Efficient Learning Processes By Design: Analysis of Usage Patterns in Differently Designed Digital Self-Learning Environments

Malte Neugebauer[1][a], Ralf Erlebach[2][b], Christof Kaufmann[1][c], Janis Mohr[1][d] and Jörg Frochte[1][e]

[1]*Bochum University of Applied Sciences, 42579 Heiligenhaus, Germany*

[2]*University of Wuppertal, 42119 Wuppertal, Germany*

{*malte.neugebauer, christof.kaufmann, janis.mohr, joerg.frochte*}*@hs-bochum.de, ralf.erlebach@uni-wuppertal.de*

Keywords: Learning Analytics, Learning Management System, Gamification, Pedagogical Agent, A/B Testing, Self-regulated Learning, Higher Education.

Abstract: The relevance of e-learning for higher education has resulted in a wide variety of online self-learning materials over the last decade like pedagogical agents (PA) or learning games. Regardless of this variety, educators wonder whether they can make use of these tools for their goals and if so, which tool to choose and in which context a specific tool performs best. To do so, the collection and analysis of learning data – referred to as Learning Analytics (LA) – is required. Along with digital learning environments the possibilities of applying LA are growing. Often, LA focuses on data that can easily be quantified: drop-out quota, time or grade performance. To facilitate learning in a more procedural sense, a deeper understanding of learners' behavior in specific contexts with specific exercise designs is desired. This study therefore focuses on usage patterns. Learners' movements through three different designs of mathematical exercises – (i) plain exercises, (ii) PA supported and (iii) fantasy game design – are analyzed with Markov chains. The results of an experiment with 503 students inform about which design facilitates what kind of learning. While the PA design lets learners enter more partial solutions, the fantasy game design facilitates exercise repetition.

1 INTRODUCTION

Digital exercises have long been a standard part of higher education institutions. Most recently, their use has been fueled by distance learning during the Covid-19 pandemic (Turnbull et al., 2021; Lisnani et al., 2020; Irfan et al., 2020). At the same time, an increasingly heterogeneous student body additionally facilitated the development of digital material for self-learning (Boelens et al., 2018). The latter benefited from digital tasks by increased internal differentiation through a greater choice of learning opportunities. Through self-regulated learning, lower-skilled students are enabled to catch up while higher-skilled students are enabled to specialize (McKenzie et al., 2013; Wanner and Palmer, 2015).

The raise of digital exercises also facilitated a raise of opportunities to measure learning. Learning Analytics (LA) investigates the process of learning by collecting and analyzing user-generated data (Long and Siemens, 2011). However, it still remains unclear how and to what extent digital exercises facilitate learning processes (Nguyen, 2015). Especially in the face of a large amount of self-learning tools, students and teachers ask themselves which learning tools are suitable for their context. A characterization of self-learning materials for specific contexts would be helpful to gain a clear view here.

As a special form of LA, Educational Process Mining (EPM) focuses on the collection and analysis of learners' pathways along different materials during learning (AlQaheri and Panda, 2022; Bogarín et al., 2017). This allows to elucidate learners' usage patterns of learning materials and how learning material design influences students' learning behavior. The present study makes use of Markov chains for EPM in order to distinguish effects of different exercise designs on learners' usage patterns within the same set of exercises. By analyzing the influence of the design on learners' behavior, a specific statement can be made about the appropriate context of the learning material.

[a] https://orcid.org/0000-0002-1565-8222
[b] https://orcid.org/0000-0002-6601-3184
[c] https://orcid.org/0000-0002-0191-3341
[d] https://orcid.org/0000-0001-6450-074X
[e] https://orcid.org/0000-0002-5908-5649

For the present study we used three different design variants of digital exercises within mathematics pre-courses – courses that try to bridge the gap between school and university regarding mathematical competencies. 503 students were randomly assigned to either the control group or one of two experimental groups. With the help of the presented approach, specific differences in the usage patterns were identified.

Our contributions are summarized as follows:

- Presenting three variants of a digital self-learning environment based on STACK (see Section 4.1) within a Moodle quiz, differing in the employment of feedback and motivators.
- Introducing an approach based on Markov chains as an LA method to analyze emerging usage patterns and learning behavior within these variants.
- Demonstrating the approach with data from 503 students, showing that the experimental designs foster deeper learning processes.
- Providing a proposal to align the emerging usage patterns with didactical functions and user expectations when employing one of the variants.

2 PREVIOUS WORK

LA plays a major role in measuring the impact of digital learning interventions like game-based learning (Emerson et al., 2020) or collaborative digital learning (Elstner et al., 2023). Modern Learning Management Systems (LMS) are able to collect numerous data about their users automatically. Thus, by employing LA inside LMS the specific effects of digital learning interventions on learners behavior can be measured. As a consequence of that, behavior data is – besides learning level data – the commonly used type of student-analytics data in LMS (Kew and Tasir, 2021). This data is often used as the LA algorithms' input variable, e. g. to predict or monitor learners' performance (Choi et al., 2018; Gašević et al., 2016; Lowes et al., 2015; Lu et al., 2018). This study takes the opposite approach and focuses on behavior as the output variable of interest. By comparing learners' usage of different designs, the question which design influences behavior to what extent and which design is recommended for which setting can be addressed.

Some studies already use LA to measure learning behavior, e. g. the spent time within an activity or the interaction with the LMS to derive implications for lecturers from that. Rienties and Toetenel (2016) use LMS data to relate the amount of time learners spent on doing digital activities to differences in the learning design. Although the spent time in learning activities is an interesting value for the development of learning designs in general, it is not sufficient for giving lecturers advice on which design is suitable for which context, which is the aim of the present study.

Vanacore et al. (2023) on the other hand use different designs within a computer-assisted learning platform in an experimental research setting. They apply different non-cognitive interventions like displaying motivating messages during learning to middle-school students. They test not only learners' performance, but also their response time and hint usage. Here again the data basis is not sufficient for suggesting specific interventions for specific contexts to lecturers. Apart from that, the few significant effects that were found were not strong enough to make an actual recommendation. In contrast to this, the present study tests two experimental designs that have a strong impact on learners' usage patterns compared to a control design. The focus lies on the pathways users make within the given exercises.

3 THEORETICAL FOUNDATIONS

Before discussing a study on a mathematical self-learning tool for future university students, we must first outline its theoretical basis. This tool aims to facilitate review and practice of mathematical exercises, targeting the initial levels of Bloom's taxonomy – Remember and Understand – as outlined by Anderson et al. (2000) – in an LMS. Characteristically, such self-directed learning offerings are characterized by the absence of direct interaction with an instructor. Therefore, the design of the learning materials significantly impacts their utilization. Feedback mechanisms and motivational elements within the resource play a role. Both feedback (Section 3.1) and motivation (Section 3.2) will be further elaborated. The research question is derived from that (Section 3.3). Finally, Markov chains and their role for answering the research question are described (Section 3.4).

3.1 Feedback

Feedback plays a crucial role in guiding learning processes and has several functions. According to research, effective feedback must be clear, specific, timely, process-oriented, and task-related (Hattie and Timperley, 2007; Wisniewski et al., 2020). Formative feedback provided during the learning process helps students improve their performance, while positive feedback serves as a motivational factor. However, understanding the nuances of feedback is essential for educators and educational systems to optimize learning outcomes. In this article, three forms of feedback are distinguished based on timing and function: (F1) Assistive Feedback, (F2) Corrective Feedback, and (F3) Motivational and Learning-organizing Feedback.

(F1) *Assistive Feedback* refers to guidance provided to learners while they solve problems, offering clues on how to correct their work without revealing the solution directly.

(F2) After submitting their input, learners receive *Corrective Feedback* with information on whether it's correct or not. In cases where errors match specific patterns, the feedback also provides guidance on how to avoid those errors in future attempts.

(F3) Lastly, *Motivational and Learning-organizing Feedback* goes beyond a simple indication of solution success. By incorporating corrective feedback, learners are presented with the opportunity to repeat the specific task with different sets of values, facilitating further practice and skill development.

As a specialized form of providing feedback, digital Pedagogical Agents (PA) are often used. PA are computer-generated depictions of a person that can be integrated into software or websites. PA provide personalized feedback and guidance to students, with small-to-medium effect sizes observed in learning outcomes and motivation (Schroeder et al., 2013; Castro-Alonso et al., 2021). PA's adaptive non-verbal or emotional feedback has shown particular efficacy in enhancing learner motivation and engagement (Guo and Goh, 2015; Wang et al., 2022).

3.2 Motivation

Apart from feedback, which also provides motivational aspects to the learning process, there are further mechanisms that can be embedded in self-learning materials in order to specifically positively influence learners' motivation and usage behavior. A framework for designing such mechanisms can be derived from the Self-Determination Theory (SDT) (Ryan and Deci, 2000). SDT delineates the impact of four intrinsically motivating factors: *social relatedness*, *autonomy*, *mastery*, and *purpose*. A meta-analysis confirmed that meeting psychological needs improves motivation and learning outcomes (Niemiec and Ryan, 2009). Conventional instruction focuses on setting goals through teacher planning and providing meaningful content within a controlled classroom environment. In contrast, self-directed learning lacks these control mechanisms, making it more challenging to compete with other stimuli for learners' attention. A potential solution is to incorporate goal-setting and meaning choices into the learning material by creating a coherent narrative and storytelling. Narratives provide structure and relevance, helping learners connect their goals with the content.

3.3 Research Question

As outlined above, both feedback as well as motivation essentially influence learning behavior. How both aspects are considered in digital exercises hinges in turn on how the exercises are designed. This gives rise to the following research question:

RQ: What kinds of learning action patterns emerge within the self-learning material as a result of the manipulation of the factors design and feedback?

3.4 Markov Chains

The research question makes a systematic statistical description of the sequential learning process necessary. The learning process is, in the scope of this contribution, conceptualized as attainment and progression through various states. A state, for instance, may be the presentation of a task or a question. Similarly, the outcomes of such engagements can be characterized as such states as well, encompassing "task correctly answered," "task partially correct answered," or "task incorrectly answered."

The concatenation of transitions from any individually learning path can be modeled through Markov chains, a well-established method (Asmussen and Steffensen, 2020) used, e. g., in LA (Jeong et al., 2010) or Bayesian Knowledge Tracing (Corbett and Anderson, 1995; Yudelson et al., 2013; Moraffah and Papandreou-Suppappola, 2022). Our usage of Markov chains is to compare transitions in differently designed activities in LMS and derive effects from them in an experimental research design, which has not yet been done. This, as well as relating the derived effects to specific didactical functions is the main contribution of the present paper.

4 EXPERIMENT

The following section describes the exercise set and the different designs more deeply to explain the used material (Section 4.1). Furthermore, the used research method is presented (Section 4.2) and the collected data is described (Section 4.3).

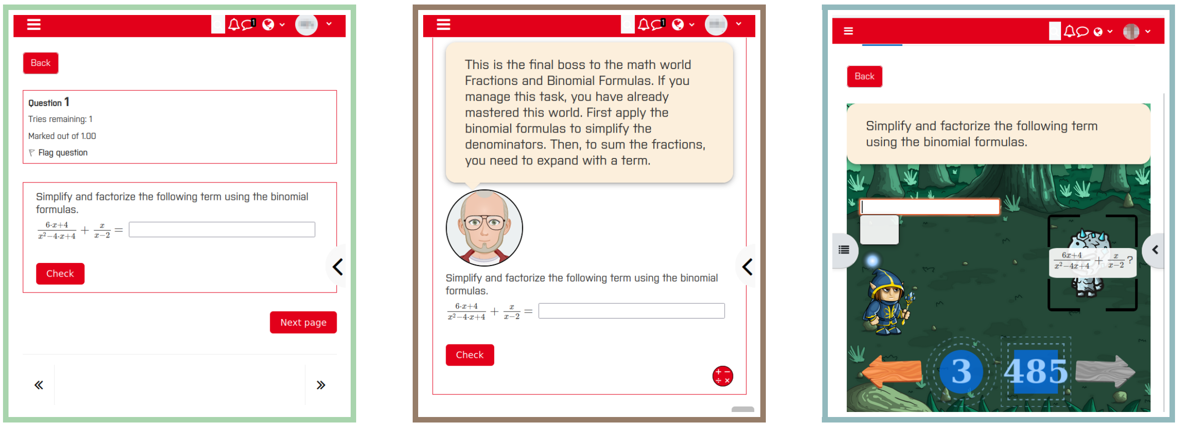


Figure 1: Screenshots of the tested versions. Left to right: Normal version (A), PA version (B), fantasy game version (C).

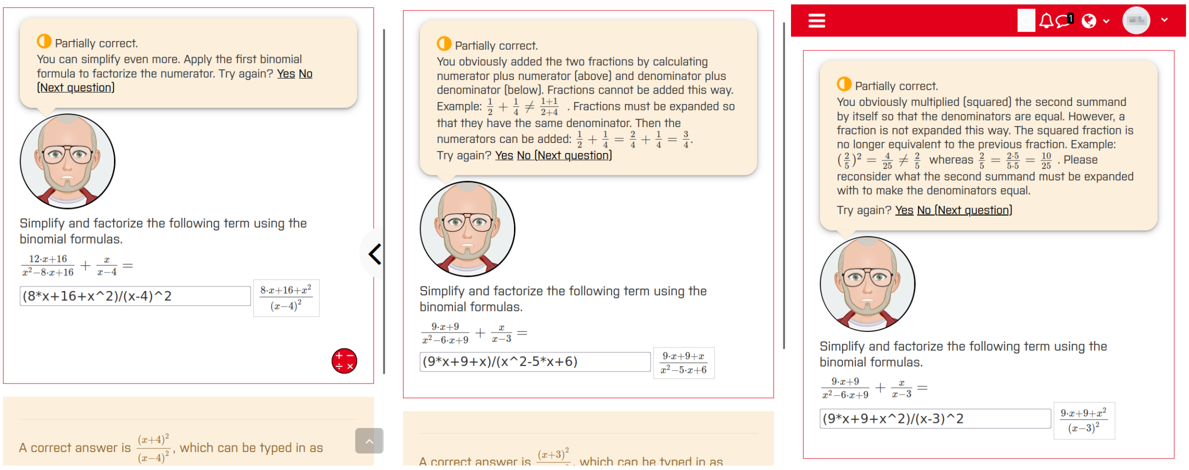


Figure 2: Feedback examples in design B. Left to right: Further simplification needed, naive addition, bad fraction expansion.

4.1 Learning Material

The exercises are worked on by the students in the LMS Moodle. Learners can freely jump between the exercises, with one semi-restriction in one exercise design which is explained in more detail below. Each of the tested exercise designs consists of the same set of 61 exercises. The exercise content covers a basic entry level for the start of the studies. The exercises are grouped into six topics, namely (i) syntax, (ii) fractions, (iii) binomial formulas, (iv) pq formula, (v) power laws and (vi) derivations. The exercises within each topic are sorted by difficulty.

After submitting a response, the students get immediate feedback to their input. Each exercise can be repeated with different numbers after at least one response.

To showcase how the approach differentiates the specific effects of an exercise design, one control design (hereafter referred to as design A) is tested against two different treatment designs (referred to as designs B and C). The screenshots in Figure 1 give an insight into the different designs.

Each exercise is of the STACK type (Sangwin, 2015). STACK is a plugin for LMS that allows to create exercises where learners enter mathematical expressions with their keyboard or touchpad in the input field as their answer. After submitting a response, the LMS gives immediate feedback to the learners' input, i. e., whether correct or wrong. Thanks to the STACK exercise type, the LMS also gives learners additional feedback when they get trapped in a specific error pattern, e. g., in case of a signage error or giving only one possible solution where two were expected. In this case, the exercise is counted as partially correct. How three possible feedbacks appear in design B is shown in Figure 2.

A JavaScript code inside the question texts of the

Table 1: Differences in the Tested Designs

	A (LMS Default)	B	C
Appearance	LMS default	Add PA icon to LMS default	Wraps exercise in comic fantasy design
Narrative	None	“Solve the hardest exercises!”	“Save the fairies!”
Feedback: Point of Time	After submitting a response	After submitting an intermediate step	After submitting a response
Editable Response After Submit	No	Yes	Yes
Prompt to Repeat Exercise with Different Numbers: Point of Time	Always after submitting a response	Only after correct response	Only after correct response
Learning Path Decision	Autonomous choice	Autonomous choice	Pay for skips with points

exercises enriches the exercises by adding design-specific interactive elements. Thus, by making use of a frontend-oriented software architecture (Neugebauer et al., 2023), no additional plug-in is needed to enrich the exercises. In the specific case of enriching STACK exercises, as it is done in the present study, the STACK plugin is needed, which is currently available for the LMS Moodle and ILIAS. See the project's repository (http://bit.ly/3HRpyu0) for further information.

The exercise content as well as the feedback content is equal in the other designs. The differences with special attention to the design and the feedback types as described in Section 3 are described below.

4.1.1 Feedback

While the feedback content is consistent across the designs, the ways in which it is presented differ. Design A displays the feedback below the exercise text. In contrast, design B features the feedback in a speech bubble pinned to the PA, as shown in Figure 2. Design C includes an accompanying fairy that hovers at the bottom center of the screen and displays the feedback in a speech bubble attached to the fairy. All designs cater to learners' need for *mastery*, but while the control design uses impersonal language, both experimental designs use personal language to create a sense of *relatedness*.

Moreover, design B provides feedback after each intermediate step, whereas designs A and C require learners to input their mathematical answers directly. This adds *corrective feedback* (F2) to design B, distinguishing it from designs A and C, which rely on *assistive feedback* (F1).

4.1.2 System's Behavior after Submit

By default (design A), the LMS gives a sample solution after submitting an exercise, provides feedback, and allows for repeated submission with different numbers. Once submitted, the beforehand entered response is no longer editable. To address mastery, the experimental designs (B & C) do not provide solutions after submission. Instead, feedback is provided, and responses remain editable, enabling learners to adjust their responses. Mastery is addressed by providing immediate feedback that can be applied to the still-editable response.

4.1.3 Prompt to Repeat Exercises

Consequently, the sample solution as well as the opportunity to repeat the exercise is not shown in the experimental designs (B & C) until learners have fully completed the exercise. Presenting the sample solution and leaving the task editable at the same time is unfavorable, as students could typewrite the solution.

The prompt for exercise repetition is personalized in the experimental designs (B & C) and impersonal in the control design (A). The LMS default is a button labeled “Try another question like this one.” In design B, the PA suggests, “You can repeat this task with other numbers if it gives you more confidence,” linking to a similar exercise. In design C, a monster turns into a fairy upon exercise completion, urging the learner to “save my friends of the same kind before proceeding into the forest,” aiming to fulfill learners' need for *purpose*.

4.1.4 Learning Path Decision

Finally, the designs differ in how learners can move through the exercises. In all designs learners can jump to any of the 61 exercises, which addresses the learners' need for *autonomy*. In design C learners have to pay for each skip with points. This payment is more symbolic in nature, as learners already have enough points after completing the first world to be able to reach almost all exercises. In summary, see Table 1 for the relevant differences.

4.2 Research Method

Data on learners' usage patterns is collected and analyzed to evaluate the impact of different exercise designs on their behavior. Exercises are first arranged in a set, and then three different exercise designs are applied to generate three separate quizzes. Each participant is randomly assigned to one quiz, resulting in three distinct datasets containing usage data for each design (see Figure 3).

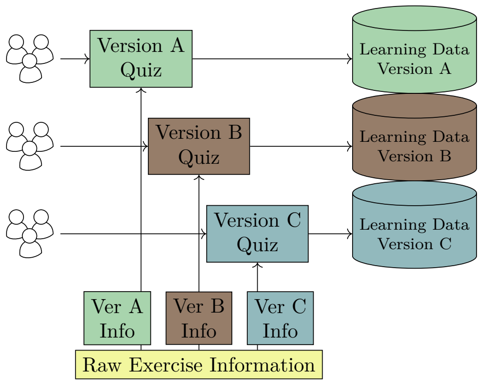


Figure 3: By applying the designs to the tasks, three different versions are created, which in turn results in three sets of learning data.

In the present study, the data are automatically collected by the LMS and are visible to the lecturers by default. Just like the enrichment of exercises as described in Section 4.1, the data extraction is also possible without a plugin (see the project's repository http://bit.ly/3HRpyu0 for more information). This data is used to visualize pathways taken inside the quiz (Figure 4). Transition probabilities are calculated by cumulating and dividing transition amounts, and expressed as Markov chains (Figures 5 and 7).

In order to analyze the effect of feedback and designs on usage patterns, we distinguish the most obvious states and transition types. Firstly, we distinguish transitions depending on the answer states *correct*, *partially correct* or *wrong*. Moreover, we distinguish the transition types: A transition to the *sequentially* next exercise, a *repetition* of the same exercise or a *non-sequential* transition to any other exercise (e. g., a later or a previous exercise). In the Markov chain each transition is expressed as a probability, normalized with respect to all outgoing transitions.

This results in a Markov chain with an input state, three answer states and four additional states for the transition types (Figure 5). While the three answer states are visualized vertically as c, p and w for *correct*, *partially correct* and *wrong* respectively, the five transition types are arranged horizontally, which are:

1. Initial transitions (gray) from the input node to one of the states, mathematically referred to as T,
2. a repetition (blue) of the same exercise, referred to as R,
3. a movement to the sequentially next exercise (orange), referred to as S,
4. a non-sequential transition (violet), called N,
5. finishing the practice session (black), referred to as the finish state F.

To express this mathematically, let s be one of the states c, p or w. Then $A^{(k)}_{s_i,E_j}$ denotes the amount of transitions of user k from exercise i to exercise j after leaving exercise E_i with the state s (either c, p or w for correct, partially correct or wrong, respectively). An example of A for one user is shown in Figure 4. The total amount of correct, partially correct or wrong responses can then be calculated by summing up all transitions from any exercise to any other exercise with the given corresponding state s_i, mathematically expressed as $\sum_{i,j} A^{(k)}_{s_i,E_j}$. In doing this it is crucial to consider a finish state F, with which the last state is linked to. Otherwise, the last state is not represented by an edge and thus not counted. This is represented in Figure 4 by the link between the last wrong state and the finish state, which corresponds to the very last matrix entry $A^{(k)}_{w_n,F}$.

To gain the transition probabilities $\bar{T}_s$ from the exercise input to one of the states, the absolute transitions have to be summed up over all users and then be divided by the overall amount of correct, partially correct or wrong responses of all users. This can be expressed by:

$$T^{(k)}_s = \sum_{i,j} A^{(k)}_{s_i,E_j} + \sum_i A^{(k)}_{s_i,F} \quad T_s = \sum_k T^{(k)}_s \quad \bar{T}_s = \frac{T_s}{\sum_{\tilde{s}} T_{\tilde{s}}} \tag{1}$$

We already defined that after this initial transition the next question can take one of the following forms. The mathematical expression is given respectively:

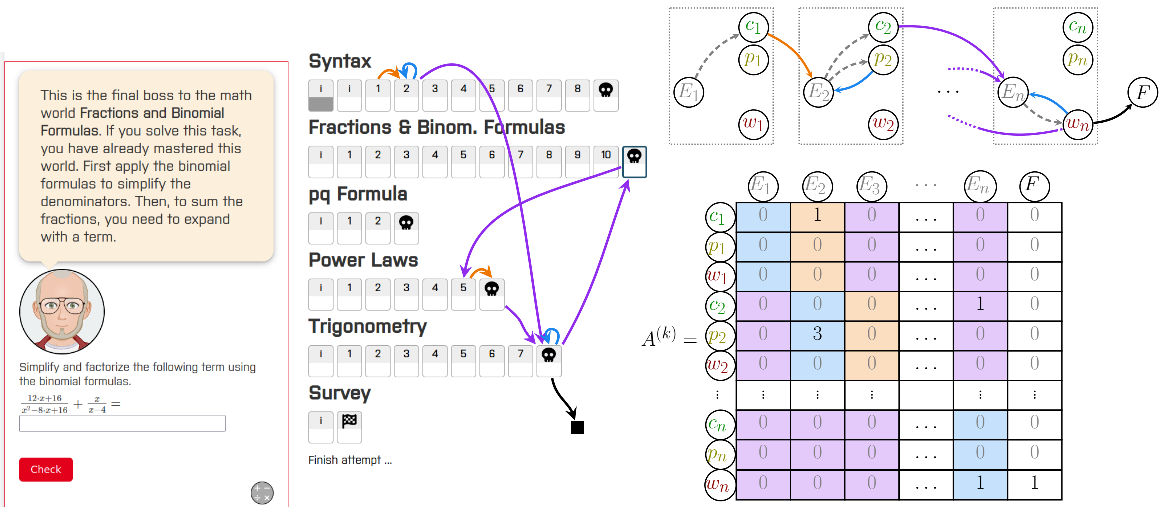


Figure 4: Example of expressing transitions from one exercise to another for one learner. Left: state-independent as overlay on the LMS frontend. Right: containing the different states – correct (green, c), partially correct (yellow, p) and wrong (red, w) – and the transition types – sequential (orange), non-sequential (violet) and repetition (blue) – and the according table $A^{(k)}$.

(R) The same question is visited again: *Repetition*, mathematically expressed as $A^{(k)}_{s_i,E_i}$.

(S) Transition to the sequentially following exercise of the given order: *Sequential transition*, expressed as $A^{(k)}_{s_i,E_{i+1}}$.

(N) Transition to another exercise, i. e., a previous one or a later one, but not the next: *Non-sequential transition*, expressed as $A^{(k)}_{s_i,E_j}$ with $j \neq i$ and $j \neq i+1$.

(F) Transiting to the absorbing finish state F, expressed as $A^{(k)}_{s_i,F}$.

To gain the overall transition counts we accumulate these expressions over all exercises and users as mathematically expressed in the following equations.

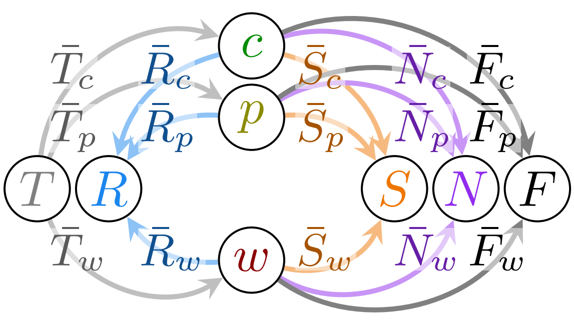


Figure 5: Markov chain with transition probabilities as defined in (1) and (6).

$$R^{(k)}_s = \sum_i A^{(k)}_{s_i,E_i}, \qquad R_s = \sum_k R^{(k)}_s \tag{2}$$

$$S^{(k)}_s = \sum_{i=1}^{n-1} A^{(k)}_{s_i,E_{i+1}}, \qquad S_s = \sum_k S^{(k)}_s \tag{3}$$

$$N^{(k)}_s = \sum_i \sum_{\substack{j\neq i\\ j\neq i+1}} A^{(k)}_{s_i,E_j}, \qquad N_s = \sum_k N^{(k)}_s \tag{4}$$

$$F^{(k)}_s = \sum_i A^{(k)}_{s_i,F}, \qquad F_s = \sum_k F^{(k)}_s \tag{5}$$

By denoting O as all outgoing transitions from a state s for all users, the overall transition counts from (2)–(5) can be normalized to get the overall transition probabilities (6):

$$O_s = R_s + S_s + N_s + F_s = \sum_{i,j,k} A^{(k)}_{s_i,E_j} + \sum_i A^{(k)}_{s_i,F}$$

$$\Rightarrow \bar{R}_s = \frac{R_s}{O_s}, \quad \bar{S}_s = \frac{S_s}{O_s}, \quad \bar{N}_s = \frac{N_s}{O_s}, \quad \bar{F}_s = \frac{F_s}{O_s} \tag{6}$$

These probabilities are visualized using a Markov chain (see Figure 5). Figure 6 displays the calculations visually.

4.3 Sampling & Measurement

The study took place in summer 2023 across three universities in the same country (Bochum University of Applied Sciences (UAS), Westphalian UAS, University of Wuppertal), involving $n = 503$ participants, primarily aged 18-21. Most were computer science, engineering, economics, and mathematics education backgrounds, and participants were randomly assigned to a single design each.

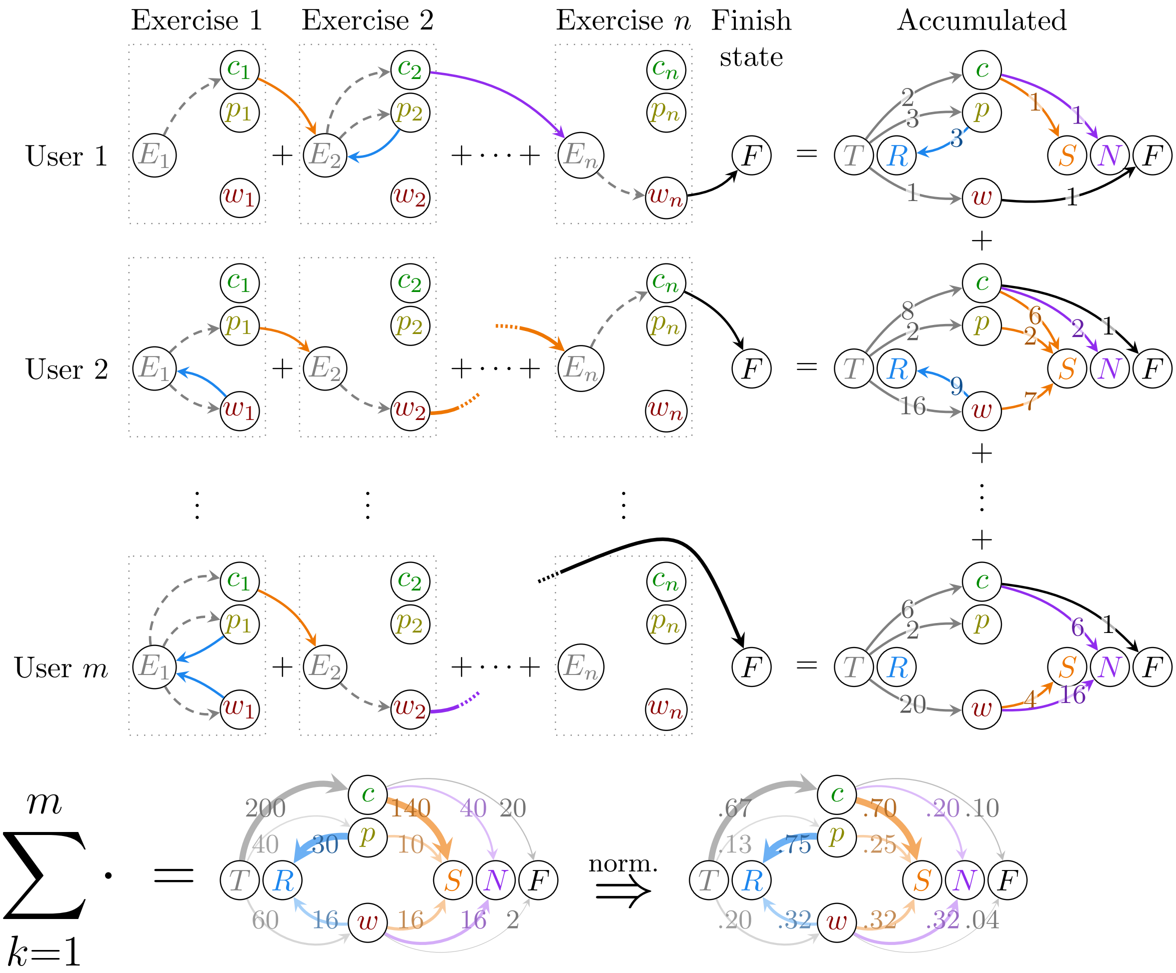


Figure 6: Example of summarizing exercise transitions for one design in a representative chain node by accumulating learners' overall transitions. The summarized absolute values are used to create the resulting representative chain node.

Table 2: Overview of participant amounts.

	A	B	C	Total
Bochum UAS	52	38	49	139
Westphalian UAS	163	146	-	309
University of Wuppertal	21	21	13	55
Total	236	205	62	503

During the mathematics pre-courses the learners were asked to practice with the learning material in a given time slot from 20 to 30 minutes. To encourage the universities involved to cooperate, the universities were left to decide which of the available designs they wanted to test. Since the university with the greatest amount of participants decided to only test two of the presented designs, there is far more data for the designs A & B. Table 2 shows the amount of participants by university and by design.

Before merging a single dataset out of the data of the three universities, t-tests were performed for each transition type to rule out significant differences among the universities. 36 calculations were performed (12 transition types respectively compared for each university to each other) with 32 calculations showing no significant difference ($p > 0.05$). Given the few differences, the data sets were merged.

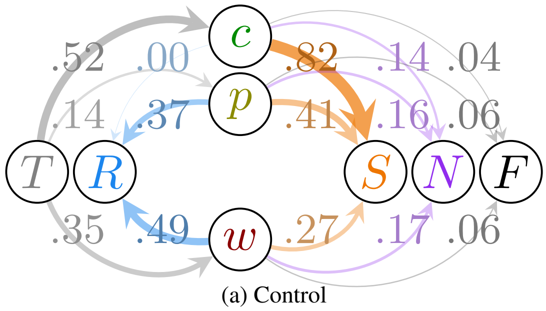
5 RESULTS

The usage patterns that emerged in three different versions of the same mathematical exercises have been analyzed with the help of a Markov chain based method as presented in Section 4.2. The results are visualized as Markov chains in Figure 7. To identify significant differences among the designs, t-tests of the respective transitions have been performed for the experimental groups against the control group in the merged dataset.

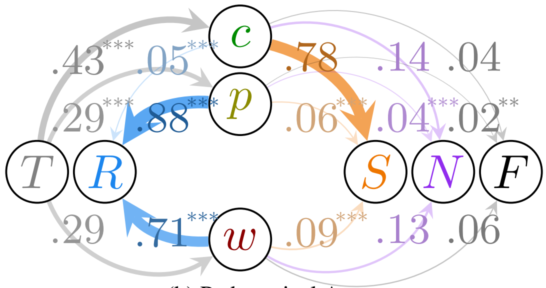
Comparing the individual nodes with each other, some significant differences become noticeable:

1. The experimental designs B (PA) and C (fantasy game) show a significant rise in content repetition. Learners are more inclined to revisit materials, especially if not initially mastered. This behavior is especially marked in the fantasy game design, where repetition rates are high even for correctly solved tasks. Opting to redo exercises, learners make fewer direct moves to the next question after a correct response, resulting in a higher total of correct responses.
2. The occurrences of sequential transitions from states categorized as wrong or partially correct to the subsequent question are markedly reduced in the experimental designs, with the fantasy game design exhibiting the lowest such transitions.
3. Non-sequential transitions from partially correct states to questions other than the immediate next one are significantly diminished in both experimental designs.
4. The application of assistive feedback in the PA design leads to a significant increase in counts of partially correct answer states. Remarkably, learners persist in attempting to resolve questions correctly and refrain from skipping questions at this stage, in contrast to the plain control design setting.

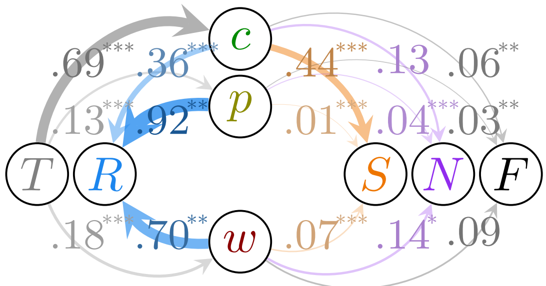
In design C exercises are repeated more often even after correct responses. This design obviously supports a behavior that fosters automation of the targeted skill. Design B allows for quicker progression through materials, as only partially correct or incorrect responses trigger repetition. Furthermore, providing feedback on intermediate solutions potentially fosters a deeper understanding here. Contrastingly, in the control design (A), despite being Moodle's default, an undesired behavior becomes noticeable in comparison to the experimental designs: Learners' skip to other exercises even after being provided with feedback to their wrong or partially correct input.



(a) Control



(b) Pedagogical Agent



(c) Fantasy Game

Figure 7: Consolidating all movements into a representative chain node per design. From T: distribution of correct / partially correct / wrong answers. To S (orange): advancing to the next sequential task. To R (blue): repeating an exercise. To N (violet): jumping to a different exercise. To F: ending the session. Asterisks denote significant deviations from the control design: * for $p < 0.05$, ** for $p < 0.01$, *** for $p < 0.001$.

6 DISCUSSION

The presented method may help lecturers to choose appropriate learning materials according to their aims throughout a semester. When introducing and training new skills, design C might be considered as a good choice as it seems to motivate learners to deal with similar problems several times, encouraging a thorough acquisition of the new skills and methods. When on the other hand lecturers aim to revisit skills students acquired earlier, design B would be preferable. By using design B, students tend to proceed more quickly on correct responses and also repeat when their answers do not fulfill the requirements. This would be helpful, e. g., in preparing for an exam.

While this study sheds light on a PA design (B) and a fantasy game (C) design – which causes multiple design differences – the presented method could also distinguish between single design changes in future research. This could demonstrate more specifically which design difference causes what effect.

Besides this micro-testing of chosen features, further investigation could also widen the scope by comparing different designs with the here presented designs A, B and C. As long as it is taken into account that learners are enabled to skip and repeat exercises, the approach can be applied to other exercise designs in LMS or even beyond that into other learning environments, e. g., virtual reality learning rooms or learning games.

Our study's findings should be cautiously interpreted due to its constraints. First, it was conducted in a lecture hall under controlled conditions, akin to a lab study, rather than in a natural self-learning setting. Thus, learning materials faced no competition from everyday distractions, leading to a more focused engagement compared to a real-world scenario.

Second, participants had 20 to 30 minutes to complete tasks, covering a syntax tutorial and some math concepts. Therefore, the exercises set consisted of new and probably already familiar knowledge at the same time. For a more thorough research, longer usage periods that allow to distinguish between training of new and existing skills is needed.

Additionally, exploring motivational factors is vital. The connection between our findings and specific motivational triggers is still vague, highlighting the need to consider students' majors and expectations. Continued research integrating the learning material into actual teaching scenarios is necessary to further clarify our knowledge in this area.

7 CONCLUSION

This work presented an approach based on Markov chains that allows the comparison of specific effects of different exercise designs on learners' transitions through a given set of exercises. The application of the approach on usage data from students solving mathematical exercises in LMS revealed significant differences in the usage of two experimental designs when compared to the use of a control design. The specific differences in the usage patterns of the designs qualify the designs to foster desired usage patterns in different phases throughout a semester. While design C supports a behavior where already acquired knowledge is repeated, design B leads learners to proceed on correct responses while repeating exercises more frequently when answers are partially correct or incorrect. While the former usage pattern is desirable when introducing new topics and skills, the latter usage patterns correspond to the desired behavior when revisiting knowledge, e. g., for exam preparation.

Furthermore, the presented method has been shown to be able to measure significant differences between digital exercises' designs while being robust for use in different locations. Thus, measurement beyond the domain of mathematics or in systems other than LMS are likely possible as well. Validating this remains a task for future research.

ACKNOWLEDGEMENTS

This work is part of the Digital Mentoring project, which is funded by the Stiftung Innovation in der Hochschullehre under FBM2020-VA-219-2-05750. Additionally this work was funded by Federal Ministry of Education and Research under 16DHB4023. We thank all participating universities.

REFERENCES

AlQaheri, H. and Panda, M. (2022). An education process mining framework: Unveiling meaningful information for understanding students' learning behavior and improving teaching quality. *Information*, 13(1):29.

Anderson, L. W., Krathwohl, D. R., Airasian, P. W., Cruikshank, K. A., Mayer, R. E., Pintrich, P. R., Raths, J., and Wittrock, M. C. (2000). *A Taxonomy for Learning, Teaching, and Assessing*. Allyn & Bacon.

Asmussen, S. and Steffensen, M. (2020). *Probability Theory and Stochastic Modelling*, chapter 5, pages 113–139. Springer.

Boelens, R., Voet, M., and De Wever, B. (2018). The design of blended learning in response to student diversity in higher education: Instructors' views and use of differentiated instruction in blended learning. *Computers & Education*, 120:197–212.

Bogarín, A., Cerezo, R., and Romero, C. (2017). A survey on educational process mining. *WIREs Data Mining and Knowledge Discovery*, 8(1).

Castro-Alonso, J., Wong, R., Adesope, O., and Paas, F. (2021). Effectiveness of multimedia pedagogical agents predicted by diverse theories: a meta-analysis. *Educational Psychology Review*, 33:1–27.

Choi, S., Lam, S., Li, K., and Wong, B. (2018). Learning analytics at low cost : At-risk student prediction with clicker data and systematic proactive interventions. *Educational Technology & Society*, 21(2):273.

Corbett, A. T. and Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modelling and User-Adapted Interaction*, 4(4):253–278.

Elstner, T., Loebe, F., Ajjour, Y., Akiki, C., Bondarenko, A., Fröbe, M., Gienapp, L., Kolyada, N., Mohr, J., Sandfuchs, S., Wiegmann, M., Frochte, J., Ferro, N., Hofmann, S., Stein, B., Hagen, M., and Potthast, M.

(2023). Shared tasks as tutorials: A methodical approach. *Proc. of the AAAI Conf. on Artificial Intelligence*, 37(13):15807–15815.

Emerson, A., Cloude, E. B., Azevedo, R., and Lester, J. (2020). Multimodal learning analytics for game-based learning. *Educational Technology*, 51(5):1505–1526.

Gašević, D., Dawson, S., Rogers, T., and Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, 28:68–84.

Guo, Y. and Goh, D. (2015). Affect in embodied pedagogical agents: Meta-analytic review. *Journal of Educational Computing Research*, 53.

Hattie, J. and Timperley, H. (2007). The power of feedback. *Review of Educational Research*, 77(1):81–112.

Irfan, M., Kusumaningrum, B., Yulia, Y., and Widodo, S. A. (2020). Challenges during the pandemic: Use of e-learning in mathematics learning in higher education. *Infinity Journal*, 9(2):147.

Jeong, H., Biswas, G., Johnson, J., and Howard, L. (2010). Analysis of productive learning behaviors in a structured inquiry cycle using hidden markov models. In *Educational Data Mining 2010*, pages 81–90.

Kew, S. N. and Tasir, Z. (2021). Learning analytics in online learning environment: A systematic review on the focuses and the types of student-related analytics data. *Technology, Knowledge and Learning*, 27(2):405–427.

Lisnani, L., Putri, R. I. I., Zulkardi, and Somakim (2020). Designing moodle features as e-learning for learning mathematics in COVID-19 pandemic. *Journal of Physics: Conf. Series*, 1657:012024.

Long, P. and Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *Educause Review*, 46(5):31–40.

Lowes, S., Lin, P., and Kinghorn, B. (2015). Exploring the link between online behaviours and course performance in asynchronous online high school courses. *Journal of Learning Analytics*, 2(2):169–194.

Lu, O., Huang, A., Lin, A., Ogata, H., and Yang, S. (2018). Applying learning analytics for the early prediction of students' academic performance in blended learning. *Educational Technology & Society*, 21(2):220–232.

McKenzie, W. A., Perini, E., Rohlf, V., Toukhsati, S., Conduit, R., and Sanson, G. (2013). A blended learning lecture delivery model for large & diverse undergraduate cohorts. *Computers & Education*, 64:116–126.

Moraffah, B. and Papandreou-Suppappola, A. (2022). A complete recipe for bayesian knowledge transfer: Object tracking. Published via arXiv:2210.13232.

Neugebauer, M., Tousside, B., and Frochte, J. (2023). Success factors for mathematical e-learning exercises focusing first-year students. In *Proc. of the 15th Int'l Conf. on Computer Supported Education*.

Nguyen, T. (2015). The effectiveness of online learning: Beyond no significant difference and future horizons. *Online Teaching and Learning*, 11:309–319.

Niemiec, C. P. and Ryan, R. M. (2009). Autonomy, competence, and relatedness in the classroom. *Theory and Research in Education*, 7(2):133–144.

Rienties, B. and Toetenel, L. (2016). The impact of learning design on student behaviour, satisfaction and performance: A cross-institutional comparison across 151 modules. *Computers in Human Behavior*, 60:333–341.

Ryan, R. M. and Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1):68–78.

Sangwin, C. (2015). Computer aided assessment of mathematics using STACK. In *Selected Regular Lectures from the 12th Int'l Congress on Mathematical Education*, pages 695–713. Springer Int'l Publishing.

Schroeder, N., Adesope, O., and Barouch Gilbert, R. (2013). How effective are pedagogical agents for learning? A meta-analytic review. *Journal of Educational Computing Research*, 49:1–39.

Turnbull, D., Chugh, R., and Luck, J. (2021). Transitioning to e-learning during the covid-19 pandemic: How have higher education institutions responded to the challenge? *Education and Information Technologies*, 26(5):6401–6419.

Vanacore, K., Gurung, A., Mcreynolds, A., Liu, A., Shaw, S., and Heffernan, N. (2023). Impact of non-cognitive interventions on student learning behaviors and outcomes: An analysis of seven large-scale experimental inventions. In *LAK23: 13th Int'l Learning Analytics and Knowledge Conf.* ACM.

Wang, Y., Gong, S., Cao, Y., Lang, Y., and Xu, X. (2022). The effects of affective pedagogical agent in multimedia learning environments: A meta-analysis. *Educational Research Review*, 38:100506.

Wanner, T. and Palmer, E. (2015). Personalising learning: Exploring student and teacher perceptions about flexible learning and assessment in a flipped university course. *Computers & Education*, 88:354–369.

Wisniewski, B., Zierer, K., and Hattie, J. (2020). The power of feedback revisited: A meta-analysis of educational feedback research. *Frontiers in Psychology*, 10.

Yudelson, M. V., Koedinger, K., and Gordon, G. J. (2013). Individualized bayesian knowledge tracing models. In *Int'l Conf. on Artificial Intelligence in Education*.