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Learning analytics dashboard design: Workplace learner preferences for reference frames in immersive training in practice

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Abstract

Background: Learning analytics dashboards are increasingly being used to communicate feedback to learners. However, little is known about learner preferences for dashboard designs and how they differ depending on the self-regulated learning (SRL) phases the dashboards are presented (i.e., forethought, performance, and self-reflection phases) and SRL skills. Insight into design preferences for dashboards with different reference frames (i.e., progress, social, internal achievement and external achievement) is important because the effectiveness of feedback can depend upon how a learner perceives it.

Objective: This study examines workplace learner preferences for four dashboard designs for each SRL phase and how SRL skills relate to these preferences.

Methods: Seventy participants enrolled in a chemical process apprenticeship program took part in the study. Preferences were determined using a method of adaptive comparative judgement and SRL skills were measured using a questionnaire. Preferences were tested on four dashboard designs informed by social and temporal comparison theory and goal setting theory. Multinomial logistic regressions were used to examine the relationship between dashboard preferences and SRL.

Results and Conclusions: Results show that the progress reference frame is more preferred before and after task performance, and the social reference frame is less preferred before and after task performance. It was found that the higher the SRL skill score the higher the probability a learner preferred the progress reference frame compared to having no preference before task performance. The results are consistent with other findings, which suggest caution when using social comparison in designing dashboards which provide feedback.

KEYWORDS

immersive learning environments, learning analytics dashboards, reference frames, social comparison theory, temporal comparison theory, workplace learning

1 | INTRODUCTION

Immersive environments are increasingly being used for workplace-based training (Langley et al., 2016; Li et al., 2017). A main advantage here is the application of learning analytics dashboards (LADs). Learning analytics involves the measurement, collection, analysis and reporting of learner data to support and optimise learning (Siemens & Gasevic, 2012). LADs visualise learner data (e.g., performance score) by providing different types of reference frames, which are data comparison points (e.g., time, peers) which orient learners' interpretation of provided analytics data (Wise, 2014). Comparing data from different viewpoints can support learners by providing feedback on task performance (Valle et al., 2021; Wise, 2014) and stimulate self-regulated learning (SRL) behaviours (Jivet et al., 2017; Matcha et al., 2019). SRL has been coined as "the control students have over their cognition, behaviour, emotions and motivation through the use of personal strategies to achieve the goals they have established" (Panadero & Alonso-Tapia, 2014, pp. 1–2). It is a cyclical process which consists of three interrelated phases, which should all be stimulated by the LAD design (Winne, 2017; Zimmerman, 2013):

- forethought phase: taking place before the task and involving learners' implementing task strategies such as goal setting and strategic planning (Panadero & Alonso-Tapia, 2014; Zimmerman, 2002).
- performance phase: taking place during task performance and involving learners to monitor their own performance and optimise their learning efforts (Panadero, 2017; Zimmerman, 2002; Zimmerman & Moylan, 2009).
- self-reflection phase: taking place after task performance and involving learners to self-evaluate and attribute their success or failure to particular causes (Panadero & Alonso-Tapia, 2014; Zimmerman, 2013).

The effectiveness of LADs is, however, affected by how learners perceive and use them (Jivet et al., 2018; Nicol, 2020; Winstone et al., 2017). To address this, we combine insights from LADs, social and temporal comparison theory and goal setting theory. Based on these insights, different types of LAD's will be developed and augmented in an immersive learning environment for a workplace setting. Workplace learners' preferences for LADs and their perceived self-regulation behaviour will be examined to gain more insight into their interrelationship.

The significance of this research lies in its novel focus on the often-overlooked demographic of workplace learners, exploring their learning preferences within professional, immersive environments. Moreover, it provides a detailed examination of the different phases of the SRL cycle in this context, probing into learner preferences related to each phase. The insights gained from this research will enhance our understanding of workplace learner perceptions of LADs and also contribute to the broader literature on learning analytics and self-regulated learning.

2 | DESIGNING LADs

Although the use of reference frames might stimulate performance and SRL behaviour, clear rules of thumb for designing them are lacking (Janson et al., 2022; Wilson & Shanahan, 2020). A first step in this direction is examining what is known about the use of comparisons in general and more specifically, into the relationship between SRL behaviour and learners' preferences. These generic insights could be valuable for designing LADs for the workplace setting this study is targeting. Social comparison, temporal comparison and goal setting theory are explored to gain insight into which types of references frames might be valuable. Furthermore, generic insight into learner preferences are provided.

2.1 | Types of reference frames

Comparing performance scores might stimulate learners to determine how much progress they have made, if this was satisfactory for them, and utilise opportunities to improve themselves (Fleur et al., 2023; Suls et al., 2002). Comparisons can be made from a temporal as well as social viewpoint (Barreiros et al., 2023). Temporal comparison theory deals with comparing oneself at different points in time (Albert, 1977; Wilson & Shanahan, 2020). For example, one can make judgements about their performance on a particular task by comparing it with their past level of performance on a similar task. Social comparison theory deals with comparing oneself to others (Festinger, 1954; Wilson & Shanahan, 2020). For example, one can make judgements about their performance by comparing it to those of others on a similar task. By taking note of the achievement of others, people are able to gauge their own task efficacy, with varying degrees of accuracy (Cleary, 2009). Learners might be more inclined to use social comparisons when information on prior task performance is lacking (Bandura, 1997; Wilson & Shanahan, 2020).

Another perspective on comparisons is offered by goal setting theory. A goal is "the object or aim of an action, for example, to attain a specific standard of proficiency" (Locke & Latham, 2002, p. 705). Goal setting is used to stimulate behavioural change which, in turn, may enhance one's performance" (Epton et al., 2017; Locke & Latham, 2002). According to Zimmerman (2013), goal setting is a forethought phase process. The targeting of goals can be self-set by the learner or set for them by someone else (Hollenbeck & Brief, 1987). The effects of both types of goal setting are mixed (Osman, 2012). Assigned goals can lead to greater task performance in the context of academic writing and proof reading (Ariely & Wertenbroch, 2002), while in the context of improving athletic performance, assigned goals do not differ from self-set goals (Fairall & Rodgers, 1997). A plausible reason for this may be that learners differ in goal setting skills and might find it difficult to set challenging goals and achieve them (Epton et al., 2017). Self-set goals may satisfy learners' need for autonomy which could promote their intrinsic motivation (Ryan & Deci, 2000). Interventions (e.g., setting aside a specific amount of time on specific days to complete coursework) aimed at encouraging commitment could promote the achievement of self-set goals (Seo et al., 2018). Goals assigned to a learner, for example, by a trainer, have the potential to be more appropriately challenging (Epton et al., 2017; Latham & Locke, 1991). A trainer presumably has more insight into what the criteria for good performance are.

2.2 | Learner preferences

As indicated above, the effectiveness of LADs also depends on learner preferences. We can look at prior studies to gain valuable insights. For example, Ruble and Flett (1988) examined learner preference for reviewing one's own or a peers performance score on a math exam. Results indicate learners preferred social comparison, especially low ability learners were less inclined to opt for temporal comparison. Interestingly, the appreciation of temporal comparison appeared to increase as learners got older.

Tuning into settings where learning analytics was used also revealed interesting findings. Konert et al. (2016) augmented Moodle with an LAD aimed at improving learner SRL skills by enabling them to set goals, keep track of knowledge gained from the course and time investment. A social comparison feature enabled them to compare their own knowledge level and time investment with their peers. The evaluation of the LAD indicated that learners were most positive about the social comparison feature. Tabuenca et al. (2015) asked learners to rate their preferences with regard to personal learning analytics, social analytics and teacher estimations. Each of these included a form of progress, social and external achievement reference frame respectively. Results indicated that the progress reference frame was preferred over the social and external achievement reference frame.

Guerra et al. (2016) evaluated a learning analytics system augmented with temporal and social comparison features. Results indicated that student engagement, efficiency and effectiveness were positively affected by social comparison features. Furthermore, results of a usability and usefulness survey indicated that both comparison types were appreciated by learners, particularly those who were highly motivated. Gasevic et al. (2013) analysed workplace learner perceptions of usefulness of a learning environment augmented with learning analytics. Results indicated that workplace learners use social comparisons when engaging in SRL processes such as goal setting. The study suggests that interventions aimed at supporting self-regulatory processes in the workplace should account for social and organisational elements, such as the alignment of learning goals and activities of colleagues and organisational goals. Gallagher et al. (2022) conducted a study with an immersive training environment for a workplace. They compared trainee engagement with two LADs, one designed with a progress reference frame and one with a social reference frame. Results indicated that trainees receiving a progress reference frame were more likely to engage with the LAD than those receiving the social reference frame.

Finally, there are indications that learner preferences for a specific type of reference frame may also depend on their SRL skill level and the specific SRL activities they are involved in (Zimmerman, 2013). SRL skill level affects one's ability to set their own goals (Epton et al., 2017; Latham & Locke, 1991; Zimmerman, 2002). A higher skilled SRL learner may prefer setting their own goals because they recognise their ability to successfully execute goal related SRL processes. On the other hand, lower SRL skilled learners may prefer goals assigned by their trainers or managers as they may believe they have more insight into what goals are best.

Reference frames may provide valuable comparisons, but it is up to the learner to navigate the cyclical SRL phases and act upon the provided information (Panadero, 2017; Zimmerman, 2002). Learners make choices about how to execute SRL processes based on their self-evaluations derived from the provided comparisons. Interesting here is that the same performance outcome can look like success or failure depending on the point of comparison being used to contextualise feedback. For example, if a learner scores 85% on a training task and is offered a social reference frame with a point of comparison of 75%, this would likely trigger positive self-evaluations because their performance outcome is greater than the point of comparison. However, if a different reference frame, such as an external achievement reference frame, with a point of comparison of 90% was offered, then this may trigger negative self-evaluations because their performance outcome is lower than the point of comparison. This illustrates that although the performance outcome in both examples remains constant at 85%, the point of comparison can differ and in turn potentially trigger either positive or negative self-evaluations. Due to the cyclical nature of SRL, this has implications on the other phases of the cycle because positive or negative self-evaluations likely differentially affect forethought phase processes, which in turn affect performance phase processes.

3 | THIS STUDY

This study examines learner preferences for four mock LADs aimed at stimulating SRL behaviour. The LADs are augmented in a virtual reality based immersive learning environment developed for the chemical process industry. The environment will serve a dual purpose. Firstly, it will train employees on the procedural steps involved in the production-specific chemical compounds. Secondly, it will equip operators with the necessary skills and knowledge to respond effectively to emergency situations. By doing so, the platform aims to increase safety and efficiency within the chemical production process. Three primary topics will be explored to gain a more in-depth understanding of learner preferences for LAD design within immersive learning environments. Firstly, we explore whether or not learner preferences for reference frames in LADs differ depending on if the LAD is designed for before, during or after task performance. It may be the case that preferences differ because different SRL skills are required depending on the phase of the SRL cycle. For example, learners may prefer a progress reference frame during the 'before task phase' more than any other reference frame, because they may think they can use temporal comparison more effectively. They could see temporal comparison as advantageous because it offers them insight into if they are progressing compared to prior tasks attempts or not, which may be valuable goal setting and/or strategic planning information.

Secondly, we explore whether or not a workplace learner's perceived SRL skills relates to their preference. For example, it is unclear if higher skilled self-regulated learners prefer one reference frame type while lower skilled self-regulated learners prefer another. For example, we speculate that high skilled self-regulated learners are better supported by a progress reference frame because they are able to make use of temporal comparison during the three phases of the SRL cycle (Winne, 2017; Zimmerman, 2013).

By doing so, we will answer two research questions, namely:

RQ 1. In the context of an immersive learning environment, what are workplace learner preferences for learning analytics reference frames in LADs designed for before, during and after task performance?

RQ 2. In the context of an immersive learning environment, how are workplace learner preferences for learning analytics reference frames in LADs related to their perceived SRL skills?

4 | METHOD

4.1 | Participants

The participants (*N* = 70) were employees of a science and technology company located in Germany and were all trainees of the company's chemical process apprenticeship program. The employees' working language was German. See Tables 1 and 2 for demographic details.

This sample size was chosen for contextual reasons. These 70 participants represented the available members of the apprenticeship program at the time of the study. More importantly, the immersive learning environment, for which the LADs were being designed, was specifically intended for this program. Thus, the choice of participants aligns directly with the real-world application of our research, providing valuable, context-specific insights.

Out of the total 70 participants, data from everyone was utilised for group level results. However, for individual level results, data were only used from a subsection of the participants. We collected data on individual reference frame preference for before task performance from 54 participants, for during task performance from 62 and for the after task performance from 58. There were three reasons why some participants did not have their data collected. Firstly, due to technical issues (i.e., the system did not offer one or more reference frames to the participants for comparison which led to researchers being unable to determine a reference frame preference) (before: 9, during: 2, after: 7). Secondly, due to participants dropping out of the comparisons and completing less than six rounds of comparison (before: 4, during: 3, after: 3). If participants completed less than six rounds of comparisons, it was not possible to determine a reference frame preference. Finally, because the participants did not complete the SRL questionnaire ($n = 4$).

Participation in this study was entirely voluntary; participants were neither compensated financially nor in credits for the apprenticeship program. The researchers asked for active consent and informed the participants that they could withdraw at any moment without a given reason. There were no participants who asked to withdraw from the study, however, as described earlier, some dropped out while completing aspects of the study. The responses to the questionnaires were pseudonymised which concealed the identity of the participants.

TABLE 1 Gender of participants.

Gender	Number of participants
Male	48
Female	15
Not specified	7
Total	70

TABLE 2 Age of participants.

Age (years)	Number of participants
18–21	30
22–25	25
26–29	10
Over 30	3
Not specified	2

4.2 | Design

A within-group design, was used in which learner preferences were tested using adaptive comparative judgement. Adaptive comparative judgement enables us to place each reference frame design (i.e., social, progress, internal achievement and external achievement) in a rank order from most to least preferred for the entire group of participants. In addition, a parameter value is assigned to each reference frame to give an indication of how much more or less one reference frame is preferred over another. We also determine each participant's reference frame design preference before, during and after task performance, which is used in a within group design to test the relationship between SRL skill and reference frame preference.

4.3 | Materials

4.3.1 | Learning analytics dashboards

The learning analytics feedback used for this research came in the form of 12 distinct mock LADs with fictitious data; four per task stage (before, during, and after task performance) designed for three task

TABLE 3 Design guidelines based on recommendations from Jivet et al. and their manifestation in the mock learning analytics dashboards (LADs) and Study design.

Design guidelines	Manifestation of recommendations in mock LADs or study design
Design LADs as pedagogical tools to enhance awareness and reflection, and to promote changes in cognitive, behavioural, and emotional competences.	By offering feedback on performance before, during, and after task performance, learners are made aware of their strengths and weaknesses related to their task, which can develop cognitive, behavioural, and emotional competences. Self-reflection is enhanced through the offering of a reference frame, which learners can use to better understand how their performance compares to a particular point of comparison.
Use educational concepts from learning sciences to guide design decisions.	The decision to offer LADs before, during, and after task performance is motivated by theories of SRL and the three phases of the SRL cycle. The design of each reference frame is informed by temporal comparison theory, social comparison theory, and goal setting theory.
Use social comparison cautiously.	One of the motivating factors for comparing the four dashboard designs is to collect additional evidence related to this recommendation.
Customise LADs to cater to different groups of users with the aim of providing equal support to all.	One of the motivating factors for examining the relationship between SRL skills and reference frame preference is derived from this recommendation.
Integrate the dashboard seamlessly into the learning environment and learners' usual activities.	This recommendation informed the decision to present the LAD before, during and after task performance because if an LAD is to support SRL, it seems beneficial for it to be presented at each phase of the SRL cycle.

phases. Each dashboard differed by which reference frame it was designed with (i.e., social reference frame, progress reference frame, internal achievement reference frame, external achievement reference frame) and which task stage it was designed for (i.e., before task, during task, after task).

To support the design choices made for the mock LADs and the study design, we draw on design recommendations for learner facing LADs which were the result of a literature review by Jivet et al. (2018). Table 3 restates these recommendations as design guidelines and explains how they manifest in the mock LADs presented to participants and the study design.

The mock LADs were tailored for a chemical process industry immersive learning environment and were the result of a collaboration between educational scientists and instructional designers and subject matter experts from the field of chemistry and chemical engineering. For illustrative purposes we briefly describe five mock LADs here.

Figures 1–4 are the mock LADs designed with a progress, social, internal achievement, and external achievement reference frame for the 'after task phase' before being translated into German. All mock LADs can be found in the supplementary materials. Figure 5 is the mock LAD for the progress reference frame for the 'during task phase'. Fictitious performance data were used for all dashboards.

Each dashboard includes a sentence highlighting the type of comparison within the LAD (i.e., "Your score is being compared with your score on previous attempts"). This helps ensure participants are able to easily distinguish between reference frames. The score is a performance measure and refers to the percentage of the task completed correctly. Each dashboard includes an indicator highlighting the stage of the task the learner is in (i.e., "session ready", "training paused", "session complete").

For the before and after task phases, an indicator titled "Training Effort" highlights how much time the learner has spent in the simulator practicing the task. The equivalent indicator for the during task phase provides a task progress bar indicating how much of the task has been completed and how much is left to complete.

For the before task phase, the task that is to be performed is stated and for the after task phase the task which has just been completed is stated. For the during task phase, an indication of sub-steps within the phase is shown. Task performance feedback is indicated by each dashboard using a bar chart for the before and after task phases which is presented alongside the point of comparison while in the during task phase, the percentage is stated in numbers.

The LADs were designed to appear within the immersive learning environment, however, due to the feasibility of sharing the designs in that format, screenshots of the mock LADs were taken and shared with participants. All mock LADs can be found in the supplementary materials.

4.4 | Instruments

4.4.1 | Demographic data questionnaire

A demographic questionnaire was completed by all participants which asked them their age and gender. This questionnaire was distributed using Microsoft Forms.

4.4.2 | Adaptive comparative judgement software

RM Compare was used to investigate learner preferences for the learning analytics reference frames (https://www.compare.rm.com/). RM Compare is an online tool for conducting adaptive comparative judgement which is a method by which individuals are given a series of dichotomous choices between stimuli, from a larger pool of stimuli, and asked

FIGURE 1 Learning analytics dashboard with a progress reference frame for the 'After Task Phase' before translation.

FIGURE 2 Learning analytics dashboard with social reference frame for 'After Task Phase' before translation.

which one they prefer based on a given question (Pollitt, 2012; Verhavert et al., 2019). In the case of this research, the stimuli are screenshots of the mock LADs. RM Compare's design is informed by the theory of comparative judgement (Pollitt, 2012; Thurstone, 1927) that states when presented with a series of stimuli in which an individual must make subjective judgements on which stimulus is better or worse

FIGURE 3 Learning analytics dashboard with an internal achievement reference frame for 'During Task Phase' before translation.

FIGURE 4 Learning analytics dashboard with an external achievement reference frame for 'After Task Phase' before translation.

compared to another stimulus, it is rational to compare each stimulus with each other stimulus. After a group of individuals have made these subjective judgements, it is then possible to apply a mathematical model which takes into account each individual's judgements to calculate the rank order and parameter value of the compared stimuli for the entire group (Pollitt, 2012). (Figure 6).

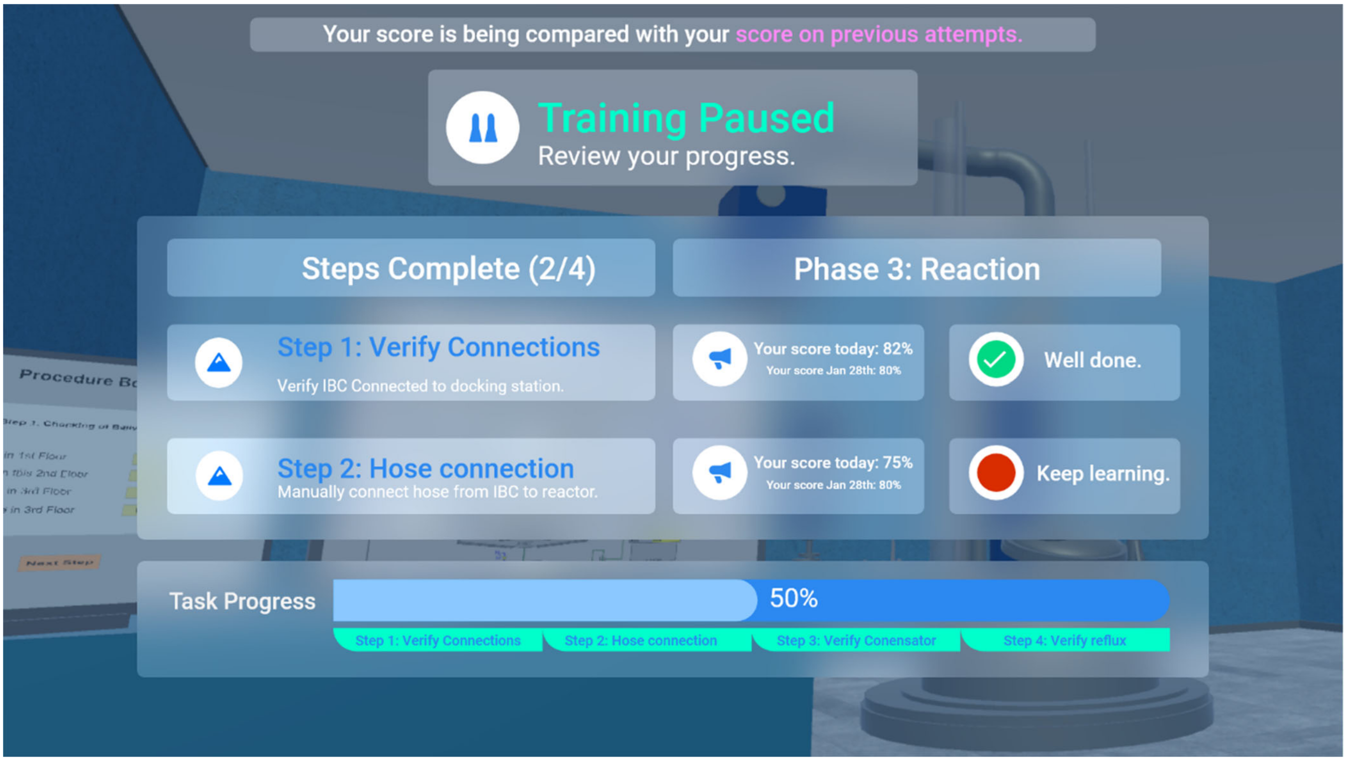

FIGURE 5 Learning analytics dashboard with progress reference frame for 'During Task Phase' before translation.

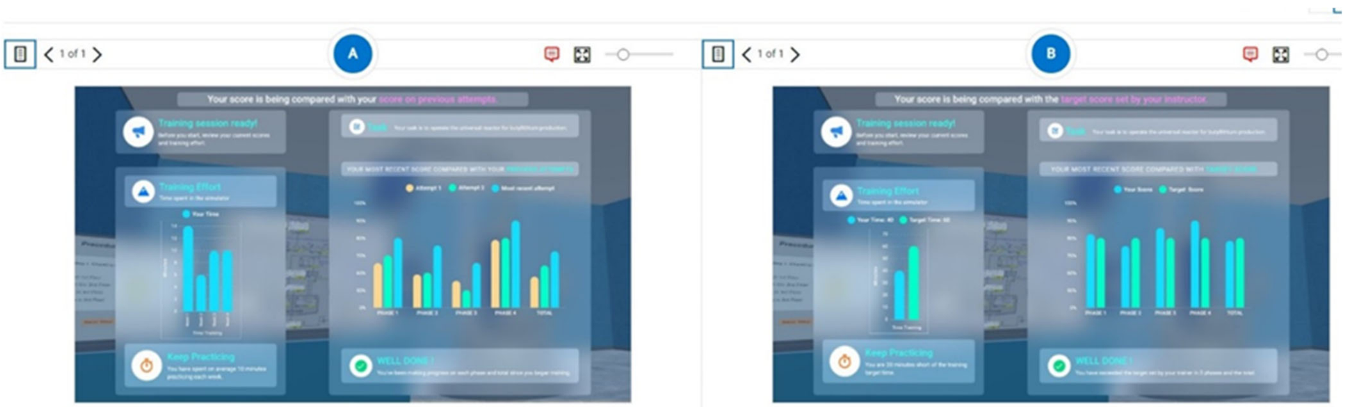

FIGURE 6 Participant view when performing adaptive comparative judgement in RM compare.

4.4.3 | Self-regulated online learning—Questionnaire

Learners' SRL was measured using the SOL-Q-R which was designed to measure SRL behaviours in online educational contexts (Jansen et al., 2017). Of the many different instruments available to measure SRL, the SOL-Q-R, was selected due to its validity (RMSEA ≤ 0.102) and reliability ($\alpha \geq 0.740$) for researching SRL (Jansen et al., 2017).

Participants completed the SOL-Q-R, which is made up of 42 items. Each item is presented in randomised order and answered on a 7-point Likert scale, ranging from "not at all true for me" (=1) to "very true for me" (=7). It provides an overall score for perceived SRL skill and also provides sub-scale scores. For this research we chose to use the overall score.

4.5 | Translation process (English to German)

4.5.1 | Questionnaire translation process—Front-translation, back-translation, reconciliation

Both questionnaires were originally developed in English; therefore, translation was required and was done following a front-translation, back-translation, and reconciliation process.

The mock LADs as well as the questions posed for each round of the adaptive comparative judgement were originally developed in English and were translated into German following a standard front translation process.

4.6 | Procedure

After signing informed consent, participants were invited to attend one of six research sessions. The introduction to the research and data collection was completed online using a video conferencing tool. During these sessions, participants were guided through the research procedure by one of the authors who is a native German speaker. This research procedure included an introduction to the research which provided a brief overview of the research aims and details on how they could log into the RM Compare website using usernames and passwords which were assigned to them. Participants were shown a video of the immersive learning environment which was being developed for the company they worked for and were told that the research was focused on improving the design of this prototype, in particular, the LADs. As it was expected that LADs as a concept were new to the participants, a short presentation on LADs and reference frames was shared. During the research session, participants were told that they were to make their judgements based exclusively on the different reference frames they preferred and asked to do their best to ignore any aesthetic preferences they may have. Once the introduction to the research and data collection was complete, participants were able to ask any questions.

The order in which the instruments were administered was as follows. First, the demographic data questionnaire was completed and was followed by a Goal Orientation questionnaire. The goal orientation questionnaire was used by a collaborating researcher and the results from this questionnaire are not reported here. Next, participants were asked to log into the RM Compare website to begin the adaptive comparative judgement session.

Once participants had logged into RM Compare, they were presented with the first round of comparisons, which asked them to compare the four different LAD reference frame designs, designed for before task performance. In this first round, before making each comparative judgement, they were prompted with the question: "Which design do you think will help you best with planning, goal setting and motivation?". Note that this question aligns with the forethought phases processes of SRL cycle.

Upon completion of this first round focusing on before task performance, participants then moved on to the second round focusing on LADs designed for during task performance. For this task stage they were prompted with the question: "Which design do you think will help you best with keeping track of how well you are doing at the task and following a plan you made?". Note that this question aligns with the performance phases processes of SRL cycle.

For the third and final round, participants were prompted with the question: "Which design do you think is best for helping you reflect upon your performance and judging or assessing your own performance?" Note that this question aligns with the self-reflection phases processes of SRL cycle.

After participants had completed the adaptive comparative judgement, they were then asked to complete the SRL online learning questionnaire which was administered using Microsoft Forms.

4.7 | Scoring and data analysis

4.7.1 | Self-regulated online learning

JASP version 0.16 is used for the statistical analysis of the validity and reliability of the SOL-Q-R. A confirmatory factor analysis is used to determine validity and a unidimensional reliability test to calculate Cronbach's α. Four statistical tests measure validity, including the Root Mean Square Error of Approximation (RMSEA) with values below 0.08 indicate adequate fit (Chen et al., 2008; Maccallum et al., 1996), the standardised Root Mean Residual (SRMR) with values below 0.05 indicating good fit, the Comparative Fit Index (CFI) with values above 0.90 indicating good fit and the Tucker Lewis Index (TLI) with values above 0.95 indicating good fit (Hu & Bentler, 1999).

For the SOL-Q-R, the confirmatory factor analysis thresholds for validity were met (RMSEA $= 0.076$, SRMR $= 0.043$, CFI $= 0.979$, TLI $= 0.969$), as was the reliability threshold ($\alpha = 0.898$).

4.7.2 | Adaptive comparative judgement (RM compare)

This study analyses the results from the adaptive comparative judgement on a group level and individual level. Group level results refer to how all participants valued the reference frames from most preferred to least preferred. Individual level results refer to which reference frame (if any) was most preferred by each individual. Individual level data was required to analyse the relationship between SRL skill and reference frame preference.

Therefore, we report results from the adaptive comparative judgement in two categories: group level results and individual level results.

4.7.3 | Group level results

Parameter value along with the standard error (SE) is used to answer Research Question 1 and was automatically calculated by RM Compare.

The parameter value indicates to what degree a reference frame was preferred by the group over another reference frame and is calculated based on the win/loss record of each reference frame (Bartholomew et al., 2018; Whitehouse & Pollitt, 2012). Scores closer to 1.0 indicate stronger preference while scores closer to -1.0 indicate weaker preference. The difference between two parameter values is the likelihood that the reference frame with the higher parameter value is preferred in judgement in comparison with the reference frame with the lower parameter value.

We used parameter values in concert with the SE to interpret reliability of the parameter values. The SE estimates the potential error for a particular parameter value and therefore indicates how confident we can be of the parameter value assigned to each reference frame. To determine if two parameter values are meaningfully different, we will check the standard error of each parameter value and compare it with the standard error of each other parameter value. If there is any overlap between two reference frame SE ranges then we will treat those reference frames as not being meaningfully different.

The scale separation reliability score (SSR) helps us interpret internal consistency of the results (Verhavert et al., 2018). The closer SSR is to 1, the more likely it is that if the comparisons were done again, we would get the same results. An SSR value greater than 0.7 suggests good internal consistency (Marshall et al., 2020). In that way, SSR is analogous to Cronbach's alpha (Marshall et al., 2020; Pollitt, 2012).

The internal consistency which is represented by the SSR score shows good levels of consistency for results examining before (0.82) and after (0.9) task performance preferences, but not during (0.58) task performance preferences. Therefore, we are confident that the results for the before and after task performance preferences are reliable, however, the relatively low SSR score for during task performance preferences results means we cannot confidently draw conclusions for this phase.

4.7.4 | Individual level results

There is one variable from the individual level results for each task stage (before, during, after task performance). This variable is the learner reference frame preference. The reference frame preference variable indicates if the learner holds a reference frame preference or not and if there is a preference, what that preference is.

The reference frame preference variable was coded as one of the following options: progress, internal achievement, external achievement, social, no preference.

Coding the reference frame preference variable was done manually by looking at each pairwise comparison the learners made and inferring which reference frame they preferred (if any). For example, if the results of one participant showed that the social reference frame was preferred over the progress reference frame in one comparison, and in the next two comparisons, the progress reference frame was preferred over the external achievement reference frame and the internal achievement reference frame, it was inferred that the social reference frame was the most preferred for that participant. If, however, there was a contradiction in comparisons, no preference was inferred. For example, if the social reference frame was preferred over the progress reference frame, the progress reference frame was preferred over the internal achievement reference frame and the internal achievement reference frame was preferred over the social reference frame, we would conclude a logical inconsistency had occurred and that the learner holds no clear reference frame preference.

4.7.5 | Multinomial logistic regressions

To examine the relationship between learner preferences and SRL skills, three multinomial logistic regressions (before, during and after task performance) were conducted. In SPSS, reference frame preferences were set as the dependent variable and SRL score obtained from the SOL-Q-R as the independent variable. Before conducting the analyses, the independent variable (SRL skill) was tested a priori to verify there was no violation of the assumptions required for multinomial logistic regressions and none were violated.

5 | RESULTS

5.1 | Preferences for LADs

We answer Research Question 1 by taking into account each parameter value with the SE, as well as the SSR score, all of which were yielded by the adaptive comparative judgement. For before and after task performance the parameter values paired with the SE (Figure 7) indicate that the opportunity to compare one's own performance over time was substantially preferred over all other types of comparison (0.41, SE = 0.14). The parameter values paired with SE fail to indicate that comparison with a trainer-assigned goal (0.03, SE = 0.13) is more preferred than a self-set goal (−0.07, SE = 0.13). The results indicate that both comparisons with a trainer-assigned goal and self-set goals are substantially preferred over the comparison with peer performance (−0.37, SE = 0.14).

For during task performance (Figure 8), the parameter values and SE show that comparison with one's own performance over time (0.22, SE = 0.13) is not substantially preferred over the comparison

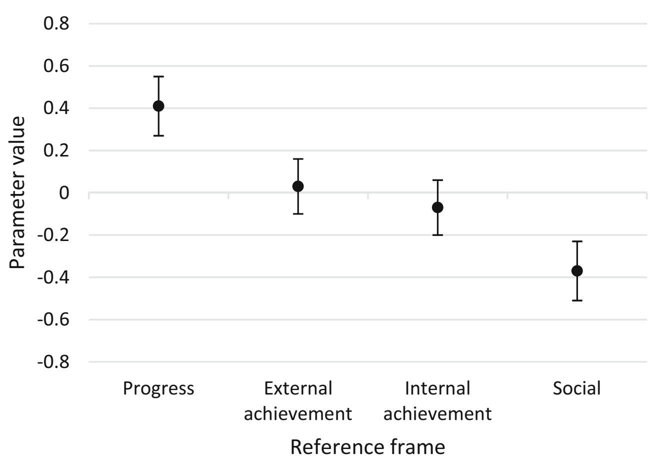

FIGURE 7 Before task phase parameter values and standard errors. SSR = 0.82 (SSR > 0.7 = good internal consistency).

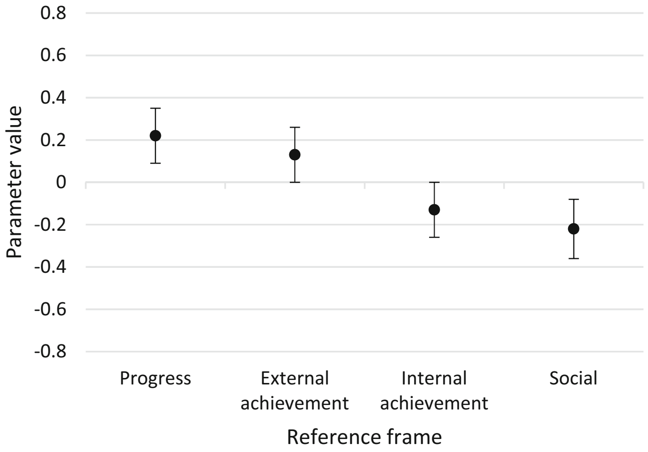

FIGURE 8 During task phase parameter values and standard errors. SSR = 0.58 (SSR > 0.7 = good internal consistency).

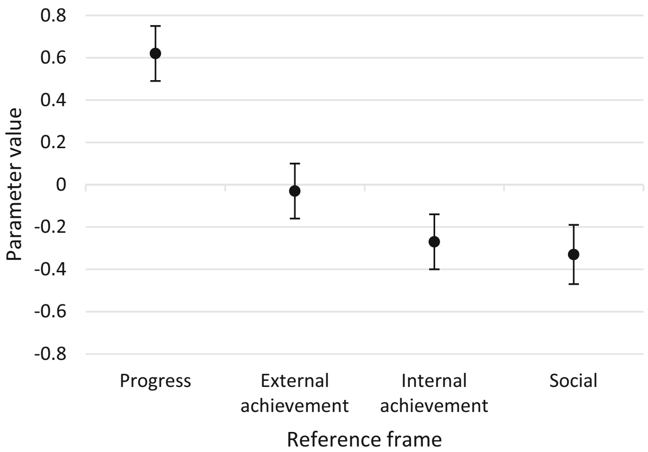

FIGURE 9 After task phase parameter values and standard errors. SSR = 0.90 (SSR > 0.7 = good internal consistency).

with goals assigned by one's trainer (0.13, SE = 0.13). Both are substantially preferred over the comparison with self-set goals (−0.13, SE = 0.13) and comparison with the performance of others (−0.22, SE = 0.14). The comparison with self-set goals is not substantially preferred over the comparison with peer performance when taking into account the parameter values paired with the SE. However, as indicated earlier, the SSR score (0.58) indicates that the reliability of these results fails to meet the threshold of good reliability.

For after task performance (Figure 9), the parameter values and SE show that the comparison with one's own performance over time (0.62, SE = 0.14) is substantially preferred over all other comparison types. Comparisons with trainer-assigned goals (−0.03, SE = 0.14) are not substantially preferred over comparisons with self-set goals (−0.27, SE = 0.14), however, they are substantially preferred over comparisons with peers (−0.33, SE = 0.14). It is worth noting that the overlap of the lowest point of the SE for trainer-assigned goal comparisons and highest point of the SE for the self-set goal comparisons is marginal (0.04). Self-set goal comparisons are not substantially preferred over comparison with peers.

5.2 | Interplay between learner preferences and their perceived SRL skill

We answer Research Question 2 by conducting three multinomial logistic regressions; one for each set of preferences before, during and after task performance. We report descriptive statistics for before, during and after task performance preferences in Table 4, which are followed by the results from the multinomial logistic regression for before task performance in Table 5, during task performance in Table 6 and after task performance in Table 7.

The results provide information comparing each reference frame preference group (Progress, Social, Internal achievement, External achievement) against the reference category (No preference). Specifically, the regression coefficients indicate the odds ratios change as the score on SRL skill increased by one unit.

The result for before task performance shows that the model (Table 5) is approaching significance ($p = 0.068$) and taking into account the small sample size, further investigation would be fruitful. Table 5 indicates to a statistically significant degree ($p = 0.015$) that the higher the SRL skill score, the higher the probability a learner had of being in the progress reference frame preference group. The results for during task performance (Table 6) and after task performance (Table 7) indicate there are no statistically significant results.

6 | DISCUSSION

Set within a workplace learning context, this study set out to investigate learner preferences for four mock LAD designs aimed at stimulating SRL behaviour. The LADs provide feedback on an immersive learning environment task designed for training apprentices in the chemical process industry. The four LAD designs differed by reference frame (i.e., social, progress, internal achievement and external achievement) and therefore, the point of comparison used to help learners make sense of their feedback (i.e., social comparison, temporal comparison, comparison with self-set goal, comparison with assigned goal). The main finding of our study lies in the comparison of these different reference frame designs rather than the specific information shown in the dashboards. The study also sought to determine if there is a relationship between learner preferences for a particular reference frame before, during and after task performance and overall SRL skills in the context of a workplace learning environment.

The first research question examined learner preferences for reference frames before, during and after task performance. Results indicate a learner preference for the progress reference frame. This may be because temporal comparison, stimulated by the progress reference frame, is perceived by learners to be supportive of their forethought and self-reflection processes (Zimmerman, 2002). Strategic

TABLE 4 Descriptive statistics for reference frame preferences for each task phase.

Task reference frame preference	Task phase Before		During		After	
Progress	$n = 17$	31.5%	$n = 14$	22.6%	$n = 20$	34.5%
Internal achievement	$n = 10$	18.5%	$n = 2$	3.2%	$n = 4$	6.9%
External achievement	$n = 10$	18.5%	$n = 20$	32.3%	$n = 13$	22.4%
Social	$n = 3$	5.6%	$n = 7$	11.3%	$n = 3$	5.2%
No preference	$n = 14$	25.9%	$n = 19$	30.6%	$n = 18$	31%
Total	$n = 54$		$n = 62$		$n = 58$	

Note: $n =$ Number of participants. The reference frame with the highest n does not necessarily have the highest parameter value because the rank order is also a factor. This is why external achievement reference frame has the highest n in this table but not the highest parameter value in Figure 8.

TABLE 5 Multinomial logistic regression for before task phase with no preference set as reference category.

		b (SE)	p	95% CI for odds ratio Lower	Odds ratio	Upper
External versus no preference	SRL Skill	0.141 (0.628)	0.822	0.337	1.151	3.939
Internal versus no preference	SRL Skill	0.379 (0.647)	0.558	0.411	1.460	5.185
Progress versus no preference	SRL Skill	1.695 (0.698)	0.015*	1.387	5.444	21.367
Social versus no preference	SRL Skill	0.965 (1.095)	0.378	0.307	2.624	22.418

Note: $\chi^2 = 8.75$; df $= 4$; $p = 0.068$.
*$p < 0.05$.

TABLE 6 Multinomial logistic regression for during task phase with no preference set as reference category.

		b (SE)	p	95% CI for odds ratio Lower	Odds ratio	Upper
External versus no preference	SRL Skill	0.073 (0.461)	0.875	0.435	1.075	2.656
Internal versus no preference	SRL Skill	0.117 (1.081)	0.914	0.135	1.124	9.353
Progress versus no preference	SRL Skill	0.676 (0.547)	0.217	0.672	1.965	5.744
Social versus no preference	SRL Skill	0.547 (0.677)	0.419	0.458	1.728	6.515

Note: $\chi^2 = 2.16$; df $= 4$; $p = 0.706$.

TABLE 7 Multinomial logistic regression for after task phase with no preference set as reference category.

		b (SE)	p	95% CI for odds ratio Lower	Odds ratio	Upper
External versus no preference	SRL Skill	0.171 (0.575)	0.767	0.384	1.186	3.661
External versus no preference	SRL Skill	0.928 (0.943)	0.325	0.398	2.530	16.061
Progress versus no preference	SRL Skill	0.723 (0.543)	0.183	0.711	2.061	5.971
Social versus no preference	SRL Skill	2.062 (1.169)	0.078	0.796	7.863	77.683

Note: $\chi^2 = 5.03$; df $= 4$; $p = 0.284$.

planning is one such process which helps learners master skills and perform optimally (Zimmerman, 2000, 2013). As one develops skills on a particular task, initial strategies to acquire those skills can decline in effectiveness and new strategies are required for further improvement. If it becomes apparent that a learner's performance has plateaued or declined, this potentially indicates that the chosen strategies are insufficient, and they may benefit from planning and executing new ones.

Another possible explanation as to why the progress reference frame was preferred over other types of references frames before and after task performance is because participants of the study may have held mastery goal orientations. This aligns with findings from Jivet et al. (2020); learners with a mastery orientation, rated temporal comparison feedback to be very relevant.

Our findings indicate there were no substantial preferential difference for before and after task performance between the external achievement (assigned goal as a point of comparison), and the internal achievement (self-set goal as a point of comparison) reference frames. This aligns with research (Epton et al., 2017) indicating that goal achievement was not affected by the type of goal setting (self, assigned). Learners who have experienced success as well as failure with both types of goal setting, may have no preference for either type of reference frame. It contradicts a finding by Jivet et al. (2020) indicating that learners preferred an LAD feature labelled as "seeing requirements for passing the course", above the feature "seeing my performance in comparison to my goals". However, this study did not directly test if this perception of relevance was significantly different.

The social reference frame was the least preferred reference frame before task performance and equally least preferred during and after task performance. This may be because the participants perceive social comparisons to be detrimental to self-motivational beliefs. Self-motivational beliefs play an important role in the SRL cycle and are key in motivating learners to execute task analysis strategies such as goal setting and strategic planning (Zimmerman, 2013). For example, a study by El-Beheiry et al. (2017) indicated that 76% of 25 participating first year surgical residents would not be motivated by social comparison in the form of a leader board intervention. However, contradictorily, the presence of leader board did in fact enhance residents practice with an immersive learning environment. This suggests that while learners may not prefer social reference frames over other types, such as progress reference frames, social reference frames may still result in positive learning behaviours. Other studies have obtained findings indicating that learners in some contexts do positively react to social reference frames. Guerra et al. (2016) found that learner engagement, efficiency and effectiveness were positively affected by social comparison features of an LAD and the progress as well as the social reference frame were appreciated by learners. Brusilovsky et al. (2016) found that LADs designed with both a progress and social reference frame were much more successful at engaging learners than those designed with only a progress reference frame. These inconclusive findings are supported by a literature review by Jivet et al. (2018), examining learner evaluations of LADs, which found that while in some cases social comparison via a social reference frame can have a positive effect on motivation, in other cases it can have negative effects.

Perhaps these inconclusive findings can be accounted for by differences between learners. Learners might cope in different ways with the feedback offered by the comparisons (Pintrich, 2000; Zimmerman, 2013). If, for example, a learner receives a social reference frame which they dislike, they may then ignore the feedback within the LAD all together, which may lead them to poorly execute the SRL phases for which the LAD was intended to support. On the other hand, if a learner receives a reference frame which matches their preference, we may see beneficial effects on the execution of SRL processes. For example, Janson et al. (2022) conducted a study in examining the effects of learners' own preferences for temporal versus social comparison on learning persistence and performance in a digital learning environment and found a beneficial effect of matching feedback design with comparison preferences. This result suggests that we should be concerned with the mismatch between design choices and preferences and warrants further research into how the different types of reference frames affect learner engagement with feedback delivered via LADs at the different SRL phases.

The second research question examined the interplay between learner preferences for reference frames and their perceived SRL skills. Our findings indicate an interplay for one pair of before task performance preferences (progress reference frame versus no preference); learners with higher perceived SRL skills are more likely to prefer the progress reference frame than having no preference for before task performance LADs. A possible explanation is that higher SRL skilled learners have a better idea about the type of reference frame they need to help them with forethought phase processes. However, this reasoning fails to hold for during and after task performance preferences. The inconsistent results for before, during and after task performance could also be due to the methodological approach undertaken and the number of participants in the study. A qualitative investigation could shed further light on the results. For example, an interview could gain more insight into the rationale behind the indicated preferences.

In recognising the novelty of our work, it is important to underline a few key aspects. Firstly, our research uniquely targets the often-overlooked demographic of workplace learners (Poquet et al., 2022). The nature of learning within a professional environment differs notably from traditional educational settings (Ruiz-Calleja et al., 2017). As such, our study unveils valuable context specific insights into the preferences of this specific group, thereby expanding our understanding of the learner population. This intentional choice of our sample deserves emphasis. Given this intentional focus, the pool of available participants was inherently limited, leading to a smaller sample size of our study. However, despite its size, this select group offers critical information, providing us with a deeper understanding of learning preferences within professional environments. Furthermore, while the relationship between LADs and SRL is well-researched (Matcha et al., 2019), our study distinguishes itself by taking a granular look at the different phases of the SRL cycle. This nuanced approach allows us to better discern learners' distinct preferences across various stages of learning, with implications for more personalised and effective LAD designs, an area of research that has been called upon by various research in the learning analytics field (Wong et al., 2022).

In addition, our study examines the learner preferences among four distinct reference frame types—namely, progress, social, internal achievement, and external achievement. To our knowledge, no other research to date has comprehensively evaluated learner preferences across these four distinct categories. This new comparison offers valuable insights into the respective appeal of different LAD designs, which can directly inform the development of future learning analytics tools. Furthermore, our approach not only advances our understanding of learner preferences but also potentially opens the door for future studies on how these preferences may evolve or vary under different conditions or learning contexts.

Lastly, the immersive learning environment, the backdrop for our study, represents a relatively uncharted territory in LAD research (Beck et al., 2023). As this mode of learning continues to gain traction, our study provides early insights into learner preferences within this specific context. This knowledge can guide the development of LADs that cater to the unique needs of learners in immersive environments, thereby advancing our practice in this emerging field.

In summary, while working within the established domains of LAD and SRL, our research shines a light on under-researched areas and provides fresh perspectives on well-known concepts, thereby pushing forward our collective understanding of learning analytics and self-regulated learning.

7 | LIMITATIONS

When interpreting the obtained findings, one should also take its limitations into account. Firstly, the study is conducted within the context of a workplace learning environment which limits the generalisability of the findings. Although such a context was suggested by others (Gedrimiene et al., 2020; Ruiz-Calleja et al., 2017). Another limitation is that the reference frame preferences were yielded from mock LAD designs with fictitious data and therefore, it is not clear if preferences of learners would differ when learners are faced with authentic LADs in real time. Perhaps preferences based on real time data might yield different findings. Future research based on real time actual performance scores could provide valuable insight into learner preferences for LADs, how and why LADs are used (e.g., interaction, feedback processing, uptake feedback) and their effect on SRL and performance behaviour.

An additional limitation is the sample size of our study. While our sample was representative of a specific group of apprentices, it was relatively moderate in size, which may constrain the broader generalisability of our results and limit the extent to which our findings can be applied to a wider population. It is important to note that this limitation is, in part, a consequence of our intent to enhance the ecologicall validity of the study. On one hand, this approach provides us with context-specific insights that hold substantial real-world value. On the other hand, the very nature of such studies places boundaries on the sample size. Despite this, our findings align with existing research in the field on learner reference frame preferences. This consistency, even within our specific context, underscores the value of our study and boosts our confidence that our work meaningfully contributes to the broader understanding of learner preferences in LAD designs.

Another limitation is that the feedback in the LADs always showed downward comparisons, except for one indicator in the during task phase LAD, meaning the fictitious level of performance was greater than the point of comparison. It may be the case that when learners are required to make lateral or upward comparisons, preferences differ. The decision to primarily test downward comparisons was made to not overburden participants with visually similar comparative judgements. Finally, the number of participants in the study was rather small for the multinomial logistic regressions, which means we are unable to draw any strong conclusions regarding the relationship between SRL skill level and reference frame preference. Nevertheless, the results do indicate that further investigation into this line of inquiry would be fruitful.

8 | CONCLUSION

We investigated learner preferences for LADs designed with different reference frames for before, during and after task performance. We used mock LADs which were designed to stimulate SRL in the context of an immersive training environment for the chemical process industry. For the before and after task phases, we found that the progress reference frame was most preferred. The results of the study can be used by LAD designers who wish to design LADs with reference frames that are appreciated by learners. Further research is needed to determine why learners appreciate different types of reference frames and how they affect learner performance and SRL processes.

AUTHOR CONTRIBUTIONS

Timothy Gallagher: Conceptualisation, methodology, formal analysis, investigation, data curation, writing – original draft, writing – review & editing, visualisation, project administration. Bert Slof: Conceptualisation, methodology, writing – review & editing, supervision, funding acquisition. Marieke van der Schaaf: Conceptualisation, methodology, writing – review & editing, supervision, funding acquisition. Michaela Arztmann: Methodology, investigation, resources, project administrator. Sofia Garcia Fracaro: Investigation, resources, project administrator. Liesbeth Kester: Conceptualisation, methodology, writing – review & editing, supervision, funding acquisition.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/jcal.13042.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ETHICS STATEMENT

All procedures performed in the present study that involved human participants were conducted in accordance with the ethical standards of the institutional and/or national research committee and with the

1964 Helsinki declaration and its later amendments or comparable ethical standards.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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