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Students' Use of a Learning Analytics Dashboard and Influence of Reference Frames: Goal Setting, Motivation, and Performance

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ABSTRACT

Background: University students need to self-regulate but are sometimes incapable of doing so. Learning Analytics Dashboards (LADs) can support students' appraisal of study behaviour, from which goals can be set and performed. However, it is unclear how goal-setting and self-motivation within self-regulated learning elicits behaviour when using an LAD.

Objectives: This study's purpose is exploring reference frames' influence on goal setting, LAD elements' influence on student motivation, and the predictive value of goal setting and motivation on behaviour, adding to our understanding of the factors predicting task attainment and the role of reference frames.

Methods: In an experimental survey design, university students ($n = 88$) used an LAD with a peer reference frame (Condition 1) or without one (Condition 2), set a goal, determined goal difficulty, self-assessed motivation and LAD elements' influence on motivation. Researchers coded goal specificity. Four weeks later, students self-assessed task attainment, task satisfaction, time on task, and task frequency. *T*-tests and MANOVA explored effects of the reference frame. Regression analyses determined predictive potential of goal difficulty, goal specificity, and motivation on goal attainment.

Results and Conclusions: Results showed no difference between conditions on goal specificity, difficulty, or motivation. The peer reference frame's perceived influence on motivation was small. LAD elements' influence on motivation varied but were mainly positive. Regression models were not predictive, except the task satisfaction exploratory model. Most participants (77%) attained their goals. Reference frame integration should be carefully considered, given potential negative effects. Students may require educators' support when setting goals, but the support should balance students' autonomy.

1 | Introduction

Engaging in self-regulation is important for university students, leading to higher academic achievement (Hadwin et al. 2025; Schneider and Preckel 2017) and higher levels of study satisfaction (Liborius et al. 2019). Self-regulated learning (SRL) is a cyclical process, consisting of a preparatory, performance, and appraisal phase, and is goal driven as students' goals direct their self-regulatory actions (Panadero 2017). Goals are set within the preparatory phase, and can be assigned by (e.g.) instructors, self-set, or participatively set (Latham and Seijts 2016). Self-set goals lead to students taking ownership and responsibility of their goals (Elliot and Fryer 2008) and, therefore, improve students' learning the most (Zimmerman 1990). Besides goal setting, the preparatory phase of SRL also includes (self-)motivation (Boekaerts 2011; Pintrich 2000; Zimmerman 2000). Motivation theory pertains to individuals behaving the way they do, and what initiates, directs, sustains, and terminates behaviour (Graham and Weiner 2012). The self-motivation to achieve goals is crucial in SRL (Zimmerman 2000), and performance phase

Summary

- What is currently known about this topic?
  - Self-regulated learning is important for students, but they are not always capable of doing so.
  - Learning Analytics Dashboards (LADs) provide information to support self-regulation of learning.
  - Goal setting and motivation are important processes within SRL.
- What does this paper add?
  - This paper shows that a reference frame in an LAD does not influence goal difficulty or specificity.
  - Students' perceived influence of an LAD on motivation varied but was mostly positive.
  - Goal difficulty, goal specificity, and motivation did not predict goal attainment.
  - Students setting goals when using an LAD mostly perform them (at least somewhat).
- Implications for practice/or policy
  - Practitioners may include reference frames in an LAD to support interpretation but must be cautious of potential negative effects.
  - Supporting students with goal setting may lead to goals with appropriate difficulty and specificity, and motivation.

behaviour depends on students' self-set goals and their motivation to achieve those goals. If a student self-sets a goal but is not motivated enough to achieve that goal, the goal will probably not be (fully) achieved.

Students' SRL may be supported via a Learning Analytics Dashboard (LAD), which can provide information about students' learning processes (Marzouk et al. 2016). LADs vary in the type of information they display, which influences students' self-regulation and associated motivation (Aguilar et al. 2021). LADs have been shown to positively influence self-regulation (e.g., de Vreugd et al. 2023), but some visualisations or functionalities in an LAD are also associated with maladaptive outcomes (Beheshitha et al. 2016; Aguilar et al. 2021). The information in a LAD can be used by students in the appraisal phase, to reflect on strengths and determine points of improvement. In the subsequent preparatory phase, students can set goals from these insights. As SRL is a goal-driven activity (Panadero 2017), setting goals is key.

Given the importance of goal setting in SRL, the current study explores the interplay between students' self-goal setting, task specific motivation, and subsequent performance phase behaviour when using an LAD. Furthermore, as specific information in an LAD may affect students' motivation, the influence of LAD elements on aspects of students' motivation is explored as well.

1.1 | Self-Regulated Learning

This study applies Panadero (2017) definition of SRL as a cyclical process consisting of an appraisal phase, a preparatory phase, and a performance phase. In the appraisal phase, learners use performance feedback (Boekaerts 2011), reflect on performance (Pintrich 2000), and make self-judgements (Zimmerman 2000). These appraisals may instigate the preparatory phase, in which goals are set (Boekaerts 2011), a planning is made (Hadwin et al. 2011), and task analysis occurs (Zimmerman 2000). In the performance phase, learners strive to attain goals (Boekaerts 2011), monitor performance (Pintrich 2000), and apply tactics and strategies to reach goals (Winne and Hadwin 1998). A critique of SRL has been that it treats social and well-being goals as 'background variables' (Boekaerts 2002, 599), whilst non-academic goals are an essential aspect of students' lives (Hofer and Fries 2016). Kim et al. (2023) argue that academic goals are part of a larger set of goals, both academic and non-academic. Given that this study's focusses on setting and attaining academic goals to improve study behaviour, SRL is an appropriate theoretical lens.

Goal setting is important in the preparatory phase of SRL (Sedrakyan et al. 2020), because self-regulatory actions are goal driven (Panadero 2017). However, setting goals does not guarantee behavioural changes in the performance phase. The discrepancy between setting goals and attaining goals is referred to as the 'intention-behaviour gap'. Some authors estimate a strong relation between intention (e.g., setting a goal to do something) and behaviour, other analyses show that medium-sized changes in intention leads to trivial-sized behavioural changes (Rhodes and de Bruijn 2013). Recent literature identified 77 potential moderators for the relationship between intention and performing of intention (Rhodes et al. 2022). For example, 'consciousness' (i.e., being self-disciplined and ordered) and 'intention stability' (i.e., maintaining similar intentions over time) positively moderate the intention-behaviour relation (Rhodes et al. 2022). Conversely, 'goal conflict' (i.e., when pursuing one goal undermines pursuit of another) negatively moderates the intention-behaviour relation (Rhodes et al. 2022). For students, a potentially big discordance exists between their intention to perform tasks (i.e., goals and motivation in the preparatory phase), and the actual task attainment (i.e., altered or new behaviour in the performance phase).

1.1.1 | SRL and Learning Analytics

Supporting students' SRL may be done with an LAD (Marzouk et al. 2016). An LAD visually displays indicators about learning processes and/or learning contexts (van Leeuwen et al. 2022). Effects of learning analytics (LA) systems, such as LADs, on behaviour and learning are mixed (Bodily and Verbert 2017). Some studies showed an effect of behavioural change (e.g., Holanda et al. 2012), whereas other studies found no effects (e.g., Janssen et al. 2007). Aguilar et al. (2021) found that LAD exposure predicted changes in motivation and SRL strategies and stress the importance of research investigating the relation between LAD use, effects on motivation, and application of SRL strategies. Likewise, Viberg et al. (2020) argue that the intersection between LA and SRL is understudied.

Providing information to students in an LAD supports the appraisal phase and internal feedback generation (de Vreugd et al. 2023). Internal feedback is a key catalyst in the appraisal phase and refers to the knowledge generated when current knowledge and competence are compared against some reference information (Nicol 2021). Wise and Vytasek (2017) argue that an appropriate reference frame is required to determine the meaning of information in LADs. Reference frames are '*the comparison points which orient students' interpretation of analytics*' (Wise et al. 2016, 170), and function as comparators to support data interpretation (Jivet et al. 2017). However, reference frames in LADs can also have negative effects. For example, comparison with peers can induce social anxiety and negatively impact motivation (Lim et al. 2019), and negatively affect self-efficacy beliefs (Gallagher et al. 2024). For this study's LAD, de Vreugd and colleagues (2023) found that availability of a peer reference frame (presenting a peer average) induced more internal feedback compared to having no reference frame, and likely more than a criterion reference frame (presenting a predetermined criteria). In that study, participants without a reference frame generated internal feedback using other comparison points, such as their own perception of proficiency or other scores in the LAD. The effects of a peer reference frame on preparatory activities (such as goal setting) were not clear in that study. Given that peer reference frames can have both positive and negative effects, exploring the effects on goal setting is vital, especially since SRL is a goal driven activity (Panadero 2017).

The variance of LAD effects can be due to various reasons, because of LAD characteristics (e.g., specific information, or specific dashboard functionalities such as a reference frame), because of students' goals quality, and their motivation to perform differently. This study therefore explores the interplay of dashboard functionalities with goal setting and motivation in the preparatory phase of SRL, and the extent to which this interplay elicits performance phase behaviour.

1.1.2 | Preparatory Phase: Goal Setting

Within SRL, goals direct students' self-regulatory actions (Panadero 2017) and provide standards to monitor learning process and progress (Winne and Hadwin 1998). Goals are set within the preparatory phase, and can be provided by (e.g.) teachers, self-set, or participatively set (Latham and Seijts 2016). Provided goals clarify expectations and where to concentrate (e.g.) study efforts (Sedrakyan et al. 2020). Provided, specific goals may increase motivation compared to telling students to 'do your best' (Locke and Latham 2002), and improve achievement (Latham and Locke 2007). When expectations and objectives are clear, feedback seeking more likely occurs (Hattie and Timperley 2007). However, students self-setting goals shows the most promise. Self-setting goals may improve study behaviour and academic performance (Morisano et al. 2010), result in empowering and proactive goal-directed behaviour (Elliot and Fryer 2008), and improve student motivation and learning (Zimmerman 1990).

Although the value of self-set goals is already known (e.g., Morisano 2013), Alessandri et al. (2020) argue that goal potential depends upon students' ability to self-set goals with appropriate difficulty and specificity. Goal difficulty specifies '*a certain level of task proficiency, measured against a standard*' (Locke et al. 1981, 127). Goal specificity refers to '*the degree of quantitative precision with which the aim [goal] is specified*' (Locke et al. 1981, 126). For example, challenging, specific goals lead to higher performance compared to specific easy goals or abstract goals (Latham and Seijts 2016). Within SRL, students pursue, connect, and merge multiple higher-order (i.e., distal) goals simultaneously, and prioritise specific goals (Kim et al. 2023). After organising higher-order goals, task-specific sub goals (TSSGs) are defined: proximal, more manageable, concrete goals, connected to overarching higher-order distal goals (Sedrakyan et al. 2020). TSSGs are especially important for self-regulatory processes (Hadwin et al. 2025). Defining TSSGs may increase attainment of higher-order goals, as more direct feedback on strategy effectiveness is obtained and progress is self-monitor easier (Latham and Locke 2007).

Alessandri et al. (2020) claim that 'almost no study' examined effects of self-set goal specificity and difficulty. Given the importance of goal setting in SRL, we therefore explore whether students' TSSG difficulty and specificity (in the preparatory phase) after using an LAD predicts behaviour within the performance phase of SRL.

1.1.3 | Preparatory Phase: Motivation

Besides setting goals in the preparatory phase students develop a (self)motivation to apply strategies or achieve goals, which is key for performance of set goals (Zimmerman 2000). Motivation explains why people do the things they do (Graham and Weiner 2012). This study examines motivation using the Unified Model of Task Specific Motivation (UMTM), which '*focuses on task-specific motivation, a readiness for a relatively specific action option available to the actor*'. (De Brabander and Martens 2014, 1). The UMTM combines several motivational theories, such as Self-Determination Theory (Deci and Ryan 2000) and expectancy-value theory (Wigfield and Eccles 2000), providing a broader perspective on students' motivation. For example, important in self-determination theory is competence—individuals' feeling competent to perform certain tasks (Deci and Ryan 2000). In the UMTM, competence is complemented by perceived external support, the perceived available external support (e.g., resources or instructional videos) (from Theory of Planned Behaviour, Ajzen 2011). For example, writing a paper without feeling competent may seem like an insurmountable challenge, but having ample support available (e.g., writing courses or a tutor) mitigates the feeling of low competence. The UMTM consists of multiple motivational antecedents. These antecedents (e.g., 'sense of personal competence' and 'perceived external support') result in readiness for action, the motivation to act out a specific task. In this study, the 'task' to be motivated for is the self-set TSSG. For example, a student may generate internal feedback regarding LAD scores ('*My Planning score is pretty low*'), which may lead to higher order goal setting ('*I am going to become a better planner*'). This may be broken down in several TSSGs ('*I'm going to plan better during the next course and I'm going to keep a schedule*'). Readiness for action is the motivation to carry out these TSSGs.

UMTM aspects may be influenced by LAD elements. For example, this study's LAD offers external support (e.g., referrals for

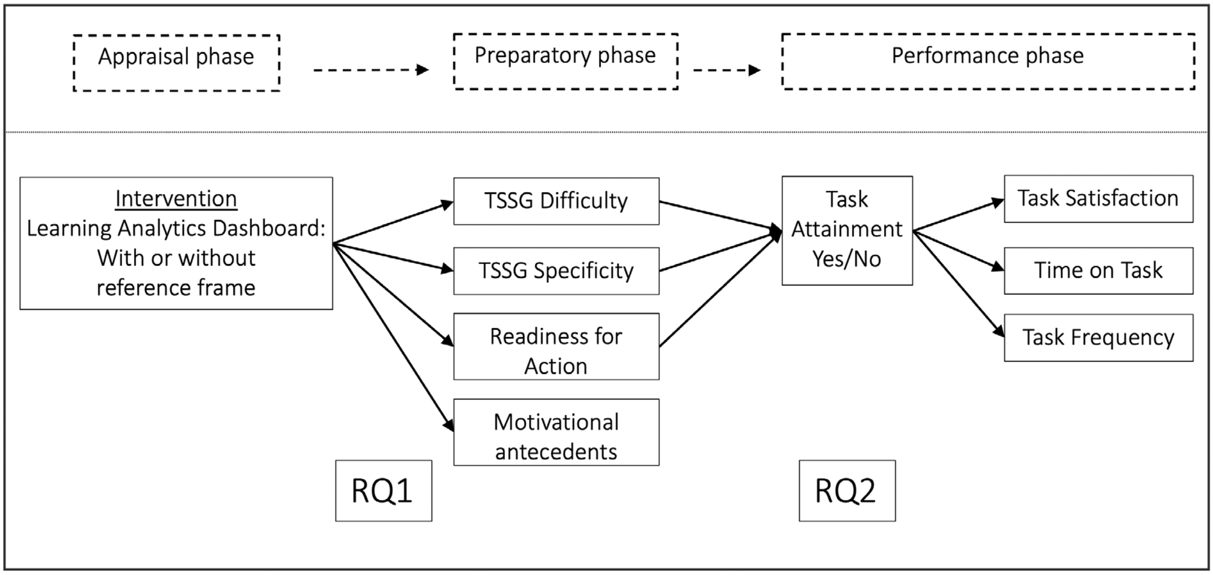

FIGURE 1 | Visual representation of the study's design. SRL phases are depicted above the dotted line, variables and RQs are represented below.

workshops) which may positively impact students' perceived external support. Likewise, providing a reference frame may affect students' motivation to act. The UMTM's subjective norm (the inclination to abide by the task-related norms of important others) may be influenced by presenting a social reference frame. Understanding students' perceptions of a LAD's influence on motivation provides insight into what LAD elements support or undermine motivation.

Given the importance of motivation in SRL, and as it remains unclear if and how LAD elements affect readiness for action and motivational antecedents, we will study this question.

1.2 | Current Study

SRL is a conceptual framework to understand motivational, cognitive, and emotional aspects of learning. Within the preparatory phase of SRL, goal setting is crucial for self-regulatory behaviour (Panadero 2017). Several SRL models (e.g., Zimmerman 2000) include self-motivation as a key component in the preparatory phase as antecedent of performance phase behaviour. de Vreugd and colleagues (2023) found that the current study's LAD supports students' appraisal phase in SRL, especially when a peer reference frame was presented to students. The effects of a peer reference frame on preparatory activities (e.g., goal setting) where unclear. As presenting reference frames can have negative effects (e.g., Beheshitha et al. 2016; Lim et al. 2019), understanding reference frames' effects on goal setting and motivation is essential.

It remains unclear how students 'self-set goals' difficulty and specificity, combined with motivation in the preparatory phase relate to goal performance in the performance phase of SRL. Also, the influence of LAD elements (e.g., graphs, information, and reference frames) on students' motivation to achieve self-set goals is unclear. Given the importance of goal setting in SRL, this study therefore explores two main research question (see Figure 1).

The first research question is: What is the influence of LAD elements on students' goal setting and motivation in the preparatory phase? This research question is divided into two sub questions:

a. 'To what extent does the availability of a reference frame in an LAD affect students' TSSG difficulty, TSSG specificity, readiness for action, and motivational antecedents?'
b. 'To what extent do students perceive an influence of LAD elements on readiness for action and motivational antecedents?'

The second research question is: What is the relation between TSSG difficulty, TSSG specificity, and readiness for action on the (level of) performance of intended behaviour in the performance phase? This research question is divided into two sub questions:

a. 'To what extent do students' TSSG difficulty, TSSG specificity and readiness for action in the preparatory phase predict task attainment in the performance phase'?
b. 'To what extent do students' TSSG difficulty, TSSG specificity and readiness for action in the preparatory phase predict task satisfaction, time on task, and task frequency in the performance phase'?

2 | Method

2.1 | Design and Participants

This study applied an experimental design with 2 conditions, containing 88 students (76 female, 7 males, 5 other/prefer not to say) from a Dutch research university (undergraduate 1, 2, and 3) from different study programs (e.g., Educational sciences and Biomedical sciences) which implemented this study's LAD. The LAD's implementation differed between study programs; in some it was part of an individual reflection whereas for

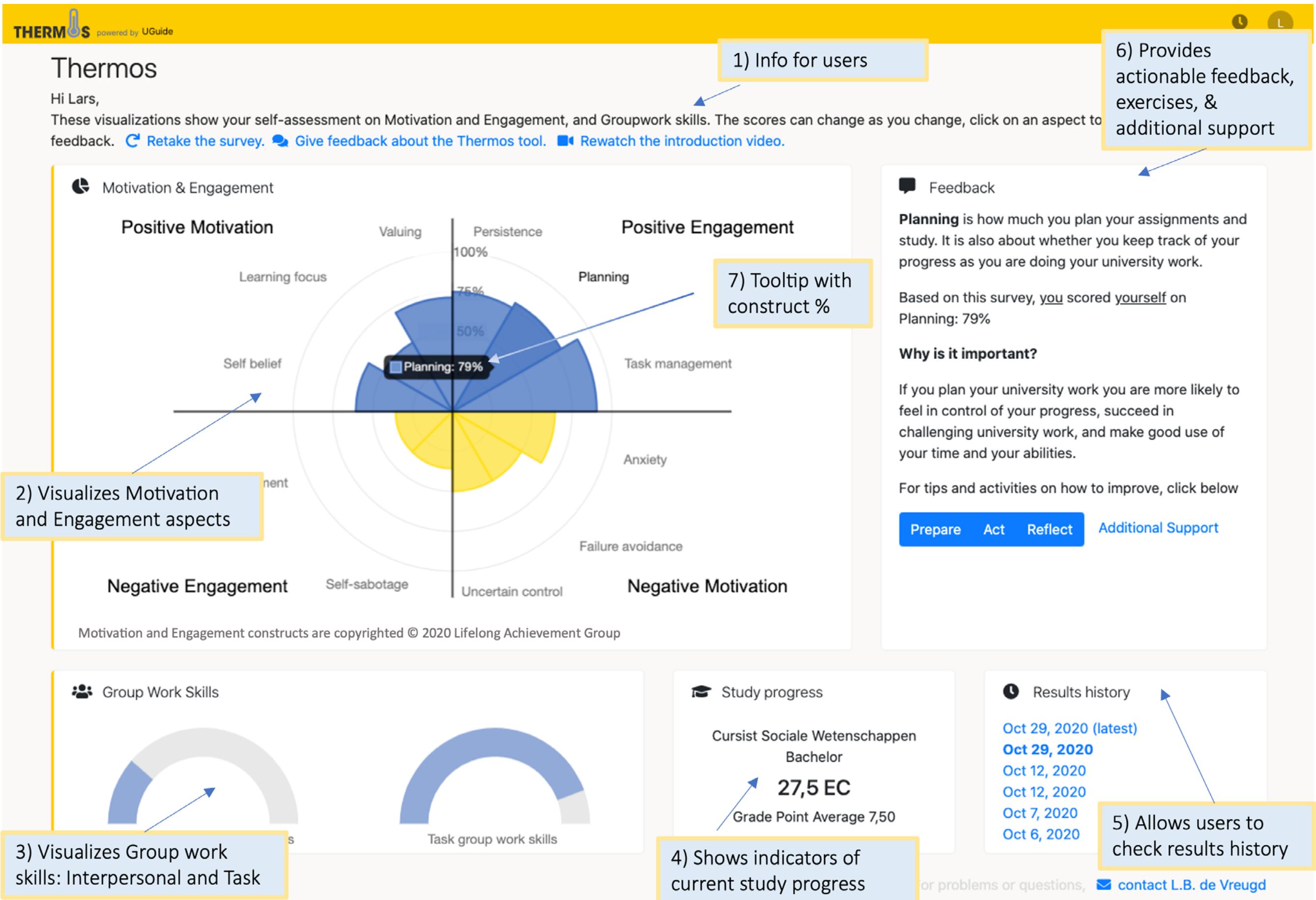

FIGURE 2 | The LAD (without reference frames) with indicators and brief explanation of the different parts in it.

others it was the starting point for peer-to-peer feedback conversations. All study programs presented the LAD to their students as part of their curriculum. Students were invited to participate via email, a message on the digital learning environment, or by the first author (e.g., before a lecture). Students were asked to send an email to the first author to indicate their willingness to participate. Participants were placed in one of two conditions in order of signing up, meaning participant 1 was placed in condition 1, participant 2 in condition 2, and soforth. By doing so, participants were randomly divided over the two conditions in an attempt to make the two groups as comparable as possible. Participants in condition 1 ($n = 45$, 37 female, 4 male, 4 other/prefer not to say) used the LAD without a reference frame. Participants in condition 2 ($n = 43$, 39 female, 3 males, 1 other/prefer not to say) used the dashboard with a peer reference frame. Besides the explanation of the LAD in the study program, it was also explained in the information letter, and via a video in the LAD, to mitigate novelty effects. All data were gathered in 2023 on two measurement points, all regulations regarding the COVID pandemic were cancelled from the start of this academic year. Participants first interacted with the LAD individually and filled out a survey on goal setting and motivation. Participants were invited for a second survey 4 weeks later, measuring subsequent performance. Seventy-eight participants filled out both surveys. For condition 1 the time between filling out survey 1 and survey 2 was $(M\Delta_{\text{time}}) = 30.63$ days, $SD\Delta_{\text{time}} = 6.07$, and for condition 2 it was $M\Delta_{\text{time}} = 32.94$ days, $SD\Delta_{\text{time}} = 9.21$. For three participants, the response for survey 2 was excluded based on extremely short or long time ($X > M \pm 2SD$), between survey completion (69, 9, and 7 days). For one participant the data for 'Time spent in Hours' (455) in survey 2 was excluded, as this participant stated to have spent 455 h in 37 days (i.e., 12.3 h, every day). This was deemed highly improbable.

All participants provided informed consent and received €10 compensation after completion of both surveys. The study was approved by the Ethics Committee of the Faculty of Social and Behavioural Sciences of Utrecht University under file number 23-0148.

2.2 | Materials

2.2.1 | Learning Analytics Dashboard

In this study, an LAD (called 'Thermos') (Figure 2) was used to support students' appraisal of study behaviour (de Vreugd et al. 2024). It supports students' reflection on study behaviour, helps determine points of improvement, and offers suggestions for concrete actions to take. When first using the LAD, a video explains the dashboard's functionalities. Data are gathered via a self-assessment questionnaire, including demographics, the validated Motivation and Engagement Scale (MES, Martin 2007) and the validated Group work Skills Questionnaire (GSQ, Cumming et al. 2015). Results are presented in several graphs

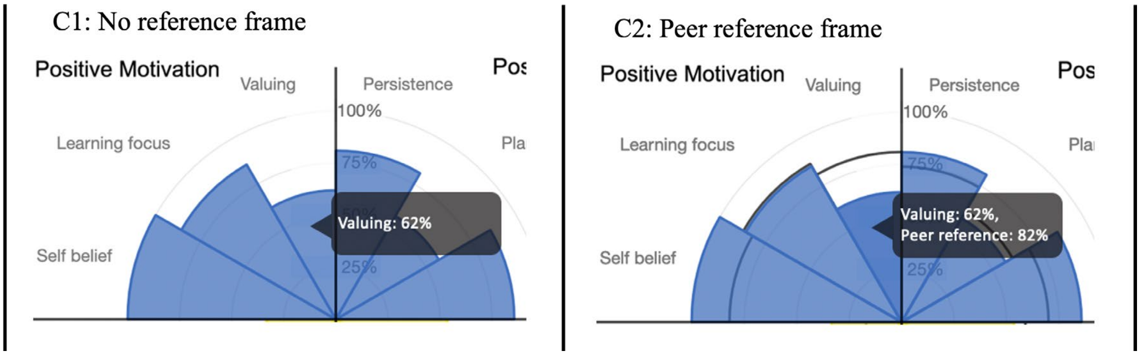

FIGURE 3 | Example of reference frame presentation and tool-tip information for Condition 1 and Condition 2.

(Figure 2, part 2 and 3). Study progress data is gathered from the university's data management system and presented as well (Figure 2, part 4). When students revisit the dashboard earlier data is accessible (Figure 2, part 5). If a user clicks or hovers on a construct, feedback is presented in the feedback box (Figure 2, part 6). This explains the meaning of that construct, presents the user's score as a percentage, and informs the user why the construct is important when studying at university. Via the 'Prepare', 'Act', and 'Reflect' buttons, actionable feedback is available. These show exercises to individually engage in. Via the 'Additional support' button, suggestions for further support (e.g., a study coach) are offered.

In Condition 1, participants had no direct reference frame. When hovering over a construct, these participants saw their percentage in a tooltip: a small, see-through textbox showing (e.g.) 'Valuing: 62%' (Figure 2, part 7). Participants in Condition 2 were presented with a peer reference frame in the dashboard, which in an earlier study showed a positive effect on internal feedback generation. This reference frame represents the peer average per construct and is visualised with a line per construct in the LAD. Percentages for the reference frame were based on MES guidelines (Martin 2016) and aggregated data from one earlier cohort of students. The reference frame was also explained in the feedback widget (Figure 2, part 6) as, e.g., 'For Valuing, the average score of your peers (peer reference) is: 82%'. When hovering over a construct, participants in this condition saw their score and the peer reference frame in the tooltip, for example, 'Valuing: 62% (Peer reference: 82%)' (Figure 3).

2.3 | Instruments

2.3.1 | TSSG Difficulty and Specificity

After using the LAD, participants were asked to formulate a higher order goal, in line with goal setting theory in SRL (Kim et al. 2023). Then participants articulated their most important, specific TSSG by answering an open-ended question, '*The actions or behaviours I'm going to perform to reach my goal are…*'. This two-phase procedure was chosen to ensure the TSSG would be aligned with a higher order goal.

TSSG difficulty was self-assessed by participants with one item ('*Performing this action is…*') on a 7-point Likert scale (0 = "Not at all difficult"' – 7 = 'Very difficult') (see Alessandri et al. 2020).

TSSG specificity was obtained by coding participants' formulated TSSG with the TASC framework (see McCardle et al. 2017), which provides 4 indicators of goal specificity: (1) if a specific Timeframe is determined to achieve the goal (e.g., 'within one week'), (2) if clear Actions or processes are defined (e.g., 'improve'), (3) if Standards are created for self-evaluation (e.g., 'at least 3 times'), and (4) if the Content is clearly defined (e.g., 'My planning' or 'an exercise') (Appendix A). All dimensions were scored with either 0 (not present) or 1 (at least somewhat present). TSSG specificity values could thus range from 0 to 4, with higher values indicating a higher specificity. Inter coder reliability was established by the first author and a research assistant after individually coding samples, calculating inter coder reliability using Krippendorff's α, and discussing interpretation differences. After 3 rounds, Krippendorff's α showed good reliability with 0.89, values of $\alpha \geq 0.80$ are deemed reliable (Krippendorff 2018). To check coding consistency over time (O'Connor and Joffe 2020), a fourth and fifth round of coding were done approximately 2 months later. As Krippendorff's α fluctuated in these coding rounds, we coded the entire dataset and discussed discrepancies.

2.3.2 | Readiness for Action and Motivational Antecedents

The UMTM survey was adapted to fit this study's purpose. It consists of 10 items (nine for motivational antecedents and one for readiness for action), all measured on a bipolar 7-point Likert scale (de Brabander and Glastra 2021; Jansen In De Wal et al. 2023). Measuring constructs with one item is not standard within social sciences, but short surveys make administering more appealing and can enhance response rates (Gogol et al. 2014).

2.3.3 | Perception of Dashboard Influence

To measure perceived influence of LAD elements on UMTM aspects, participants indicated per UMTM survey item if an LAD element influenced the UMTM item ('yes' or 'no'). If answered 'yes', participants saw a screenshot of the LAD with indications of LAD elements (Figure 2). Participants chose the element and how much that element affected the UMTM aspect (negative or positive). For example, if a participant experienced external support from the 'additional support' function, for the UMTM-item 'perceived external support' the participant would select 'yes' (for influence), choose 'additional support buttons', and select 'positive influence'.

2.3.4 | TSSG Attainment

The extent to which a task is performed can consist of various indicators (see e.g. Kim and Soergel 2005). In this study, this is indicated by four components. For task attainment, participants indicated if they had (at least partially) performed their self-set TSSG (yes/no). If they selected 'no', an explanation was asked. If answered yes, the extent of task attainment was measured through three separate indicators: task satisfaction, time on task, and task frequency.

Task satisfaction pertains to the gratification or satisfaction from reflection on goal execution, for example, feeling satisfied when completing a difficult task. Participants answered a question on a scale of 0–10 ('*How satisfied are you with the quality of task performance?*').

Time-on-task refers to the time spent on achieving the task, for example, spending an hour every day working on a task. For time on task, participants answered one question with a number up to 1 decimal ('*How much time did you spend on your task in hours?*').

Task frequency pertains to the frequency of task engagement, for example, finishing seven preparatory exercises before an exam. For task frequency, participants answered one question with a whole number ('*How often did you perform your task?*').

2.4 | Procedure

Before data collection, participants received an information letter, asked questions via email, and provided informed consent. They were then placed in one of two conditions. For survey 1, participants received an email with instructions and a link to the LAD. Instructions consisted of two parts, to (1) first use the LAD and (2) then fill out survey 1 (goal setting and motivation). Absence of instructions for LAD use were intentional, to minimise influence on LAD use and facilitate 'natural' use.

After 4 weeks, participants received another email with an invitation to fill out survey 2, measuring TSSG attainment. Participants' TSSG response from survey 1 was presented in survey 2 as a reminder of their self-set goal when answering the TSSG attainment questions.

2.5 | Data Analysis

RQ1a. *Differences between conditions on difficulty, specificity, and UMTM aspects.*

Independent samples *t*-tests were used to determine differences between conditions on TSSG specificity and on TSSG difficulty. To determine differences between conditions on UMTM aspects, MANOVA was used.

RQ1b. *Perceived Influence of LAD elements on UMTM aspects.*

Experienced influence of LAD elements on UMTM aspects will be presented with descriptive statistics in an overview table.

RQ2a. *Predictive value of difficulty, specificity, and readiness for action on task attainment.*

Logistic regression was used to determine the predictive value of TSSG difficulty, TSSG specificity, and readiness for action on task attainment. A model was devised based on this study's theoretical framework (as of now the predetermined model), with the following predictors: readiness for action (De Brabander and Martens 2014; de Brabander and Glastra 2021), TSSG difficulty, TSSG specificity, TSSG difficulty^2, and TSSG specificity^2 (Alessandri et al. 2020) (quadratic terms are added because non-linear effects were found for prediction of performance). TSSG attainment (yes/no) was the dependent variable. If the predetermined model resulted in a high p value with wide confidence intervals (CIs) and low explained variance, another logistic regression using stepwise backward deletion was run to explore the best fitting statistical model (from now on the exploratory model). In this model, the interaction terms for readiness for action, TSSG difficulty, and TSSG specificity were added as well.

The explanations participants gave after answering 'no' on Task were grouped into broad categories by the first author, then discussed with the second author. This qualitative data provides insight into the underlying reasons for not attaining a self-set goal.

RQ2b. *Predictive value of difficulty, specificity, and readiness for action on task satisfaction, time on task, and task frequency.*

To determine the predictive value of the predetermined model on task satisfaction, time on task, and task frequency, the procedure was similar to RQ2a. First, we tested the predetermined model's predictive value on the three dependent variables task satisfaction, time on task, and task frequency. If the predetermined model resulted in high p values with wide CIs and low explained variances, multiple regression analyses using stepwise backward deletion were run to explore the best fitting statistical model. Interaction terms for readiness for action, TSSG difficulty, and TSSG specificity were added in the exploratory models as well.

2.5.1 | Statistical Interpretation

When interpreting statistical output, we avoided 'statistically significant' as a label and reported all p values as continuous quantities (Wasserstein et al. 2019). We used 0.05 as an anchoring point to interpret continuous p values. We provided measures of uncertainty alongside p values where possible, (e.g.) standard errors or confidence intervals. Confidence intervals were interpreted as 'compatibility intervals' (Amrhein et al. 2019), showing the range of p values most compatible with the data under the applied model.

3 | Results

Descriptive statistics for all variables used in the study are presented in Table 1, split per condition. We explored whether this study's variables were potentially influenced by implementation differences between study programs (Appendix C) and gender (Appendix D). There seemed to be minor differences between study programs and between gender. However, the sample size did not allow for statistical testing of these differences. Some uncertainty regarding the influence of these variables therefore remains.

RQ1a. *Differences between Conditions on Difficulty, Specificity, and UMTM aspects.*

Differences between conditions on TSSG difficulty and TSSG specificity were assessed using separate t-tests. The assumption of equal variances was met (Brown-Forsythe $p=0.363$ for Difficulty and $p=0.743$ for specificity), the assumption for normality was met under the central limit theorem.

For difficulty, the mean difference between the no reference frame condition ($M=4.91$, SD $=1.33$) and the peer reference frame condition ($M=5.21$, SD $=0.94$) was 0.30 (95% CI [−0.192, 0.788]), resulting in $t(86)=1.21$, $p=0.229$, with Cohen's $d=0.26$ (95% CI [−0.677, 0.162]). From this p value with its CI and effect size with its CI, we concluded that no difference was found between conditions on TSSG difficulty.

For specificity, the mean difference between the no reference frame condition ($M=2.38$, SD $=0.72$) and the peer reference frame condition ($M=2.51$, SD $=0.67$) was 0.13 (95% CI [−0.428, 0.160]), resulting in $t(86)=0.905$, $p=0.368$, Cohen's $d=0.19$ (95% CI [−0.612, 0.226]). From this p value with its CI and effect size with its CI, we concluded that no difference was found between conditions on TSSG specificity.

Differences between conditions on UMTM aspects were assessed using a 1 (condition)×10 (UMTM aspects) MANOVA. The assumption of normality was met under the central limit theorem, the homogeneity of covariance assumption was met as well given the equal sample sizes (Field 2018). Using Pillai's trace, the MANOVA resulted in $V=0.100$, F (10, 77) $=0.90$, $p=0.574$, $\eta_p^2=0.100$. Given this large p value, the analysis found no difference between conditions on UMTM aspects.

RQ1b. *Perceived influence of LAD elements on UMTM aspects.*

Results of perceived influence of LAD elements on UMTM aspects (Appendix B) resulted in four points of interest. First, LAD elements differed in whether students named them as influencing UMTM aspects. The motivation and engagement graph was mentioned most, 65 times as a positive influence and 10 times as a negative influence. Additional support was mentioned least: 3 times as a positive influence and once as a negative influence. Second, UMTM aspects differed in frequency of being influenced. Positive Cognitive Valence was positively influenced 41 times and negatively influenced 2 times, whereas Negative Cognitive Valence was positively influenced 6 times and negatively influenced 3 times. Third, LAD elements influenced UMTM aspects in a mostly positive manner, as there are 209 counts of positive influence and 29 counts of negative influence. Fourth, the peer reference frame was not highly influential, as it was mentioned 7 times as a positive influence and 5 times as a negative influence.

RQ2a. *Predictive value of difficulty, specificity, and readiness for action on task attainment.*

Logistic regression analysis with the predetermined model on task attainment was applied to assess the extent to which readiness for action, TSSG difficulty, and TSSG specificity predicted participants (at least partial) performance of their TSSG. Results for the predetermined model are presented in Table 2. Model accuracy was 77.3%. Assumption of normality was met. Assumption of multicollinearity (i.e., VIF values below 10; Field 2018), was met for all regression analyses using the predetermined model (VIF values ranging from to 1.095 to 1.817).

As the predetermined model showed a high p value and low explained variance, another logistic analysis was performed with backward stepwise as method to explore the best fitting statistical model (based on model p value and explained variance). This resulted in the model shown in Table 3. Assumptions of normality and multicollinearity were met (VIF values between 1.358 and 2.512). Model accuracy was 80.0%. This model has a high p value (albeit lower than the predetermined model), with an equally low explained variance.

Participants who had not performed their self-set goal (18 out of 78) were asked to explain. Five participants indicated an absent context for task execution, (e.g.) having no exams to work on goals. Three participants indicated task execution was unnecessary, for example, '*I didn't think it was necessary as the exam material wasn't that much*'. Two participants indicated being distracted, two due to procrastination, and two because they forgot about it. Other reasons were a lack of motivation, less available time, and a difficulty of matching skills to real-life situations.

RQ2b. *Predictive value of difficulty, specificity, and readiness for action on task satisfaction, time on task, and task frequency.*

The predetermined model's predictive value was first assessed per dependent variable, task satisfaction, time on task, and task frequency (Tables 4–6). For all predetermined regression models, assumptions of normality were met. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are presented in Table 7, as commonly used metrics for model evaluation (Hodson 2022). Scores can range from 0 to ∞, with lower scores indicating better fit.

All predetermined models showed p values well above 0.05, and low to medium explained variance, indicating poor fit. Therefore, backward stepwise regression was used to explore the best fitting

TABLE 1 | Descriptive statistics for UMTM aspects, variables in the predetermined model, and dependent variables, split per condition.

Variable	Condition	Mean	Std. deviation	Skewness	Kurtosis
Sense of personal autonomy	1	5.13	1.39	−0.88	1.19
	2	5.35	1.36	−0.56	−0.28
Perceived freedom of action	1	5.07	1.27	−0.62	0.16
	2	4.91	1.27	−0.40	−0.13
Perceived external support	1	4.67	1.04	0.22	−0.36
	2	4.65	1.00	0.01	0.90
Sense of personal competence	1	4.60	1.27	−0.10	0.00
	2	4.74	1.45	−0.07	−0.91
Subjective norm	1	5.02	1.16	0.05	−0.80
	2	5.09	1.07	0.43	−0.62
Positive affective valence	1	4.64	1.25	−0.24	−0.04
	2	4.46	1.45	−0.39	0.02
Negative affective valence	1	3.49	1.12	0.03	0.24
	2	3.51	1.32	0.07	0.19
Positive cognitive valence	1	5.93	1.05	−0.96	0.83
	2	6.16	0.79	−0.61	−0.14
Negative cognitive valence	1	4.53	1.36	−0.39	−0.17
	2	4.95	1.5	−0.25	−1.15
Readiness for action	1	4.33	1.19	−0.35	−0.25
	2	4.86	1.44	−0.85	0.43
TSSG difficulty	1	4.91	1.33	−1.11	1.40
	2	5.21	0.94	−0.26	0.17
TSSG specificity	1	2.38	0.72	0.06	−0.12
	2	2.51	0.67	0.96	−0.17
TSSG difficulty^2	1	1.75	3.34	2.86	8.91
	2	0.89	1.22	1.85	2.62
TSSG specificity^2	1	0.42	0.64	3.77	15.49
	2	0.48	0.84	3.00	8.74
TSSG attainment (yes/no)	1	0.71	0.46	−0.95	−1.16
	2	0.85	0.36	−2.09	2.50
Task satisfaction	1	6.32	1.60	−1.70	2.54
	2	6.06	1.62	−1.55	2.49
Time on task (hours)	1	11.84	18.95	2.67	7.34
	2	5.88	7.90	2.29	6.06
Task frequency	1	6.31	6.01	2.10	5.28
	2	7.07	7.46	2.24	4.83

statistical model per dependent variable (Tables 8–10). For all models, assumptions of normality were met. As multicollinearity issues can arise when adding interaction terms in regression, all independent variable means were first centred around zero (Shieh 2011). After centring variable means, multicollinearity assumptions were met for all exploratory models (VIF values between 1.023 and 1.138). Table 11 provides accuracy metrics for the exploratory regression models (MAE and RMSE).

TABLE 2 | Logistic regression of the predetermined model on task attainment.

	B	SE	*p*
Constant	1.121	2.58	0.664
Readiness for action	0.30	0.22	0.170
TSSG difficulty	−0.22	0.33	0.506
TSSG specificity	−0.08	0.47	0.858
TSSG difficulty^2	0.10	0.19	0.579
TSSG specificity^2	0.09	0.47	0.852

Note: Model $\chi^2(5)=3.87$, $p=0.568$, $R^2=0.05$ (Cox-Snell), 0.08 (Nagelkerke). Method of regression was 'Enter'.

TABLE 3 | Best logistic regression model (5 out of 8) with readiness for action, TSSG difficulty, TSSG difficulty^2 TSSG specificity, TSSG specificity^2, and interaction terms on task attainment.

	B	SE	*p*
Constant	4.50	2.18	0.039
TSSG difficulty	−0.53	0.30	0.079
TSSG specificity	−0.85	0.62	0.174
TSSG difficulty * TSSG specificity * readiness for action	0.03	0.02	0.087

Note: Model $\chi^2(3)=4.57$, $p=0.206$, $R^2=0.06$ (Cox-Snell), 0.09 (Nagelkerke). Method of regression was 'backward'.

TABLE 4 | Predetermined model regression on dependent variable task satisfaction.

	B	[95% CI]	SE	*p*
Constant	6.37	[2.80, 9.95]	1.78	<0.001
Readiness for action	0.37	[0.02, 0.72]	0.18	0.040
TSSG difficulty	−0.21	[−0.67, 0.25]	0.23	0.364
TSSG difficulty^2	−0.02	[−0.21, 0.17]	0.09	0.837
TSSG specificity	−0.31	[−0.97, 0.35]	0.33	0.344
TSSG specificity^2	−0.11	[−0.80, 0.58]	0.34	0.749

Note: Model F(5) = 1.40, $p=0.238$, $R^2=0.12$. Method of regression was 'Enter'.

This result shows that this exploratory model may predict task satisfaction, based on the *p* value well below 0.05. Task satisfaction is negatively influenced by TSSG difficulty and TSSG specificity as single independent variables. However, task satisfaction is positively affected by readiness for action, and both interaction terms are positive predictors as well.

A satisfactory task performance therefore seems more easily achieved when goals are less difficult and less specified, for example, '*I'm going to study every day*' is not difficult and not specific, so more easily achieved than '*I want to study for at least two hours every day following a predetermined study schedule*'. Also, readiness for action adds to the model's strength in the interaction with TSSG difficulty, and with TSSG specificity. This indicates that higher TSSG difficulty and higher TSSG specificity require a high readiness for action to attain high task satisfaction. However, the amount of variance explained by the model is relatively low, which indicates other variables are likely influential.

TABLE 5 | Predetermined model regression on dependent variable time on task (Hours).

	B	[95% CI]	SE	*p*
Constant	12.28	[−22.21, 46.76]	17.18	0.478
Readiness for action	1.54	[−1.70, 4.77]	1.61	0.345
TSSG difficulty	0.42	[−4.17, 5.02]	2.29	0.854
TSSG difficulty^2	−0.44	[−2.25, 1.36]	0.90	0.623
TSSG specificity	−5.84	[−11.88, 0.21]	3.01	0.058
TSSG specificity^2	4.49	[−1.91, 10.89]	3.19	0.165

Note: Model F(5) = 1.24, $p=0.307$, $R^2=0.11$. Method of regression was 'Enter'.

This result indicates that this model does not adequately predict time on task, given the *p* value well above 0.05 and the relatively low explained variance.

TABLE 6 | Predetermined model regression on dependent variable task frequency.

	B	[95% CI]	SE	*p*
Constant	13.61	[−1.77, 28.99]	7.66	0.082
Readiness for action	−1.00	[−2.51, 0.51]	0.75	0.190
TSSG difficulty	0.10	[−1.89, 2.08]	0.99	0.924
TSSG difficulty^2	−0.26	[−1.06, 0.55]	0.40	0.525
TSSG specificity	−0.82	[−3.65, 2.02]	1.41	0.566
TSSG specificity^2	−0.73	[−3.69, 2.23]	1.47	0.622

Note: Model F(5) = 0.85, $p=0.519$, $R^2=0.08$. Method of regression was 'Enter'.

This result shows that this model does not predict task frequency, given the *p* value well above 0.05 and the low explained variance.

TABLE 7 | Accuracy metrics for the predetermined regression model.

Dependent variable	Sum of squared residuals	MAE	RMSE
Task satisfaction	128.8	1.15	1.59
Time on task	10625.65	10.48	14.58
Task frequency	2381.26	4.48	6.83

TABLE 8 | Exploratory model (4 out of 8) for task satisfaction.

	B	[95% CI]	SE	*p*
Constant	6.144	[5.717, 6.572]	0.213	< 0.001
Readiness for action	0.369	[0.030, 0.708]	0.169	0.033
TSSG difficulty	−0.305	[−0.648, 0.038]	0.171	0.080
TSSG specificity	−0.473	[−1.067, 0.121]	0.296	0.116
TSSG difficulty * readiness for action	0.259	[−0.033, 0.551]	0.146	0.081
TSSG specificity * readiness for action	0.553	[−0.116, 1.222]	0.333	0.103

Note: Model F(5) = 2.74, $p = 0.029$, $R^2 = 0.21$. Method of regression was 'backward'.

TABLE 9 | Exploratory model (6 out of 9) for time on task.

	B	[95% CI]	SE	*p*
(Constant)	6.844	[2.106, 11.583]	11.297	0.005
TSSG specificity	−5.702	[−11.300, −0.105]	2.791	0.046
TSSG specificity^2	5.047	[−0.821, 10.915]	2.926	0.090
TSSG difficulty * specificity * readiness for action	−3.406	[−8.694, 1.882]	0.2.636	0.202

Note: Model F(3) = 2.20, $p = 0.099$, $R^2 = 0.11$. Method of regression was 'backward'.

TABLE 10 | Exploratory model (8 out of 8) for task frequency.

	B	[95% CI]	SE	*p*
(Constant)	6.693	[4.953, 8.432]	0.869	< 0.001
Readiness for action	−1.193	[−2.559, 0.213]	0.702	0.095

Note: Model F(1) = 2.89, $p = 0.095$, $R^2 = 0.05$. Method of regression was 'backward'.

TABLE 11 | Accuracy metrics for exploratory regression models.

Dependent variable	Sum of squared residuals	MAE	RMSE
Task satisfaction	115.70	1.05	1.51
Time on task	10595.44	10.63	14.27
Task frequency	2450.09	4.48	6.67

4 | Discussion

This study explored the influence of a reference frame on goal difficulty, specificity, and motivational antecedents. Furthermore, it explored students' perceived influence of LAD elements on motivational antecedents. Also, the predictive value of TSSG difficulty, TSSG specificity, and readiness for action was assessed for task attainment, task satisfaction, time on task, and task frequency. By doing so, we gained insight in the factors that may contribute to goal performance and how LAD elements contribute to this performance.

RQ1a focussed on differences between conditions on TSSG difficulty, TSSG specificity, readiness for action, and motivational antecedents. Neither *t*-tests nor MANOVA showed any differences between conditions. RQ1b explored the perceived influence of LAD elements on UMTM aspects. The amount of perceived influence on UMTM aspects varied, as did the amount of perceived influence from LAD elements. The peer reference frame had little perceived influence on UMTM aspects, which could explain the similarity in scores on motivational antecedents and readiness for action. Overall, the perceived influence of LAD elements on UMTM aspects was positive. These results suggest that goal-setting and self-motivation in the preparatory phase of SRL is not influenced by availability of reference frames. This could be due to students' use of the reference frame. It serves as comparator for internal feedback generation in the appraisal phase (de Vreugd et al. 2023), but once a topic is selected to work on, the reference frame may not be included in the process of goal-setting or self-motivation. Other components like the actionable feedback, exercises, or additional support (Figure 2, part 6) are more relevant for goal-setting and self-motivation in the preparatory phase (and designed to support that phase). The actionable feedback and exercises had the 2nd and 3rd highest perceived influence on UMTM aspects, the additional support the 2nd least. The lack of difference between conditions could also be due to the reference frames' magnitude as an intervention. The LAD consists of multiple components (Figure 2), adding a reference frame makes a small change in the totality of components.

The lack of difference between conditions on motivation in this study aligns with findings from Lim et al. (2019), who found no difference on motivation between four conditions with varying reference frames. Our findings contrast findings from Beheshitha et al. (2016) who found reference frames influencing learners' goal orientation undesirably. These differences could be due the different motivational perspectives. The UMTM (in this study) is intended to be broad enough to accommodate different kinds of goals. However, the goal orientation perspective (as used by Beheshitha and colleagues) is not included in the UMTM. Lim et al. (2019) applied the Motivated Strategies for Learning Questionnaire, which is based on three general motivational constructs; expectancy, value, and affect (see Duncan and McKeachie 2005). Within the UMTM, expectancy value theory and affective measures are included as well, potentially explaining the alignment in findings. This implies that reference frames may affect distinct elements of motivation. Furthermore, both affective valences in the UMTM (see Appendix B) had a relatively low but positive perceived influence. These findings differ from Lim et al. (2019), as 69% of their participants reported negative affect (e.g., 'stressed' or 'worried') when perceiving reference frames. The potential elicitation of negative affect could be due to the reference frame's interaction with the LAD's content. Lim et al. (2019) LAD presented course activities and accompanying completion rates. The most reported reasons for negative affect were 'lack of effort' (disappointment because there was much more that should have been done) and 'comparison with peers' (anxiety from thinking about peers engaging and performing at higher levels). The LAD in the current study showed no objectives or activities to complete, but aspects of study behaviour. Participants were not confronted with unfinished objectives, and consequently, the 'lack of effort' (and subsequent negative affect) may have been avoided. The 'comparison with peers' reason is not applicable either, as the peer reference frame in our study presented an average study behaviour, not their performance on higher levels.

RQ2a regarded the extent to which TSSG difficulty, TSSG specificity and readiness for action were predictive of task attainment. RQ2b pertained to the extent to which TSSG difficulty, specificity and readiness for action are predictive of task satisfaction, time on task, and task frequency. The predetermined model was not predictive for any of the dependent variables, only the exploratory model for task satisfaction showed predictive potential.

The results show there was no intention-behaviour gap for most participants (contrary to expectations), as 58 out of 75 participants (77%) had a least partially performed their intended task. Neither the predetermined nor the exploratory models predicted this level of task attainment, indicating that it is likely influenced by other factors such as conscientiousness or intention stability (Rhodes et al. 2022). The attainment rate could also be caused by the prompt of being asked to formulate one higher order goal and one subsequent TSSG. Kim et al. (2023) describe goal setting as dynamic and within a broader context of multiple goals, which must be constantly managed, prioritised, evaluated, and revised. The prompt within this study could have increased the self-set goal's priority, which may have led to more time or effort being spent on its attainment. Also, by deliberately setting a goal because of this study's prompt, students may have avoided goal-conflicts which negatively moderate the intention-behaviour relation (Rhodes et al. 2022). It could also be that students' need for autonomy and the applied amount of prompting were properly balanced. Being able to exercise autonomy with respect to a specific task improves motivation (Deci and Ryan 2000). Self-setting goals may increase this autonomy, resulting in ownership, proactivity, and empowerment (Elliot and Fryer 2008).

Participants in this study were only prompted to set a goal but not supported by providing (e.g.) the TASC framework or information about desirable difficulties. Asking participants to set goals with the TASC framework may lead to more specific goals. Also, asking students to set goals with a 'desirable difficulty' could lead tasks with an adequate difficulty, which can support learning (Bjork and Bjork 2020). The exploratory model showed that the interaction between TSSG difficulty, specificity, and readiness for action may predict higher task satisfaction. Conversely, higher TSSG specificity and difficulty separately led to lower task satisfaction. Supporting students in balancing TSSG specificity, difficulty, and readiness for action when self-setting goals could be worthwhile.

On the other hand, sense of personal autonomy had a high count of perceived LAD influence (39 positive, 11 negative) (Appendix B). If students' goal-setting process are supported or structured, their autonomy may be impacted. Of the participants in this study that did not perform their task, five explained the context for task performance was absent (e.g., an irregular study roster), two were distracted, two were procrastinating, and two forgot about the goal. These causes may be caused the integration of the LAD. If an LAD is integrated into an educational context, it should be an integral element in students' learning processes, aligning with for example, their goals and planned learning process (Wise et al. 2016). If students are supported when self-setting goals, factors of LAD integration (e.g., available time or deadlines) could also be considered.

Furthermore, for TSSG specificity and difficulty our findings conflict with Alessandri et al. (2020). They found that both self-set TSSG specificity and difficulty influenced students' behaviour. This difference in findings could be due to the operationalization of variables. In Alessandri et al. (2020), both specificity and difficulty were coded by the researchers. As we deemed TSSG difficulty to depend on (e.g.) available skills or prior knowledge, participants in the current study determined the TSSG's difficulty. Alessandri et al. (2020) stress the importance of students' ability of defining goals with appropriate difficulty and specificity. However, perception of a goal's specificity and difficulty can vary among individuals. It could be worthwhile to match researcher coded and participants' self-reported difficulty and specificity, to determine how well they relate to (e.g.) task satisfaction. Also, there are multiple frameworks to assess a TSSG's specificity. Besides the TASC model (McCardle et al. 2017) applied in this study, the SMART framework (Specific, Measurable, Achievable, Relevant, and Time-bound) may influence TSSG specificity assessment.

Moreover, for task-specific motivation our findings conflict with literature showing that motivation is predictive for behaviour, for example, transfer of training (Jansen In De Wal et al. 2023) or learning ICT skills (de Brabander and Glastra 2021). However, in these studies, the goal and task that is referred to are the same for all participants, (e.g.) putting the training content into practice. In the current study, participants' varying self-set goals may have led to varying build ups of motivation. Furthermore, students' motivational processes develop and change in an interplay with their context (Turner and Patrick 2008), and goal pursuit processes are impacted by environmental conditions such as peer relationships or instructor support (Massey et al. 2008). It could well be that students' task-specific motivation is influenced between goal setting and task attainment, resulting in no predictive properties of readiness for action when the goal is set.

4.1 | Implications

From these results, we present two implications.

First, deciding if and what reference frame to include in an LAD should be carefully considered by educators. The peer reference frame in this study had a limited influence. Since a peer reference frame supports internal feedback generation (de Vreugdet et al. 2023) and reference frames in general may support learners' interpretation of data (Wise et al. 2016), including a reference frame may be advisable. However, reference frames may also elicit negative emotions (e.g., Lim et al. 2019) or influence learners' goal orientation in an undesirable way (Beheshitha et al. 2016). The type of reference frame and how it interacts with the LAD's content is part of this consideration. A social norm reference frame can present an average peer student (like in this study), or scores of top-achieving students that present something to achieve or strive towards. Both these reference frames could elicit feelings of anxiety or performance goal orientation (Beheshitha et al. 2016). Compared to a social reference frame, a progress reference frame (which presents learner progress over time) may lead to greater positive changes in self-efficacy (Gallagher et al. 2024). All in all, careful deliberation and thorough evaluation is required when integrating reference frames in an LAD for students.

Second, educators should consciously balance students' autonomy and provision of support for students' goal setting when integrating the LAD into an educational context. In this study, participants were only asked to formulate their higher order goal and task specific subgoal but were not supported in their goal setting. Supporting students when they set their goals may result in more balanced goals in terms of specificity, difficulty, and readiness for action. However, this support could also be perceived by students as restrictive to their autonomy, which could negatively affect their motivation to pursue goals. Educators could also consider providing other technology to support students. Recent studies found that Generative AI (e.g., chat bots or large language models) may support students' personal needs in SRL (Wong and Viberg 2024) and support problem-solving within SRL (Cohen and Cohen 2024). Balancing student needs and provision of support is part of the broader LAD integration into an educational context. Participants' reasons for not attaining their goal (e.g., forgetting about the goal) may be mitigated by a different integration. Balancing student autonomy and provision of support when students self-set goals, as well as other factors of LAD integration, may further increase their task attainment.

4.2 | Limitations

This study bears some limitations. First, self-report instruments are criticised regarding their relation to behaviour. They can be suitable in tertiary education where observational assessment methods are neither interpretable nor practical outside a laboratory setting (Roth et al. 2016). In this study, the behaviour for which participants set goals (i.e., study behaviour) can be fluid and take place at varying moments, in varying context, and over the course of several weeks. This might make it difficult for students to reliably assess (e.g.) the amount of time spent working on that goal, potentially influencing measurement reliability.

Second, participants in this study came from several study programs which integrated the LAD in their educational program. These integrations differed from one another, potentially influencing (e.g.) how LAD use was structured in the program which could affect the available time to attain tasks.

Third, the voluntary participation within this study could have led to a potential selection bias. The selection bias may have led to an overrepresentation of highly motivated or conscientious students, resulting in the lack of intention behaviour gap in this study.

Finally, multiple other factors potentially influence students' goal setting and goal achievement within SRL but were not included in this study. For example, variables like conscientiousness or intention stability (Rhodes et al. 2022), as well as social and cultural identity (Kim et al. 2023) were not included. Both gender and study program were included as variables, but sample sizes were too small to statistically assess potential differences. For gender, the balance of female ($n = 76$) compared to male students ($n = 7$) does not reflect the university's population.

4.3 | Future Research

We provide several suggestions for future research. First, research where participants report (e.g.) their time on task and task frequency regularly (e.g., daily) could provide a more fine-grained insight in the potentially dynamic processes of working on and achieving goals. Combined with regular measurements of motivational processes, this could shed light on the aforementioned potential motivational changes, and map aspects of students' motivation over time. The stability of students' intentions may also be included, as this is an important potential mediator of the intention—behaviour relation. If these aspects are measured on multiple moments over a period of time, this provides insight in how goal attainment and motivational factors evolve over time.

Second, the current study focused on participants' (perceived) most important TSSG to achieve their most important higher order goal. Future research could explore the intricacies of the multi-layered goal network in SRL (Kim et al. 2023), and how factors as goal specificity and difficulty, availability of reference frames, and motivation interact over time. Including non-academic goals in this research could prove valuable, as students' goal setting is embedded in wider social and cultural contexts (Kim et al. 2023). This could help understand how students regulate multiple goals, make prioritizations, give up on certain goals, and what drives them to achieve certain goals.

Third, the current study included two conditions, one without reference frame and one with a peer reference frame. No difference between these conditions were found on goal specificity and difficulty or motivation, but other studies found differences between reference frames on different aspects of learning (e.g., goal orientation, Beheshitha et al. 2016; self-efficacy change, Gallagher et al. 2024). Exploring how different types of reference frames interact with LAD content, and how they may influence aspects of learning in multiple goals regulation processes would advance our understanding of LADs supportive properties in SRL.

Finally, future research could explore the potential influence of additional factors when it comes to a LAD's influence on students' goal setting and goal attainment. These are, among others, conscientiousness, intention stability, and students' social and cultural identity.

4.4 | Conclusion

In this study we examined the perceived influence of LAD-elements' on task-specific motivation, and a peer reference frame's influence on self-set goal difficulty, specificity, and readiness for action. Furthermore, we explored how these three variables predict of task attainment. Our results suggest that an LAD has a (mostly) positive effect on task-specific motivation, and that a peer reference frame is not very influential on this motivation. The results also suggest that task attainment, time on task, and task frequency are likely predicted by other factors than those in this study. Only task satisfaction may be predicted by the three variables in this study.

The scientific contribution of this study is adding to our understanding of the factors that predict whether students attain their goals. Given our results, other factors such as intention stability or conscientiousness may be pieces of the puzzle to include in further research.

The practical contribution of this study is providing arguments to the ongoing discussion of including reference frames in LADs. Our results argue in favour of including reference frames in an LAD. Educators can support students when they set goals, but caution is advised as it may negatively impact their autonomy. Understanding how to support students when they set goals, or during the process of attaining these goals remains an important topic.

Author Contributions

Lars de Vreugd: conceptualization, investigation, formal analysis, writing – original draft, methodology, data curation. **Anouschka van Leeuwen:** conceptualization, investigation, writing – review and editing, methodology, formal analysis. **Marieke van der Schaaf:** conceptualization, supervision, writing – review and editing, funding acquisition, methodology.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data available by contacting corresponding researcher.

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Appendix A

Codebook for Coding Specificity

Construct	Definition	Example	Notes
*T*imeframe	A *timeframe* is defined within the action is to be performed or achieved.	… within 4 weeks … … a moment each day … … when …	
*A*ctions	An *action* is defined, for example identify, evaluate, apply, process. These can be cognitive and/or behavioural.	… following a… … making a… … thinking about… … reflecting on …	> This is something you do, not the content. These are often verbs.
*S*tandards	*Standards* are defined which can be used for self-evaluation. For example, an amount, a degree, or demands to achieve the action	… At least 3 h… … at least 6 times … … get at least a 7/10 …	> For example, 'get clear what of who and when' > these are sort of assessment criteria
*C*ontent	The goal defines the *content* (or concepts) that are to be learned/practiced/changed, or what the insight/reflection should be about.	… my planning … … being nervous …	> this is the 'what'

Appendix B

Perceived Influence (Positive/Negative) of LAD Elements on Motivational Antecedents

Motivation antecedent	Condition	Motivation and engagement graph	Feedback box	Self-completion exercises	Tooltip with construct %	Dashboard in general	Peer reference frame (C2)	Group work skills graph	Study progress widget	Additional support	I do not know	Total
Sense of personal autonomy	C1	5/1	4/1	1/—	6/1	3/—	—	—	—	—	—	19/3
	C2	11/3	2/—	—	3/1	1/1	2/3	—	—	—	—	20/8
Positive cognitive valence	C1	8/—	5/—	3/—	3/—	—	—	2/—	1/—	1/—	—	24/—
	C2	4/—	4/2	3/—	2/—	—	1/—	—	—	—	1/—	17/2
Sense of personal competence	C1	7/2	2/—	4/—	2/1	1/—	—	—	—	—	—	16/3
	C2	7/—	5/—	3/—	2/—	1/—	—	—	1/—	—	—/1	19/1
Readiness for action	C1	2/2	4/—	—	—	3/—	—	2/—	1/—	—	—	12/2
	C2	9/—	3/—	—	2/—	4/—	1/—	—	1/—	—	—	20/—
Perceived external support	C1	1/—	3/—	4/—	—	—	—	—	—	—/1	—	7/1
	C2	—	4/—	4/—	—	1/—	1/—	—	—	—	—	10/—
Positive affective valence	C1	3/—	3/—	—	1/—	1/—	—	—/1	—	1/—	—	9/1
	C2	2/—	1/—	—	—/1	3/—	1/—	—	—	—		7/1
Perceived freedom of action	C1	—/1	1/—	3/—	—	1/—	—	—	—	—	—	5/1
	C2	—	2/—	—	—	1/—	—	—	—	—	1/—	4/—
Negative affective valence	C1	1/—	—	1/—	—	—	—	—	—	1/—	—	3/—
	C2	3/—	2/—	—	—/1	—	—	—	—	—	—	5/1
Negative cognitive valence	C1	1/—	—	—	1/1	—	—	—	1/—	—	—	3/1
	C2	—/1	—	3/—	—	—/1	—	—	—	—	—	3/2
Subjective norm	C1	—	—	—	—	1/—	—	1/—	—	—	—	2/—
	C2	1/—	—	—	—	—	1/2	2/—	—	—		4/2
Total	C1	28/6	22/1	16/—	13/3	10/—	—	5/1	3/—	3/1	—	101/12
	C2	37/4	23/2	13/—	9/3	11/2	7/5	2/—	2/—	—	2/1	108/17

Appendix C

Variables per Study Program

Variable	Study program	*N*	Study program mean	ΔStudy program mean—variable mean	Std. deviation
TSSG difficulty	1	19	5.32	0.03	0.67
	2	1	5.00	−0.29	0.00
	3	62	4.90	−0.38	1.25
	4	2	6.50	1.21	0.71
	5	3	6.00	0.71	1.00
	6	1	4.00	−1.29	0.00
		Variable mean:	5.29		
TSSG specificity	1	19	2.32	−0.02	0.67
	2	1	3.00	0.67	0.00
	3	62	2.52	0.18	0.70
	4	2	2.50	0.17	0.71
	5	3	1.67	−0.67	0.58
	6	1	2.00	−0.33	0.00
		Variable mean:	2.33		
TSSG difficulty^2	1	19	0.49	−0.70	0.48
	2	1	0.00	−1.19	0.00
	3	62	1.64	0.45	2.95
	7	2	2.32	1.14	2.04
	11	3	1.55	0.36	1.97
	13	1	1.12	−0.06	0.00
		Variable mean:	1.19		
TSSG Specificity^2	1	19	0.44	0.04	0.65
	2	1	0.36	−0.04	0.00
	3	62	0.46	0.06	0.66
	7	2	0.25	−0.15	0.06
	11	3	0.76	0.36	1.06
	13	1	0.13	−0.27	0.00
		Variable mean:	0.40		
Readiness for action	1	19	4.42	0.01	1.39
	2	1	5.00	0.59	0.00
	3	62	4.71	0.30	1.23
	4	2	2.00	−2.41	1.41
	5	3	4.33	−0.08	2.08
	6	1	6.00	1.59	0.00
		Variable mean:	4.41		

Variable	Study program	*N*	Study program mean	ΔStudy program mean—variable mean	Std. deviation
Task attainment	1	16	0.88	0.24	0.34
	2	1	1.00	0.36	0.00
	3	52	0.77	0.13	0.43
	4	2	0.50	−0.14	0.71
	5	3	0.67	0.03	0.58
	6	1	0.00	−0.64	0.00
		Variable mean:	0.64		
Task frequency	1	14	6.07	−0.74	3.97
	2	1	3.00	−3.81	0.00
	3	40	6.98	0.17	7.60
	4	1	15.00	8.19	0.00
	5	2	3.00	−3.81	0.00
	6	0	—	—	—
		Variable mean:	6.81		
Task satisfaction	1	14	6.04	−0.11	1.69
	2	1	6.00	−0.15	0.00
	3	40	6.26	0.11	1.63
	4	1	6.50	0.35	0.00
	5	2	5.95	−0.20	2.19
	6	0	—	—	—
		Variable mean:	6.15		
Time on task (hours)	1	14	10.56	4.52	17.57
	2	1	1.00	−5.04	0.00
	3	40	8.65	2.61	14.35
	4	1	2.00	−4.04	0.00
	5	2	8.00	1.96	9.90
	6	0	—	—	—
		Variable mean:	6.04		

Appendix D

Variables per Gender

Variable	Gender (1 = male, 2 = female, 3 = other, 4 = prefer not to say)	*N*	Gender mean	ΔGender mean—variable mean	SD
TSSG difficulty	1	7	4.71	−0.68	0.95
	2	76	5.03	−0.37	1.18
	3	2	5.50	0.11	0.71
	4	3	6.33	0.94	0.58
		Variable mean:	5.39		

Variable	Gender (1 = male, 2 = female, 3 = other, 4 = prefer not to say)	*N*	Gender mean	ΔGender mean—variable mean	SD
TSSG difficulty[2]	1	7	0.90	−0.24	1.55
	2	76	1.37	0.23	2.69
	3	2	0.44	−0.69	0.62
	4	3	1.84	0.71	1.66
		Variable mean:	1.14		
TSSG specificity	1	7	2.43	0.20	0.54
	2	76	2.47	0.25	0.72
	3	2	2.00	−0.23	0.00
	4	3	2.00	−0.23	0.00
		Variable mean:	2.23		
TSSG specificity[2]	1	7	0.22	−0.08	0.19
	2	76	0.49	0.19	0.69
	3	2	0.28	−0.02	0.09
	4	3	0.22	−0.08	0.06
		Variable mean:	0.30		
Readiness for action	1	7	4.71	0.50	1.60
	2	76	4.65	0.43	1.32
	3	2	4.50	0.29	0.71
	4	3	3.00	−1.21	0.00
		Variable mean:	4.21		
Task attainment	1	5	0.60	−0.04	0.55
	2	65	0.80	0.16	0.40
	3	2	0.50	−0.14	0.71
	4	3	0.67	0.03	0.58
		Variable mean:	0.64		
Task frequency	1	3	15.33	6.60	12.50
	2	52	6.10	−2.64	6.05
	3	1	2.00	−6.73	—
	4	2	11.50	2.77	9.19
		Variable mean:	8.73		
Task satisfaction	1	3	6.87	0.77	0.55
	2	52	6.19	0.09	1.66
	3	1	6.00	−0.10	—
	4	2	5.35	−0.75	1.49
		Variable mean:	6.10		
Time on task (hours)	1	3	11.00	5.76	12.29
	2	50	9.22	3.98	15.22
	3	1	0.00	−5.24	—
	4	2	0.75	−4.49	0.35
		Variable mean:	5.24		