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A Mechanism-Based Analysis of AI-Driven Personalization: Linking Self-Efficacy, Engagement, and Employability through Micro-Credentials

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Abstract

The study investigates how AI-supported personalisation influences learning persistence and employability in digital learning environments. Existing research usually considers technological, psychological and labour market-related perspectives separately, leaving the causal relationships insufficiently specified. Based on a comparative, mechanism-based design, the platforms Coursera, edX and Udacity are analysed. The results show that AI does not exert direct effects, but operates through a sequence of interlinked mechanisms: personalisation strengthens self-efficacy, increases engagement and thereby stabilises learning persistence. However, the transition to employability depends on institutional validation mechanisms. These findings indicate that the impact of digital learning systems emerges from the interplay of technological, psychological and institutional processes rather than from technological innovation alone.

Keywords: AI-driven personalization, self-efficacy, student engagement, learning persistence, micro-credentials

JEL Classification: I23, I25, J24, O33, M53

1. Introduction

Digital learning environments have become a key component of modern education systems in recent years. The use of artificial intelligence in particular is creating new opportunities to personalise learning processes. AI-supported personalisation enables the dynamic adaptation of learning content, feedback and learning paths and is seen as an important approach to increasing the efficiency and individualisation of learning processes (Luckin et al., 2016; Dede, 2014). At the same time, digital learning platforms are seen as playing a growing role in the development of skills relevant to the labour market, particularly in the context of lifelong learning and changing skills requirements (Frey & Osborne, 2017; OECD, 2023).

At the same time, it is clear that existing research is highly fragmented. Technological perspectives focus primarily on the performance of adaptive systems, while psychological approaches emphasise the importance of motivation, self-efficacy and engagement (Bandura, 1997; Fredricks et al., 2004; Kahu, 2013). In parallel, labour market-related studies examine the function of educational qualifications and certificates for

employability (Spence, 1973; Marginson, 2019). However, these perspectives are predominantly considered separately, which means that there is no consistent understanding of the causal logic of digital learning systems.

In particular, it remains unclear how AI-supported personalisation actually works. It is often implicitly assumed that technological innovations lead directly to better learning outcomes or higher employability. However, there is a lack of theoretically sound models that systematically explain the underlying mechanisms of action. Existing findings indicate that effects do not arise directly, but are mediated via psychological and behavioural processes, the interaction of which has so far been insufficiently understood (Bond et al., 2020; Means et al., 2014).

Against this background, this study addresses the following research question:

How does AI-supported personalisation in digital learning environments affect learning persistence and employability, and through which mechanisms are these effects mediated?

To answer this question, a mechanism-based explanatory model is developed that brings together technological, psychological and institutional factors in a consistent causal structure. The starting point is the assumption that AI does not have a direct effect on learning outcomes, but initially influences self-efficacy, which is then transferred into persistent learning behaviour through engagement. The transfer of these learning processes into labour market-relevant outcomes takes place via institutional validation mechanisms, in particular in the form of micro-credentials (Nullmeier & Kuhlmann, 2022; OECD, 2023).

The study makes three contributions. First, it develops an integrated theoretical model that connects previously separate strands of research and describes the impact of AI as a multi-level mechanism. Second, engagement is conceptualised as a mediating variable that translates psychological effects into observable learning behaviour. Thirdly, the role of micro-credentials is redefined by understanding them not as a mere outcome but as a component of the impact structure between education and the labour market.

Empirically, the analysis is based on a comparative, mechanism-based research design in which three digital learning platforms Coursera, edX and Udacity are analysed in contrast. This case selection makes it possible to identify conditions under which the postulated mechanisms become effective or lose their effect.

The results show that the influence of AI-supported personalisation is indirect, multi-level and context-dependent. While effects on self-efficacy and engagement are comparatively stable, the transition to employability depends largely on institutional framework conditions. It follows that technological innovation alone is not sufficient, but must be embedded in an interplay of psychological and institutional mechanisms.

The paper is organised as follows. Section 2 develops the theoretical framework, section 3 presents the conceptual model, section 4 describes the methodological approach, section 5 presents the results, section 6 discusses the findings and section 7 summarises the most important findings and provides an outlook for further research.

2. Literature Review

Research on digital learning environments is characterised by a pronounced fragmentation, as central dimensions such as AI-supported personalisation, self-efficacy, student engagement, learning persistence and employability are predominantly investigated separately from one another. The aim of this section is therefore to systematically integrate the relevant strands of research and create the basis for a consistent, mechanism-based explanatory model.

The literature on AI in the educational context focuses primarily on the potential of adaptive systems to optimise learning processes. AI-supported personalisation enables the dynamic adaptation of learning content, feedback and learning paths and is seen as a key driver for more efficient and individually tailored learning processes (Luckin et al., 2016). Empirical studies show that continuous and targeted feedback in particular has positive effects on learning outcomes (Means et al., 2014). At the same time, it is emphasised that the effect of these systems cannot be explained by technology in isolation, but depends significantly on their didactic embedding and their ability to activate learners (Dede, 2014; Bond et al., 2020).

A central psychological mechanism in this context is self-efficacy. According to Bandura (1997), the conviction that one can successfully master one's own challenges directly influences motivation, effort and perseverance in the learning process. Self-efficacy is promoted in digital learning contexts primarily through feedback mechanisms and the subjective evaluation of learning tasks (Gan et al., 2023). Recent studies indicate that AI-based systems can further intensify these effects through personalised feedback and adaptive learning settings (Liu et al., 2026). However, the extent to which these psychological effects are reflected in the behaviour of learners in the long term remains to be seen.

The link between motivational factors and observable learning behaviour is bundled in the concept of student engagement. Engagement encompasses cognitive, emotional and behavioural dimensions and is considered a key predictor of learning success (Fredricks et al., 2004). Kahu (2013) argues that engagement cannot be understood as an isolated characteristic, but rather as the result of an interplay of individual, institutional and structural factors. In the context of digital learning environments, systematic analyses show that interactivity, feedback and learning structure in particular are decisive influencing factors for engagement (Bond et al., 2020). At the same time, research indicates that engagement is heterogeneous and manifests itself in different usage patterns and learning strategies.

A central problem of digital learning systems is the high drop-out rate. MOOCs are characterised by high levels of attrition, with only a small proportion of learners completing courses in full (Allione & Stein, 2016; Jordan, 2014). Early engagement is considered a key indicator of further learning persistence. Studies also show that learners develop different patterns of engagement, ranging from non-committal exploration to targeted completion of courses (Kizilcec et al., 2013). These results show that dropouts should not be viewed as a homogeneous phenomenon, but rather reflect different learning goals and utilisation patterns.

In addition to individual and structural factors, social interaction plays a complementary role in learning processes. Digital learning platforms enable collaborative forms of learning, particularly via discussion forums and peer communication. Empirical findings show that active participation in such interaction formats correlates positively with learning persistence and course success (Means et al., 2014; Bond et al., 2020). At the same time, this interaction is socially selectively distributed, which indicates that digital learning environments do not automatically reduce existing inequalities, but rather reproduce them under certain circumstances.

The link between learning processes and labour market outcomes is traditionally explained by human capital theory, which assumes a linear relationship between education and economic success. However, critical perspectives show that this assumption does not adequately reflect the complexity of real educational processes, as institutional and social factors play a central role (Marginson, 2019). In this context, micro-credentials are becoming increasingly important as an alternative form of skills validation. They act as signals on the labour market that reduce information asymmetries and increase the visibility of skills (Spence, 1973). At the same time, political and empirical analyses show that their impact depends heavily on standardisation, recognition and institutional embedding (OECD, 2023; European Commission, 2022).

To summarise, the literature shows that the relevant strands of research have so far been insufficiently interconnected. In particular, there is a lack of an integrated perspective that brings together technological, psychological and institutional factors in a consistent causal structure. This study addresses this research gap by developing a mechanism-based model that systematically explains the effect of AI-supported personalisation on learning persistence via self-efficacy and engagement and its translation into employability.

3. Theoretical Framework

This section develops an integrated theoretical model to explain the causal effect of AI-supported personalisation on learning persistence and employability. The starting point is a mechanism-based understanding of causality, according to which effects do not arise directly, but through a sequence of interlinked mechanisms of action (Nullmeier & Kuhlmann, 2022). The aim is to integrate technological, psychological and institutional factors into a consistent causal structure.

The central assumption is that AI-supported personalisation works primarily via psychological mechanisms. At the micro level, self-efficacy forms the central starting point of the causal logic. Bandura (1997) shows that the conviction of being able to overcome one's own challenges has a significant influence on motivation, commitment and perseverance. AI-supported learning systems promote this self-efficacy by providing continuous feedback, adaptive support and personalised learning paths (Luckin et al., 2016; Means et al., 2014). Empirical studies show that feedback and perceived task value in particular are key influencing factors for self-efficacy and learning behaviour (Gan et al., 2023; Liu et al., 2026).

However, the effects of increased self-efficacy do not have a direct impact on learning outcomes, but unfold via engagement. Engagement can be understood as a mechanism

that translates motivation, system design and social interaction into concrete learning behaviour. It encompasses cognitive, emotional and behavioural aspects and is an important predictor of learning success (Fredricks et al., 2004). Kahu (2013) emphasises that engagement arises from the interplay of individual, institutional and structural factors. In digital learning contexts, it is primarily characterised by interactivity, feedback and structure (Bond et al., 2020).

In addition, structural and social conditions also influence the learning process. MOOCs are characterised by high dropout rates, whereby persistence is closely linked to early engagement and active participation (Allione & Stein, 2016; Jordan, 2014). At the same time, different usage trajectories are evident, ranging from exploratory behaviour to consistent completion (Kizilcec et al., 2013). Social interaction has a supportive effect as it increases engagement and is positively related to learning success (Means et al., 2014; Bond et al., 2020).

Engagement is therefore understood as a mediating mechanism that integrates the effects of self-efficacy, interaction and system design on learning persistence. Learning persistence in turn represents a necessary condition for the development of competences. It describes continuous participation in learning processes and forms the prerequisite for sustainable learning outcomes (Means et al., 2014).

However, the translation of skills development into labour market-relevant outcomes does not happen automatically, but is mediated by institutional mechanisms. Micro-credentials act as central validation instruments that make acquired competences visible and comparable. In terms of signalling theory, they reduce information asymmetries on the labour market and increase the usability of qualifications (Spence, 1973). However, empirical and political analyses show that their impact is heavily dependent on standardisation, recognition and institutional embedding (OECD, 2023; European Commission, 2022).

This perspective is in conflict with classical human capital theory, which assumes a direct relationship between education and economic success. Critical approaches show that returns on education are not determined solely by individual competences, but are mediated by institutional and social conditions (Marginson, 2019). This means that AI-supported learning systems can only have an impact on the labour market if they are embedded in functioning validation structures.

A multi-level impact model can be derived from these relationships. First, AI-supported personalisation has an impact on self-efficacy via feedback and adaptive learning structures (Luckin et al., 2016; Means et al., 2014). These effects are then transferred into stable learning behaviour via engagement (Fredricks et al., 2004; Kahu, 2013). Whether this results in employability ultimately depends on institutional validation mechanisms in the form of micro-credentials (OECD, 2023; European Commission, 2022). The impact of AI is therefore not a direct result, but rather a sequence of interlinked mechanisms and is context-dependent.

The underlying model is visualised in Figure 1 and shows the causal mechanisms and the assumed relationships between personalisation, engagement, learning persistence and

employability.

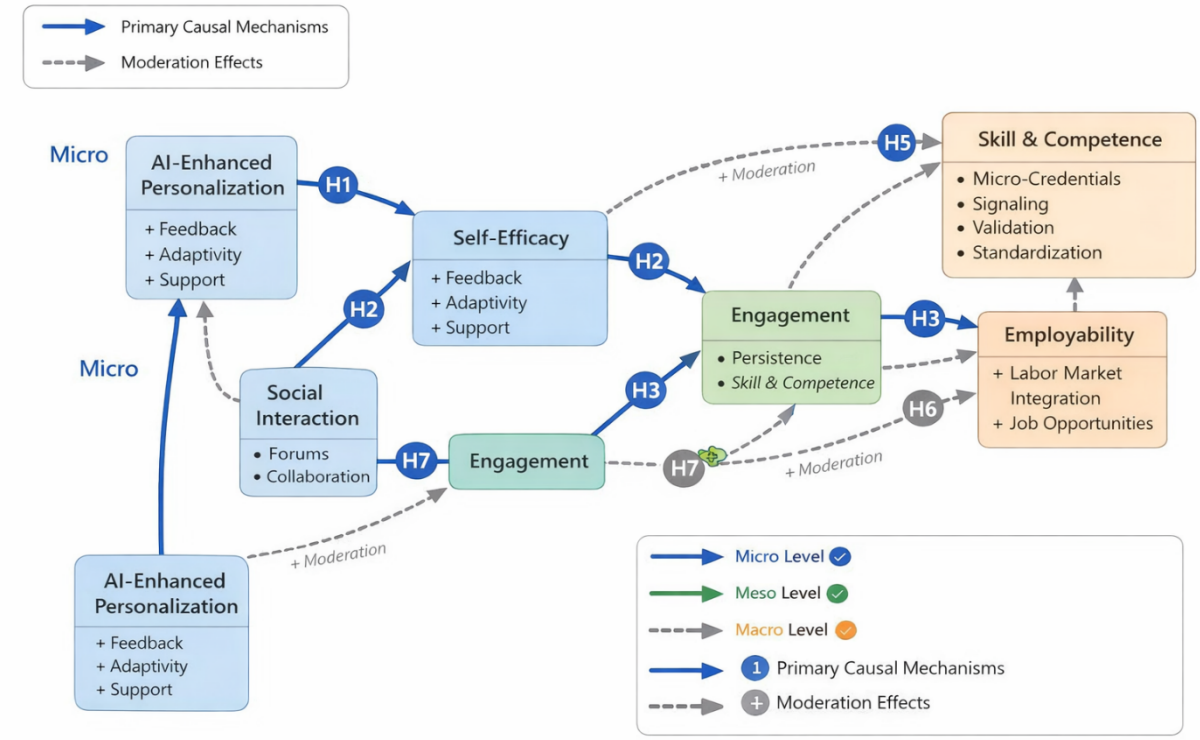

Figure 1: Conceptual model of AI-driven personalization, engagement, and employability Source: Own illustration

3.1 Hypotheses

H1: AI-supported personalisation increases the self-efficacy of learners.

H2: Self-efficacy has a positive effect on student engagement.

H3: Student engagement has a positive effect on learning persistence.

H4: Learning persistence has a positive effect on skill building and performance.

H5: The relationship between competence development and employability is mediated by micro-credentials.

H6: The effect of micro-credentials on employability is dependent on institutional recognition and standardisation.

H7: Social interaction strengthens the relationship between engagement and learning persistence.

4. Methods

The methodological design of the study follows a comparative, mechanism-based research design. The aim is to systematically reconstruct the causal relationships between AI-supported personalisation, self-efficacy, student engagement, learning persistence and employability. The focus is not on estimating average effects, but on identifying and tracing causal mechanisms. Causality is understood as a sequence of interlinked processes in which effects do not arise directly, but are mediated via clearly identifiable intermediate steps (Nullmeier & Kuhlmann, 2022; Hedström & Swedberg, 1996).

Methodologically, the study combines elements of process tracing with a contrastive case comparison. Process tracing is used to reconstruct the internal logic of effects within individual cases in detail. Case comparison makes it possible to visualise differences in the causal relationships and to identify the conditions under which certain mechanisms become effective or fail to take effect. The combination of both approaches allows a precise analysis of both the internal logic and the context dependency of the investigated processes.

The case selection is theory-led and follows a contrastive logic. Three real digital learning platforms are analysed: Coursera, edX and Udacity. Coursera represents a system with pronounced AI-supported personalisation and a strong integration of micro-credentials in the form of professionally usable certificates. edX represents a more academic platform with moderate personalisation and formalised certification. Udacity serves as a case with a strong labour market orientation, in which so-called nanodegrees establish a close link between learning processes and employability. The selection of these cases enables a systematic variation of central influencing factors, particularly with regard to the degree of personalisation, the intensity of feedback and interaction structures and the institutional embedding of validation mechanisms.

The database consists of a combination of secondary data, platform documentation and existing empirical studies. In addition, available information on user behaviour,

interaction patterns, engagement and completion rates are taken into account. This form of data triangulation serves to reconstruct the internal mechanisms of action from different perspectives and to increase the validity of the analysis. At the same time, the fact that data availability varies between cases and not all constructs can be empirically recorded in the same depth is openly taken into account.

The operationalisation of the central concepts is closely aligned with the theoretical assumptions of the model. AI-supported personalisation is captured via the degree of adaptation of learning content, feedback and learning paths (Luckin et al., 2016; Means et al., 2014). Self-efficacy is understood as the subjective expectation of being able to successfully master learning challenges (Bandura, 1997). Engagement is conceptualised as a multidimensional construct that is expressed in activity, interaction and cognitive involvement (Fredricks et al., 2004; Kahu, 2013). Learning persistence is operationalised via continuous participation and completion behaviour (Allione & Stein, 2016; Jordan, 2014). Employability refers to the labour market-relevant usability of acquired skills, while micro-credentials are understood as institutional validation mechanisms whose effect depends on standardisation, recognition and embedding (OECD, 2023; European Commission, 2022).

The analytical strategy takes place in two steps. Firstly, the relevant impact mechanisms are identified within the individual cases and reconstructed along the theoretical causal chain. This is followed by a comparative analysis in which similarities and differences between the cases are systematically analysed. The focus is on the question of the conditions under which AI-supported personalisation leads to increased learning persistence via self-efficacy and engagement and when these processes are translated into results relevant to the labour market.

The methodological design aims for a high internal coherence of the causal explanation. Statistical generalisability is deliberately not sought. Instead, the gain in knowledge lies in the identification of transferable mechanisms of action that may also be relevant in other contexts.

5. Results

The results are presented along the impact mechanisms specified in the theoretical model and combine the case-based analysis with the systematic comparison of the three investigated platforms Coursera, edX and Udacity. The aim is to empirically reconstruct the causal process chains between AI-supported personalisation, self-efficacy, engagement, learning persistence and employability and to make the conditions of their effectiveness visible.

In the first step, the analysis shows clear differences in the influence of AI-supported personalisation on self-efficacy. In the case of Coursera, adaptive recommendation systems, individualised learning paths and continuous feedback mechanisms lead to a noticeable reduction in uncertainty in the learning process. Learners report an increased perception of control, which is consistently reflected in increased self-efficacy (Luckin et al., 2016; Means et al., 2014; Bandura, 1997). In contrast, the edX case shows smaller effects. The more standardised course structure and limited personalisation mean that learners receive less adaptive support, resulting in a more moderate increase in self-

efficacy. Udacity shows a differentiated pattern. Project-based learning formats and structured feedback significantly increase self-efficacy, particularly among goal-orientated learners, while less committed users show lower effects.

These differences continue in the second mechanism, the link between self-efficacy and engagement. In the Coursera case, increased self-efficacy leads to more intensive platform use, more frequent interaction with learning content and greater use of feedback functions. Engagement manifests itself here in continuous activity and systematic processing of learning modules (Fredricks et al., 2004; Gan et al., 2023). In the edX case, engagement is more often episodic and less stable, as the lower level of personalisation creates fewer incentives for continuous interaction. Udacity, on the other hand, shows highly selective engagement. Learners with clear professional objectives show a high level of activity and intensive use of the structures provided, while other users drop out early. Engagement thus proves to be a central mechanism in all cases, which translates psychological effects into observable behaviour, but is highly context-dependent (Kahu, 2013; Bond et al., 2020).

In the third step, the relationship between engagement and learning persistence becomes visible. In the Coursera case, high engagement leads to more stable learning trajectories and lower dropout rates, although a significant proportion of learners still participate selectively or drop out early (Allione & Stein, 2016; Jordan, 2014). In the edX case, there is a stronger polarisation between full completion and early dropout, as the lower level of interactivity offers fewer opportunities to maintain engagement over time. Udacity shows the highest persistence among committed learners, as the close integration of learning content with concrete projects and professional objectives stabilises participation. At the same time, persistence here also remains highly dependent on initial engagement and clarity of goals (Kizilcec et al., 2013). Across all cases, it is confirmed that early engagement is a key predictor of stable learning trajectories and that social interaction plays a reinforcing role, especially when it is integrated into the learning process in a structured manner (Means et al., 2014; Bond et al., 2020).

The fourth mechanism concerns the translation of learning persistence into employability. This is where the clearest differences between the cases can be seen. In the Coursera case, professional certificates enable a partial visualisation of acquired competences, resulting in a limited transition to labour market-relevant effects. In the edX case, this transition remains less pronounced, as certificates are more academically oriented and have less of a direct signalling effect on the labour market. The Udacity case shows the strongest link between learning and employability. Nanodegrees are closely linked to business requirements and act as clearly recognisable signals of specific competences, enabling a more direct transition to labour market outcomes (Spence, 1973; OECD, 2023; European Commission, 2022).

The comparative analysis makes it clear that a consistent sequential causal structure can be identified across all cases, although the extent of this varies. AI-supported personalisation initially has an impact on self-efficacy, which influences engagement, engagement stabilises learning persistence and persistence forms the basis for skills development. However, institutional validation is crucial for the translation of these competences into employability. While the first mechanisms are relatively robust across

different contexts, the last step is highly dependent on the design and recognition of micro-credentials (Marginson, 2019; OECD, 2023).

Against this background, the formulated hypotheses can be systematically categorised. The assumption that AI-supported personalisation increases self-efficacy is confirmed in all cases, albeit to varying degrees. The effect of self-efficacy on engagement is consistent, but depends on the structure of the learning system. The influence of engagement on learning persistence is also confirmed and proves to be a central mechanism. However, the assumption of a direct transition from persistence to employability is relativised. Persistence is necessary, but not sufficient. Labour market-relevant effects only arise through institutional validation. The role of micro-credentials as a mediating mechanism is clearly confirmed, as is their dependence on standardisation and recognition. Finally, it is shown that social interaction strengthens the relationship between engagement and persistence, but is unevenly distributed.

Overall, the results confirm the multi-level effect structure developed in the theoretical model. The influence of AI on learning and labour market outcomes is indirect, context-dependent and arises from the interplay of technological, psychological and institutional mechanisms.

6. Discussion

The results make a substantial contribution to the theoretical and empirical classification of AI-supported personalisation in digital learning environments by showing that its impact cannot be understood as a direct technological effect, but rather as the result of a sequential chain of interlinked mechanisms that integrate psychological, behavioural and institutional levels (Nullmeier & Kuhlmann, 2022). This corrects a central implicit assumption of previous research, which explains the influence of AI primarily through increases in efficiency or direct improvements in performance.

An initial key contribution lies in the clarification of the causal logic of AI in the educational context. The comparative case analysis shows that differences in the degree of personalisation are directly related to the level of self-efficacy. In the Coursera case in particular, it is clear that adaptive feedback systems and individualised learning paths increase the perceived control over the learning process and thus systematically strengthen self-efficacy (Luckin et al., 2016; Means et al., 2014). In contrast, more standardised structures such as in the edX case show lower effects, while in the Udacity case the effect depends heavily on goal orientation and task structure. These differences make it clear that technological functions do not work per se, but that their effects arise from the interaction with didactic design and context of use. AI is therefore not to be understood as an autonomous cause, but as part of an embedded mechanism (Dede, 2014; Bandura, 1997).

A second contribution concerns the theoretical re-evaluation of engagement. The results consistently show that engagement is not to be interpreted as a mere dependent variable, but functions as a central integrating link that translates individual motivation, system design and social interaction into observable behaviour (Fredricks et al., 2004; Kahu, 2013). The case comparison makes it clear that engagement is highly context-dependent: while continuous activity is promoted in highly personalised environments, episodic

usage patterns tend to emerge in less adaptive systems. In labour market-oriented contexts such as Udacity, it is also clear that engagement is closely linked to clarity of purpose. These findings extend existing engagement approaches by explicitly emphasising its mediating function within a causal structure (Bond et al., 2020).

Thirdly, the results contribute to a differentiated explanation of learning persistence. Instead of a purely structural interpretation of dropout, the findings show that persistence arises from the interplay of self-efficacy and engagement. This becomes particularly clear when comparing the cases: High self-efficacy only leads to stable participation if it is supported by continuous engagement. At the same time, it can be seen that early engagement is a key factor in setting the course, as it significantly influences the further course of learning (Allione & Stein, 2016; Jordan, 2014). Persistence is therefore not an isolated result, but an expression of a stabilised mechanism that encompasses both psychological and structural conditions.

A fourth and central contribution lies in the integration of institutional perspectives. The analysis shows that the translation of skills development into employability does not occur automatically, but depends on validation mechanisms. The differences between the cases are particularly pronounced here: While in the Udacity case, nanodegrees designed to be close to the labour market create direct connectivity to employment, this transition remains limited in more academically oriented contexts such as edX. Coursera occupies an intermediate position in which certificates have a partial signalling effect. These findings confirm that micro-credentials act as an institutional interface between education and the labour market and that their impact is largely dependent on standardisation, recognition and embedding (Spence, 1973; OECD, 2023; European Commission, 2022).

The results are thus in tension with classical human capital theory, which assumes a direct relationship between education and economic returns. Instead, this analysis shows that this relationship is mediated by institutional structures and is therefore context-dependent (Marginson, 2019). Competences alone are not sufficient to generate employability; their visibility and recognition in the respective institutional framework is crucial. This relativises linear education models and points to the importance of validation architectures.

Taken together, this results in a consistent causal logic that also empirically supports the model structure shown in Figure 1. AI-supported personalisation has an effect on engagement by increasing self-efficacy, engagement stabilises learning persistence and persistence forms the basis for skills development. However, the transition to labour market-relevant results only occurs through institutional validation. The effect of AI is therefore indirect, multi-levelled and context-dependent.

Beyond the theoretical contributions, there are implications for the design of digital learning systems. The results show that technological optimisation alone is not enough. The integration of personalisation in didactically structured learning environments and the link to functioning validation mechanisms are crucial. Platforms that combine both dimensions show significantly more stable impact paths than those that primarily focus on technological efficiency (Dede, 2014; Bond et al., 2020).

Furthermore, the findings point to a structural shift in the relationship between the education system and the labour market. Digital platforms are increasingly taking over skills transfer functions, while institutional actors remain responsible for their validation. This results in a hybrid structure in which technological and institutional mechanisms jointly determine the conditions of learning and labour market outcomes (OECD, 2023).

Overall, the discussion shows that the influence of AI in education can only be understood through the interplay of several mechanisms. The central contribution of the study is to systematically identify these mechanisms, differentiate them empirically and transfer them into a consistent theoretical structure.

7. Implications

The results of the study have differentiated implications for theory, practice and education policy. These arise from the identified impact structure in which AI-supported personalisation has an effect on learning persistence via self-efficacy and engagement and whose labour market-relevant effects are mediated by institutional validation mechanisms (Nullmeier & Kuhlmann, 2022).

In terms of theory, the key implication is the need to systematically integrate previously separate strands of research. The results show that neither technological nor psychological or labour market-related perspectives provide a sufficient explanation in isolation. Rather, a multi-level model is required that understands AI as part of a causal process chain (Luckin et al., 2016; Dede, 2014). In particular, it becomes clear that self-efficacy and engagement are key mediating variables that translate technological interventions into observable behaviour (Bandura, 1997; Fredricks et al., 2004). This extends existing engagement research by conceptualising engagement not only as an explanatory variable, but as an integrative mechanism between system design and learning outcomes (Fredricks et al., 2004; Kahu, 2013). At the same time, the study contributes to the further development of the literature on micro-credentials by shifting their role from a pure outcome to an active component of the causal structure (OECD, 2023; Spence, 1973).

There are practical implications for the design of digital learning platforms. The results show that the implementation of AI functions alone is not enough to achieve sustainable learning outcomes. The focus is on the question of how these functions are specifically designed and integrated into learning processes. Systems that provide continuous feedback, adaptive support and clear structures promote self-efficacy and thereby stabilise engagement and learning persistence (Means et al., 2014; Gan et al., 2023). At the same time, it has been shown that social interaction plays a supportive role and should be specifically encouraged (Bond et al., 2020). At the same time, it is clear that without institutional validation, the economic benefits of these learning processes remain limited (Marginson, 2019). Platform operators should therefore increasingly enter into cooperation with certifying institutions or develop their own recognised credential structures in order to increase the impact of their offerings on the labour market (OECD, 2023; European Commission, 2022).

At the level of education policy, there is a need to create a framework for the standardisation and recognition of micro-credentials. The results show that their impact

depends heavily on institutional embedding and external recognition (OECD, 2023; European Commission, 2022). Without clear standards, there is a risk that certificates will lose their signalling effect and thus weaken the link between learning processes and the labour market (Spence, 1973). At the same time, the findings make it clear that AI-supported learning systems are increasingly taking on a central role in skills development (Frey & Osborne, 2017). This results in the challenge of developing regulatory structures that both enable innovation and ensure the quality and comparability of qualifications.

The implications show that the impact of digital learning systems cannot be understood in isolation at a technological level. Rather, an integrated approach is required that takes psychological mechanisms, institutional validation and technological infrastructure into account together and systematically harmonises them (Nullmeier & Kuhlmann, 2022).

8. Limitations and Future Research

Due to the theoretical integration and the systematic reconstruction of causal mechanisms, the present study has several limitations that must be taken into account when interpreting the results and at the same time offer starting points for future research.

A first limitation concerns the research design. The study follows a mechanism-based, comparative approach and aims to identify causal process chains, not to estimate average effects. This achieves a high internal coherence of the argumentation, but the external validity is limited. The results cannot be generalised in a statistical sense, but should be understood as analytically transferable mechanisms (Nullmeier & Kuhlmann, 2022; Hedström & Swedberg, 1996). Future studies should therefore use quantitative designs to test the identified relationships in larger samples.

A second limitation results from the data basis. The analysis is predominantly based on secondary data, platform documentation and existing studies. This means that distortions in the underlying data cannot be ruled out. In particular, standardised measurements of central constructs such as self-efficacy or commitment are lacking in many cases, which limits comparability (Fredricks et al., 2004; Bond et al., 2020). Future research should therefore conduct its own data collection and use validated measurement instruments in order to increase the robustness of the results.

Another limitation concerns the operationalisation of engagement. Although engagement is understood as a multidimensional construct (Fredricks et al., 2004; Bond et al., 2020), it is often empirically measured using observable behavioural indicators such as activity or interaction. However, these only incompletely reflect the cognitive and emotional dimensions. Future studies should therefore develop more differentiated measurement approaches that take all dimensions of the construct into account.

Furthermore, the effect of micro-credentials is highly context-dependent. The present study shows that their effectiveness depends on institutional recognition and standardisation (OECD, 2023; European Commission, 2022). However, this context dependency is not systematically varied, meaning that no generalisable statements can be made about different institutional framework conditions. Further research should carry out comparative analyses between different education systems and labour markets in

order to examine these differences in more detail. There is a need for further research into the long-term effects of AI-supported personalisation. The present study focusses primarily on short-term and medium-term mechanisms of action in the learning process. It remains unclear to what extent these effects are stable in the long term and how they affect sustainable career paths (Frey & Osborne, 2017). Longitudinal studies could provide important insights here.

Finally, the study opens up perspectives for further theoretical development. In particular, the role of engagement as a central integration mechanism should be further differentiated, for example by analysing the interactions between individual, social and technological factors (Kahu, 2013). It also appears promising to test the identified mechanisms in experimental designs in order to isolate causal effects even more precisely.

To summarise, the limitations show that the present study makes an important contribution to the integration of existing research strands, but at the same time further empirical and theoretical work is required to validate and expand the identified relationships (Nullmeier & Kuhlmann, 2022).

9. Conclusion

The study investigates the causal relationships between AI-supported personalisation, learning persistence and employability in digital learning environments, integrating technological, psychological and institutional perspectives in a consistent, mechanism-based model (Nullmeier & Kuhlmann, 2022). The starting point was the observation that existing strands of research largely consider these dimensions in isolation and thus lack a comprehensive understanding of the logic of digital learning systems (Bond et al., 2020; Luckin et al., 2016).

The results show that AI-supported personalisation does not have a direct effect on learning outcomes or labour market-relevant outcomes, but is mediated via a sequential chain of mechanisms. The focus is on increasing self-efficacy, which is achieved via adaptive feedback processes and individualised learning paths (Bandura, 1997; Gan et al., 2023; Means et al., 2014). These psychological effects are translated into observable learning behaviour via student engagement, which in turn forms the basis for learning persistence (Fredricks et al., 2004; Kahu, 2013). Persistence proves to be a necessary condition for the development of competences, but is not sufficient for their utilisation in the labour market (Allione & Stein, 2016; Jordan, 2014).

The transfer of learning processes into employability depends crucially on institutional validation mechanisms. Micro-credentials act as a central interface between the education system and the labour market by making skills visible and enabling their assessment (Spence, 1973). At the same time, their impact is strongly dependent on factors such as standardisation, recognition and institutional embedding (OECD, 2023; European Commission, 2022). The study thus confirms that the relationship between education and labour market success is not linear, but is mediated by institutional framework conditions (Marginson, 2019).

The central contribution of the study lies in the development of an integrated impact model that understands AI-supported personalisation as part of a multi-level causal structure. This model shows that the impact of digital learning systems arises from the interplay of self-efficacy, engagement, persistence and institutional validation (Fredricks et al., 2004; OECD, 2023). This broadens the perspective on AI in the educational context from a technological to a systemic view (Dede, 2014; Luckin et al., 2016).

In addition, the study provides important implications for research and practice. It shows that future analyses must take greater account of the interdependence of technological, psychological and institutional factors (Bond et al., 2020). At the same time, it becomes clear that the design of effective learning systems does not depend solely on technological innovation, but also on their integration into functioning learning and validation structures (European Commission, 2022; OECD, 2023).

The study shows that AI-supported personalisation has significant potential for improving learning processes, but that its realisation depends on complex, interlinked mechanisms. A deeper understanding of these mechanisms is therefore crucial in order to explain the effect of digital learning systems both theoretically and to make them usable in practice (Nullmeier & Kuhlmann, 2022).

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