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Learning Analytics Acceptance in Higher Education: An Extension of the TAM with Motivational and Self-Regulatory Factors

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Akzeptanz von Learning Analytics im Hochschulkontext: Eine Erweiterung des TAM um motivationale und selbstregulatorische Aspekte

ZUSAMMENFASSUNG: Im Zuge der digitalen Transformation der Hochschulbildung werden Learning Analytics (LA) Systeme zunehmend eingesetzt, um selbstreguliertes Lernen zu unterstützen und personalisiertes Feedback bereitzustellen. Die vorliegende Studie untersucht zentrale Einflussfaktoren auf die Akzeptanz solcher Systeme, indem das Technology Acceptance Model (TAM) um motivationale und selbstregulatorische Konstrukte erweitert wird. Darüber hinaus werden die Präferenzen der Studierenden für verschiedene Formen LA-basierter visueller Feedbackformate analysiert – mit besonderem Fokus auf Funktionen des sozialen Vergleichs. Die Ergebnisse bestätigen die Bedeutung von Benutzerfreundlichkeit und wahrgenommener Nützlichkeit und identifizieren Aufmerksamkeitskontrolle sowie Zeitmanagement als relevante Prädiktoren für die Akzeptanz von LA. Entgegen der ursprünglichen Annahme wurde sozial referenziertes Feedback als weniger interessant wahrgenommen als individualisierte Formate. Zu den Limitationen der Studie zählen das Querschnittsdesign sowie der Erhebungszeitpunkt, der vor der praktischen Nutzung des Systems lag. Dennoch liefern die Ergebnisse wichtige Erkenntnisse für eine lernendenzentrierte Gestaltung von LA-Systemen und unterstreichen die Notwendigkeit anpassbarer Feedbackstrategien, die den individuellen Präferenzen und regulatorischen Fähigkeiten der Lernenden gerecht werden.

Schlüsselwörter: Learning Analytics, Technology Acceptance Model, Selbstgesteuertes Lernen, Hochschulbildung, Bildungstechnologie

Learning Analytics Acceptance in Higher Education: An Extension of the TAM with Motivational and Self-Regulatory Factors

ABSTRACT: Amid the digital transformation of higher education, Learning Analytics (LA) systems are increasingly used to support self-regulated learning and provide personalized feedback. This study investigates key factors influencing students' acceptance of such systems by extending the Technology Acceptance Model (TAM) with motivational and self-regulatory constructs. It also examines students' preferences for different types of LA-based visual feedback, with a particular focus on social comparison features. The findings confirm the importance of usability and perceived usefulness, and identify attention control and time management as relevant predictors of LA acceptance. Contrary to initial assumptions, socially referenced feedback was perceived as less interesting than individualized formats. Limitations of the study include the cross-sectional design and the timing of data collection, which occurred before students had hands-on experience with the system. Nevertheless, the results provide important insights into learner-centered LA design and highlight the need for adaptable feedback strategies that align with individual preferences and regulatory capacities.

Keywords: Learning Analytics, Technology Acceptance Model, Self-Regulated Learning, Higher Education, Educational Technology

1 Introduction

The digital transformation, coupled with societal trends such as individualization and globalization, has profoundly reshaped the landscape of higher education. Traditional teaching formats—centered around in-person lectures and standardized learning materials—are increasingly insufficient to address the growing heterogeneity of student populations and their diverse learning needs (Eckert et al., 2015). In this context, data-informed technologies such as Learning Analytics (LA) have gained attention as promising instruments for fostering personalized, self-regulated, and adaptive learning (Banihashem et al., 2022).

LA is defined as the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purpose of understanding and optimizing learning and the environments in which it occurs (Siemens & Long, 2011; Viberg et al., 2018). LA tools enable students to reflect on their own learning processes by providing feedback on learning behaviours, task progress, and performance patterns. At the same time, these tools support instructors by identifying at-risk students and promoting targeted support strategies. Especially in hybrid or blended learning environments, LA can increase transparency, enhance motivation, and foster more active engagement with learning content (Ifenthaler et al., 2023). The present study is situated within the KNIGHT (Artificial Intelligence in Education at HFT Stuttgart) project, which investigates how LA and Artificial Intelligence can be meaningfully and responsibly integrated into teaching and learning processes in higher education. As part of this initiative, LA dashboards were used in selected courses to provide students with feedback on their individual learning activities—such as engagement with videos, tasks, and materials—while simultaneously offering aggregated insights into overall course dynamics. This dual perspective enabled learners to reflect on their own progress in relation to course goals and, where applicable, in comparison to peer behaviors.

However, the effectiveness of LA depends not only on its technical capabilities, but also on its acceptance and meaningful use by students. Learners must perceive LA systems as beneficial, easy to use, and aligned with their learning goals—otherwise, these systems risk being ignored or even rejected. Accordingly, a nuanced understanding of learner acceptance is critical to ensure the successful integration of LA into educational settings (Roberts et al., 2016).

TAM provides a well-established framework for examining the adoption of new technologies, focusing on key determinants such as perceived usefulness, ease of use, attitude toward technology, and behavioural intention to use (Davis, 1989; Venkatesh et al., 2003). Nevertheless, the explanatory power of TAM may benefit from the inclusion of additional psychological factors—particularly in educational settings, where individual motivation and self-regulation play a decisive role. This study therefore extends TAM by integrating selected motivational and self-regulatory constructs from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991). For reasons of parsimony and contextual relevance, only those dimensions were selected that were assumed to play a particularly meaningful role in the use of LA tools. Specifically, the following MSLQ dimensions were included: intrinsic goal orientation, extrinsic goal orientation, self-regulation, time management, concentration, and self-efficacy. These constructs were examined as potential predictors of perceived usefulness and ease of use, as they are expected to influence how effectively learners interpret and act upon feedback provided by LA systems. Another significant focus of this study is the role of social dimensions in LA. Drawing on Self-Determination Theory (SDT; Ryan & Deci, 2017), which emphasizes autonomy, competence, and relatedness as fundamental psychological needs, this research examines the potential of social comparison features to enhance motivation and engagement. Fleur et al. (2023) demonstrated that upward social comparisons—where students compare their performance with slightly better-performing peers—can increase extrinsic motivation and improve academic performance (Fleur et al., 2023). This suggests that dashboards incorporating well-designed social comparison features may address the psychological need for relatedness while promoting self-improvement.

This study seeks to address the following research questions: First, how applicable is the TAM framework for understanding the acceptance of LA tools in higher education? Second, how do motivational and self-regulatory factors, as captured by the MSLQ, influence the acceptance of and attitudes toward LA tools? Third, to what extent do social comparison features in LA dashboards align with students' preferences and their perceived impact on learning? By addressing these questions, this study aims to provide new insights into how LA tools can be designed and implemented to meet the diverse needs of students.

The paper is organized as follows: Chapter 2 provides a theoretical overview. Chapter 3 presents the research questions and hypotheses. Chapter 4 details the methodology, including study design, instruments, and data collection. Chapter 5 reports the results, followed by an in-depth discussion in Chapter 6.

2. Theoretical Background and Research Status

LA is a multidisciplinary and inherently complex field, combining expertise from computer science, education, psychology, and data science (Hirsch & Uckelmann, 2024). Its primary aim is to enhance learning environments and outcomes by leveraging data on learners and their interactions with digital systems. However, the implementation of LA requires a nuanced understanding of not only technical aspects but also the psychological and motivational dimensions that drive learner engagement and acceptance. This chapter addresses these challenges by integrating an established acceptance model alongside theoretical frameworks from motivation and self-regulated learning.

2.1 Technology Acceptance Model (TAM)

TAM provides a widely validated framework for analyzing the acceptance of technological systems. Derived from the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980) and the Theory of Planned Behavior (TPB) (Ajzen, 1991), TAM posits that perceived usefulness (PU) and perceived ease of use (EoU) are central determinants of attitude toward technology (Att), which in turn influences behavioral intention (IoU) and actual usage (Davis, 1989; Venkatesh & Davis, 2000). TAM has been successfully applied in numerous educational contexts (Granić & Marangunić, 2019; Pletz, 2021), including the study of learning technologies such as e-learning platforms, educational software, and more recently, LA systems (Mukred et al., 2024). In these settings, TAM provides a useful theoretical lens for understanding how learners perceive and engage with digital tools intended to support academic success.

PU refers to the degree to which a person believes that using a particular technology will enhance their performance. In educational settings, this may include expectations that a system will improve learning outcomes, increase productivity, or facilitate the achievement of academic goals. In contrast, EoU refers to the degree to which the system is seen as intuitive, accessible, and free of effort. Systems perceived as overly complex or difficult to navigate are less likely to be accepted, particularly among users with lower technical affinity (Barz et al., 2024). Attitude toward technology represents the user's overall affective evaluation of the system, encompassing both cognitive judgments and emotional responses. A positive attitude increases the likelihood of behavioral engagement, while negative attitudes often act as a barrier to adoption. Finally, behavioral intention to use the system is considered the most immediate predictor of actual use, reflecting the user's motivational readiness to integrate the tool into regular practices (Venkatesh et al., 2003).

Fig. 1 illustrates the core structure of TAM as applied in educational technology contexts. Its parsimonious structure and predictive validity have contributed to its widespread use in educational research.

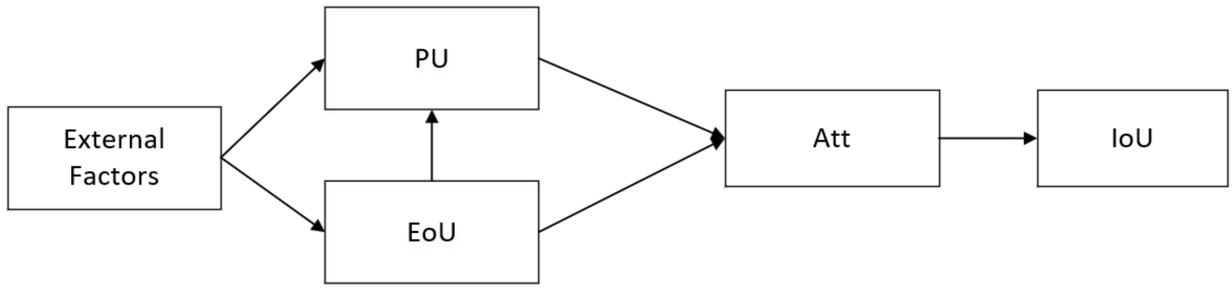

Fig. 1: Technology Acceptance Model Based on Davis et al. (1989). PU = Perceived Usefulness, EoU = Ease of Use, Att = Attitude, IoU = Intention to Use (Own Illustration).

While the original TAM focused on rational-cognitive judgments, its explanatory power in educational contexts has been increasingly expanded by integrating additional constructs that account for the complexity of learning environments. Numerous studies have highlighted that learners' acceptance of educational technologies is not solely determined by perceived usefulness and usability, but also by motivational, affective, and social-cognitive factors. For example, Vanduhe et al. (2020) incorporated constructs such as Task-Technology Fit, Social Influence, and Social Recognition to better explain the adoption of gamified e-learning environments (Vanduhe et al., 2020). Lin and Yeh (2019) introduced Perceived Playfulness as a key intrinsic motivator in their study of virtual reality applications for spatial learning (Lin & Yeh, 2019). These examples illustrate the necessity to broaden the TAM framework in educational research to include both social-cognitive and motivational-affective factors.

2.2 *Self-Regulated Learning*

Self-Regulated Learning (SRL) is an essential aspect of effective learning, encompassing learners' ability to actively direct and control their educational processes. This includes setting goals, organizing ideas, monitoring performance, and managing time efficiently (Schunk & Ertmer, 2000; Zimmerman, 2002). In higher education, these skills are particularly important as students are expected to independently navigate complex learning environments and adapt to diverse demands in academia and the workplace (Buckingham Shum et al., 2019).

Zimmerman's cyclical model of SRL (Zimmerman, 2002, 2008, 2015) is one of the most widely referenced frameworks for understanding self-regulated learning processes. This model identifies three interconnected phases that guide learners' regulation of their learning activities. The forethought phase involves task analysis, goal setting, and strategic planning, all influenced by learners' self-motivational beliefs. The performance phase focuses on the execution of learning tasks, where learners employ self-control (e.g., attention focusing, self-instruction) and self-observation (e.g., metacognitive monitoring). Finally, the self-reflection phase involves evaluating task performance, which generates self-reactions that influence subsequent learning cycles.

LA tools, particularly visual dashboards, are designed to enhance SRL by providing actionable insights into learners' progress and behaviors. These tools are often aligned with Zimmerman's SRL model to support learners in all three phases. For instance, during the forethought phase, dashboards can present personalized learning paths and visualizations of goal progress, helping students to establish clear objectives. In the performance phase, real-time feedback mechanisms enable learners to monitor their engagement and adapt strategies in response to challenges. Finally, during the self-reflection phase, performance analytics allow learners to evaluate their progress, understand areas for improvement, and adjust their approaches for future tasks (Panadero, 2017).

To operationalize and assess these self-regulatory processes in educational research, the Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich et al. (1991) has become one of the most prominent instruments. It captures a broad range of motivational and learning strategy dimensions, including intrinsic and extrinsic goal orientation, task value, control of learning beliefs, self-efficacy for learning and performance, test anxiety, rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time and study environment management, effort regulation, peer learning, and help seeking (Pintrich et al., 1991). In this study, the following dimensions were included: intrinsic and extrinsic goal orientation, self-efficacy, self-regulation, time management, and concentration. These dimensions are closely aligned with the phases of Zimmerman's model of self-regulated learning and reflect essential motivational dispositions and metacognitive strategies that shape how students approach learning tasks, interpret feedback, and regulate their academic behavior. They are particularly relevant for understanding students' interactions with LA tools, as these systems often require learners to engage in autonomous decision-making based on performance data. By integrating these constructs into Learning Analytics research, it becomes possible to move beyond descriptive usage patterns and toward a more nuanced understanding of individual learner differences. This approach highlights the role of personal dispositions in shaping the perceived usefulness and effectiveness of LA systems and contributes to aligning tool design with principles of learner-centered pedagogical support.

2.1.2 Social and motivational Theories

Learning is not an isolated process; it is deeply influenced by observing the behaviors of others and their consequences, as outlined in Bandura's Social Learning Theory (Bandura, 1977), which emphasizes the acquisition of competencies through observation and social interaction. In digital learning contexts, Learning Analytics dashboards that incorporate social comparison functions operationalize these principles by providing learners with performance-related insights relative to their peers. However, while social comparison can enhance motivation through vicarious reinforcement, its effects are not universally beneficial.

Research underscores the potential motivational benefits of dashboards that integrate social comparisons. For instance, Davis et al. (2017) developed a personalized feedback system that enabled learners to compare their behaviors with those of previously successful peers using interactive visualizations of multiple learning indicators. Their study showed that learners in MOOCs exhibited increased engagement and higher completion rates when such a dashboard was employed (Davis et al., 2017). Nonetheless, the effects of social comparison in dashboard environments are not uniformly positive. Rank-order visualizations, which display learners' standings relative to their peers, may lead to divergent responses. While some students are motivated by "healthy peer pressure" (Tan et al., 2016), others may feel discouraged or demoralized—especially those with low self-efficacy or limited academic confidence (Cherry & Ellis, 2005; Gašević et al., 2015). These ambivalent effects highlight the necessity of tailoring such tools to different motivational profiles and underscore the role of self-perception and context-sensitive feedback design.

Complementing social-cognitive perspectives, Self-Determination Theory (Ryan & Deci, 2000, 2017, 2020) provides a motivational framework centered on the fulfillment of basic psychological needs as a prerequisite for sustained engagement. SDT posits that intrinsic motivation flourishes when autonomy, competence, and relatedness are supported. Autonomy refers to the perception of control over one's learning, where students feel that they can make meaningful choices regarding their educational activities. Learning environments that provide personalized feedback and adaptive pathways support autonomy by allowing students to tailor their learning experience to their individual needs and goals (Ryan & Deci, 2020). Competence pertains to the feeling of being capable and effective in one's learning efforts. LA tools that provide structured feedback on performance, skill development, and learning progress can enhance competence by helping learners track their improvement and adjust their strategies accordingly (Chiu, 2021). Relatedness involves the sense of belonging and meaningful connection with others in the learning environment. Features such as social comparison dashboards and collaborative learning platforms fulfil this need by fostering a sense of connection, thereby enhancing motivation and engagement (Lee & Kim, 2024).

The integration of SDT into LA research offers insights into how data-driven feedback can be designed to support motivation and self-regulation. For instance, LA dashboards that offer personalized learning trajectories and recommendations can reinforce students' sense of autonomy by allowing them to make informed decisions about their learning. Similarly, diagnostic and prescriptive feedback that highlights areas of strength and improvement can contribute to learners' competence by providing actionable insights for academic growth. Additionally, social learning features, such as peer comparisons and collaborative performance metrics, can influence relatedness by creating a sense of shared learning experiences (Ferguson & Clow, 2017).

Despite these potential benefits, the application of SDT in LA-based feedback systems presents challenges. While some students may find social comparison features motivating, others may perceive them as discouraging, particularly if they struggle with self-efficacy. Similarly, feedback that lacks personalization or is overly prescriptive may undermine autonomy by making learners feel constrained rather than empowered (Wisniewski et al., 2020). These considerations underscore the need for a learner-centered approach in designing LA tools that align with motivational principles and support diverse learning needs.

Taken together, Social Learning Theory and SDT provide a robust theoretical basis for examining how social dynamics and motivational affordances of LA systems influence learner perceptions. When data-based feedback supports psychological needs and includes peer comparisons, it may increase their willingness to engage with such tools. Conversely, unmet motivational needs or unbalanced social comparison may lead to resistance or disengagement.

3. Hypotheses

Based on the research questions outlined in Chapter 1 and the theoretical foundation presented in Section 2, this study explores the applicability of the TAM in understanding students' acceptance of LA tools. Previous research has demonstrated the robustness of TAM across various technological domains, including educational applications (Granić & Marangunić, 2019; Pletz, 2021). In the context of LA, it is essential to examine whether the core constructs of TAM—EoU, PU, Att and IoU—retain their predictive power regarding students' intentions to adopt LA tools. Furthermore, this study seeks to expand TAM by integrating motivational and self-regulatory dimensions to capture the multifaceted dynamics that influence the acceptance of these tools.

Acceptance is conceptualized as a multidimensional construct, encompassing both IoU and PU. This reflects the assumption that students' internal dispositions—such as motivational orientation and self-regulatory abilities—substantially contribute to how LA tools are perceived, valued, and incorporated into academic behavior.

Motivational orientations, particularly intrinsic goal orientation (IGO) and extrinsic goal orientation (EGO), describe students' underlying reasons for engaging with academic content. IGO represents a focus on interest and personal development, while EGO is associated with achievement driven by external incentives. Both orientations may influence students' willingness to adopt LA tools, albeit through different mechanisms: students high in IGO may use LA tools to enhance metacognitive insight and foster mastery, whereas those high in EGO may use them to maximize visible performance outcomes. Therefore, the following hypotheses are proposed:

H1.1: IGO positively predicts students' IoU of LA tools.
H1.2: EGO positively predicts students' IoU of LA tools.

In addition to motivational dispositions, self-regulatory competencies are central to the meaningful use of LA systems. Learners who are capable of monitoring and adjusting their learning behavior (SR), managing their time efficiently (TM), maintaining attentional focus (Con), and acting with confidence in their abilities (SE) are more likely to benefit from the affordances of LA tools. These tools often provide structured feedback and progress visualizations that presuppose a certain degree of self-regulatory engagement. Thus, students who exhibit these competencies may perceive LA tools as more useful and relevant to their learning. Accordingly, the following hypotheses are formulated:

H2.1: SR positively predicts PU of LA tools.
H2.2: TM positively predicts PU of LA tools.
H2.3: Con positively predicts PU of LA tools.
H2.4: SE positively predicts PU of LA tools.

Finally, this study examines how students evaluate social comparison features integrated into LA dashboards. These features enable learners to situate their performance relative to peers, potentially stimulating motivation through feedback and orientation. When implemented appropriately, such features can support reflection, encourage persistence, and foster a sense of transparency in the learning process. To assess the perceived added value of these features, we propose:

H3: LA tools that include social comparison features are perceived as more engaging and supportive of learning than tools without such features.

4. Methods

This chapter outlines the methodological framework of the study, including the research design, LA infrastructure, sample characteristics, data collection procedures, and instruments used to investigate the research questions and test the proposed hypotheses.

4.1 Research Context

This study was conducted as part of the KNIGHT project at the HFT Stuttgart, which aims to integrate LA tools into various courses. The primary objective was to explore students' attitudes and acceptance toward LA tools, as well as the influence of motivational and self-regulatory factors on their engagement with and preferences for these systems. A quantitative, cross-sectional design was employed to capture data at the beginning of the Winter Semester 2024/2025, providing an initial evaluation of students' perceptions before engaging with the LA tools during the courses.

To support this initiative, a Learning Analytics infrastructure based on the Moodle plugin Excalibur (Judel et al., 2024) was implemented. The system enables detailed behavioral tracking via xAPI and delivers feedback through integrated dashboards. However, at the time of the survey, students had not yet interacted with the system; they were only informed about its planned features and goals. All processes adhered to current data protection standards.

4.2 Sample and Data Collection

The study involved a total of 140 bachelor's students enrolled in the courses Mathematics 1, Mathematics 2, and IT in Enterprise Networks. These courses were selected due to their active integration of LA tools into the curriculum. All three courses were delivered in a hybrid format. Prior to data analysis, one participant was excluded due to an excessive number of missing responses, resulting in a final sample of 139 students. Demographic information such as age, gender, and specific course enrollment was not collected, as these variables were not pertinent to the study's central research focus on motivational, cognitive, and behavioral predictors of LA acceptance. This decision was made deliberately to minimize participant burden and ensure a concise, construct-focused questionnaire, in line with established guidelines for survey-based research (Tourangeau et al., 2000).

Data collection took place at the beginning of the semester during the first session of each course. Participants completed an online questionnaire implemented via Unipark. To ensure informed participation, students first viewed a short explanatory video that introduced the LA infrastructure, described its intended educational benefits, and outlined relevant data privacy provisions. The video is available for viewing at the following link: https://vimeo.com/1099266111. The video also emphasized that participation was voluntary, anonymous, and that responses would be used exclusively for scientific purposes. Students were informed of their right to withdraw at any time without consequences.

4.3 Instruments

4.3.1 Technology Acceptance Model Constructs

To assess students' acceptance of LA systems, constructs from the TAM were adapted, including perceived usefulness, perceived ease of use, attitude toward technology, and behavioral intention. Each construct was measured using a 5-point Likert scale, with items derived from established TAM studies (Davis, 1989; Pletz, 2021; Venkatesh & Davis, 2000). The questionnaire was administered in German. Example items include: "I believe that using Learning Analytics will improve my academic performance" (PU), "I believe that using the Learning Analytics infrastructure will be easy" (EoU), "I have a positive attitude toward using Learning Analytics" (Att), and "I intend to use Learning Analytics in the future" (IoU).

4.3.2 Motivational and Self-Regulatory Factors

Motivational and self-regulatory factors were measured using subscales from MSLQ. The dimensions assessed included: Intrinsic Goal Orientation, Extrinsic Goal Orientation, Self-Regulation, Time Management, Self-Efficacy and Concentration. Each dimension was measured using multiple items rated on a 5-point Likert scale, with higher scores indicating stronger alignment with the respective dimension.

4.3.3 Learning Analytics Feedback Preferences

To explore students' preferences regarding specific types of feedback provided by LA tools, the questionnaire included a set of 13 items, each rated on a 5-point Likert scale (1 = Not interesting, 5 = Very interesting). The feedback options reflected a diverse set of LA outputs commonly discussed in educational research and practice. For example, the item "How interesting do you find a visualization of your learning time compared to your peers over the last few weeks?" assessed interest in socially referenced feedback. In total, five items included a social reference, while eight items addressed individual feedback without peer comparison. Tab. 1 provides an overview of all feedback types used in the questionnaire, categorized by whether or not a social reference was included**.**

Tab. 1: Items Used to Assess Interest in Different Learning Analytics Features, Including their Social Reference and Feedback Type

Learning Analytics	**Social Reference**
Visualization of learning time compared to peers over the last few weeks	Yes
Overview of completed tasks and tests compared to course objectives	No
Diagram showing progress in different course topics	No
Visualization of correct answers compared to the average of all students	Yes
Display of course activity (e.g., number of logins, completed tasks) compared to peers	Yes
Visualization of participation in discussions and forums compared to others	Yes
Predicted success based on past activity and performance	No

Dashboard with recommendations for improving learning behavior	No
Overview of learning activities throughout the semester in a learning calendar	No
Visualization of how current performance aligns with personal learning goals	No
Graphic showing how many resources (videos, texts, tasks) have been used compared to peers	Yes
Display of self-tests and exercises with suggestions for improvement based on results	No
Analysis of learning interruptions with suggestions to minimize them	No

4.4 Data Analysis

All statistical analyses were performed using R version 4.3.1 (R Core Team, 2023). Before conducting the main analyses, the dataset was screened for accuracy and data quality. One participant was excluded at the outset due to an extensive pattern of missing responses. To identify outliers, both univariate and multivariate procedures were applied. Univariate outliers were detected using standardized z-scores ($|z| > 3.29$). Although several such cases were identified, they were retained, as their values were plausible in the context of student responses and did not unduly influence the distribution. Multivariate outliers were examined using Mahalanobis distance, with a critical threshold set at $p < .001$ based on the χ^2 distribution. One multivariate outlier exceeded this threshold and was excluded from further analysis to enhance the robustness of the multivariate modeling. Missing data were assessed using Little's MCAR test, which yielded a non-significant result ($p = .236$), suggesting that the data were missing completely at random (MCAR).

To evaluate the psychometric quality of the measurement instruments, descriptive statistics (mean, standard deviation), item difficulties, and corrected item-total correlations (discrimination power) were calculated for each item. Internal consistency was assessed using Cronbach's alpha (α). Reliability values were interpreted following the common benchmarks (George & Mallery, 2018): $\alpha \geq .80$ = good, .70–.79 = acceptable, .60–.69 = questionable, and < .60 = poor. Discrimination power values above .30 were considered acceptable (Moosbrugger & Kelava, 2008).

To test the hypothesized relationships among the TAM constructs and the motivational and self-regulatory predictors, Path Model Analysis (PMA) was performed using the lavaan package (Rosseel, 2012). PMA was based on variables that met the assumption of multivariate normality; hence, the maximum likelihood estimator (ML) was applied. Model fit was evaluated using standard indices: chi-square (χ^2), degrees of freedom (df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The structural path diagram of the final SEM model was created in Microsoft Visio, based on the standardized coefficients derived from the model estimation.

For the analysis of interest in different types of LA feedback, descriptive statistics were computed for each of the 13 items. Interest ratings were grouped based on whether the feedback contained social comparison features or not. Normality of the aggregated scores for both groups was tested using the Shapiro–Wilk test. Due to significant deviations from normality in both groups ($p < .001$), a Wilcoxon signed-rank test for paired samples was applied to compare interest levels between feedback types with and without social comparison.

5. Results

5.1 Reliability Analysis

The reliability values (Cronbach's alpha) for the scales ranged from .51 to .85. The highest reliability was observed for SE (α = .85), IoU (α = .84) and PU (α = .83), indicating strong internal consistency for these measures. EoU and Attitude showed acceptable reliability values (α = .73 and α = .76, respectively), supporting their consistency. Conversely, IGO and SR demonstrated the lowest reliability (α = .51 and α = .57), highlighting potential limitations in the consistency of these scales. EGO (α = .71) and TM (α = .67) showed moderate reliability, while Concentration had a slightly lower value (α = .62). These results suggest that some scales, particularly IGO and SR, may require refinement in future studies.

Tab. 2: Psychometric Properties of the Scales Used.

Scale	Number of Items	M	SD	Discrimination Power	Reliability
PU	4	3.82	0.60	.64 - .78	.83
EoU	4	3.59	0.58	.48 - .73	.73
Att	4	3.76	0.61	.56 - .81	.76
IoU	3	3.60	0.73	.72 - .82	.84
IGO	3	3.98	0.51	.40- .57	.51
EGO	4	3.75	0.77	.47 - .71	.71
SR	4	3.37	0.59	.32 - .60	.57
TM	4	3.31	0.69	.49- .77	.67
SE	4	3.41	0.74	.64 - .81	.85
Con	4	3.40	0.70	.40 - .63	.62

Notes: PU = Perceived Usefulness, EoU = Perceived Ease of Use, Att = Attitude, IoU = Intention of Use, IGO = Intrinsic Goal Orientation, EGO = Extrinsic Goal Orientation, SR = Self-Regulation, TM = Time Management, SE = Self-Efficacy, Con = Concentracion. All scales were measured on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

5.1 Descriptive Results

The descriptive statistics for the scales used in the study are presented in Tab. 2. Overall, the results indicate that participants perceived LA as highly useful (PU: M = 3.82, SD = 0.60) and user-friendly (EoU: M = 3.59, SD = 0.58). Participants also reported a high intention to use LA (IoU: M = 3.60, SD = 0.73) and expressed a positive attitude toward LA (Att: M = 3.76, SD = 0.61).

In terms of motivational orientations, IGO had the highest mean among all scales (M = 3.88, SD = 0.51). This indicates that participants were highly motivated by intrinsic factors, such as personal interest or enjoyment in learning. EGO was also relatively high (M = 3.75, SD = 0.77), showing that external rewards or outcomes influenced participants' motivation as well.

Scales related to learning strategies displayed lower mean values. For example, SR had a mean of 3.37 (SD = 0.59) and TM had a mean of M = 3.31, (SD = 0.50). SE showed a moderately high mean (M = 3.41, SD = 0.74), Con had a mean of 3.40 (SD = 0.70).

5.2 Path Model Analysis and Hypotheses Testing

To examine the hypothesized relationships, a path model was estimated using the lavaan package in R, employing maximum likelihood estimation (ML). The model incorporated the core constructs of the Technology Acceptance Model (PU, EoU, Att, IoU) and was extended with selected motivational (EGO) and self-regulatory (SR, TM, Con, SE) predictors. The evaluation followed established criteria for model fit (CFI and TLI $\geq .95$, RMSEA $\leq .06$, SRMR $\leq .08$), and statistical significance was determined at $p < .05$ (Hu & Bentler, 1999). The model demonstrated excellent fit to the data, $\chi^2(11) = 8.00$, $p = .713$, CFI = 1.000, TLI = 1.024, RMSEA < .001, SRMR = .023. The amount of explained variance was substantial for IoU (54%) and Att (62%), while more modest for PU (19%). A visual representation of the structural model, including all standardized coefficients, is provided in Fig. 2.

As anticipated, the central relationships posited by the TAM were fully supported. PU exhibited a strong and significant effect on IoU ($\beta = .477$, $p < .001$), and Att also significantly predicted IoU ($\beta = .482$, $p < .001$). EoU was positively associated with both PU ($\beta = .369$, $p < .001$) and Att ($\beta = .252$, $p < .001$), confirming the mediating role of usability perceptions in shaping students' acceptance intentions. These findings align with prior empirical research and reinforce the robustness of the TAM framework in the context of Learning Analytics.

The hypothesized effects of motivational factors could only be partially addressed. H1.1, which posited a positive effect of IGO on IoU, could not be empirically tested, as IGO was excluded from the model due to insufficient reliability and low item discrimination. H1.2, proposing that EGO would positively influence IoU, was not supported; the corresponding path was non-significant ($\beta = .068$, $p = .224$), indicating that extrinsic goal orientation did not meaningfully contribute to students' behavioral intentions toward LA tools within the tested model.

Partial support was found for the proposed role of self-regulatory competencies. Con demonstrated a significant positive effect on PU ($\beta = .203$, $p < .05$), as did TM ($\beta = .153$, $p < .05$), thereby supporting hypotheses H2.2 and H2.3. In contrast, the effects of SR ($\beta = .022$, $p = .797$) and SE ($\beta = -.084$, $p = .182$) on PU were not statistically significant, leading to the rejection of H2.1 and H2.4. These results suggest that attentional control and effective time allocation are more critical for the perception of usefulness in LA tools than broader metacognitive strategies or confidence in academic abilities under the present conditions.

Fig. 2 displays all statistically significant paths within the model along with their standardized coefficients.

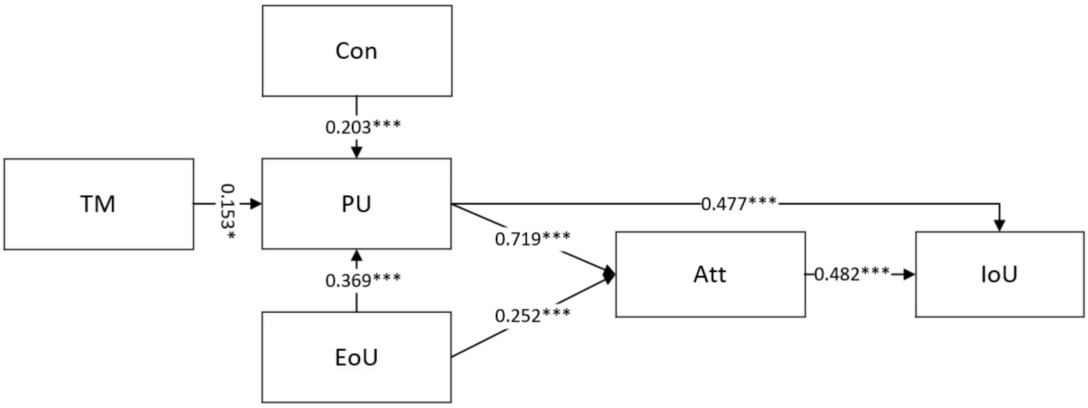

Fig. 2: Path model of Learning Analytics acceptance, including significant paths. Con = Concentracion, TM = Time Management, PU = Perceived Usefulness, EoU = Ease of Use, Att = Attitude, IoU = Intention to Use. Own illustration and computation. Significance levels: * p < .05, ** p < .01, *** p < .001.

5.3 Social Comparison Features in Learning Analytics Tools

To examine whether LA tools incorporating social comparison features were perceived as more engaging and impactful on learning compared to those without social comparison features, the interest ratings of students for the two groups of items were analyzed. The descriptive analysis was first conducted using boxplots (Fig. 3).

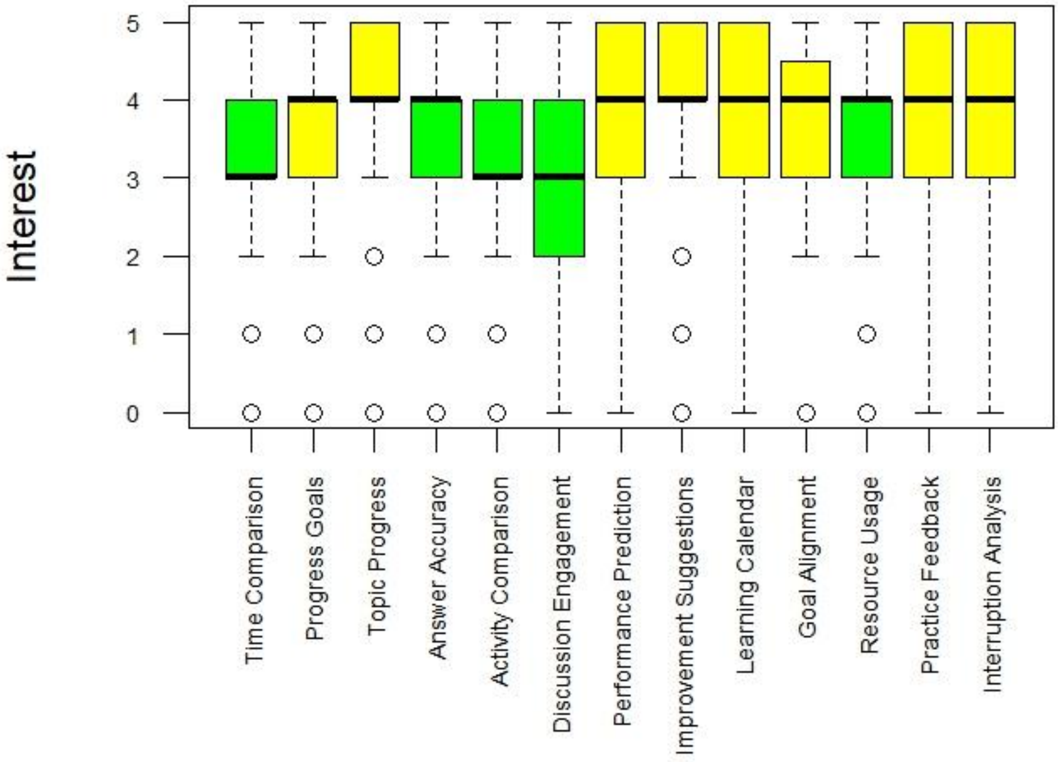

Fig. 3: Distribution of interest ratings for different Learning Analytics feedback types. Items incorporating social comparison features are highlighted in green, while items without social comparison features are marked in yellow.

The figure shows the distribution of interest ratings for each of the 13 LA feedback types included in the study. Items incorporating social comparison features are marked in green, while items without social comparison features are marked in yellow.

The boxplots reveal a noticeable trend: Items without social comparison features generally received higher interest ratings compared to items with social comparison features. The median interest levels for non-social items consistently appeared higher than those for social items, with fewer outliers indicating more consistent perceptions among students. This suggests that feedback types emphasizing personal progress and individual performance were perceived as more engaging compared to those requiring social reference.

To test the statistical significance of the observed differences, appropriate analyses were conducted. The Shapiro–Wilk test was used to assess the normality of the summed scores for items with and without a social reference. The results indicated a significant deviation from normality in both groups ($W = 0.980$, $p < 0.05$ for the sum of items without a social reference; $W = 0.956$, $p < 0.01$ for the sum of items with a social reference), which necessitated the use of a non-parametric test for group comparisons.

Subsequently, a Wilcoxon signed-rank test for paired samples was conducted to examine differences in interest ratings between the two item groups. The results revealed a highly significant difference ($V = 135$, $p < 0.01$, $r > 0.5$), indicating that items incorporating social comparison features were rated significantly lower in interest than those without a social reference. This finding directly contrasts with the initial hypothesis (H3), which proposed that LA tools incorporating social comparison features would be perceived as more engaging and impactful on learning.

In conclusion, the results suggest that students prefer LA tools that emphasize individual progress and self-referenced feedback over those incorporating social comparison features.

6. Discussion

The findings of this study contribute to the growing body of research on LA acceptance by integrating motivational and self-regulatory learner characteristics into TAM. As outlined in the introduction, while TAM has consistently demonstrated predictive utility across technological domains, its application in education often remains limited to usability-related aspects. By extending TAM with selected constructs from the MSLQ, this study aimed to capture the psychological dynamics underlying students' perceptions of and behavioral intentions toward LA tools.

Consistent with prior TAM-based research, the analysis confirmed that both PU and Att significantly predicted IoU. Furthermore, EoU was positively associated with both PU and Att, reinforcing the notion that usability continues to be a key determinant in students' acceptance of data-driven learning technologies. These findings underscore the importance of maintaining user-friendliness as a central design principle in educational analytics systems.

Beyond these core relationships, the hypothesized effects of motivational goal orientations yielded more limited insight. Due to poor reliability and item discrimination, IGO had to be excluded from the model, preventing empirical testing of H1.1. Although EGO remained in the model, it did not significantly predict IoU, leading to the rejection of H1.2. This finding diverges from earlier assumptions that extrinsically motivated students would leverage LA tools to optimize performance outcomes. It is conceivable that LA systems—particularly when used early in a semester—do not yet present sufficient performance-related incentives to engage extrinsically driven learners. Alternatively, the strategic use of such tools may presuppose prior familiarity with data-based feedback systems or a greater degree of metacognitive sophistication than EGO captures.

In contrast, more differentiated effects were observed for self-regulatory competencies. Con and TM significantly predicted PU, supporting H2.2 and H2.3. This suggests that students who can manage their attention and allocate time effectively are better positioned to interpret the feedback offered by LA tools and perceive it as beneficial for their learning. These findings align with the idea that LA tools require a certain degree of cognitive engagement to unfold their full potential. However, SR and SE were not significant predictors of PU, resulting in the rejection of H2.1 and H2.4. One explanation may lie in the nature of the dashboards examined, which primarily focused on visualizations of task completion and peer comparison rather than prompting metacognitive reflection or encouraging confidence in one's academic abilities. These results imply that self-regulatory dimensions such as attentional control and time allocation may be more immediately relevant to students' judgments of utility than broader self-monitoring strategies or general academic confidence.

The findings on social comparison features (H3) were particularly noteworthy. Contrary to widespread assumptions, peer-related feedback was rated as less interesting than individual visualizations. This challenges the notion, often derived from social learning theory, that social comparison necessarily promotes engagement. One possible explanation is that students were unfamiliar with interpreting comparative metrics without having interacted with the dashboard. Alternatively, the results may reflect a deliberate avoidance of competitive framing, particularly among students who prefer self-paced and individualized feedback. This interpretation aligns with prior studies that found mixed responses to social comparison, depending on learners' self-efficacy, academic confidence, and perceived threat of evaluation (Gašević et al., 2015). The observed preference for non-social, individual feedback suggests that learner autonomy and control may outweigh the motivational benefits of peer benchmarking in certain educational contexts. From a design and implementation perspective, these results argue against a one-size-fits-all approach to LA dashboards. While some learners may benefit from social benchmarks, others may experience increased anxiety or disengagement. Rather than eliminating social features altogether, LA tools should enable users to choose, configure, or deactivate peer comparisons based on their preferences and motivational orientation. This aligns with psychological needs for autonomy and competence (Ryan & Deci, 2020) and may foster a greater sense of ownership and sustained engagement. Configurability should thus not be seen as a superficial personalization layer, but as a pedagogically justified strategy to support diverse learner profiles.

Several practical implications can be derived from these findings. First, the strong influence of EoU on both PU and Att reinforces the critical role of intuitive interface design. LA tools should minimize complexity, reduce navigational barriers, and ensure that learners can easily interpret the feedback provided. Second, the predictive value of Con and TM suggests that effective use of LA tools depends on learners' attentional and time-management capacities. Instructors and designers might consider embedding scaffolds—such as reflective prompts, goal-setting templates, or progress-tracking aids—to support students in interpreting data and aligning it with personal learning strategies. Finally, the differentiated reception of social comparison features points to the need for customizable dashboards that respond to diverse learner preferences and psychological profiles. Such flexibility can foster agency and increase sustained engagement by aligning feedback mechanisms with individual needs and learning dispositions.

At the same time, several limitations must be acknowledged. Data collection occurred at the beginning of the semester, before students had hands-on experience with the dashboard. As such, responses regarding PU and EoU were based on anticipatory perceptions rather than actual interaction with the system, which may limit the ecological validity of the results. Additionally, the study relied exclusively on self-report data, which are susceptible to bias and may not fully capture behavioral engagement. Some scales, such as TM and SR, showed suboptimal reliability, limiting the strength of interpretation for these constructs. The exclusion of IGO due to insufficient psychometric quality also reduced the ability to test a complete model of motivational influence. Moreover, the sample was restricted to students in technical programs at a university of applied sciences, which may limit generalizability to other academic disciplines or more heterogeneous student populations. Finally, the cross-sectional design precludes causal interpretation; future studies should employ longitudinal or experimental designs to capture changes in perceptions over time and their relationship to actual usage behaviors.

Despite these limitations, the findings offer important insights into the psychological factors shaping LA acceptance and provide concrete guidance for the design and implementation of learner-centered analytics systems in higher education. They also underscore the value of interdisciplinary frameworks that bridge usability, motivation, and self-regulation in the pursuit of effective educational technologies.

7 Conclusion

This study highlights the importance of integrating motivational and self-regulatory factors into established technology acceptance frameworks to better understand students' engagement with LA tools in higher education. By extending TAM with constructs from the MSLQ, we demonstrated that learners' internal dispositions significantly contribute to the perceived usefulness and behavioral intention to use LA systems. The findings underscore the need for learner-centered LA design and call for continued empirical and theoretical refinement to foster meaningful, ethical, and motivationally sound learning analytics applications.

Literatur

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1980). Understanding Attitudes and Predicting Social Behavior.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. Psychological Review, 84(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

Banihashem, S. K., Noroozi, O., van Ginkel, S., Macfadyen, L. P., & Biemans, H. J. A. (2022). A systematic review of the role of learning analytics in enhancing feedback practices in higher education. Educational Research Review, 37, 100489. https://doi.org/10.1016/j.edurev.2022.100489

Barz, N., Benick, M., Dörrenbächer-Ulrich, L., & Perels, F. (2024). Students' acceptance of e-learning: Extending the technology acceptance model with self-regulated learning and affinity for technology. Discover Education, 3(1), 114. https://doi.org/10.1007/s44217-024-00195-7

Buckingham Shum, S., Ferguson, R., & Martinez-Maldonado, R. (2019). Human-Centred Learning Analytics. Journal of Learning Analytics, 6(2). https://doi.org/10.18608/jla.2019.62.1

Cherry, T. L., & Ellis, L. V. (2005). Does Rank-Order Grading Improve Student Performance?: Evidence from a Classroom Experiment. International Review of Economics Education, 4(1), 9–19. https://doi.org/10.1016/S1477-3880(15)30140-7

Chiu, T. K. F. (2021). Digital support for student engagement in blended learning based on self-determination theory. Computers in Human Behavior, 124, 106909. https://doi.org/10.1016/j.chb.2021.106909

Davis, D., Jivet, I., Kizilcec, R. F., Chen, G., Hauff, C., & Houben, G.-J. (2017). Follow the successful crowd: Raising MOOC completion rates through social comparison at scale. Proceedings of the Seventh International Learning Analytics & Knowledge Conference, 454–463. https://doi.org/10.1145/3027385.3027411

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. Management Science, 35(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Eckert, C., Seifried, E., & Spinath, B. (2015). Heterogenität in der Hochschule aus psychologischer Sicht: Die Rolle der studentischen Eingangsvoraussetzungen für adaptives Lehren. In K. Rheinländer (Hrsg.), Ungleichheitssensible Hochschullehre: Positionen, Voraussetzungen, Perspektiven (S. 257–274). Springer Fachmedien. https://doi.org/10.1007/978-3-658-09477-5_14

Ferguson, R., & Clow, D. (2017). Where is the evidence? A call to action for learning analytics. Proceedings of the Seventh International Learning Analytics & Knowledge Conference, 56–65. https://doi.org/10.1145/3027385.3027396

Fleur, D. S., van den Bos, W., & Bredeweg, B. (2023). Social comparison in learning analytics dashboard supporting motivation and academic achievement. Computers and Education Open, 4, 100130. https://doi.org/10.1016/j.caeo.2023.100130

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. TechTrends, 59(1), 64–71. https://doi.org/10.1007/s11528-014-0822-x

George, D., & Mallery, P. (2018). IBM SPSS Statistics 25 Step by Step: A Simple Guide and Reference (0 Aufl.). Routledge. https://doi.org/10.4324/9781351033909

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. British Journal of Educational Technology, 50(5), 2572–2593. https://doi.org/10.1111/bjet.12864

Hirsch, S., & Uckelmann, D. (2024). Effective Feedback Systems in Learning Analytics: Didactic and Psychological Foundations, Implementations, and Perspectives. 2024 21st International Conference on Information Technology Based Higher Education and Training (ITHET), 1–10. https://doi.org/10.1109/ITHET61869.2024.10837632

Ifenthaler, D., Schumacher, C., & Kuzilek, J. (2023). Investigating students' use of self-assessments in higher education using learning analytics. Journal of Computer Assisted Learning, 39(1), 255–268. https://doi.org/10.1111/jcal.12744

Judel, S., vom Felde, J., & Schroeder, U. (2024). Video Analytics in Moodle Using xAPI. Technology, Knowledge and Learning, 29(4), 1939–1963. https://doi.org/10.1007/s10758-023-09720-3

Lee, J., & Kim, D. (2024). From awareness to empowerment: Self-determination theory-informed learning analytics dashboards to enhance student engagement in asynchronous online courses. Journal of Computing in Higher Education. https://doi.org/10.1007/s12528-024-09416-2

Lin, P.-H., & Yeh, S.-C. (2019). How Motion-Control Influences a VR-Supported Technology for Mental Rotation Learning: From the Perspectives of Playfulness, Gender Difference and Technology Acceptance Model. International Journal of Human–Computer Interaction, 35(18), 1736–1746. https://doi.org/10.1080/10447318.2019.1571784

Moosbrugger, H., & Kelava, A. (Hrsg.). (2008). Testtheorie und Fragebogenkonstruktion. Springer. https://doi.org/10.1007/978-3-540-71635-8

Mukred, M., Mokhtar, U. A., Hawash, B., AlSalman, H., & Zohaib, M. (2024). The adoption and use of learning analytics tools to improve decision making in higher learning institutions: An extension of technology acceptance model. Heliyon, 10(4). https://doi.org/10.1016/j.heliyon.2024.e26315

Panadero, E. (2017). A Review of Self-regulated Learning: Six Models and Four Directions for Research. Frontiers in Psychology, 8, 422. https://doi.org/10.3389/fpsyg.2017.00422

Pintrich, P. R. (1991). A Manual for the Use of the Motivated Strategies for Learning Questionnaire (MSLQ). https://eric.ed.gov/?id=ED338122

Pletz, C. (2021). Technologieakzeptanz von virtuellen Lern- und Arbeitsumgebungen [doctoralThesis]. https://doi.org/10.18419/opus-12021

Roberts, L. D., Howell, J. A., Seaman, K., & Gibson, D. C. (2016). Student Attitudes toward Learning Analytics in Higher Education: "The Fitbit Version of the Learning World". Frontiers in Psychology, 7. https://doi.org/10.3389/fpsyg.2016.01959

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. Journal of Statistical Software, 48(2). https://doi.org/10.18637/jss.v048.i02

Ryan, R. M., & Deci, E. L. (2000). Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. American Psychologist.

Ryan, R. M., & Deci, E. L. (2017). Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness. Guilford Publications.

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. Contemporary Educational Psychology, 61, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860

Schunk, D. H., & Ertmer, P. A. (2000). Self-Regulation and Academic Learning. In Handbook of Self-Regulation (S. 631–649). Elsevier. https://doi.org/10.1016/B978-012109890-2/50048-2

Siemens, G., & Long, P. (2011). Penetrating the Fog: Analytics in Learning and Education. EDUCAUSE Review, 5, 30–32. https://doi.org/10.17471/2499-4324/195

Tan, J. P.-L., Yang, S., Koh, E., & Jonathan, C. (2016). Fostering 21st century literacies through a collaborative critical reading and learning analytics environment: User-perceived benefits and problematics. Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, 430–434. https://doi.org/10.1145/2883851.2883965

Tourangeau, R., Rips, L. J., & Rasinski, K. (2000). The psychology of survey response. Cambridge University Press.

Vanduhe, V. Z., Nat, M., & Hasan, H. F. (2020). Continuance Intentions to Use Gamification for Training in Higher Education: Integrating the Technology Acceptance Model (TAM), Social Motivation, and Task Technology Fit (TTF). IEEE Access, 8, 21473–21484. https://doi.org/10.1109/ACCESS.2020.2966179

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. Computers in Human Behavior, 89, 98–110. https://doi.org/10.1016/j.chb.2018.07.027

Wisniewski, B., Zierer, K., & Hattie, J. (2020). The Power of Feedback Revisited: A Meta-Analysis of Educational Feedback Research. Frontiers in Psychology, 10, 3087. https://doi.org/10.3389/fpsyg.2019.03087

Zimmerman, B. J. (2002a). Becoming a Self-Regulated Learner: An Overview. Theory Into Practice, 41(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2

Zimmerman, B. J. (2002b). Becoming a Self-Regulated Learner: An Overview. Theory Into Practice, 41(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2

Zimmerman, B. J. (2008). Investigating Self-Regulation and Motivation: Historical Background, Methodological Developments, and Future Prospects. American Educational Research Journal, 45(1), 166–183. https://doi.org/10.3102/0002831207312909

Zimmerman, B. J. (2015). Self-Regulated Learning: Theories, Measures, and Outcomes. In International Encyclopedia of the Social & Behavioral Sciences (S. 541–546). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.26060-1

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