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The impact of cognitive and motivational resources on engagement with automated formative feedback

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ABSTRACT

The effectiveness of automated formative feedback highly depends on student feedback engagement that is largely determined by learners' cognitive and motivational resources. Yet, most studies have only investigated either cognitive resources (e.g., mental effort), or motivational resources (e.g., expectancy-value-cost variables). The purpose of this study is to examine the development (indicated by time) and relationship of 1) cognitive, 2) affective, and 3) behavioral feedback engagement as a function of cognitive and motivational resources in a computer-based learning environment with automated formative feedback. Data was collected from $N = 330$ German B.Ed. Elementary Education students who worked four consecutive sessions on summarizing texts. Previously invested mental effort ($t - 1$) affected situational expectancy and cost but not situational value. 1) Cognitive feedback engagement was positively associated with previous performance but neither associated with cognitive nor motivational resources. 2) Affective feedback engagement was positively associated with intrinsic value and negatively associated with situational expectancies, invested mental effort and previous performance. 3) Behavioral feedback engagement was positively associated with situational expectancies and invested mental effort. This study contributes to the understanding of student's cognitive and motivational structures when engaging with automated formative feedback.

1. Introduction

In higher education, summarizing skills are important to quickly extract and process relevant information from scientific texts (Kürschner et al., 2006). However, undergraduates struggle to grasp scientific texts in depth, distinguish important information from unimportant information, and link information to their prior knowledge (Kintsch, 1990). Consequently, they experience difficulties in summarizing scientific texts precisely and in their own words (Kim & McCarthy, 2021). One way to promote summarizing skills is to provide automated formative feedback which assesses linguistic features related to the properties of a summary at word, sentence, and document level using natural language processing (Kim & McCarthy, 2021; Wade-Stein & Kintsch, 2004). In the present study, for example, the system informs about content coverage, copied words, redundancies, irrelevant information, and adequate length, accessible in multiple iterations (Barkela, & Leuchter, in revision).

However, the effectiveness of such feedback highly depends on the individual engagement with feedback (Handley et al., 2011; Price et al., 2011). Especially in computer-based learning environments, it is the learners' responsibility to use feedback in a way that supports their learning processes (Ali et al., 2018; Winstone et al., 2017). Kinsey (2022) showed that individual engagement is largely determined by learners' cognitive and motivational resources.

Although a growing body of research has investigated associations between cognitive resources and learning engagement (Dong et al., 2020; Y. Liu & Sun, 2021) or motivational resources and learning engagement (Putwain et al., 2019; Sun & Rueda, 2012), research about

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the relationship between cognitive and motivational resources and feedback engagement is scarce (Han, 2017). For researching cognitive and motivational influences on feedback engagement we used two theoretical perspectives. 1) The amount of invested mental effort as a cognitive resource and, 2) expectancy-value theory (EVT) as a framework for motivational resources might explain decisions to engage with feedback. In addition, we consider time, as the invested mental effort and EVT variables vary across learning situations (Eccles & Wigfield, 2020; Paas et al., 2005). Therefore, the purpose of this study is to examine the relationships between mental effort and EVT variables with feedback engagement over multiple time points in computer-based learning environments with automated formative feedback on summarizing texts. Information about which resources influence feedback engagement may indicate ways to promote student feedback engagement.

1.1. Student engagement with automated formative feedback

The formative feedback process is a communicative act formed by feedback provider and recipient (Price et al., 2011). In computer-based learning environments, feedback is often computed by algorithms, hence on the part of the provider, the communicative act is limited. Therefore, the quality of the feedback communication processes depends highly on the recipients and their use of the feedback to its full potential (Handley et al., 2011; Van der Kleij & Lipnevich, 2021; Winstone et al., 2017). Following, the feedback recipients' individual levels of engagement determine if the feedback processes will be successful and support the achievement of the learning goals (Ali et al., 2018; Hyland & Zhang, 2018). Engagement is a multi-dimensional construct which encompasses cognitive, affective, and behavioral aspects (Ellis, 2010; Handley et al., 2011).

Cognitive feedback engagement describes the willingness to process and apply feedback to improve the outcome (Handley et al., 2011). Zhang and Hyland (2022) analyzed students processes of text revisions to examine cognitive engagement. They argue that cognitive engagement results in identifying errors and weaknesses and setting goals for improvement. These operations translate into improvement in text quality (Butler & Britt, 2010). Therefore, in this study, we chose the change in text quality from the initial summary to the finally submitted summary as an indicator of cognitive feedback engagement.

Affective feedback engagement relates to the perceived valence of the feedback (Mayordomo et al., 2022). Students' perception of the valence of the feedback determines the successful use of feedback and influences its effectiveness on learning (Seifried et al., 2016; Van der Kleij & Lipnevich, 2021). However, students often are discontent with the feedback they received (Adams et al., 2020; Zhang & Hyland, 2022). Especially when receiving automated feedback, students raise concerns about its accuracy and helpfulness (Lipnevich & Smith, 2009). Studies have shown that students who assumed they were receiving automated feedback accepted it to a lesser extent than students who assumed they were receiving feedback from a human, regardless of whether the feedback came from a human or was automated (Seifried et al., 2016). Therefore, in this study, we chose feedback acceptance as an indicator of affective feedback engagement.

Behavioral feedback engagement refers to the activity initiated by the recipient after having received feedback (Handley et al., 2011; Price et al., 2011). In the context of summarizing, this means that students with a high behavioral feedback engagement revise a text more often and process more feedback than students with low behavioral feedback engagement (Liu et al., 2017). Thus, in a computer-based learning environment that provides automated feedback, students with high behavioral feedback engagement tend to request newly calculated feedback more often (Van der Kleij & Lipnevich, 2021; Zhang & Hyland, 2022). Therefore, in this study, we chose the number of feedback iterations (the number of submissions of revised summaries and associated calculated feedback in one session) as an indicator of behavioral feedback engagement.

1.2. Cognitive resources

Successfully engaging in complex tasks such as summarizing requires cognitive resources to process new information and integrate it into the individual's knowledge network (Sweller, 2020). Humans perceive mental effort as costly and tend to minimize its expenditure (Kool et al., 2017; Shenhav et al., 2017; Yee & Braver, 2018). Kool et al. (2010) showed that people tend to repeatedly choose actions that are associated with fewer cognitive demands. This is confirmed by Gieseler et al. (2020) who found that people choose less effortful task alternatives when exerting mental effort on an initial task. However, the prospect of reward and the expected efficacy of task performance may positively influence the willingness to invest mental effort (Frömer et al., 2021). Automated feedback and support in composing a summary might serve as such reward and affect efficacy judgements.

1.3. Motivational resources

Building on EVT, expectancies, task values, and costs are key factors that influence decisions to engage in learning processes and to pursue activities that benefit learning (Eccles & Wigfield, 2020; Rosenzweig et al., 2019). Thus, in our case, we assume that students' expectancies, values, and costs influence their decision to engage with automated formative feedback in order to succeed in the task.

Expectancies. Expectancies for success refer to future performances through the anticipation of how well one will perform on an upcoming task. Expectancies thus express a situation-specific interpretation of one's own competence beliefs about the task (Eccles & Wigfield, 2020). Individuals' competence beliefs are derived from past performances. They are broad and stable subjective perceptions of respective current abilities (Marsh et al., 2012).

Task values. Task values describe subjective perceptions of the valence of a task and comprise the dimensions intrinsic value, utility value, attainment value, and costs. Subjective task values impact individual choices to engage with a learning activity (Rosenzweig et al., 2019). Intrinsic value comprises interest and enjoyment as well as willingness to engage in a task. Eccles and Wigfield (2020) link intrinsic value to the concepts of situational interest (Ryan & Deci, 2020) and intrinsic motivation (Hidi & Renninger, 2006) emphasizing the variability depending on task and time. Utility value denotes that the task is perceived as useful for goal achievement. According to Eccles and Wigfield (2020), utility value can be closely related to the concept of extrinsic motivation (Ryan & Deci, 2020). Attainment value refers to the personal value a student attributes to the task (Wigfield et al., 1997). Cost is conceptualized as perceived negative consequences of engaging with a task such as emotional distress and fear of missing opportunities. Eccles and Wigfield (2020) emphasize that every learning activity has costs, which are related to the benefits resulting in a cost to benefit ratio.

In EVT, the total value of a task is conceptualized as the sum of intrinsic value, utility value, attainment value, and cost (Eccles & Wigfield, 2020). Therefore, in many studies the value components were aggregated to a composite value scale (Alipio, 2020; Perez et al., 2014; Viljaranta et al., 2009; Wang & Eccles, 2013). In recent years, however, researchers suggested to exclude cost due to its negative valence (Barron & Hulleman, 2015; Flake et al., 2015; Jiang et al., 2018).

1.4. The joint impact of cognitive and motivational resources on feedback engagement in the perspective of time

Feedback engagement might be related to the level of mental effort students invest in a summarizing task. Students with low engagement might expend few mental effort and process text and feedback superficially, resulting in little cognitive feedback engagement, in our case improvement of the summary, less affective feedback engagement, such as acceptance of feedback, and less behavioral feedback engagement, such as feedback iteration (Miller, 2015). The opposite applies to high engaged students. However, the willingness to allocate mental effort might also depend on students' motivational resources (Dunn et al., 2019; Feldon et al., 2019). For example, Putwain et al. (2019), Fan and Williams (2010), and Wang and Eccles (2013) showed in samples of primary and secondary school students that expectancies, values, and their interactions predict different manifestations of student engagement. Furthermore, Guo et al. (2016) investigated in a series of factor analyses the unique contributions of self-concept and the four value components of EVT. Their findings indicate that the value components, particularly intrinsic value and low cost, are important predictors of student-reported effort and teacher-reported engagement. Moreover, Goldstein (2006) conducted interviews with students about their decision to engage in feedback in an ESL writing course and found that motivation was an important factor in their decision to engage with feedback. Thus, in our study, different associations between the aspects of cognitive and motivational resources may lead to differences in cognitive (change in text quality), affective (feedback acceptance), and behavioral feedback engagement (feedback iteration).

In the perspective of time, research has shown that students' motivational states fluctuate from one learning situation to another (Dietrich et al., 2019; Eccles & Wigfield, 2020). According to the model of interest development (Hidi & Renninger, 2006), external influences, in our study e.g., the opportunity to learn about summarizing intensively, can create situational interest which can then be maintained for a longer period. However, several studies have shown that intrinsic value can decline over time during a university course (Darby et al., 2013; Seifried et al., 2016). Focusing on the reciprocal relationship between motivation and effort, Marsh et al. (2016) identified that prior effort had a negative effect on subsequent self-concept and prior self-concept had a positive effect on subsequent effort. Furthermore, Han (2017) found that learner beliefs, such as self-concept and success expectation, can change depending on the context, and that there is a mutually reinforcing relationship between learner beliefs and feedback engagement. Dietrich et al. (2017) showed that students invested more effort in situations where they had previously expected to be successful or valued the task highly. Yet, they also had higher expectancies and intrinsic value when they had invested more effort in the previous situation. A subsequent profile analysis showed that experienced costs remained fairly stable (Dietrich et al., 2019). This contradicts the findings of Perez et al. (2019), which suggest less stability of the cost construct over time compared to the other task value constructs.

2. Rationale of our study

Based on the literature, motivational resources can be expected to influence cognitive, affective, and behavioral feedback engagement both directly and moderated by the invested mental effort (Paas et al., 2005; Shenhav et al., 2021). Yet, previously invested mental effort can also affect situational motivational resources which impact feedback engagement (Dietrich et al., 2017; Gieseler et al., 2020). Since previous performance has been found to be related to EVT variables and mental effort, it also ought to be considered as a control variable (Paas et al., 2005; Trautwein et al., 2009). From these theoretical considerations, a cross-lagged model can be assumed which describes the reciprocal relationship between cognitive and motivational resources and cognitive, affective, and behavioral engagement (Fig. 1). To the best of our knowledge, there has been no previous research on the joint influence of cognitive and motivational resources on feedback engagement in a computer-based learning environment with automated feedback for summarizing.

3. Research question and hypotheses

With this study, we want to assess the explanatory power of the theoretical model in relation to our empirical data. Therefore, we specified the following research question and five hypotheses:

RQ: How do cognitive and motivational resources and previous performance affect feedback engagement over time?

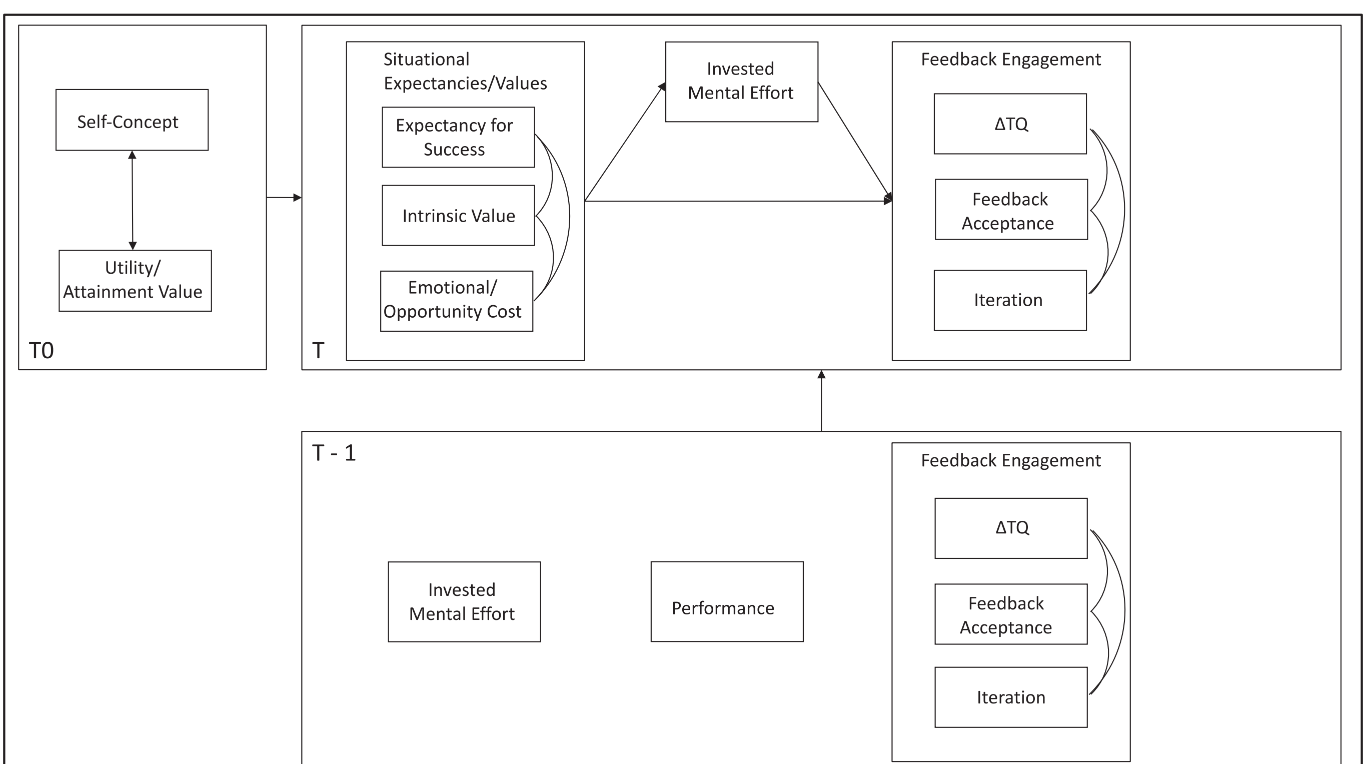

Fig. 1. Theoretical model describing reciprocal associations between invested mental effort, performance, motivational resources, and feedback engagement.

We expect **direct** effects:

H1: Feedback engagement (cognitive, affective, behavioral) is positively affected by

- learner beliefs (self-concept, attainment/utility value, expectancy for success, intrinsic value),
- invested mental effort,

and negatively affected by

- cost.

Furthermore, we expect **indirect** paths:

H2: Invested mental effort is positively affected by

- learner beliefs (self-concept, attainment/utility value, expectancy for success, intrinsic value, cost).

Moreover, we expect **lagged** effects:

H3: Feedback engagement is positively affected by previous

- feedback engagement,
- performance.

H4: Learner beliefs (expectancy for success, intrinsic value, cost) are positively affected by previous

- feedback engagement,
- invested mental effort,
- performance.

H5: Invested mental effort is positively affected by previous

- feedback engagement,
- invested mental effort,
- performance.

4. Methods

4.1. Participants

In total, $N = 330$ German B.Ed. Elementary Education students participated in the study (274 female, 56 male). They were on average $M = 23.09$ ($SD = 2.89$) years old and at least in their fifth bachelor semester. In Germany, B.Ed. Elementary Education students take domain specific subjects in the first four semesters of their program and specialize in a particular type of school, in this case elementary school, in the last two semesters of their bachelor studies. 278 participants had not yet taken a course on teacher-student interaction which was the topic of the texts to be summarized. Data collection took place between April 2021 and December 2021.

The study was approved by the institutional review board according to faculty regulations. The students provided informed consent for the use of their data. Confidentiality and personal data protection were guaranteed in accordance with relevant data privacy laws.

4.2. Computer-based learning environment and Procedure

The *computer-based learning environment* is composed of a client side and a server side (see supplement, Fig. A.1). The client side consists of a) the text to be summarized (Fig. A.2), b) prompts encouraging the use of cognitive strategies for summarizing (Fig. A.3), and c) stimuli for self-assessment presented once before students first access the feedback interface (Fig. A.4). The feedback interface displays semantic feedback and score feedback. Semantic feedback provides information about copied words, redundancies, irrelevant sentences, and unknown words, which are marked in different colors in the text box (Fig. A.5). Score feedback provides information about the summaries' length, how well the source text is covered, and how well copied words and repeating information are avoided (Fig. A.6). The scores are saved as single scores and a composed score that is text quality. Semantic and score feedback can be obtained up to ten times.

The server's main task is to evaluate the summaries and to provide semantic feedback and score feedback. For this purpose, the source texts, expert summaries, and a semantic space were implemented on the server for calculation with latent semantic analysis. A more detailed description of the learning environment can be found in Barkela and Leuchter (in revision).

Procedure. The intervention for summarizing was implemented in an online seminar about academic writing and lasted four weeks. Students had one week to complete each assignment within 90 min. Before the first session, students received video lectures on the required aspects of text quality and information about how to decode the automated feedback. In each session, students' task was summarizing a text. After receiving stimuli for self-assessment, they could revise the first draft, upload the revision, and receive automated formative feedback up to ten times. Before starting the intervention, the students were asked to complete a questionnaire about demographics, self-concept of summarizing, attainment value, and utility value. At each session, the students were asked about their expectancies for success, intrinsic value, and costs before starting the task and their invested mental effort and feedback acceptance after having finished the task.

4.3. Measures

The following variables were assessed once. *Self-concept of summarizing* focused on students' ability to summarize texts (Marsh et al., 2012). It was measured with five items on a four-point Likert-scale, e.g., 'Summarizing is one of my strengths' (Cronbach's $\alpha = 0.85$). *Summarizing utility value* measured the perceived utility of writing summaries in relation to studying successfully. The construct consisted of three items, e.g., 'I find summarizing very useful for my studies' (Cronbach's $\alpha = 0.76$). *Summarizing attainment value* was conceptualized as students' perceived value of summarizing to their studies. It was measured with five items, e.g., 'I find that summarizing is an important learning strategy' (Cronbach's $\alpha = 0.78$). In our study design, we incorporated findings from the literature, indicating that student teachers do not find theoretical knowledge (acquired through summarizing) that important (Bråten & Ferguson, 2015). Thus, we assumed that attainment and utility value would remain stable throughout the weeks and assessed them once before the course started.

The following variables were assessed in each session. *Cognitive feedback engagement* (change in text quality per session) is calculated by the difference of the last submitted summary and the first draft within the session. The range could theoretically span from -100 to $+ 100$. *Affective feedback engagement* (feedback acceptance) was measured with eight questions taken from Seifried et al. (2016), e.g., 'The feedback was fair'. It was measured on a four-point Likert-scale ($1 =$ strongly disagree, $4 =$ strongly agree; Cronbach's $\alpha_{t1} = 0.94$, $\alpha_{t2} = 0.95$, $\alpha_{t3} = 0.96$, and $\alpha_{t4} = 0.97$). *Behavioral feedback engagement* (feedback iteration) is the number of how often the summary was resubmitted and feedback was requested. *Invested mental effort* was measured with three items based on Naismith et al. (2015) and Paas (1992), e.g., 'Today I had to concentrate very hard to understand the text' (Cronbach's $\alpha_{t1} = 0.72$, $\alpha_{t2} = 0.79$, $\alpha_{t3} = 0.71$, $\alpha_{t4} = 0.70$). *Expectancy for success was assessed* with one question about the students' belief how well their summary will score on a dimension with ten percent intervals (Doménech-Betoret et al., 2017).

Values about summarizing were assessed in line with conceptualizations by Wigfield et al. (1997) on a four-point Likert-scale ($1 =$ strongly disagree, $4 =$ strongly agree). *Intrinsic value of summarizing* was constructed as the commitment on learning about summarizing, and comprised four items e.g., 'Today I like to summarize a text' (Cronbach's

$\alpha_{t1} = 0.78$, $\alpha_{t2} = 0.83$, $\alpha_{t3} = 0.84$, and $\alpha_{t4} = 0.85$). *Perceived cost* of working with the learning environment was conceptualized as perceived emotional distress and fear of missing out on other opportunities when working with the learning environment (Eccles & Wigfield, 2020). It was measured with four items, e.g., 'To write a good summary today, I must give up something I would have preferred to do right now' (Cronbach's $\alpha_{t1} = 0.72$, $\alpha_{t2} = 0.80$, $\alpha_{t3} = 0.81$, and $\alpha_{t4} = 0.79$). According to the literature (Hidi & Renninger, 2006), we assumed that intrinsic value and cost vary depending on task and time. We therefore assessed them before every session. *Previous performance* was measured as the summary's final text quality score of the previous session. All self-report items are provided in the supplement B.

4.4. Data analysis

We used the statistics program R, version 4.2.1, (R Core Team (2022), 2022) for data analyses. An a priori power analysis was conducted using „semPower" (Moshagen & Erdfelder, 2016) to determine the minimum sample size required to test the study hypotheses. Results indicated the required sample size to achieve 90% power for detecting a medium effect, at a significance criterion of $\alpha = 0.05$, was $N = 218$ for structural equation modelling. Thus, the obtained sample size of $N = 330$ is a little overpowered but still adequate to test the study hypotheses.

Data processing and preparation was done using the R-package "psych" (Revelle, 2022). Confirmatory factor analyses and estimation of model fits were carried out using "lavaan" (Rosseel, 2012). The data were organized in a long format to represent one time point per subject in each row. Thus, the unit of analysis was each measurement occasion for each student to model the change in the variables over time. To create lagged variables, the variables' values were shifted by one measurement point. This was done for the cognitive, affective, and behavioral feedback engagement and the invested mental effort variables.

5. Results

The main interest of this study was to examine the development and relationship of cognitive, affective, and behavioral feedback engagement as a function of cognitive and motivational resources, for which structural equation modeling is most appropriate. Descriptive statistics and correlational analysis are reported in supplement C. Informed by the literature (Eccles & Wigfield, 2020; Jiang et al., 2018; Viljaranta et al., 2009), and given the strong correlation in our study between summarizing utility and attainment value ($r = 0.65$; Table C.3), we created a composite value score with a high internal consistency (Cronbach's $\alpha = 0.85$). Intrinsic value was measured at a situation-specific level and thus considered separately in the model.

5.1. Structural equation modeling

Following the theoretical assumptions, we specified and tested a cross-lagged model (Fig. 2). *CFI*, *RMSEA,* and *SRMR* fell above or below the cut-offs (Hu & Bentler, 1999) and thus, indicated a good fit (CFI = 0.98 > 0.95; *TLI* = 0.96 > 0.95; RMSEA = .03 < 0.10; SRMR = 0.02 < 0.08). The chi-square/df-ratio did not exceed the cut-off factor 2 ($\chi^2(36) = 69.58$; $\chi^2/df = 1.93$; Kyriazos, 2018).

5.2. Hypothesis testing

We used structural equation modeling with the maximum likelihood estimator (ML) to test direct, indirect, and lagged relationships (Fig. 2). All reported associations were significant at a $p = .05$ level (see also supplement D).

Direct Paths on feedback engagement (H1). Neither learner beliefs nor invested mental effort had a direct significant association with cognitive feedback engagement (change in text quality). Affective feedback engagement (feedback acceptance) had a negative association with expectancy for success ($\beta = -0.11$) and a positive association with intrinsic value ($\beta = 0.18$). Furthermore, affective feedback engagement was

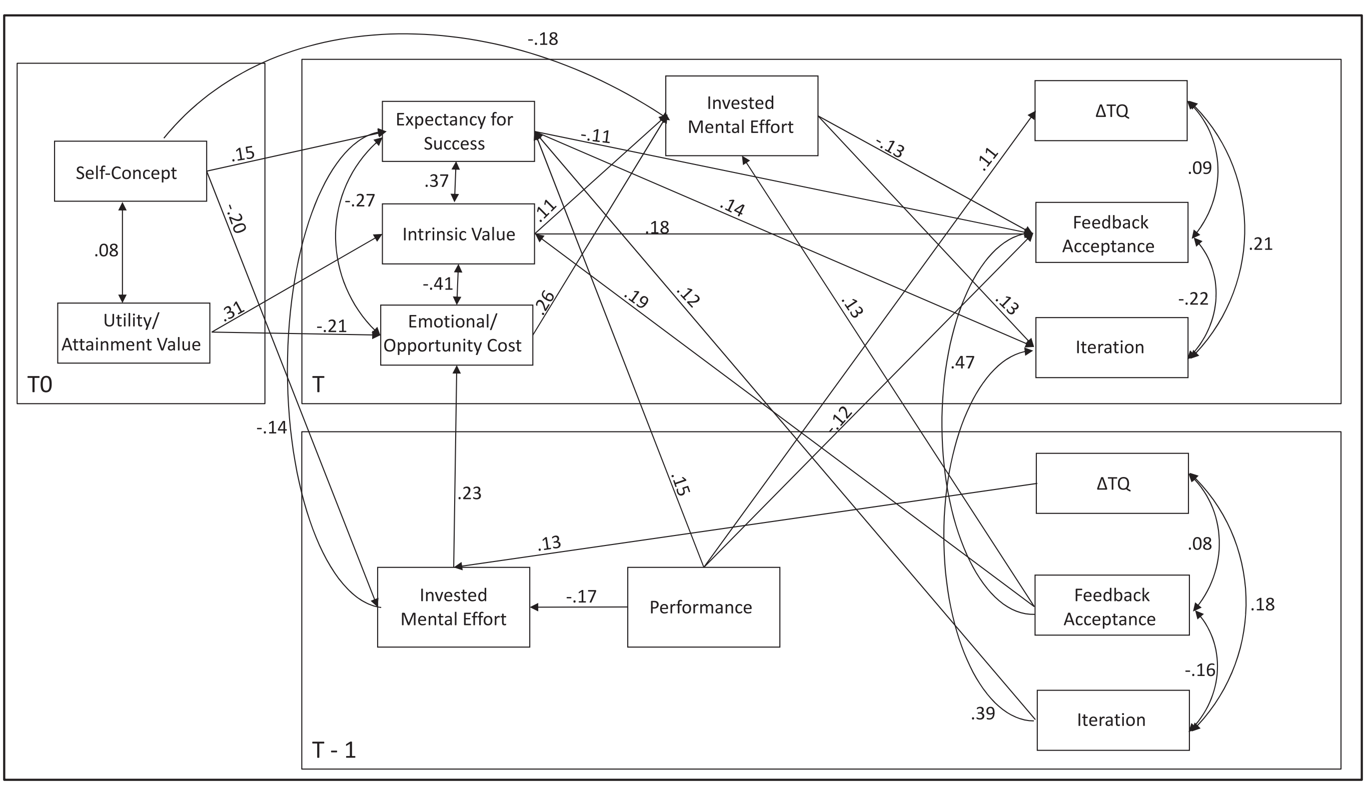

Fig. 2. Standardized path estimates and residual variances. Please note that only significant paths are printed, and all estimates are significant at a p = .05 level.

negatively associated with invested mental effort ($\beta = -0.13$). Behavioral feedback engagement (feedback iteration) was positively associated with expectancy for success ($\beta = 0.14$) and invested mental effort ($\beta = 0.13$). Cost had no direct effect on cognitive, affective, or behavioral feedback engagement.

Indirect Paths on feedback engagement (H2). We found positive associations between invested mental effort and intrinsic value ($\beta = 0.11$) and cost ($\beta = 0.26$). Furthermore, invested mental effort was negatively associated with self-concept ($\beta = -0.18$). Besides, we found positive associations between self-concept and expectancy for success ($\beta = 0.15$) and attainment/utility value and intrinsic value ($\beta = 0.31$). Furthermore, attainment/utility value had a negative effect on cost ($\beta = -0.21$).

Lagged Associations. Concerning H3, only previous performance ($\beta = 0.11$) had a positive effect on cognitive feedback engagement. Affective feedback engagement was negatively associated with previous performance ($\beta = -0.12$) and positively associated with previous affective feedback engagement ($\beta = 0.47$). Behavioral feedback engagement was positively associated with previous behavioral feedback engagement ($\beta = 0.39$). Regarding H4, we found significant associations between expectancy for success and previous behavioral feedback engagement ($\beta = 0.12$), previously invested mental effort ($\beta = -0.14$), and previous performance ($\beta = 0.15$). Furthermore, intrinsic value was positively associated with previous affective feedback engagement ($\beta = 0.19$) and cost was positively associated with previously invested mental effort ($\beta = 0.23$). Lastly, for H5, we found a positive association between invested mental effort and previous affective feedback engagement ($\beta = 0.13$). Besides, previously invested mental effort was significantly associated with previous cognitive feedback engagement ($\beta = 0.13$) and previous performance ($\beta = -0.17$).

6. Discussion

This study investigated the joint impact of cognitive and motivational resources on the development of cognitive, affective, and behavioral feedback engagement in one model to draw conclusions on how to optimize a computer-based learning environment about summarizing and how to foster students' feedback engagement. Since studies have shown that invested mental effort is related to engagement (Dong et al., 2020; Liu & Sun, 2021), and motivational variables can balance the costs to exert mental effort (Feldon et al., 2019; Yee & Braver, 2018), as well as reciprocal relationships between mental effort, motivational variables, and (feedback) engagement (Dietrich et al., 2017; Han, 2017; Marsh et al., 2016), we specified and tested a model with direct, indirect and lagged effects. Absolute model comparisons suggested a good fit implying that in this computer-based learning environment, students' feedback engagement is affected by motivational variables and invested mental effort. Moreover, situational motivational variables and invested mental effort are affected by previous feedback engagement and previous invested mental effort.

An integration of the three outcome variables in one model allows to account for the three dimensions of the engagement construct and their relation. Cognitive feedback engagement (change in text quality) correlates slightly positive with affective feedback engagement (feedback acceptance), suggesting that students who achieve higher change tend to better accept the feedback. Additionally, cognitive feedback engagement is moderately correlated with behavioral feedback engagement (feedback iteration), indicating that students revising their paper and receiving feedback more often are more likely to achieve higher change in text quality. Moreover, affective feedback engagement is negatively correlated with behavioral feedback engagement on a medium level, suggesting that students who accept their feedback tend to request less feedback. In the following, we will discuss the interplay of the cognitive and motivational resources with the three outcome variables.

Associations of T0 on T: In line with the theory, the positive relationship between self-concept and expectancy for success implies that students who think that they are good at summarizing expect high scores (Eccles & Wigfield, 2020). Self-concept influences negatively the invested mental effort, which is in line with previous research suggesting that students who believe to be capable of succeeding in a task experience less mental load than students who believe that they would not succeed in this task (Xu et al., 2021). Redifer et al. (2021) assume two causes for this relation. Students with high self-concept may a) shift attentional resources away from the demands of the task, thereby reducing their own cognitive load which results in less mental effort or b) experience a confidence booster and thus perceive the task as less difficult. Utility/attainment value is positively associated with intrinsic value and negatively associated with cost. This indicates that students who think that summarizing is important also experience high situational enthusiasm about writing a good summary and experience less emotional and opportunity costs (Perez et al., 2019). Unlike other studies (Guo et al., 2016; Meyer et al., 2019) utility/attainment value and self-concept are only slightly correlated, which may be attributable to the course topic (cf. Bråten & Ferguson, 2015).

Associations at T: Contrary to our hypothesis, expectancy for success is negatively associated with affective feedback engagement, indicating that students who expect lower summary scores are more likely to accept their feedback and are willing to improve their summaries according to the feedback. Students who expect higher summary scores might be disappointed by the feedback and therefore are less willing to accept it. Such behavior is known from research on self-efficacy and feedback acceptance. Within this framework, individuals tend to protect their self-efficacy beliefs when they receive feedback that is inconsistent with their efficacy judgments. They might question the accuracy of the feedback or attributing unsuccessful performance to bad luck (Nease et al., 1999; Silver et al., 1995). Furthermore, expectancy for success positively affects behavioral feedback engagement implying that students who expect to write a good summary tend to take more iterations (cf. Eccles & Wigfield, 2020; Putwain et al., 2019; Wu & Kang, 2021). However, there is a possibility that students who have high expectations but receive low scores do not engage thoroughly with the feedback but rather test the adaptivity of the automated feedback thus iterating more.

Moreover, the positive impact of intrinsic value on affective feedback engagement in the same learning situation illustrates that students who are more dedicated to writing a good summary attribute a high valence to their feedback. Additionally, intrinsic value is positively associated with the invested mental effort, indicating that students who are motivated to achieve higher scores also invest more mental effort. Cost is not directly associated with affective feedback engagement. However, cost is moderately associated with the invested mental effort. Thus, students might understand the investment of more mental effort as costs (Feldon et al., 2019). Invested mental effort positively impacts behavioral feedback engagement, indicating that students who allocated more cognitive resources requested feedback more often (Zhang & Hyland, 2022). On the contrary, invested mental effort is negatively associated with affective feedback engagement. Accordingly, students who experience higher mental effort are less likely to accept feedback. Thus, when having invested a high level of cognitive resources but not received the intended reward (good feedback), students may be disappointed and devalue the feedback, accepting it less (cf. Frömer et al., 2021).

Associations at $T - 1$: Cognitive feedback engagement positively affects invested mental effort indicating that students who strongly improved their drafts invested more mental effort (cf. Sweller, 2020). Furthermore, performance negatively affects the invested mental effort (cf. Marsh et al., 2016).

Associations of $T - 1$ on T: Previously invested mental effort is negatively associated with subsequent expectancy for success and positively associated with subsequent cost. This indicates that students who had allocated more cognitive resources earlier predicted a lower text quality in the subsequent learning situation. Effort is often considered a "double-edged sword" in previous research because it can affect students' self-perceptions, as having to invest more mental effort can imply less ability (Dietrich et al., 2017; Marsh et al., 2016).

Furthermore, students who invested more mental effort in one learning situation experienced higher costs in the following session. This is in line with other studies which have shown that exerting cognitive control is effortful and therefore costly (Kool et al., 2017; Shenhav et al., 2021). The increase in students' costs depending on previous mental effort might be related to the finding that after having completed a high demanding task, people tend to choose less demanding tasks (Gieseler et al., 2020). In this study, however, the task difficulty remained comparably the same at each session and might thus have increased students' costs.

Previous performance positively affects expectancy for success. This finding is in line with EVT which states that expectancies for success build on experiences from past learning situations (Eccles & Wigfield, 2020). Furthermore, it positively impacts cognitive feedback engagement, indicating that students with a better summary are more likely to improve their summary in a subsequent learning situation (cf. Putwain et al., 2019). Moreover, students who wrote a good summary in a previous learning situation are less affectively engaged in the subsequent learning situation, indicating that they perceive the feedback as less informative or helpful. This can denote that students with high quality previous summaries might have more difficulty identifying areas for improvement than students with low previous summaries (Xu & Zhang, 2022). This might be reinforced by our tool. Students with high quality previous summaries received high score feedback and might not have seen much value in applying the feedback further. At last, previous affective feedback engagement highly affects subsequent affective feedback engagement. This indicates that once students appreciate the automated feedback to be fair and representative of their summary, they continue to do so throughout the course, employing more motivational and cognitive resources. This is in line with studies that show that the way students perceive the valence of feedback is a determining factor in the successful utilization of feedback (Van der Kleij & Lipnevich, 2021). Likewise, previous behavioral feedback engagement highly affected subsequent behavioral feedback engagement indicating that students who tend to iterate more often in one session maintain this behavior throughout the course (Liu et al., 2017).

6.1. Limitations

This study was conducted with an online computer-based learning environment implemented in a university course about scientific writing. Students had to work weekly assignments to pass the course. However, they were free to decide when and where to work on the assignments. Thus, we had little control whether the students followed the instructions and worked properly with the program. However, this shortage contributes to the ecological validity of this study, as online courses have become a common practice at universities. Yet, students might not have taken the tasks and feedback as seriously as they would have in a higher-stakes situation.

With our data, we were unable to significantly relate cognitive feedback engagement to cognitive or motivational resources, which may have been due to the supportive potential of the feedback algorithm. The automated feedback is calculated based on predefined criteria about content, copied words, redundancies, and length. It seems that students with poor previous performance could use this information to substantially improve their drafts and are thus stimulated in their zone of proximal development (Vygotsky, 1978). However, students who already wrote good summaries could not use the information they received from the feedback to further improve their summaries. The feedback algorithm was not able to develop higher-order criteria and therefore could not feed back more sophisticated information about summarizing. Hence, we were not able to support the higher achieving students in their zone of proximal development. For further research, the algorithm should be extended to include higher-order information, which could be adaptive in the way that only high-scoring students are shown this information. Thus, our study indicates that the development of a more intelligent algorithm that also detects errors in the structure and ideation of a summary itself may be worthwhile.

6.2. Conclusion

Automated formative feedback helps to overcome the dilemma between individual student support and limited resources in large university courses. However, learning successfully in such learning environments depends on the individual feedback engagement. We showed that motivation reduces cost as well as invested mental effort and thus increases behavioral feedback engagement. In addition, we showed that students who have high behavioral feedback engagement tend to have high cognitive feedback engagement. Consequently, when designing learning environments with automated formative feedback, the willingness to allocate more mental resources and to request feedback more often needs to be addressed to motivate students to engage more deeply in their learning processes. However, our study allowed for insights into the interplay between feedback engagement and cognitive and motivational aspects. These might be useful for further studies that consider e.g., students' beliefs about learning and transfer the findings to other computer-based learning environments.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cedpsych.2023.102234.

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