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Generative AI, academic skill structure and innovation: A theory-integrative model of transformation effects

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Abstract

Competence structures and their significance for innovation remain insufficiently explained. This paper develops a theory-integrative model to analyse these relationships. The starting point is the assumption that generative systems influence epistemic core processes. These include problem recognition, ideational variation and knowledge integration. Based on approaches of distributed cognition, skill-bias technological change and innovation search, a dual transformation mechanism is derived. Firstly, generative AI reorganises academic skills architectures. Routinisable cognitive activities lose operational relevance. Evaluative, integrative and problem-formulating meta-competences gain strategic weight. Secondly, this shift in competences is changing the structure of scientific innovation. Recombinative search spaces are expanding. Incremental innovations are accelerated. Under conditions of epistemic standardisation, the probability of radical knowledge formation can decrease. Central mechanisms of action are cognitive outsourcing, algorithmically supported variation and human judgement as an instance of epistemic quality assurance.

Keywords: Generative artificial intelligence, Academic competence structure, Scientific innovation, Distributed cognition, Recombinative search

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1. Introduction

Generative systems based on artificial intelligence have quickly found their way into almost all areas of academic knowledge work (Mishra et al., 2024; Kusumegi et al., 2025). Researchers use them for literature research, to structure complex argumentation contexts, to formulate scientific texts and to develop and vary ideas (Lieberum et al., 2025; Kobak et al., 2025). This development is fundamentally changing the conditions of academic performance (Brynjolfsson et al., 2025; Noy & Zhang, 2023). Academic work is increasingly taking place in hybrid constellations in which human judgement is combined with algorithmic generation, selection and integration of content (Hollan et al., 2000; Clark & Chalmers, 1998).

In the public and academic debate, this transformation is often discussed from an efficiency perspective (Noy & Zhang, 2023; Brynjolfsson et al., 2025). Generative AI is seen as an instrument for accelerating work processes, reducing cognitive search costs and increasing individual productivity (Noy & Zhang, 2023; Brynjolfsson et al., 2025). However, the question of whether the use of such systems changes the structure of academic skills themselves has been less systematically investigated (Bentley, 2025). When central cognitive tasks are partially outsourced, it is not only time that is saved (Gilbert et al., 2023). Rather, the weighting between routine activities, analytical self-processing, critical evaluation and conceptual integration can shift (Autor et al., 2003).

At the same time, innovation research faces the challenge of theorising new forms of ideational production under conditions of algorithmic support (Karpatne et al., 2025; Zhang et al., 2025). Innovation does not arise from knowledge alone, but from the ability to reframe problems, link heterogeneous information and process uncertainty productively (March, 1991). If generative AI intervenes in precisely these processes, it is reasonable to assume that not only the speed but also the logic of scientific innovation will change (Doshi & Hauser, 2024; Kusumegi et al., 2025). To date,

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however, the effects of competences and the effects of innovation have largely been considered separately (Autor et al., 2003). An integrated theoretical perspective that systematically links the two levels is largely lacking (Karpatne et al., 2025).

Against this background, the aim of this study is to develop a theory-integrative impact model that explains how generative AI transforms the cognitive competence structure of academics and what consequences this has for innovation processes. The central research question is:

How does the use of generative AI influence the competence architecture of academic knowledge work and in what way does this transformation change the conditions of scientific innovation?

To answer this question, approaches of cognitive outsourcing and distributed cognition are combined with theories of skill-bias technological change and concepts of creativity and innovation research (Clark & Chalmers, 1998; Hollan et al., 2000; Autor et al., 2003; March, 1991). On this basis, a dual transformation model is developed that describes two intertwined changes: First, a shift in academic performance from internal generation to curatorial, evaluative and integrative meta-skills (Gilbert et al., 2023; Bentley, 2025). Secondly, a change in the innovation structure in which recombinative and incremental innovation is facilitated, while the prerequisites for deep original knowledge creation can be weakened under certain conditions (Doshi & Hauser, 2024).

The contribution of the work thus lies in the theoretical integration of previously fragmented strands of research and in the development of an explanatory model for innovation under conditions of generative AI (Karpatne et al., 2025). In addition, the analysis opens up starting points for empirical follow-up research and provides implications for the future design of academic skills development (Ahmed et al., 2023).

The rest of the presentation is structured as follows: First, generative AI systems are conceptually categorised as a new form of cognitive support. Next, the effects of

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competence on academic work are analysed and linked to theories of innovation. Building on this, the dual transformation model is developed and its mechanisms of action and contextual conditions are discussed. Finally, theoretical implications, limitations and perspectives for future research are outlined.

2. Generative AI as a new form of cognitive support

The use of generative AI marks a qualitative change in technological support in academic knowledge work (Kusumegi et al., 2025; Karpatne et al., 2025). While earlier digital tools primarily enabled access to information or data processing, generative systems intervene directly in processes of idea formation, structuring and linguistic articulation (Zhang et al., 2025; Kobak et al., 2025). Academic output is thus increasingly being created in spaces of interaction in which human expertise and algorithmically generated suggestions are intertwined (Hollan et al., 2000; Clark & Chalmers, 1998).

This development cannot be adequately explained by a pure understanding of instruments (Bentley, 2025). Generative AI not only takes on operational functions, but also participates in epistemic processes (Karpatne et al., 2025). It generates alternative lines of reasoning, structures complex topics and enables rapid variation of problem solutions (Zhang et al., 2025). In this sense, it can be understood as cognitive support with a productive effect of its own (Clark & Chalmers, 1998). Academic activity thus shifts from isolated thinking to coordinated search, evaluation and integration processes (Hollan et al., 2000; Gilbert et al., 2023).

2.1 Between tool, assistant and co-actor

A differentiation between three functional modes is helpful for theoretical categorisation (Karpatne et al., 2025).

In tool mode, generative AI is used to speed up clearly defined tasks (Noy & Zhang, 2023). Examples include the summarisation of texts or the formal structuring of

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arguments (Lieberum et al., 2025; Kobak et al., 2025). Here, the epistemic responsibility remains entirely with the user (Clark & Chalmers, 1998).

In assistance mode, AI expands the scope of action by generating suggestions, visualising alternatives and shortening search processes (Zhang et al., 2025). Academic work becomes less linear as a result. Researchers can switch more quickly between hypotheses, examine new perspectives and open up larger information spaces (Karpatne et al., 2025).

More intensive interaction is created in co-actor mode. Ideas are developed iteratively together, with algorithmic suggestions serving as a starting point for further human reflection (Boiko et al., 2023; Zhang et al., 2025). In such constellations, performance can no longer be clearly assigned to a single actor (Hollan et al., 2000). Instead, a hybrid epistemic unit is formed in which responsibility, creativity and judgement must be rebalanced (Clark & Chalmers, 1998).

This differentiation is analytically significant, as the effects of expertise and the consequences of innovation depend heavily on the mode in which AI is utilised (Brynjolfsson et al., 2025).

2.2 Human-AI interaction in knowledge work

Academic knowledge production comprises several core cognitive processes: Problem recognition, information search, analysis, synthesis, evaluation and communication (Hollan et al., 2000). Generative AI influences each of these processes in different ways (Karpatne et al., 2025; Zhang et al., 2025).

It reduces search effort by enabling relevant information to be identified more quickly (Noy & Zhang, 2023; Brynjolfsson et al., 2025). It expands the scope for variation, as alternative argumentation structures or methodological approaches are generated quickly (Zhang et al., 2025; Doshi & Hauser, 2024). At the same time, it can reinforce cognitive path dependencies if suggestions reproduce similar patterns (Doshi & Hauser, 2024).

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The interaction between humans and AI can therefore be described as a dynamic control process (Hollan et al., 2000). Humans define objectives, evaluate suggestions and integrate results into existing knowledge structures (Clark & Chalmers, 1998). The AI acts as a source of ideational variation and structural support (Karpatne et al., 2025). The decisive factor here is the quality of human judgement (Bentley, 2025). Without critical reflection, algorithmic support can lead to superficial processing (Tian & Zhang, 2025). With a high level of expertise, on the other hand, it can intensify explorative search processes (March, 1991; Brynjolfsson et al., 2025).

2.3 Cognitive outsourcing and distributed cognition

The perspective of distributed thinking is a suitable theoretical foundation for this development (Hollan et al., 2000; Clark & Chalmers, 1998). Cognition is no longer understood exclusively as an internal mental activity, but as a process that extends across artefacts, technologies and social interactions (Clark & Chalmers, 1998; Hollan et al., 2000). In this sense, generative AI represents a particularly powerful form of cognitive outsourcing (Gilbert et al., 2023; Bentley, 2025).

The externalisation of certain mental operations creates new degrees of freedom (Gilbert et al., 2023). Academics can shift resources from repetitive tasks to conceptual questions (Noy & Zhang, 2023; Brynjolfsson et al., 2025). At the same time, the practice and stability of certain skills changes (Autor et al., 2003). If analysis or formulation are frequently delegated, their independent execution can become less important (Tian & Zhang, 2025).

This ambivalence forms the starting point for the following analysis of the effects of competences (Bentley, 2025). Generative AI acts not only as an efficiency booster, but also as a structural transformer of academic performance (Karpatne et al., 2025). It is precisely this transformation that forms the basis for possible changes in innovation processes, which will be systematically developed in the further course (Doshi & Hauser, 2024; Kusumegi et al., 2025).

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3. Competence effects of generative AI on academic performance

The use of generative AI not only changes work processes, but also intervenes in the structure of academic competences (Brynjolfsson et al., 2025; Bentley, 2025). Academic performance is based on a bundle of cognitive skills that includes analysis, argumentation, synthesis, judgement and creative problem solving (Hollan et al., 2000). When parts of these skills are technologically supported or outsourced, their relative importance within academic practice shifts (Autor et al., 2003; Gilbert et al., 2023).

This shift cannot be described as a linear loss or gain of competences (Bentley, 2025). Rather, a transformation process emerges in which certain skills lose operational relevance while others gain strategic importance (Autor et al., 2003). Generative AI thus acts as a catalyst for a reorganisation of scientific ways of thinking and working (Karpatne et al., 2025; Kusumegi et al., 2025).

3.1 Technological change and shift in expertise

Theories of technological change show that innovation rarely replaces skills altogether (Autor et al., 2003). Instead, it changes the demand for specific skills profiles (Autor et al., 2003). Routinisable activities tend to be automated or supported, while complex, non-standardisable activities gain in importance (Autor et al., 2003).

In the academic context, this applies in particular to activities such as systematic literature review, formal structuring of argumentation chains or linguistic formulation of standardised sections (Lieberum et al., 2025; Kobak et al., 2025). Generative AI can accelerate and partially take over these tasks (Noy & Zhang, 2023; Brynjolfsson et al., 2025). At the same time, the need for skills that cannot be easily reproduced algorithmically is increasing (Bentley, 2025). These include conceptual framing of research problems, critical categorisation of results and normative reflection on scientific responsibility (Ahmed et al., 2023; Bentley, 2025).

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The competency structure is thus shifting from operational personal performance to controlling meta-competence (Autor et al., 2003; Gilbert et al., 2023).

3.2 De-skilling, re-skilling and upgrading meta-competences

The discussion about de-skilling describes processes in which activities become less demanding due to technical support (Autor et al., 2003). In academic knowledge work, this can be seen, for example, where generative systems provide suggestions for arguments, structures or methodological approaches (Zhang et al., 2025; Kobak et al., 2025). The danger is that independent in-depth analyses are replaced by the rapid adoption of plausible solutions (Tian & Zhang, 2025; Bentley, 2025).

At the same time, re-skilling processes arise (Autor et al., 2003). Researchers must learn to examine, contextualise and productively develop algorithmic results (Karpatne et al., 2025). These requirements promote competences such as critical evaluation, integrative synthesis and reflective decision-making skills (Ahmed et al., 2023; Bentley, 2025).

Meta-competences are therefore gaining in importance. These include:

- Precise problem definition
- Evaluation of competing solution options
- Integration of heterogeneous knowledge
- Dealing with uncertainty
- Responsibility for epistemic quality

Academic performance is thus shifting from the generation of individual content to the design of cognitive processes (Gilbert et al., 2023; Bentley, 2025; Karpatne et al., 2025).

3.3 Risks of dependency and surface processing

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New risks arise alongside potential (Bentley, 2025; Karpatne et al., 2025). High utilisation of generative AI can lead to a shortening of individual search and thought processes (Tian & Zhang, 2025). If suggestions are adopted without in-depth scrutiny, the probability of original insights decreases (Bentley, 2025). However, scientific innovation thrives on irritation, detours and intensive cognitive dialogue (March, 1991).

Another risk lies in the standardisation of argumentation patterns (Doshi & Hauser, 2024). Generative systems tend to reproduce dominant knowledge structures (Doshi & Hauser, 2024; Kusumegi et al., 2025). This can make alternative perspectives less visible (Doshi & Hauser, 2024). For academic innovation, this means a possible convergence of idea spaces, which could impair diversity and radical innovations in the long term (Doshi & Hauser, 2024).

However, these risks are not deterministic (Brynjolfsson et al., 2025). They depend heavily on expertise, depth of use and institutional framework conditions (Karpatne et al., 2025). Researchers with a high level of expertise can make targeted use of algorithmic support to intensify explorative search processes (March, 1991; Brynjolfsson et al., 2025). People with less experience run the risk of adopting suggestions without reflection (Tian & Zhang, 2025).

3.4 Skills transformation as the basis for changing innovation processes

The shifts in expertise described above have direct consequences for innovation (Autor et al., 2003; Karpatne et al., 2025). Scientific innovations arise from the ability to recombine known knowledge elements and question existing paradigms (March, 1991). If generative AI facilitates variation and reduces search costs, it can accelerate innovation (Brynjolfsson et al., 2025; Noy & Zhang, 2023). At the same time, a reduction in independent deep processing can reduce the likelihood of disruptive insights (Bentley, 2025; Tian & Zhang, 2025).

This makes it clear that innovation cannot be analysed independently of competence structures (Autor et al., 2003). Generative AI initially changes the organisation of

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cognitive performance (Gilbert et al., 2023; Karpatne et al., 2025). Only through this change does it affect innovation patterns (Doshi & Hauser, 2024; Kusumegi et al., 2025).

The following analysis therefore systematically examines how innovation can be understood as a recombinative search process and how changing competence profiles characterise the dynamics of scientific innovation (March, 1991).

4. Innovation as a result of changed competence structures

Innovation in an academic context arises from complex search, evaluation and integration processes (March, 1991; Hollan et al., 2000). New insights rarely result from linear problem solving, but rather from the ability to critically reflect on existing knowledge, recombine it and develop viable conclusions under uncertainty (March, 1991). When generative AI intervenes in these processes, it not only changes the speed of scientific work, but also the structure of epistemic exploration itself (Karpatne et al., 2025; Kusumegi et al., 2025). The transformation of academic competences described above therefore forms the basis for a deeper understanding of innovation under conditions of algorithmic support (Autor et al., 2003).

Scientific innovation can be described as a recombinative search process in which researchers search for new connections between ideas, methods and empirical findings within existing solution spaces (March, 1991). Generative AI can intensify this process as it quickly generates alternative hypotheses, lines of reasoning and perspectives (Zhang et al., 2025; Boiko et al., 2023). This expands ideational search spaces and reduces the costs of explorative activities (Brynjolfsson et al., 2025; Noy & Zhang, 2023). Innovation can occur more frequently under such conditions, particularly in the form of incremental improvements or conceptual recombination (Doshi & Hauser, 2024). At the same time, the quality of these innovations remains closely linked to the ability to critically examine algorithmic proposals and develop them further independently (Bentley, 2025).

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Innovation requires a balance between exploration and exploitation (March, 1991). Exploration aims to find new solutions to problems, while exploitation deepens and operationalises existing knowledge structures (March, 1991). Generative AI supports both dimensions (Brynjolfsson et al., 2025). It facilitates the application of established patterns and at the same time can make new combinations visible (Zhang et al., 2025). However, the human ability to recognise problems is crucial (Bentley, 2025). Scientific progress often begins with the realisation of inconsistencies or previously unnoticed gaps in research (March, 1991). If algorithmic systems reproduce dominant perspectives, this perception can be weakened (Doshi & Hauser, 2024). Conversely, comprehensive information integration can help to identify new areas of tension between existing approaches (Karpatne et al., 2025).

A central mechanism of action lies in cognitive relief (Gilbert et al., 2023). By reducing repetitive activities, resources are freed up for conceptual reflection, strategic planning and interdisciplinary synthesis (Noy & Zhang, 2023; Brynjolfsson et al., 2025). Under such conditions, innovation can be accelerated (Brynjolfsson et al., 2025). At the same time, there is a risk of shortened learning processes (Tian & Zhang, 2025). Deep scientific insights often arise from intensive analyses of data, methods or theoretical controversies (March, 1991). If such processes are partially delegated, the probability of radical innovation can decrease (Bentley, 2025). Innovation then shifts more towards variation and selection of already plausible options (Doshi & Hauser, 2024).

Furthermore, generative AI influences the structure of idea spaces (Kusumegi et al., 2025). As algorithmic systems are based on existing knowledge patterns, they can both visualise diversity and reinforce convergent developments (Doshi & Hauser, 2024). Increasing use of similar systems by many researchers can lead to epistemic harmonisation (Kusumegi et al., 2025). In the short term, this increases efficiency and connectivity (Brynjolfsson et al., 2025). In the long term, however, it can make it more difficult for profound innovations to emerge, as scientific breakthroughs often result from deviations from established paths (March, 1991). At the same time, the possibility

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of rapid iteration opens up new forms of ideational variation that were previously difficult to access (Zhang et al., 2025). Innovation thus develops in a field of tension between the expanded ability to combine and the potential standardisation of solution approaches (Doshi & Hauser, 2024).

These correlations make it clear that innovation cannot be analysed independently of competence structures (Autor et al., 2003). Generative AI initially changes the organisation of cognitive performance and only affects scientific innovations through this transformation (Gilbert et al., 2023; Karpatne et al., 2025). The following presentation therefore develops an integrated theoretical model that systematically links competence shifts and innovation dynamics (Karpatne et al., 2025).

4.1 Development of a dual transformation model of academic AI impact

The previous analysis has shown that generative AI can be understood neither exclusively as an efficiency technology nor as a pure substitution force (Brynjolfsson et al., 2025; Bentley, 2025). Rather, its central effect is a structural transformation of academic performance, which has an impact on innovation processes via changed competence profiles (Karpatne et al., 2025; Autor et al., 2003). In order to systematically explain these relationships, a theory-integrative model is developed below that describes two interlinked transformation dimensions (Karpatne et al., 2025).

The first transformation concerns the competence structure of scientific work. Generative AI reduces the need for independent execution of routinisable cognitive activities such as structured information searches, formal text production or standardised analysis procedures (Noy & Zhang, 2023; Lieberum et al., 2025; Kobak et al., 2025). At the same time, the importance of skills focussed on control, evaluation and integration is increasing (Bentley, 2025; Ahmed et al., 2023). Academic performance is thus shifting from the direct generation of knowledge to the organisation of cognitive processes (Gilbert et al., 2023). Researchers are increasingly

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assuming the role of epistemic curators who scrutinise and select algorithmic proposals and translate them into coherent argumentative contexts (Bentley, 2025).

This shift does not lead to a homogeneous gain or loss of skills, but to a reorganisation of the performance architecture (Autor et al., 2003). Operational skills lose visibility, while meta-competences gain strategic importance (Autor et al., 2003; Bentley, 2025). These include, in particular, problem identification, critical judgement, interdisciplinary synthesis and reflective decision-making under uncertainty (Ahmed et al., 2023). At the same time, there is a risk of growing dependence on technological support (Tian & Zhang, 2025). If independent in-depth processing is practised less frequently, the stability of certain skills may decline in the long term (Autor et al., 2003).

The second transformation concerns the structure of scientific innovation. As innovation is closely linked to skills profiles, a shift in cognitive resources also changes the dynamics of ideational innovation (March, 1991; Autor et al., 2003). Generative AI facilitates the variation and recombination of ideas (Zhang et al., 2025; Boiko et al., 2023). Researchers can develop alternative hypotheses more quickly, compare methodological options and explore larger knowledge spaces (Karpatne et al., 2025). Under such conditions, the probability of incremental innovation and conceptual developments of existing approaches increases (Doshi & Hauser, 2024).

At the same time, the probability of radical innovation can decrease under certain conditions (Bentley, 2025). If algorithmic systems reproduce dominant knowledge patterns and direct search processes towards probable solutions, unusual perspectives are less likely to be pursued (Doshi & Hauser, 2024). Innovation thus shifts from deep individual search movements to accelerated selection and integration processes (March, 1991). The epistemic focus is more on the evaluation and combination of existing options than on the lengthy, independent generation of new paths of thought (Bentley, 2025).

The dual transformation model combines both developments through a mechanism logic. A first mechanism consists of cognitive relief, which frees up time and attention

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for conceptual tasks (Gilbert et al., 2023; Noy & Zhang, 2023). A second mechanism lies in the substitution of routinised services, which changes the requirements for skills profiles (Autor et al., 2003). A third mechanism concerns the recombination of ideational elements, which is facilitated by algorithmic variation (Zhang et al., 2025). This is complemented by a standardisation mechanism that can lead to the convergence of argumentation patterns (Doshi & Hauser, 2024). Finally, an evaluation mechanism emerges in which human judgement becomes the central resource of scientific quality assurance (Ahmed et al., 2023; Bentley, 2025).

The effect of these mechanisms is not uniform. It depends on contextual conditions, which are explicitly taken into account in the model (Karpatne et al., 2025). These include, in particular, technical expertise, intensity of AI use, degree of task uncertainty and disciplinary knowledge structures (Brynjolfsson et al., 2025). A high level of expertise enables the productive use of algorithmic suggestions and can expand explorative search processes (March, 1991; Brynjolfsson et al., 2025). In contrast, a low level of experience increases the probability of uncritical adoption of generated content (Tian & Zhang, 2025). The openness of a research problem also influences whether AI primarily enables efficiency gains or profound conceptual innovation (Karpatne et al., 2025).

Theoretical propositions can be derived from this model logic. Firstly, the importance of evaluative and integrative meta-competences increases with the increasing use of generative AI (Bentley, 2025). Secondly, moderate utilisation can increase the speed of innovation processes, as search costs decrease and variation is facilitated (Brynjolfsson et al., 2025; Noy & Zhang, 2023). Thirdly, high dependence on algorithmic support can reduce the likelihood of radical innovation (Bentley, 2025; Doshi & Hauser, 2024). Fourthly, experienced researchers benefit more from AI-supported knowledge work than less experienced researchers (Brynjolfsson et al., 2025). Fifthly, generative AI is particularly conducive to innovation in contexts of high uncertainty and open problem definition (March, 1991; Karpatne et al., 2025).

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The dual transformation model thus provides a theoretical explanation for the ambivalent effects of generative AI on academic innovation (Karpatne et al., 2025). It shows that technological support not only influences output quantities, but also changes the logic of scientific knowledge production itself (Kusumegi et al., 2025). The following section discusses the explanatory power of this model and its implications for innovation research, university development and future empirical studies (Ahmed et al., 2023).

5. Discussion

The dual transformation model developed offers an integrated explanation of how generative AI is changing the conditions of academic knowledge production (Karpatne et al., 2025; Kusumegi et al., 2025). It combines skills theory and innovation research into a coherent perspective on technologically supported knowledge processes (Autor et al., 2003; March, 1991). In this way, it contributes to systematically linking impact dimensions that were previously treated separately (Karpatne et al., 2025).

The strength of the model lies in its differentiation of technological effects. Generative AI is not interpreted as clearly promoting or inhibiting innovation (Bentley, 2025). Rather, the analysis shows that its effect depends on the transformation of cognitive performance (Autor et al., 2003; Gilbert et al., 2023). Accordingly, innovation does not arise directly from technological use, but from the way in which skills profiles are reorganised (Autor et al., 2003). This perspective extends existing approaches that explain innovation primarily through the availability of resources, knowledge or network structures (March, 1991).

At the same time, the model enables a reassessment of the role of academic expertise. If algorithmic systems facilitate variation and information integration, human judgement becomes more important as a selective authority (Bentley, 2025; Ahmed et al., 2023). Academic quality is created more strongly through evaluation, contextualisation and responsible decision-making (Ahmed et al., 2023). This shifts

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the focus of academic excellence from operational knowledge production to epistemic control (Gilbert et al., 2023). In the long term, this development can lead to new competence requirements in research and teaching (Ahmed et al., 2023).

For innovation research, the model provides an explanation as to why generative AI can simultaneously accelerate and homogenise innovation processes (Doshi & Hauser, 2024; Brynjolfsson et al., 2025). On the one hand, search costs are reduced and explorative activities are facilitated (Noy & Zhang, 2023). On the other hand, algorithmically reproduced patterns can lead to convergent solution spaces (Doshi & Hauser, 2024). Innovation thus develops in a field of tension between increased variation and potential standardisation (March, 1991). This insight suggests that innovation dynamics should be analysed more closely in future under the conditions of digital cognition support (Karpatne et al., 2025).

There are also far-reaching implications for universities. If meta-competencies become more important, training programmes will have to focus more on critical reflection, interdisciplinary integration and dealing with uncertainty (Ahmed et al., 2023). At the same time, the question arises as to how institutional framework conditions can be designed to promote the productive use of AI without suppressing original thought processes (Ahmed et al., 2023). Science policy strategies could aim to provide targeted support for explorative research in order to offset the potential standardisation effects of technological systems (Karpatne et al., 2025).

Despite its explanatory power, the model has limitations. It is based on theory-integrative argumentation and requires empirical validation (Karpatne et al., 2025). In particular, it needs to be clarified how competence shifts can be operationalised and innovation effects made measurable (Brynjolfsson et al., 2025). In addition, disciplinary differences can lead to varying effects, as knowledge production in the natural sciences, social sciences or humanities follows different logics (Kusumegi et al., 2025). Long-term learning and adaptation processes in dealing with generative AI are also insufficiently understood to date (Tian & Zhang, 2025).

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The extent to which institutional norms and assessment practices adapt to the changed structure of scientific performance remains an open question (Ahmed et al., 2023). Innovation processes are becoming more collaborative (Kusumegi et al., 2025). Technological mediation is increasing (Karpatne et al., 2025). Criteria of individual originality could be redefined (Ahmed et al., 2023). Scientific quality is increasingly being created in hybrid performance constellations (Clark & Chalmers, 1998; Hollan et al., 2000). This development requires targeted research (Karpatne et al., 2025). Theoretical models must be combined with empirical analyses (Brynjolfsson et al., 2025).

The concluding analysis summarises the central results. It answers the research question. It also formulates a research agenda for the transformation of academic innovation under the conditions of generative artificial intelligence (Karpatne et al., 2025).

6. Conclusion

This study explored the question of how generative AI is changing the cognitive competence structure of academics and what consequences this has for scientific innovation (Karpatne et al., 2025; Kusumegi et al., 2025). The starting point was the observation that technological support in knowledge work is increasingly intervening deeply in epistemic processes (Zhang et al., 2025; Bentley, 2025). Generative systems not only act as accelerators of existing practices, but also transform the conditions of scientific performance (Brynjolfsson et al., 2025; Karpatne et al., 2025).

The analysis shows that the use of generative AI leads to a reorganisation of academic skills profiles (Autor et al., 2003; Bentley, 2025). Routinisable activities lose operational significance, while evaluative, integrative and problem-formulating skills gain strategic importance (Ahmed et al., 2023; Bentley, 2025). Academic performance is thus shifting from direct generation to the control of cognitive processes (Gilbert et al., 2023). Academics are increasingly becoming curators who scrutinise and select

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algorithmically generated variations and transfer them into coherent knowledge contexts (Bentley, 2025).

On this basis, a dual transformation model was developed that systematically links the shift in competences and the dynamics of innovation (Karpatne et al., 2025). The model illustrates that innovation undergoes a structural change under conditions of generative AI (Doshi & Hauser, 2024; Kusumegi et al., 2025). On the one hand, technological support facilitates recombinative and incremental innovations, as search costs decrease and ideational variation increases (Brynjolfsson et al., 2025; Noy & Zhang, 2023). On the other hand, an increasing dependence on algorithmic generation can weaken the prerequisites for in-depth original knowledge formation, especially if dominant knowledge patterns are reproduced and explorative search movements are shortened (Bentley, 2025; Tian & Zhang, 2025). Innovation thus develops in a field of tension between increased efficiency and potential epistemic convergence (Doshi & Hauser, 2024).

The original contribution of the work lies in the theory-integrative connection of previously fragmented strands of research (Karpatne et al., 2025). By bringing together perspectives from distributed cognition, technological competence change and creativity and innovation research, an explanatory framework for scientific knowledge production under AI conditions is created (Clark & Chalmers, 1998; Autor et al., 2003; March, 1991). The model makes it possible to understand ambivalent effects of generative systems not as a contradiction, but as an expression of structural transformation (Karpatne et al., 2025).

There are several lines of enquiry for future research. Empirical studies could investigate how competence shifts can be operationalised and how they influence innovation quality (Brynjolfsson et al., 2025). Experimental designs offer the possibility of linking different utilisation intensities of generative AI with variations in problem depth or task uncertainty (Noy & Zhang, 2023). Bibliometric analyses could provide information on whether patterns of scientific originality or thematic diversity change

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with increasing AI use (Kobak et al., 2025; Kusumegi et al., 2025). A long-term consideration of individual learning processes also appears relevant in order to identify possible effects on the development of expertise and epistemic independence (Tian & Zhang, 2025).

Institutional implications are also becoming increasingly important. Universities are faced with the task of adapting competence profiles and preparing students more for critical evaluation, interdisciplinary integration and the considered use of technological support (Ahmed et al., 2023). Science policy strategies could aim to promote explorative research in order to offset the possible standardisation effects of algorithmic systems (Karpatne et al., 2025). At the same time, the question arises as to how criteria of scientific performance can be further developed in increasingly hybrid human-technology constellations (Clark & Chalmers, 1998; Hollan et al., 2000).

At the same time, the work shows limitations. The proposed model is based on theoretical integration and requires systematic empirical testing (Karpatne et al., 2025). Disciplinary differences in knowledge production and technological dynamics can lead to varying effects (Kusumegi et al., 2025). In addition, it remains to be seen how normative expectations of originality and responsibility in the scientific field will change under conditions of generative AI (Ahmed et al., 2023).

Overall, the study shows that generative AI not only provides new tools, but also transforms the logic of academic innovation itself (Karpatne et al., 2025; Kusumegi et al., 2025). A deeper understanding of this transformation is a prerequisite for productively utilising the potential of technological support and at the same time securing the conditions for original knowledge creation (Bentley, 2025; March, 1991).

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