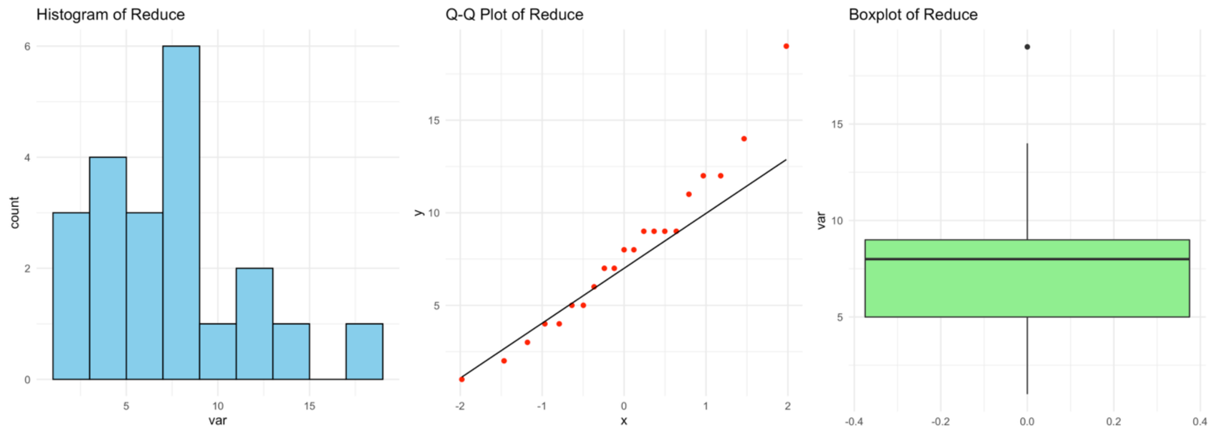
Boxplot of Self-Regulation Total Score

Table E1

Shapiro-Wilk Test Results for Normality Assumption

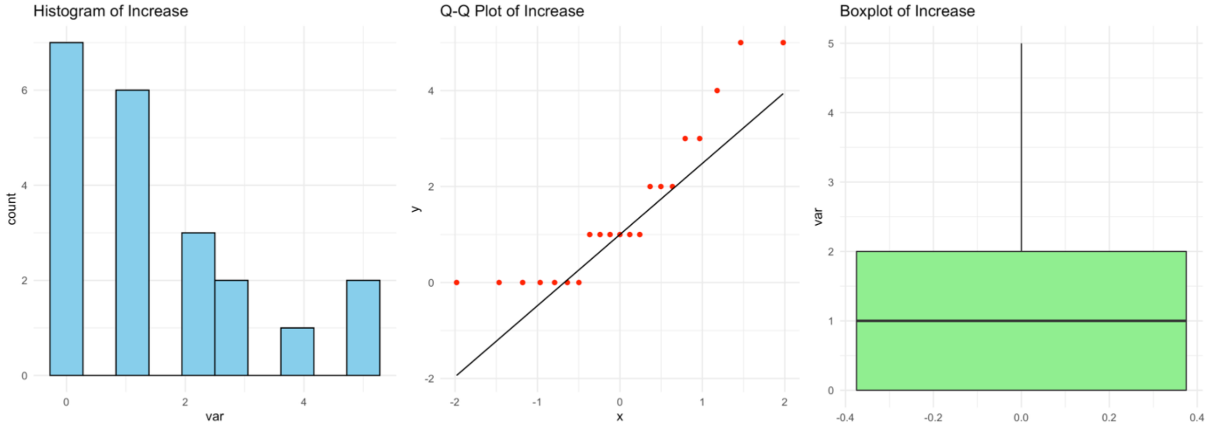
Variable	W	p-value	Normality Assumption
SRL Total	0.977	0.871	Normally distributed
Reduce	0.9607	0.5305	Normally distributed
Maintain	0.9143	0.667	Approx. normal distributed
Ignore	0.9082	0.0507	Approx. normal distributed
Increase	0.8372	0.0026	Not normally distributed
NFCS Total	0.9724	0.7850	Normally distributed

Figure E4



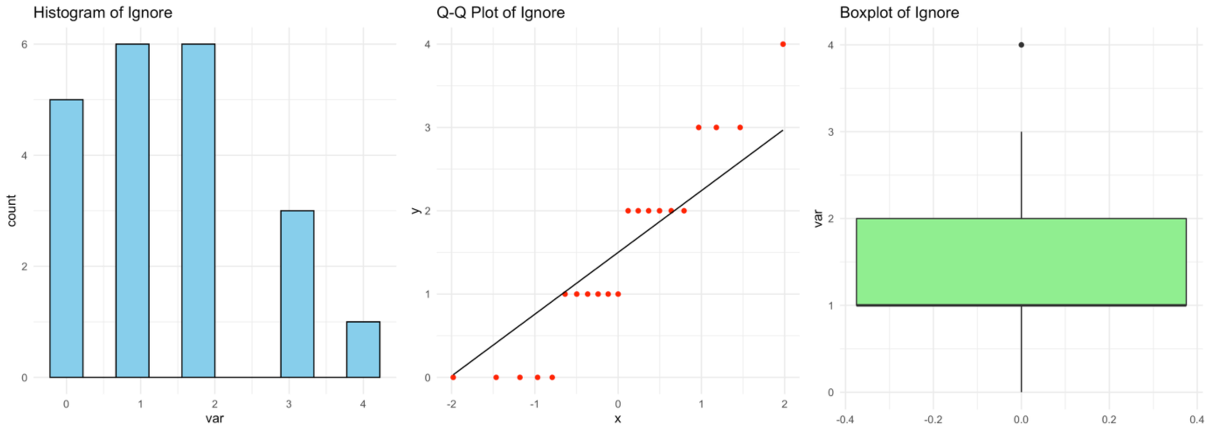
Histogram, Q-Q plot, and boxplot of the Reduce variable. These plots were used to visually inspect the distribution for normality and outliers.

Figure E5



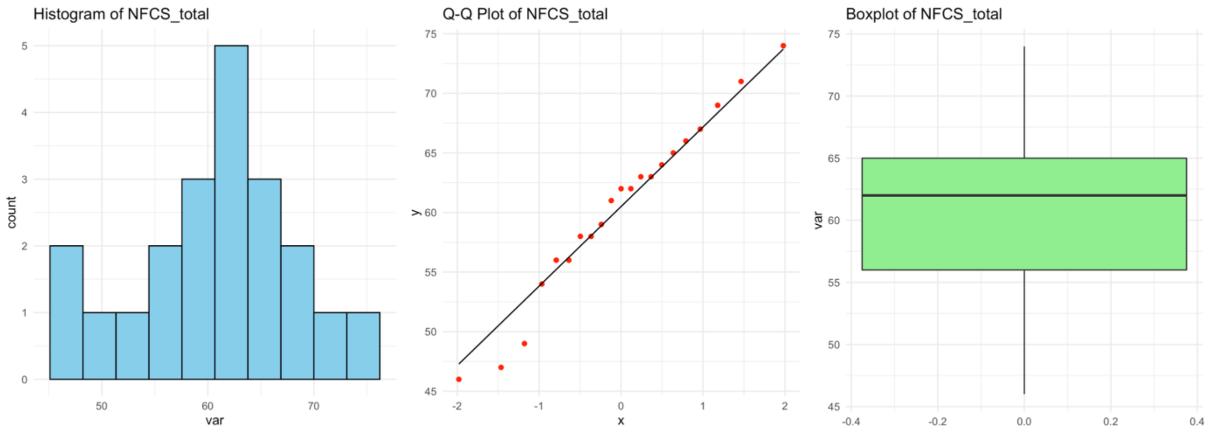
Histogram, Q-Q plot, and boxplot of the Increase variable. These plots were used to assess normality and detect deviations from a normal distribution.

Figure E6



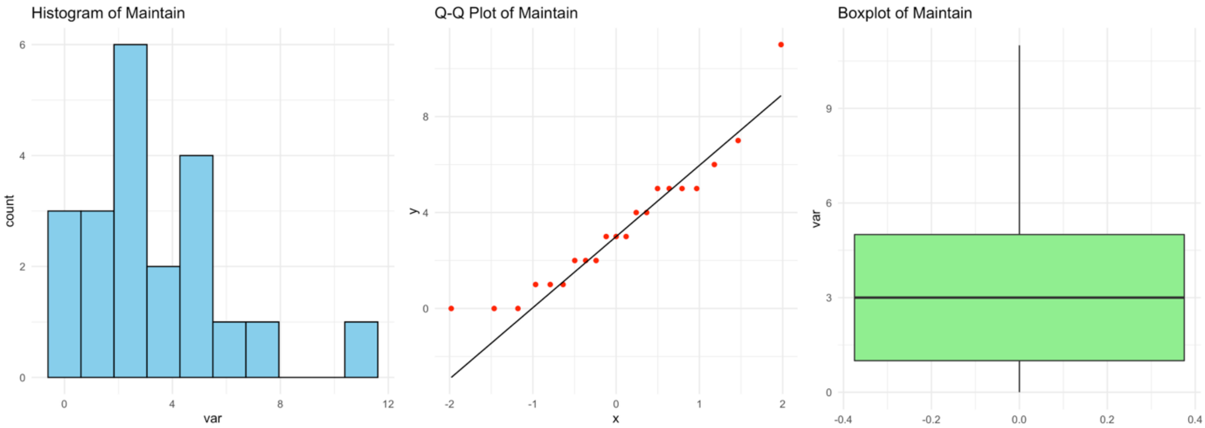
Histogram, Q-Q plot, and boxplot of the Ignore variable. Used to support the Shapiro-Wilk normality test with visual diagnostics.

Figure E7



Histogram, Q-Q plot, and boxplot of the NFCS Total variable. Used to visually inspect normality and distribution characteristics.

Figure E8



Histogram, Q-Q plot, and boxplot of the Maintain variable. Included to assess distributional assumptions for parametric testing.

Table E2

Shapiro-Wilk Test Results for Normality Assumption

Variable	W	p-value	Normality Decision
Goal Setting	0.8386	0.0027	Not normally distributed
Strategic Planning	0.8512	0.0045	Not normally distributed
Time Management	0.7805	0.0003	Not normally distributed
Environment Structuring	0.5646	<.001	Not normally distributed
Help-Seeking	0.8849	0.018	Not normally distributed
Motivation Control / Effort Regulation	0.8049	0.0008	Not normally distributed
Self-Monitoring	0.9005	0.0358	Not normally distributed
Task Strategy Use	0.9284	0.1280	Approx. normal distributed
Self-Evaluation	0.8623	0.0070	Not normally distributed
Strategy Adaption	0.8565	0.0055	Not normally distributed
Reduce	0.9607	0.5305	Normally distributed
Maintain	0.9143	0.0667	Approx. normal distributed
Ignore	0.9082	0.0507	Approx. normal distributed
Increase	0.8372	0.0026	Not normally distributed
NFCS Total	0.9723	0.7850	Normally distributed

Appendix F

Participant-Level Scores

Table 2 displays the individual-level scores for each participant across the self-regulation total, uncertainty management strategies, and the Need for Closure Scale (NFCS), grouped by team. These data provide a transparent overview of the coded behaviours and individual differences used in the correlation analyses.

Table 2

Participant-Level Overview of Self-Regulation, Uncertainty Strategies, and Need for Closure Scores

Group	Participant	SRL Total	Reduce	Maintain	Ignore	Increase	NFCS Total
1	001	8	9	4	2	0	56
1	002	2	1	0	0	0	56
1	003	11	8	3	0	2	58
2	004	38	11	1	0	0	59
2	005	55	4	3	2	2	47
2	006	59	8	0	2	2	67
3	007	56	6	6	2	4	71
3	008	37	14	5	2	3	63
3	009	10	5	1	1	0	58
4	018	52	19	2	1	0	74
4	019	76	12	11	3	5	62
4	020	39	9	5	1	5	64
5	021	28	2	4	2	1	63

Group	Participant	SRL Total	Reduce	Maintain	Ignore	Increase	NFCS Total
5	022	64	7	5	3	1	49
5	023	48	9	2	1	1	62
6	024	26	4	5	1	1	46
6	025	23	9	2	3	1	61
6	026	40	12	7	4	3	66
7	030	22	5	3	0	0	54
7	031	34	7	0	0	1	69
7	032	23	3	1	1	0	65

Note. Means (M), standard deviations (SD), and score ranges are shown for each coded self-