Rechts- und Wirtschaftswissenschaftliche Fakultät
BWL IX - Lehrstuhl Internationales Management

Lehrstuhlinhaber
Prof. Dr. Reinhard Meckl

Translating Generative Artificial Intelligence into Employee Innovation: A Multi-Level Capabilities Perspective from Organizational Foundations to Individual Mechanisms

Dissertation

zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft
der Rechts- und Wirtschaftswissenschaftlichen Fakultät
der Universität Bayreuth

Vorgelegt
von
Patrick Held
aus
Aalen

Dekan:	Prof. Dr. Claas Christian Germelmann
Erstberichterstatter:	Prof. Dr. Reinhard Meckl
Zweitberichterstatter:	Prof. Dr. Friedrich Sommer
Tag der mündlichen Prüfung:	12.03.2026

„Genius is one percent inspiration and ninety-nine percent perspiration"

– Thomas Edison

Danksagung

Die vorliegende Dissertation wäre ohne einige Personen in meinem Umfeld nicht möglich gewesen, bei denen ich mich an dieser Stelle für ihre Unterstützung bedanken möchte.

Zuallererst bedanke ich mich herzlich bei meinem Doktorvater Prof. Dr. Reinhard Meckl, der mein Promotionsvorhaben ermöglicht hat. Da der Start meiner Promotion extern, also berufsbegleitend, stattfand, war eine Unterstützung dieses Vorhabens keinesfalls selbstverständlich. Weiter ermutigte er mich als wissenschaftlicher Mitarbeiter an seinen Lehrstuhl zu wechseln – eine Entscheidung, die ich nie bereut habe und die sicherlich viele Weichen für eine gelungene Promotion gestellt hat. Ich konnte jederzeit auf seinen Rat und seine Erfahrung zurückgreifen und er gab mir die Freiheit, meine eigenen Forschungsideen zu verfolgen.

Des Weiteren möchte ich mich insbesondere bei meinem Freund, Mentor und Kollegen Dr. Tim Heubeck bedanken. Durch dein ehrliches Feedback, deine tatkräftige Unterstützung und deine Anleitung sind mir viele böse Überraschungen erspart geblieben. Ich werde unsere stundenlangen Diskussionen zu möglichen Forschungsideen immer in bester Erinnerung behalten und wünsche dir alles erdenklich Gute auf deinem weiteren Karriereweg.

Weiterhin möchte ich mich bei meiner ehemaligen Kollegin Annina Ahrens und unserer Lehrstuhlsekretärin Petra Valentin für die Einarbeitung und die Unterstützung in der Lehre bedanken.

Ein besonderer Dank gilt meiner Familie: Meinem Bruder Darius, der selbst in Bayreuth Sportökonomie studiert hat sowie meinen Eltern Heike und Holger, die mich jederzeit unterstützt und an mein Vorhaben geglaubt haben. Ich bin besonders stolz, in die Fußstapfen meines Vaters Prof. Dr. Holger Held zu treten, der ebenfalls Betriebswirtschaftslehre an der Universität Bayreuth studierte und eine Promotion bei Prof. Dr. Dr. h.c. Peter Oberender (†) erfolgreich abschloss. Die zweite Promotion der Familie an der Universität Bayreuth erfolgreich zu absolvieren, ist für mich etwas ganz Besonderes und ich bin sehr dankbar für diese Möglichkeit.

Ebenfalls möchte ich mich bei meiner Freundin Judith bedanken. Insbesondere für ihr Verständnis gegenüber der vielen Stunden Arbeit am Wochenende und endlosen Monologen beim gemeinsamen Abendessen zu potenziellen Forschungsvorhaben, die sie klaglos über sich ergehen ließ. Danke für deinen Rückhalt und, dass ich mich immer auf dich verlassen kann.

Zuletzt möchte ich mich bei meinen Freunden bedanken, die mein Studium und meine Promotion in Bayreuth unvergesslich gemacht und einen wichtigen Ausgleich zu meiner Arbeit geschaffen haben. Herzlichen Dank an Manuel Emde, Maximilian Schmidt, Florian Prohaska, Tim Neubing und Thomas Kolbeck für viele gemeinsame Erlebnisse und eine prägende Zeit.

Diese Dissertation ist meiner Familie gewidmet.

Disclaimer

Before delving into the content of this cumulative dissertation, it is important to make a few preliminary remarks to prevent any ambiguities or misunderstandings.

First, this cumulative dissertation comprises three peer-reviewed, accepted and published research papers, one research paper currently under review in a scientific journal, and one book chapter (published in an edited volume). To ensure consistency throughout this dissertation I have made minor editorial adjustments (e.g., renumbering of tables and figures, uniform layout and style) to the original publications. The scholarly content of the included works remains substantively unchanged. All representations of the papers are in accordance with the respective publisher's rights.

Second, as this is a cumulative dissertation that incorporates previously published research papers and a book chapter, Chapter 1 (Introduction) and Chapter 7 (Conclusion) synthesize and summarize the included works. To accurately describe the underlying studies, their theoretical framing, research designs, and main findings, some formulations in the framing Chapters 1 and 7 necessarily overlap with—or are very close to—the wording used in the original research papers. These overlaps concern my own prior work and arise from the cumulative structure of the thesis. This procedure aligns with good scientific practice and is characteristic of cumulative dissertations, in which introductory and concluding chapters are expected to reflect and partially reproduce the content of the underlying articles.

Third, during manuscript preparation, I occasionally used the generative Artificial Intelligence tool ChatGPT[1] and the translator DeepL[2] exclusively for linguistic refinement (e.g., clarity, grammar, and readability). These tools were not used to generate scholarly content, perform analyses, interpret findings, or develop arguments. All uses comply with the respective policies of the journal, publisher and university. No confidential, proprietary, or third-party materials were entered into such tools unless permitted to do so. I reviewed and edited all text after any generative Artificial Intelligence-assisted suggestions and accept full responsibility for the content of this dissertation.

[1] https://chat.openai.com
[2] https://www.deepl.com/de/translator

Abstract

Three years have passed since the company OpenAI transformed the world of work with the release of ChatGPT. The tool reached 100 million monthly users within two months of its launch, and by the end of 2025, many similar tools (e.g., Midjourney, Gemini, Perplexity) exist. Generative Artificial Intelligence (hereafter GenAI) has become an integral part of many people's working lives, with recent figures indicating that a large share of employees utilize GenAI at work. From an innovation management perspective, the question arises whether GenAI makes employees more innovative and what the potential underlying mechanisms are. This is relevant as employee-level innovative work behavior shapes firm-level innovation and organizational performance. Hence, the first research goal of this dissertation is to elaborate on the question of *to what extent and in which way GenAI shapes employee innovativeness*. This research goal is examined through three empirical research papers that focus on different theoretical rationales. All three papers are based on quantitative survey data and employ partial least squares structural equation modeling (PLS-SEM).

The first paper draws on the *dynamic capabilities framework* and a *microfoundations perspective* to investigate how employees' sensing capabilities and their capabilities to use and evaluate GenAI shape their innovative work behavior. The study uses survey data from 439 business consultants in Germany, Austria, and Switzerland.

The second paper complements the first paper as it addresses the potential of GenAI usage capability for idea generation, a central aspect of successful innovations. The paper integrates *cognitive experiential theory* to examine how individuals' capability to use GenAI is linked to their idea generation via experiential and rational information processing styles. The paper uses survey data from 399 consultants from a leading global consultancy located in Germany, Austria, and Switzerland.

The third paper builds on the *exploration–exploitation logic* and *regulatory focus theory* to analyze how professionals' GenAI adoption and their explorative versus exploitative GenAI usage are associated with their innovative work behavior and which role regulatory focus plays in this relationship. The study draws on survey data from 339 German business professionals, whose daily work is characterized by cognitive brain work.

Together, these three papers offer a differentiated perspective on how GenAI shapes the innovative work behavior and idea generation of employees, as well as the underlying mechanisms.

Beyond investigating this overarching research goal, a crucial issue from a managerial point of view concerns the antecedents of GenAI use; that is, which organizational conditions must be fulfilled for employees to adopt a certain technology in the first place. To address this, the dissertation subsequently shifts its perspective from the *individual level* (i.e., employees and managers) to the *firm level*. Specifically, it aims to shed light on the organizational foundations necessary to increase the use, competence, and acceptance of technology in general among employees during the broader digital transformation. Although the technological infrastructure (such as access to new technology for employees) of a firm is a fundamental condition, technology itself is only one dimension, and a human dimension needs to be considered as well. Two relevant and well-accepted factors in the literature to consider are establishing *digital leadership* and cultivating *digital culture* within a company.

Hence, the second research goal of this dissertation is to investigate *what organizational foundations can foster digital leadership and digital culture.* To address the second research goal, the level of analysis shifts from individuals to firms with a particular focus on small and medium-sized enterprises (SMEs). The fourth paper draws on the *dynamic capabilities framework* to examine how dynamic capabilities promote digital leadership and digital culture, with the latter being central human-related enablers of digital transformation. This study is based on quantitative survey data from 98 SMEs in Southern Germany and employs multiple regression analysis.

Overall, the dissertation advances research at the intersection of GenAI, innovation management, and digital transformation. It enriches the literature on innovative work behavior and idea generation by identifying GenAI-related capabilities, cognitive information processing styles, explorative GenAI usage, and promotion focus as essential enablers of employee innovativeness. Furthermore, it extends the broader research landscape on dynamic capabilities and digital transformation by positioning dynamic capabilities as organizational foundations that foster digital leadership and digital culture.

From a managerial perspective, the findings underscore that leveraging employee innovativeness requires investment in employees' GenAI-related capabilities—particularly their GenAI evaluation capability. Further organizations should develop dynamic capabilities as they build a crucial foundation to strengthen digital leadership and digital culture within the broader context of digital transformation.

Zusammenfassung

Drei Jahre sind vergangen seit das Unternehmen OpenAI mit der Einführung des Tools ChatGPT die Arbeitswelt grundlegend verändert hat. Das Tool erreichte nach Launch innerhalb von zwei Monaten 100 Millionen monatliche Nutzer und Ende 2025 existieren zahlreiche ähnliche Anwendungen (z. B. Midjourney, Gemini, Perplexity). Generative Künstliche Intelligenz (im Folgenden GenAI) ist zu einem integralen Bestandteil der Arbeitswelt vieler Menschen geworden. Aktuelle Zahlen aus Praxisreports deuten darauf hin, dass ein großer Anteil der Beschäftigten GenAI bei der Arbeit einsetzt.

Aus Perspektive des Innovationsmanagements stellt sich die Frage, ob und inwiefern GenAI Angestellte und Berufstätige innovativer macht und welche zugrundeliegenden Mechanismen dabei wirken. Die Beantwortung dieser Frage ist relevant, da das Verhalten von Angestellten und Berufstätigen (zum Beispiel ob diese innovativ agieren sowie neue Ideen vorschlagen und implementieren) die Innovationsfähigkeit von Unternehmen als auch deren Performance maßgeblich prägt. Vor diesem Hintergrund besteht das erste Forschungsziel dieser Dissertation darin zu untersuchen, *inwiefern und auf welche Weise GenAI das Innovationsverhalten von Angestellten und Berufstätigen beeinflusst*. Dieses Forschungsziel wird in drei empirischen Forschungsartikeln adressiert, die jeweils auf unterschiedlichen theoretischen Perspektiven aufbauen. Diese Beiträge basieren auf quantitativen Erhebungen mithilfe von Fragebögen und verwenden die Partial Least Squares Structural Equation Modeling-Technik für die Datenauswertung.

Der erste Forschungsartikel stützt sich auf das *Dynamic Capabilities Framework* und eine *Microfoundations*-Perspektive, um zu untersuchen, wie die *Sensing*-Fähigkeiten von Angestellten sowie ihre Fähigkeiten zur Nutzung und Evaluation von GenAI ihr Innovationsverhalten prägen. Die Studie verwendet Befragungsdaten von 439 Unternehmensberatern und Unternehmensberaterinnen in Deutschland, Österreich und der Schweiz.

Der zweite Forschungsartikel ergänzt den ersten, indem er das Potenzial der Fähigkeit GenAI kompetent zu nutzen für die Ideengenerierung, ein zentraler Bestandteil erfolgreicher Innovation, adressiert. Er integriert die *Cognitive Experiential Theorie*, um zu analysieren, wie die Fähigkeit von Individuen GenAI zu nutzen, mit ihrer Ideengenerierung über intuitive und analytische Informationsverarbeitungsstile zusammenhängt. Grundlage hierfür sind Befragungsdaten von 399 Unternehmensberatern und Unternehmensberaterinnen in Deutschland, Österreich und der Schweiz.

Der dritte Forschungsartikel baut auf der *Exploration-Exploitation-Logik* sowie der *Regulatory Focus Theorie* auf, um zu analysieren, wie die GenAI-Adoption von Berufstätigen und deren explorative versus exploitative GenAI-Nutzung mit ihrem Innovationsverhalten zusammenhängen und welche Rolle der Regulatory Focus in dieser Beziehung spielt. Die Studie greift auf Befragungsdaten von 339 deutschen Berufstätigen zurück, deren Arbeitsalltag von kognitiv fordernder Denkarbeit geprägt ist.

Zusammengenommen liefern diese drei Forschungsartikel ein differenziertes Bild, inwiefern GenAI das Innovationsverhalten und die Ideengenerierung von Angestellten und Berufstätigen beeinflusst und welche Mechanismen diesem Zusammenhang zugrunde liegen.

Über dieses übergeordnete Forschungsziel hinaus stellt sich aus Managementperspektive die Frage nach den Antezedenzien der GenAI-Nutzung, das heißt, welche organisationalen Voraussetzungen erfüllt sein müssen, damit Angestellte eine bestimmte Technologie annehmen. Um diese Frage zu adressieren, wechselt die Dissertation die Perspektive von der individuellen Ebene (Angestellte und Führungskräfte) auf die Organisationsebene. Obwohl die technologische Infrastruktur eines Unternehmens (beispielsweise der Zugang der Angestellten zu neuen Technologien) eine wichtige Grundvoraussetzung darstellt, ist Technologie nur eine Dimension, wobei die menschliche Dimension ebenso berücksichtigt werden muss. Zwei in der Literatur anerkannte Faktoren sind hierbei die Etablierung digitaler Führung (*Digital Leadership*) und die Förderung einer digitalen Kultur (*Digital Culture*) innerhalb eines Unternehmens.

Vor diesem Hintergrund besteht das zweite Forschungsziel dieser Dissertation darin, zu untersuchen, *welche organisationalen Voraussetzungen digitale Führung und digitale Kultur fördern*. Um dieses Forschungsziel zu adressieren, verschiebt sich die Analyseebene von Individuen zu Unternehmen, mit einem besonderen Fokus auf kleine und mittlere Unternehmen. Der vierte empirische Forschungsartikel greift auf das *Dynamic Capabilities Framework* zurück, um zu analysieren, wie Dynamic Capabilities digitale Führung und digitale Kultur als zentrale personenbezogene Ermöglicher der digitalen Transformation, und damit implizit die Nutzung und Akzeptanz von Technologien wie GenAI durch Mitarbeitende, fördern. Die Studie basiert auf quantitativen Befragungsdaten von 98 kleinen und mittleren Unternehmen in Süddeutschland und nutzt eine multiple Regressionsanalyse mittels SPSS für die Datenauswertung.

Insgesamt leistet die Dissertation einen Beitrag zur Forschung an der Schnittstelle von GenAI, Innovationsmanagement und digitaler Transformation. Sie erweitert die Literatur zu den

Themenfeldern Innovationsverhalten und Ideengenerierung, indem sie GenAI bezogene Fähigkeiten, kognitive Informationsverarbeitungsstile, explorative GenAI-Nutzung und Promotion Fokus als wichtige Ermöglicher von Innovationsverhalten und Ideengenerierung identifiziert. Darüber hinaus trägt die Arbeit zur Forschung zu Dynamic Capabilities und digitaler Transformation bei, indem sie Dynamic Capabilities als organisationale Voraussetzungen positioniert, die digitale Führung und digitale Kultur fördern.

Aus Perspektive des Managements unterstreichen die Ergebnisse, dass die Förderung des Innovationsverhaltens von Angestellten Investitionen in GenAI bezogene Fähigkeiten erfordert. Dies umfasst insbesondere die Fähigkeit, GenAI-Outputs kritisch zu evaluieren. Weiterhin sollten Unternehmen in die Entwicklung von Dynamic Capabilities investieren, da diese als wichtige Voraussetzung für Digital Leadership und Digital Culture im Kontext der digitalen Transformation dienen.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI	Artificial intelligence
AVE	Average variance extracted
CB-SEM	Covariance-based structural equation modeling
DMCs	Dynamic managerial capabilities
GenAI	Generative artificial intelligence
GPTs	Generative pre-trained transformers
HTMT	Heterotrait-monotrait ratio
IWB	Innovative work behavior
LLM	Large language model
PLS-SEM	Partial least squares structural equation modeling
RQ	Research question
SJR	Scimago Journal Ranking
SMEs	Small and medium-sized enterprises
VHB	Verband der Hochschullehrer für Betriebswirtschaftslehre
VIFs	Variance inflation factors

Index of Research Papers

Table 1.1. Index of research papers

Index	Title	Authors	Status	Journal	Ranking
Book Chapter	Management Capabilities in the Age of Generative Artificial Intelligence (GenAI): A Conceptual Framework and Future Research Directions	Heubeck, Tim & Held, Patrick	Published in 2025	Not applicable	Not applicable
Research Paper 1	GenAI and employee innovativeness: How employees' sensing capabilities and the capabilities to use and evaluate GenAI shape their innovative work behavior	Held, Patrick & Heubeck, Tim	Accepted and published in 2025	*Digital Business*	VHB-2024: C SJR: Q1 Impact Factor: 7.2
Research Paper 2	The influence of individuals' capability to use generative AI on their idea generation: The mediating role of cognitive information-processing styles	Held, Patrick & Heubeck, Tim & Meckl, Reinhard	Accepted and published in 2025	*European Journal of Innovation Management*	VHB-2024: C SJR: Q1 Impact Factor: 5.7
Research Paper 3	GenAI at work: How explorative GenAI usage and regulatory focus shape professionals' innovative work behavior	Held, Patrick & Heubeck, Tim & Meckl, Reinhard	Under Review	Hidden outlet due to review process	VHB-2024: B SJR: Q1
Research Paper 4	Boosting SMEs' digital transformation: The role of dynamic capabilities in cultivating digital leadership and digital culture	Held, Patrick & Heubeck, Tim & Meckl, Reinhard	Accepted and published in 2025	*Review of Managerial Science*	VHB-2024: B SJR: Q1 Impact Factor: 9.6

Notes: VHB = Verband der Hochschulehrer für Betriebswirtschaftslehre, SJR = Scimago Journal Ranking

Source: Own illustration

1. Introduction

1.1. Motivation

Around three years have passed since the company OpenAI transformed the world of work with the release of ChatGPT[3]. The tool reached 100 million monthly active users within two months of its launch, which sets a record as the fastest-growing consumer application in history (Reuters, 2023). Now, at the end of 2025, many more similar tools exist (e.g., Midjourney[4], Gemini[5], Perplexity[6]) and generative Artificial Intelligence (hereafter GenAI) has become an integral part of many people's working lives. This development is illustrated by a recent report from the consultancy Ernst and Young, which states that 75% of employees use GenAI in their work (Ernst & Young, 2024).

From an innovation management perspective, GenAI tools offer promising opportunities. At the organizational level, recent studies suggest that GenAI can shape business model innovation (Kanbach et al., 2024; Teng et al., 2025), enhance exploratory and exploitative innovation (Singh et al., 2024) and support ideation processes (Eisenreich et al., 2024). Moreover, GenAI can assist in developing marketing strategies (Cillo & Rubera, 2025) and foster digital supply chain innovation (Wang & Zhang, 2025).

However, GenAI represents not only a potential innovation booster at the organizational level. Because individuals directly interact with GenAI applications (e.g., an employee formulates a prompt with instructions for ChatGPT and receives a response) the question inevitably arises as to whether the use of GenAI makes employees more innovative. This question is highly relevant, as individual-level employee behavior and actions are crucial building blocks of organizational-level outcomes—a phenomenon often referred to as *microfoundations* (e.g., Felin et al., 2015; Palmié et al., 2023). The microfoundations literature examines how individual-level factors and behaviors shape organizations (Felin et al., 2015; Abell et al., 2008). Accordingly, employees' innovative work behavior (IWB) plays a crucial role in driving firm-level innovation (Jong & Hartog, 2010; Mazzucchelli et al., 2019; Strobl et al., 2020) and overall organizational performance (Shanker et al., 2017).

[3] https://chatgpt.com
[4] https://www.midjourney.com
[5] https://gemini.google.com
[6] https://www.perplexity.ai

Against the backdrop that innovation remains the core engine of competitive advantage (e.g., Roberts & Candi, 2024), it is essential that managers foster the innovativeness of their employees, and GenAI tools may represent an essential lever in this regard.

Recent conceptual work suggests that GenAI is not intended to replace human creativity but rather to augment it (Bilgram & Laarmann, 2023). Emerging empirical studies support this view. For instance, GenAI can promote employees' innovative behavior by augmenting work abilities (Yin et al., 2024), such as helping them solve problems in novel and valuable ways (Jia et al., 2024) and assisting employees in connecting and structuring seemingly unrelated pieces of information (Lee & Chung, 2024). Concrete use cases from industry illustrate the potential practical value of GenAI. For instance, this technology can support the iteration and improvement of semiconductor chip designs based on performance parameters, which reduces the development life cycle time (Deloitte, 2024).

Moreover, a meta-analysis shows that individuals collaborating with GenAI exhibit higher creative performance than those working without GenAI support (Holzner et al., 2025). When employees collaborate with GenAI in co-creative settings, the technology can support them with the definition of problems, the envision of solutions, and the validation of these solutions (Grange et al., 2025). While these examples illustrate the potential of GenAI to enhance individual-level innovation, empirical research on GenAI's influence on creative outcomes remains scattered (Holzner et al., 2025) and—apart from a small but growing set of studies (e.g., Dong et al., 2025; Yin et al., 2024)—GenAI's influence on employee innovation is not sufficiently explored. This dissertation aims to address this issue and derives the following research question (RQ):

RQ I. To what extent and in which way does GenAI shape employee innovativeness?

For the analysis, various perspectives and theoretical rationales are integrated to examine this foundational link and to uncover the underlying mechanisms. In line with existing research in this area, this dissertation thesis conceptualizes GenAI as an augmentation of human capabilities, resulting in a human-GenAI co-creation process (Feuerriegel et al., 2024; Raisch & Fomina, 2025). This perspective emphasizes the joint creative potential of human intelligence and GenAI.

The overarching research question is addressed through three research papers with distinct foci and theoretical foundations. Specifically, the *dynamic capabilities framework*, *cognitive experiential theory*, *regulatory focus theory* and *exploration-exploitation logic* are employed as theoretical rationales. These perspectives are elaborated in more detail in the next sub-chapter.

Beyond investigating the overarching research question, a crucial issue from a managerial standpoint concerns the antecedents of GenAI use; that is, which organizational conditions need to be fulfilled for employees to adopt a technology in the first place. To address this, the dissertation subsequently shifts its perspective from the *individual level* (i.e., employees and managers) to the *firm level*. Specifically, it aims to shed light on the organizational foundations necessary to increase the use, competence, and acceptance of technology among employees during the broader digital transformation. Although the technological infrastructure (such as access to new technology for employees) of a firm is a crucial ground condition, technology itself is only one dimension (Vial, 2019) and a human dimension needs to be considered as well (Nadkarni & Prügl, 2021).

One crucial facilitator of technology usage and acceptance is *digital leadership*. This competence enables leaders to support their employees in selecting appropriate technologies, utilizing them effectively and promoting their overall acceptance among the workforce (op't Roodt et al., 2025). In other words, digital leaders facilitate decisions on which technologies to adopt and also determine how quickly these technologies should be implemented within the company (Porfírio et al., 2021).

Another established and accepted facilitator of technology usage and acceptance among the workforce is the creation of a *digital culture*. For example, principles like "testing before implementing" reflect the values of experimentation and iterative learning in the deployment of digital technologies (Butt et al., 2024). Digital culture shapes how individuals perceive and accept digital technologies by influencing core beliefs related to usefulness, ease of use, social expectations, and support structures—making culture a critical antecedent to successful digital technology adoption (Dasgupta & Gupta, 2019). When organizational values are widely shared, the organization is better equipped to adopt new technologies effectively (Jackson, 2011).

From a managerial perspective, digital leadership and digital culture are two essential prerequisites for achieving the goal of improved usage and acceptance of technologies (such as GenAI) among the workforces. This raises the question of how digital leadership and digital culture can be cultivated and enhanced. One suitable theoretical rationale for studying the overall organizational foundations that firms must establish to strengthen digital leadership and digital culture is the dynamic capabilities framework.

Rooted in the resource-based view, dynamic capabilities are conceptualized as a company's ability to sense opportunities, seize identified opportunities, and transform resources (Teece, 2007; Teece et al., 1997). Several studies have highlighted the importance of dynamic capabilities in the digital context (e.g., Matarazzo et al., 2021; Mikalef & Gupta, 2021; Warner & Wäger, 2019), resulting in a dedicated research stream examining the interplay between dynamic capabilities and digital transformation (Kraus et al., 2022). However, there is a lack of knowledge about the interplay of both enablers—digital leadership and digital culture—with the dynamic capabilities framework. To address this gap, the second research question of this thesis is postulated:

RQ II. What organizational foundations can foster digital leadership and digital culture?

The second overarching research question is examined through a research paper that utilizes the *dynamic capabilities framework* as a conceptual lens.

1.2. Structure of the Thesis

This cumulative dissertation thesis is structured into seven chapters and comprises four research papers (three of them have been published in peer-reviewed, internationally recognized scientific journals and one is currently under review) and one published book chapter. The nature of the research papers is quantitative and empirical, utilizing survey designs with questionnaire data to validate the hypotheses and research models. Figure 1.1 illustrates the logic and structure of the dissertation.

Chapters 2 to 4 (that means research paper 1, 2 and 3) address the first Research Question (**RQ I**) of whether GenAI shapes employee innovation in the workplace and, if so, what the potential underlying mechanisms are.

Specifically, **Chapter 2** presents research paper 1 entitled "GenAI and employee innovativeness: How employees' sensing capabilities and the capabilities to use and evaluate GenAI shape their innovative work behavior". This paper is published in the journal Digital Business and co-authored by Patrick Held and Dr. Tim Heubeck.

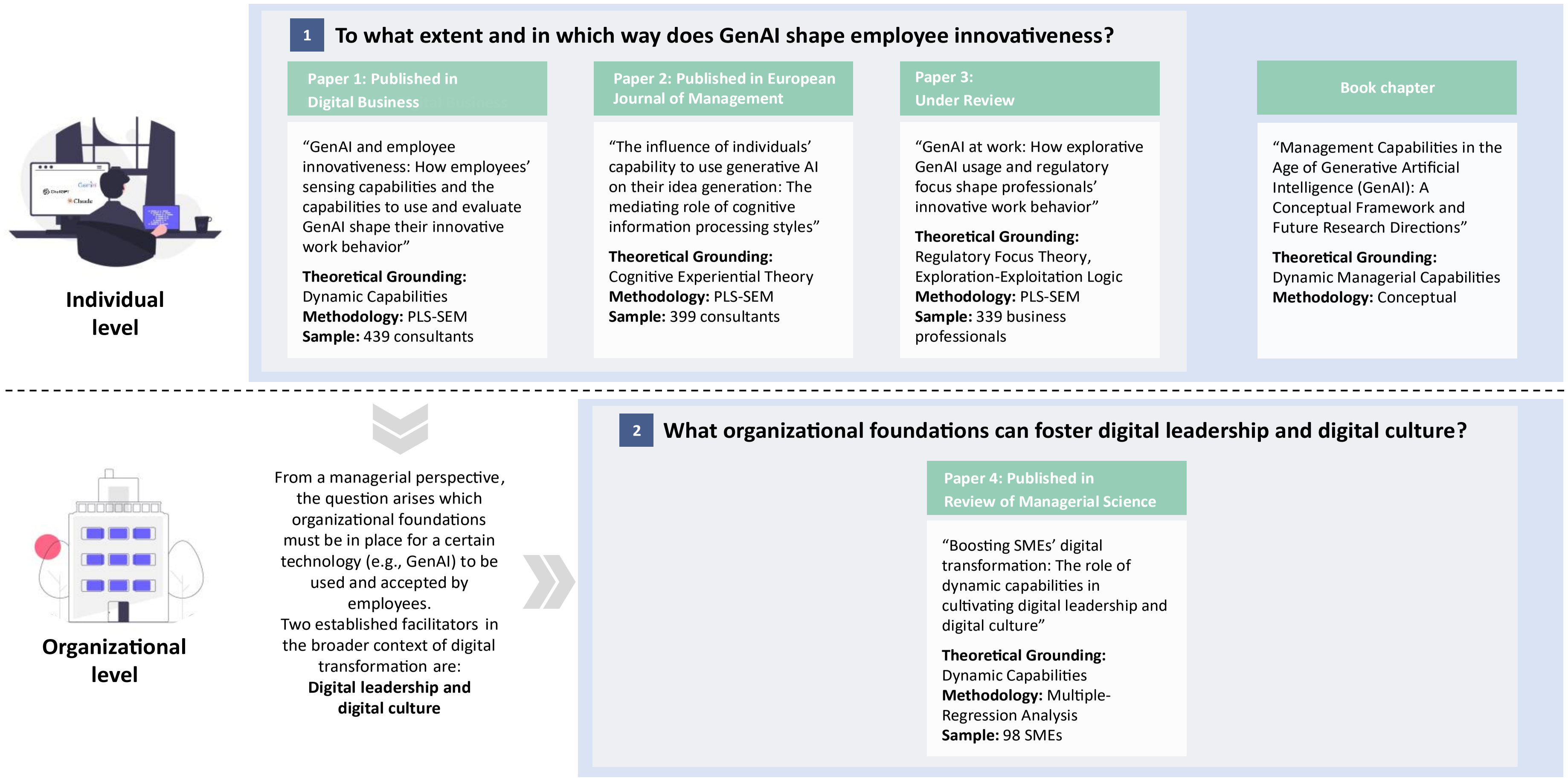


Figure 1.1 Logic and structure of the dissertation

Source: Own illustration

Patrick Held (first author and corresponding author) was responsible for conceptualization, data curation, formal analysis, methodology, project administration, writing – original draft and writing – review and editing.[7] *Dr. Tim Heubeck contributed with supervision of the project and writing – review and editing.*

The paper begins by stating that innovation is an essential success factor for companies (e.g., Roberts and Candi 2024), yet many companies fail to meet their innovation ambitions (Manly 2024). Against this backdrop, the IWB of employees represents a key microfoundation of firm-level innovation (e.g., Felin et al., 2015; Strobl, 2020). In other words, the behavior of employees within a company determines the company's ability to innovate. IWB is an accepted and well-established construct in the innovation management literature for measuring this behavior (e.g., Jong & Hartog, 2010). While prior research has identified various antecedents of IWB (e.g., Gelaidan et al., 2024; Yuan & Woodman, 2010), the potential of GenAI technologies to foster IWB remains underexplored.

The research paper addresses this gap by drawing on a capabilities perspective. Concretely, the influence of employees' capabilities to use and evaluate GenAI on their IWB is examined. Building on the dynamic capabilities view, the study further explores how employees' sensing capabilities shape the development of these GenAI capabilities in the first place and ultimately foster IWB. The study postulates the following three research questions:

RQ 1. How do employees' capabilities to use and evaluate GenAI technologies shape their IWB?

RQ 2. How do employees' sensing capabilities influence their capabilities to use and evaluate GenAI?

RQ 3. How do employees' sensing capabilities influence their IWB?

The research model is tested using survey data from 439 responses of business consultants in Germany, Austria, and Switzerland. To analyze the data PLS-SEM is utilized. The results show that employees' sensing capabilities promote both GenAI capabilities and directly enhance IWB. While employees' capability to evaluate GenAI promotes IWB, GenAI usage capability does not. Moreover, the results show a significant mediation pathway: employees' sensing capabilities enhance GenAI usage capability, which in turn enables GenAI evaluation capability and thereby fosters IWB.

[7] Role designations follow the CRediT (Contributor Roles Taxonomy) definitions.

The research paper offers several valuable contributions to the literature. It advances the literature on IWB and its antecedents (e.g., Gelaidan et al., 2024; Anser et al., 2021; AlEssa & Durugbo, 2022; Yuan & Woodman, 2010). In addition, the study contributes to the emerging literature that incorporates GenAI into innovation management (e.g., Chiarello et al., 2024; Cillo & Rubera, 2025; Kanbach et al., 2024).

Chapter 3 contains research paper 2 entitled "The influence of individuals' capability to use generative AI on their idea generation: The mediating role of cognitive information processing styles". This paper was published in the European Journal of Innovation Management and co-authored by Patrick Held, Dr. Tim Heubeck and Prof. Dr. Reinhard Meckl.

Patrick Held (first author and corresponding author) was responsible for conceptualization, data curation, formal analysis, methodology, project administration, writing – original draft and writing – review and editing.[8] *Dr. Tim Heubeck supervised the project and contributed with writing – review and editing. Prof. Dr. Reinhard Meckl contributed with writing – review and editing.*

The study complements the first research paper as it addresses the potential of GenAI for idea generation, a central aspect of successful innovations (Berg, 2016). There is already an established research stream examining the influence of GenAI technologies on idea generation (e.g., Bouschery et al., 2023; Boussioux et al., 2024; Eisenreich et al., 2024; Meincke et al., 2024). Existing research predominantly frames GenAI through human–GenAI collaboration at the individual level (Bankins et al., 2024; Boussioux et al., 2024). Yet individuals' capability to use GenAI has received limited attention. Many studies conceptualize GenAI use in terms of frequency, extent, or purpose (e.g., Zhang et al., 2025) or deal with GenAI as a uniform intervention (Eisenreich et al., 2024; Meincke et al., 2024), thereby neglecting interindividual differences in user competence. This overlooks the possibility that the creative value derived from GenAI critically depends on individuals' capability to use the technology proficiently.

Besides the suggestion that individuals' capability to use GenAI may provide a foundational condition for generating ideas, idea generation itself is a cognitive process (Paulus & Brown, 2007; Garbuio & Lin, 2021), that originates in the mind of an individual (Amabile,

[8] Role designations follow the CRediT (Contributor Roles Taxonomy) definitions.

1983; Campbell, 1960). In line with this argumentation, it becomes crucial to investigate the underlying cognitive mechanisms that may link GenAI usage capability to idea generation.

The research paper integrates Epstein's cognitive experiential theory as a theoretical rationale to study the mentioned underlying cognitive mechanisms (Epstein, 1973, 2003, 2014). Cognitive experiential theory is rooted in psychology and posits that humans process information (e.g., GenAI-generated content) through two distinct cognitive systems: an experiential system and a rational system (Epstein, 1973, 2010; Kahneman, 2011). Both the experiential and rational information processing systems are crucial for idea generation as the systems are responsible for complementary cognitive operations that collectively enhance creativity (Baldacchino et al., 2023; Eling et al., 2015). Integrating this theory leads to the following research questions:

RQ 1. To what extent does an individual's capability to use GenAI foster their idea generation?

RQ 2. To what extent does an individual's tendency to rely on experiential and rational information processing systems promote their idea generation?

RQ 3. To what extent does an individual's capability to use GenAI influence their tendency to rely on experiential and rational information processing systems?

The research paper utilizes PLS-SEM analysis on a large-scale sample of 399 consultants located in Germany, Austria and Switzerland from a leading global consultancy to test the research model. The results show that individuals' capability to use GenAI enhances their idea generation. Further, the rational system enhances idea generation directly and is also a significant mediator that translates GenAI usage capability into idea generation, whereas the experiential system does not show any influence on idea generation.

The study offers several contributions to existing innovation management literature. Specifically, it advances the research field investigating the potential of GenAI for idea generation (e.g., Eisenreich et al., 2024; Meincke et al., 2024) by highlighting the so far neglected role of GenAI usage capability. Moreover, the study complements research examining the influence of cognitive styles on idea generation (e.g., Baldacchino et al., 2023; Eling et al., 2015; Yeo et al., 2024) and extends cognitive experiential theory to the GenAI context.

Chapter 4 represents research paper 3 entitled "GenAI at work: How explorative GenAI usage and regulatory focus shape professionals' innovative work behavior". This paper is currently under review in a scientific journal. The paper was co-authored by Patrick Held, Dr. Tim Heubeck and Prof. Dr. Reinhard Meckl.

Patrick Held (first author and corresponding author) was responsible for conceptualization, data curation, formal analysis, methodology, project administration, writing – original draft, writing – review and editing.[9] *Dr. Tim Heubeck supervised the project and contributed with writing – review and editing. Prof. Dr. Reinhard Meckl contributed with writing – review and editing.*

GenAI adoption is widespread among professionals (Ernst & Young, 2024), yet its influence on their IWB is not sufficiently explored. This research paper represents a continuation and deepening of the first two research papers. It focuses primarily on the underlying mechanisms of the influence of professionals' GenAI adoption and their IWB, but from a different theoretical perspective than the first two research papers.

Concretely, the paper integrates March's (1991) proposed exploration-exploitation logic and regulatory focus theory (Higgins, 1997, 1998) as a theoretical rationale. The research idea is that professionals can theoretically utilize GenAI technologies to support both types of work activities—exploration and exploitation. For example, professionals can develop new client services (explorative GenAI usage) or automate routine tasks (exploitative GenAI usage) (Rogge et al., 2025). The study aims to understand for which types of work activities professionals use GenAI and how each type of usage may differentially affect their IWB.

In the context of exploration and exploitation logic, a dedicated research stream exists that focuses on the psychological antecedents of professionals' exploration and exploitation activities (e.g., Tuncdogan & Dogan, 2020). A suitable theoretical lens here is regulatory focus theory (Higgins, 1997, 1998). Accordingly, professionals approach pleasure and pain through two distinct self-regulatory systems: promotion focus and prevention focus. The *promotion focus* is associated with accomplishment and aspiration, and the *prevention focus* is related to security and obligation (Fuglestad et al., 2025). The regulatory focus influences whether an employee prefers exploration or exploitation in their work (Boemelburg et al., 2023; Tuncdogan et al., 2015) and also influences their IWB (Chen et al., 2022). In the context of GenAI, promotion- and prevention-focused professionals might engage in different ways with the technology. Nevertheless, their motivational orientation might also shape their IWB,

[9] Role designations follow the CRediT (Contributor Roles Taxonomy) definitions.

regardless of how they use GenAI. Based on this argumentation the paper postulates three research questions:

RQ 1. Does professionals' GenAI adoption foster their IWB?

RQ 2. For which types of activities (explorative or exploitative) do professionals use GenAI, and how does each type of use affect their IWB?

RQ 3. What role does professionals' regulatory focus play in shaping their type of GenAI usage (explorative versus exploitative) and their IWB?

Drawing on quantitative survey data of 339 German professionals, PLS-SEM is employed to examine the research questions.

The research paper contributes to theory in several ways. The findings demonstrate that GenAI adoption does not enhance professionals' IWB, but that explorative rather than exploitative GenAI usage drives IWB. Thereby, the study extends March's (1991) exploration–exploitation logic to the GenAI context. In addition, the study contributes to regulatory focus theory (Higgins, 1997; Higgins & Pinelli, 2020) by demonstrating that promotion focus fosters and prevention focus reduces professionals' IWB. Moreover, the research paper contributes to the research stream examining the role of individuals' regulatory focus on their exploration and exploitation activities (Tuncdogan & Dogan, 2020; Tuncdogan et al., 2015). Specifically, the study found that a promotion focus fosters explorative GenAI usage. Finally, the study advances research on IWB antecedents (e.g., Madrid et al., 2014; Yuan & Woodman, 2010; Zhang et al., 2024) by identifying explorative GenAI usage as a key driver of professionals' IWB.

Chapter 5 comprises a conceptual book chapter that extends the dynamic managerial capabilities (DMCs) framework—comprised of human capital, social capital, cognition, and emotions—into the GenAI age. In the chapter the authors argue that there exists a reciprocal linkage between GenAI and DMCs. On the one hand, capable executives shape the value-creating deployment of GenAI (strategy, governance, role-modeling), while on the other hand, GenAI reshapes managerial capabilities by expanding knowledge bases, reconfiguring social information flows, augmenting or challenging cognition, and eliciting emotions that require deliberate regulation. The chapter's remit is conceptual and lays the theoretical groundwork for further research.

The book chapter was co-authored by Dr. Tim Heubeck *(first author and corresponding author)* and Patrick Held and was published in the edited volume "Achieving Digital Transformation through Analytics and AI" by World Scientific.

Chapter 6 contains research paper 4 entitled "Boosting SMEs' digital transformation: the role of dynamic capabilities in cultivating digital leadership and digital culture". This paper was published in the journal Review of Managerial Science and co-authored by Patrick Held, Dr. Tim Heubeck and Prof. Dr. Reinhard Meckl.

Patrick Held (first author and corresponding author) was responsible for conceptualization, methodology, writing, data collection, data analysis and project administration.[10] *Dr. Tim Heubeck contributed with conceptualization, methodology, review & writing, data analysis and Prof. Dr. Reinhard Meckl reviewed the manuscript.*

This study contributes to the dissertation's second Research Question (**RQ II**) and shifts the focus of the level of investigation from the individual level to the organizational level. Specifically, the study aims to identify the organizational foundations necessary to foster the adoption and acceptance of technology among employees during the broader digital transformation. Therefore, the study is not explicitly focused on GenAI but rather on technology in general.

It addresses the observation that digital transformation represents a profound technological change (Nadkarni & Prügl 2021; Pfister & Lehmann 2023) that is crucial for the competitiveness of small and medium-sized enterprises (SMEs) (Skare et al., 2023), yet many SMEs struggle with its implementation (Zoppelletto et al., 2023). Although technology is a crucial factor in successful digital transformation (Vial, 2019), it is not the only enabler (Dörr et al., 2023; Saihi et al. 2023) and the human dimension needs to be integrated (Nadkarni & Prügl, 2021).

Two crucial human-related enablers are digital leadership and digital culture. Although digital leadership and digital culture are two established facilitators of digital transformation (e.g., Gyamerah et al., 2025; Ghafoori et al., 2024) their antecedents remain highly understudied.

[10] Role designations follow the CRediT (Contributor Roles Taxonomy) definitions.

Drawing on the dynamic capabilities framework (Teece, 2007), the paper hypothesizes that dynamic capabilities promote digital leadership and digital culture in SMEs, leading to the following research questions:

RQ 1. To what extent do dynamic capabilities promote digital culture and digital leadership in the context of SMEs' digital transformation?

RQ 2. What are the interdependencies between digital leadership and digital culture in the context of dynamic capabilities within SMEs' digital transformation?

To answer the research questions, survey data from 98 SMEs in Southern Germany is analyzed utilizing multiple regression analysis. The findings support the enabling role of dynamic capabilities, indicating that dynamic capabilities enhance digital leadership and foster a digital culture. Contrary to the conceptual expectations, the hypothesized mediation effects between dynamic capabilities, digital leadership, and digital culture were not supported, indicating that the translation mechanisms between digital leadership and digital culture might be less direct and straightforward than previously presumed. Thus, dynamic capabilities emerge as critical—yet separate—enablers of digital leadership and digital culture. By positioning dynamic capabilities as antecedents rather than outcomes, this study offers a novel perspective on central enablers of digital transformation, extending the dynamic capabilities framework into this context.

Chapter 7 synthesizes the multi-level findings, answers the two overarching research questions, elaborates on the practical implications and critically reflects on the limitations of this dissertation.

1.3. Technical Primer on GenAI

Since the thematic focus of this dissertation revolves around GenAI, this section provides a concise overview of the technology. This thesis adopts an innovation management perspective and targets readers who may not have a computer science background. Accordingly, the aim is to explain the concept of GenAI in an accessible manner, without delving into mathematical or algorithmic detail[11].

[11] For a deep dive into the mathematical principles and technical conceptualization of GenAI see Feuerriegel et al. (2024) and Banh and Strobel (2023).

GenAI can be defined as "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data." (Feuerriegel et al., 2024, p. 111). Although GenAI is often perceived as a recent breakthrough, it rests on decades of work, beginning with early statistical language models in the 1950s and 1960s and has evolved through neural networks and deep learning (Susarla et al., 2023). The recent breakthrough, which lead to the widely distribution of GenAI tools, can be explained by four overarching technological developments over the last years: (1) large-scale increases in computing power; (2) advances in model architectures; (3) pre-training on massive unlabeled data; and (4) refinements in training procedures (Brynjolfsson et al., 2025).

A large share of today's GenAI ecosystem is underpinned by so-called *foundation models*, that is, large-scale AI models pre-trained on broad and heterogeneous data and subsequently adapted to many downstream tasks (Schneider et al., 2024). This reuse of a few versatile foundation models across multiple applications marks a shift away from building numerous narrow, task-specific models. Such foundation models increasingly exhibit multi-modality and emergent capabilities, meaning that a single model can, for example, take an image as input, discuss it in natural language, and then generate follow-up content. This blurs traditional boundaries between separate AI systems for text, images, or other data types. Applications such as ChatGPT, Perplexity, and Gemini have made these advances tangible to a broad audience and represent an astonishing emulation of human capabilities (Hermann & Puntoni, 2024).

Within GenAI, so-called Large Language Models (LLMs) are the most prominent class (Hermann & Puntoni, 2024; Susarla et al., 2023). LLMs typically build on the transformer architecture, where self-attention enables sequence processing and the modeling of long-range dependencies in language (Vaswani et al., 2017). Generative pre-trained transformers (GPTs) generate text by predicting the next token given context, a capability learned through extensive pre-training on diverse data comprising billions of words across domains (Banh & Strobel, 2023; Brynjolfsson et al., 2025; Susarla et al., 2023). Here, a token typically corresponds to a sub-word unit or short character sequence rather than a full word, which enables the model to handle different languages, vocabularies, and writing styles flexibly. Beyond language, analogous generative model families create images, video, 3D content, and audio, underscoring the breadth of possible outputs (Strobel et al., 2024).

A defining feature of GenAI is adaptability. To avoid ambiguity, this dissertation distinguishes only between *prompting* and *fine-tuning*. Prompting refers to inference-time steering of a pre-trained model using carefully formulated instructions that specify goals, constraints, tone, or output format without changing the model's parameters (Liu et al., 2023); the systematic design of such instructions is often called *prompt engineering* (Liu & Chilton, 2022).

Fine-tuning, by contrast, updates parameters using domain-specific data (e.g., a specialist text corpus or reference images) to calibrate outputs to a target domain; both approaches are complementary rather than mutually exclusive (Strobel et al., 2024). Because GenAI models generate probabilistic—not deterministic—outputs by sampling from distributions shaped by both parameters and prompts (Liu et al., 2023), the same prompt can yield different yet plausible results, and different prompts can converge on similar answers. In practice, iterative prompt refinement (rephrasing, adding constraints, adjusting keywords) is often necessary to obtain the desired output (Banh & Strobel, 2023).

All in all, GenAI can be understood as a particularly powerful subcategory of AI (Schryen et al., 2025) and as a step beyond more traditional AI (Roberts & Candi, 2024), which is typically characterized through discriminative modelling. In technical terms, discriminative models learn to approximate conditional probabilities such as P(Y|X)—for example, the probability that an email X belongs to the class "spam" or "non-spam"—and are optimized for prediction or classification tasks. Generative models, by contrast, aim to approximate the underlying data distribution, for instance P(X) or the joint distribution P(X,Y), which allows them to sample new, synthetic instances such as texts, images, or audio (Feuerriegel et al., 2024; Strobel et al., 2024). For example, a traditional AI system might classify emails as spam or non-spam based on learned decision boundaries. In contrast, a generative model can draft entirely new email texts in a specified style. In this sense, discriminative models focus on prediction and classification, while generative models are designed to create new content. This paradigm shift in AI technology, from discriminative to generative, has sparked innovation and new application opportunities across various industries (Bengesi et al., 2024).

To summarize this technical primer in simple terms: all GenAI is AI, but not all AI is generative.

References

Abell, P.; Felin, T.; Foss. (2008): Building micro-foundations for the routines, capabilities, and performance links. *Managerial and Decision Economics,* 29 (6), 489–502. https://doi.org/10.1002/mde.1413

AlEssa, H. S., & Durugbo, C. M. (2022). Systematic review of innovative work behavior concepts and contributions. *Management Review Quarterly*, 72 (4), 1171–1208. https://doi.org/10.1007/s11301-021-00224-x

Amabile, T. M. (1983). The social psychology of creativity: A componential conceptualization. *Journal of Personality and Social Psychology*, *45* (2), 357–376. https://doi.org/10.1037/0022-3514.45.2.357

Anser, M. K., Yousaf, Z., Khan, A., & Usman, M. (2021). Towards innovative work behavior through knowledge management infrastructure capabilities: Mediating role of functional flexibility and knowledge sharing. *European Journal of Innovation Management*, 24 (2), 461–480. https://doi.org/10.1108/EJIM-09-2019-0250

Baldacchino, L., Ucbasaran, D., & Cabantous, L. (2023). Linking experience to intuition and cognitive versatility in new venture ideation: A dual-process perspective. *Journal of Management Studies*, 60 (5), 1105–1146. https://doi.org/10.1111/joms.12794

Banh, L., & Strobel, G. (2023). Generative artificial intelligence. *Electronic Markets*, 33 (63). https://doi.org/10.1007/s12525-023-00680-1

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior*, 45 (2), 159–182. https://doi.org/10.1002/job.2735

Bengesi, S., El-Sayed, H., Sarker, M. K., Houkpati, Y., Irungu, J., & Oladunni, T. (2024). Advancements in generative AI: A comprehensive review of GANs, GPT, autoencoders, diffusion model, and transformers. *IEEE Access*, 12, 69812-69837. https://doi.org/10.1109/ACCESS.2024.3397775

Berg, J. M. (2016). Balancing on the creative highwire: Forecasting the success of novel ideas in organizations. *Administrative Science Quarterly*, 61 (3), 433–468. https://doi.org/10.1177/0001839216642211

Bilgram, V., & Laarmann, F. (2023). Accelerating innovation with generative AI: AI-augmented digital prototyping and innovation methods. *IEEE Engineering Management Review*, 51 (2), 18–25. https://doi.org/10.1109/EMR.2023.3272799

Boemelburg, R., Berger, S., Jansen, J. J. P., & Bruch, H. (2023). Regulatory focus climate, organizational structure, and employee ambidexterity: An interactive multilevel model. *Human Resource Management*, 62 (5), 701–719. https://doi.org/10.1002/hrm.22155

Bouschery, S. G., Blazevic, V., & Piller, F. T. (2023). Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models. *Journal of Product Innovation Management*, 40 (2), 139–153. https://doi.org/10.1111/jpim.12656

Boussioux, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem-solving. *Organization Science*, 35 (5), 1589–1607. https://doi.org/10.1287/orsc.2023.18430

Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, 140 (2), 889–942. https://doi.org/10.1093/qje/qjae044

Butt, A., Imran, F., Helo, P., & Kantola, J. (2024). Strategic design of culture for digital transformation. *Long Range Planning*, 57 (2), 102415. https://doi.org/10.1016/j.lrp.2024.102415

Campbell, D. T. (1960). Blind variation and selective retention in creative thought as in other knowledge processes. *Psychological Review*, 67, 380–400. https://doi.org/10.1037/h0040373

Chen, L., Ruan, R., & He, P. (2022). The double-edged sword: A work regulatory focus perspective on the relationship between organizational identification and innovative behaviour. *Creativity and Innovation Management*, 31 (1), 64–76. https://doi.org/10.1111/caim.12482

Chiarello, F., Giordano, V., Spada, I., Barandoni, S., & Fantoni, G. (2024). Future applications of generative large language models: A data-driven case study on ChatGPT. *Technovation*, 133, 103002. https://doi.org/10.1016/j.technovation.2024.103002

Cillo, P., & Rubera, G. (2025). Generative AI in innovation and marketing processes: A roadmap of research opportunities. *Journal of the Academy of Marketing Science*, 53 (3), 684–701. https://doi.org/10.1007/s11747-024-01044-7

Dasgupta, S., & Gupta, B. (2019). Espoused organizational culture values as antecedents of internet technology adoption in an emerging economy. *Information & Management*, 56 (6), 103142. https://doi.org/10.1016/j.im.2019.01.004

Deloitte. (2024). Generative AI and the future of work. https://www.deloitte.com/global/en/services/consulting/research/generative-ai-and-the-future-of-work.html (last accessed 21 November 2025)

Dong, X., Tian, Y., He, M., & Wang, T. (2025). When knowledge workers meet AI? The double-edged sword effects of AI adoption on innovative work behavior. *Journal of Knowledge Management*, 29 (1), 113–147. https://doi.org/10.1108/JKM-02-2024-0222

Dörr L., Fliege K., Lehmann C., Kanbach D.K., Kraus S. (2023). A taxonomy on influencing factors towards digital transformation in SMEs. *Journal of Small Business Strategy* 33 (1), 53–69. https://doi.org/10.53703/001c.66283

Eling, K., Langerak, F., & Griffin, A. (2015). The performance effects of combining rationality and intuition in making early new product idea evaluation decisions. *Creativity and innovation management*, 24 (3), 464-477.

Eisenreich, A., Just, J., Gimenez-Jimenez, D., & Füller, J. (2024). Revolution or inflated expectations? Exploring the impact of generative AI on ideation in a practical sustainability context. *Technovation*, 138, 103123. https://doi.org/10.1016/j.technovation.2024.103123

Epstein, S. (1973). The self-concept revisited. Or a theory of a theory. *The American Psychologist*, 28 (5), 404–416. https://doi.org/10.1037/h0034679

Epstein, S. (2003). Cognitive-experiential self-theory of personality. In I. B. Weiner (Ed.), *Handbook of Psychology* (pp. 159–184). Wiley. https://doi.org/10.1002/0471264385.wei0507

Epstein, S. (2010). Demystifying intuition: What it is, what it does, and how it does it. *Psychological Inquiry*, 21 (4), 295–312. https://doi.org/10.1080/1047840X.2010.523875

Epstein, S. (2014). Cognitive-experiential theory: An integrative theory of personality. Oxford University Press.

Ernst and Young. (2024). The EY 2024 Work Reimagined Survey [Press release]. https://www.ey.com/en_gl/insights/workforce/work-reimagined-survey (last accessed 21 November 2025)

Felin, T., Foss, N. J., & Ployhart, R. E. (2015). The microfoundations movement in strategy and organization theory. *The Academy of Management Annals*, 9 (1), 575–632. https://doi.org/10.1080/19416520.2015.1007651

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, 66 (1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Fuglestad, P. T., Volz, S., Joyal-Desmarais, K., Nydick, S. W., DeYoung, C. G., & Rothman, A. J. (2025). A new measure of regulatory focus: preventing measurement error by promoting best validation practices. *Journal of Personality*, 93 (3), 683–705. https://doi.org/10.1111/jopy.12962

Garbuio, M., & Lin, N. (2021). Innovative idea generation in problem finding: Abductive reasoning, cognitive impediments, and the promise of artificial intelligence. *Journal of Product Innovation Management*, 38 (6), 701–725. https://doi.org/10.1111/jpim.12602

Gelaidan, H. M., Al-Swidi, A. K., & Al-Hakimi, M. A. (2024). Servant and authentic leadership as drivers of innovative work behaviour: the moderating role of creative self-efficacy. *European Journal of Innovation Management*, 27 (6), 1938–1966. https://doi.org/10.1108/EJIM-07-2022-0382

Ghafoori A., Gupta M., Merhi M.I., Gupta S., Shore A.P. (2024) Toward the role of organizational culture in data-driven digital transformation. *International Journal of Production Economics* 271, 109205. https://doi.org/10.1016/j.ijpe.2024.109205

Grange, C., Demazure, T., Ringeval, M., Bourdeau, S., & Martineau, C. (2025). The Human-GenAI Value Loop in Human-Centered Innovation: Beyond the Magical Narrative. *Information Systems Journal*, 12602. Advance online publication. https://doi.org/10.1111/isj.12602

Gyamerah S., Afshari L., Asante D. (2025) Digital transformation in the SME context: the nexus between leadership, digital capabilities and digital strategy. *International Small Business Journal: Researching Entrepreneurship* 43 (3), 303–328. https://doi.org/10.1177/02662426251314108

Hermann, E., & Puntoni, S. (2024). Artificial intelligence and consumer behavior: From predictive to generative AI. *Journal of Business Research*, 180, 114720. https://doi.org/10.1016/j.jbusres.2024.114720

Higgins, E. T. (1997). Beyond pleasure and pain. The American Psychologist, 52 (12), 1280–1300. https://doi.org/10.1037/0003-066X.52.12.1280

Higgins, E. T. (1998). Promotion and prevention: Regulatory focus as a motivational principle. *Advances in Experimental Social Psychology*. 30, 1–46. https://doi.org/10.1016/S0065-2601(08)60381-0

Higgins, E. T., & Pinelli, F. (2020). Regulatory focus and fit effects in organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, 7 (1), 25–48. https://doi.org/10.1146/annurev-orgpsych-012119-045404

Holzner, N., Maier, S., & Feuerriegel, S. (2025). Generative AI and Creativity: A Systematic Literature Review and Meta-Analysis. https://doi.org/10.48550/arXiv.2505.17241

Jackson, S. (2011). Organizational culture and information systems adoption: A three-perspective approach. *Information and Organization*, 21 (2), 57–83. https://doi.org/10.1016/j.infoandorg.2011.03.003

Jia, N., Luo, X., Fang, Z., & Liao, C. (2024). When and how artificial intelligence augments employee creativity. *Academy of Management Journal*, 67 (1), 5–32. https://doi.org/10.5465/amj.2022.0426

Jong, J. de, & Hartog, D. den (2010). Measuring innovative work behaviour. *Creativity and Innovation Management*, 19 (1), 23–36. https://doi.org/10.1111/j.1467-8691.2010.00547.x

Kahneman, D. (2011). Thinking, fast and slow (First paperback edition). Psychology/economics. Farrar Straus and Giroux.

Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2024). The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*, 18 (4), 1189–1220. https://doi.org/10.1007/s11846-023-00696-z

Kraus, S., Durst, S., Ferreira, J. J., Veiga, P., Kailer, N., & Weinmann, A. (2022). Digital transformation in business and management research: An overview of the current status quo. *International Journal of Information Management*, 63, 102466. https://doi.org/10.1016/j.ijinfomgt.2021.102466

Lee, B. C., & Chung, J. (2024). An empirical investigation of the impact of ChatGPT on creativity. *Nature Human Behaviour*, 8 (10), 1906-1914. https://doi.org/10.1038/s41562-024-01953-1

Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., & Neubig, G. (2023). Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing. ACM Computing Surveys, 55 (9), 1–35. https://doi.org/10.1145/3560815

Liu, V., & Chilton, L. B. (2022). Design guidelines for prompt engineering text-to-image generative models. In S. Barbosa, C. Lampe, C. Appert, D. A. Shamma, S. Drucker, J. Williamson, & K. Yatani (Eds.), CHI Conference on Human Factors in Computing Systems (pp. 1–23). ACM. https://doi.org/10.1145/3491102.3501825

Madrid, H. P., Patterson, M. G., Birdi, K. S., Leiva, P. I., & Kausel, E. E. (2014). The role of weekly high-activated positive mood, context, and personality in innovative work behavior: A multilevel and interactional model. *Journal of Organizational Behavior*, 35 (2), 234–256. https://doi.org/10.1002/job.1867

Manly, J., Ringel M, MacDougall A., Harnoss J., Wolke-Perten J., Backler W., Gjerstad K., Kimura R., &Viner B.(2024) Most Innovative Companies 2024: Innovation Systems Need a Reboot. Boston Consulting Group. https://www.bcg.com/publications/2024/innovation-systems-need-a-reboot (last accessed 10 June 2025)

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science*, 2 (1), 71–87. https://doi.org/10.1287/orsc.2.1.71

Matarazzo, M., Penco, L., Profumo, G., & Quaglia, R. (2021). Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. *Journal of Business Research*, 123, 642–656. https://doi.org/10.1016/j.jbusres.2020.10.033

Mazzucchelli, A., Chierici, R., Abbate, T., & Fontana, S. (2019). Exploring the microfoundations of innovation capabilities. Evidence from a cross-border R&D partnership. *Technological Forecasting and Social Change*, 146, 242–252. https://doi.org/10.1016/j.techfore.2019.06.003

Meincke, L., Girotra, K., Nave, G., Terwiesch, C., & Ulrich, K. T. (2024). Using large language models for idea generation in innovation. *The Wharton School Research Paper*, https://doi.org/10.2139/ssrn.4526071

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58 (3), 103434. https://doi.org/10.1016/j.im.2021.103434

Nadkarni, S., & Prügl, R. (2021). Digital transformation: a review, synthesis and opportunities for future research. *Management Review Quarterly*, 71 (2), 233–341. https://doi.org/10.1007/s11301-020-00185-7

op ´t Roodt, H., Bracht, E. M., van Dick, R., & Hernandez Bark, A. S. (2025). Navigating through the digital workplace: Measuring leader digital competence. *Journal of Business and Psychology*, 40 (1), 179–205. https://doi.org/10.1007/s10869-024-09947-6

Palmié, M., Rüegger, S., & Parida, V. (2023). Microfoundations in the strategic management of technology and innovation: Definitions, systematic literature review, integrative framework, and research agenda. *Journal of Business Research*, 154, 113351. https://doi.org/10.1016/j.jbusres.2022.113351

Paulus, P. B., & Brown, V. R. (2007). Toward more creative and innovative group idea generation: A cognitive-social-motivational perspective of brainstorming. *Social and Personality Psychology Compass*, 1 (1), 248–265. https://doi.org/10.1111/j.1751-9004.2007.00006.x

Pfister P., Lehmann C. (2023) Measuring the success of digital transformation in german SMEs. *Journal of Small Business Strategy* 33 (1), 1–19. https://doi.org/10.53703/001c.39679

Porfírio, J. A., Carrilho, T., Felício, J. A., & Jardim, J. (2021). Leadership characteristics and digital transformation. *Journal of Business Research*, 124, 610–619. https://doi.org/10.1016/j.jbusres.2020.10.058

Raisch, S., & Fomina, K. (2025). Combining human and artificial intelligence: Hybrid problem-solving in organizations. *Academy of Management Review*, 50 (2), 441–464. https://doi.org/10.5465/amr.2021.0421

Reuters. (2023). ChatGPT sets record for fastest-growing user base - analyst note. https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/ (last accessed 21 November 2025)

Roberts, D. L., & Candi, M. (2024). Artificial intelligence and innovation management: Charting the evolving landscape. *Technovation*, 136, 103081. https://doi.org/10.1016/j.technovation.2024.103081

Rogge, N. D., Lamovšek, A., & Batistič, S. (2025). AI meets IA: A typology of generative-AI-supported work through individual ambidexterity. *Business Horizons*. Advance online publication. https://doi.org/10.1016/j.bushor.2025.06.006

Saihi A., Ben-Daya M., As'ad R. (2023) Underpinning success factors of maintenance digital transformation: a hybrid reactive Delphi approach. *International Journal of Production Economics* 255, 108701. https://doi.org/10.1016/j.ijpe.2022.108701

Schneider, J., Meske, C., & Kuss, P. (2024). Foundation models: A new paradigm for artificial intelligence. *Business & Information Systems Engineering*, 66 (2), 221-231. https://doi.org/10.1007/s12599-024-00851-0

Schryen, G., Marrone, M., & Yang, J. (2025). Exploring the scope of generative AI in literature review development. *Electronic Markets*, 35 (1). https://doi.org/10.1007/s12525-025-00754-2

Shanker, R., Bhanugopan, R., van der Heijden, B. I., & Farrell, M. (2017). Organizational climate for innovation and organizational performance: The mediating effect of innovative work behavior. *Journal of Vocational Behavior*, 100, 67–77. https://doi.org/10.1016/j.jvb.2017.02.004

Singh, K., Chatterjee, S., & Mariani, M. (2024). Applications of generative AI and future organizational performance: The mediating role of explorative and exploitative innovation and the moderating role of ethical dilemmas and environmental dynamism. *Technovation*, 133, 103021. https://doi.org/10.1016/j.technovation.2024.103021

Skare M., de Las Mercedes Obesso M., Ribeiro-Navarrete S. (2023) Digital transformation and European small and medium enterprises (SMEs): a comparative study using digital economy and society index data. *International Journal of Information Management* 68:102594. https://doi.org/10.1016/j.ijinfomgt.2022.102594

Strobel, G., Banh, L., Möller, F., & Schoormann, T. (2024). Exploring generative artificial intelligence: A taxonomy and types. In T. Bui (Ed.), Proceedings of the Annual Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2024.546

Strobl, A., Matzler, K., Nketia, B. A., & Veider, V. (2020). Individual innovation behavior and firm-level exploration and exploitation: how family firms make the most of their managers. *Review of Managerial Science*, 14 (4), 809–844. https://doi.org/10.1007/s11846-018-0309-9

Susarla, A., Gopal, R., Thatcher, J. B., & Sarker, S. (2023). The janus effect of generative AI: Charting the path for responsible conduct of scholarly activities in information systems. *Information Systems Research*, 34 (2), 399–408. https://doi.org/10.1287/isre.2023.ed.v34.n2

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28 (13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18 (7). http://www.jstor.org/stable/3088148

Teng, D., Ye, C., & Martinez, V. (2025). Gen-AI's effects on new value propositions in business model innovation: Evidence from information technology industry. *Technovation*, 143, 103191. https://doi.org/10.1016/j.technovation.2025.103191

Tuncdogan, A., & Dogan, I. C. (2020). Managers' regulatory focus, temporal focus and exploration–exploitation activities. *Journal of Managerial Psychology*, 35 (1), 13–27. https://doi.org/10.1108/JMP-07-2018-0318

Tuncdogan, A., van den Bosch, F., & Volberda, H. (2015). Regulatory focus as a psychological micro-foundation of leaders' exploration and exploitation activities. *The Leadership Quarterly*, 26 (5), 838–850. https://doi.org/10.1016/j.leaqua.2015.06.004

Vaswani, A., Shazeer, N. M., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems. 31st Conference on Neural Information Processing Systems. CA, USA: Long Beach.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, 28 (2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

Wang, S., & Zhang, H. (2025). Generative artificial intelligence and internationalization green innovation: Roles of supply chain innovations and AI regulation for SMEs. *Technology in Society*, 82, 102898. https://doi.org/10.1016/j.techsoc.2025.102898

Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52 (3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001

Yeo, G. B., Celestine, N. A., Parker, S. K., To, M. L., & Hirst, G. (2024). A neurocognitive framework of attention and creativity: Maximizing usefulness and novelty via directed and undirected pathways. *Journal of Organizational Behavior*, 45 (6), 912–934. https://doi.org/10.1002/job.2787

Yin, M., Jiang, S., & Niu, X. (2024). Can AI really help? The double-edged sword effect of AI assistant on employees' innovation behavior. *Computers in Human Behavior*, 150, 107987. https://doi.org/10.1016/j.chb.2023.107987

Yuan, F., & Woodman, R. W. (2010). Innovative behavior in the workplace: The role of performance and image outcome expectations. *Academy of Management Journal*, 53 (2), 323–342. https://doi.org/10.5465/AMJ.2010.49388995

Zhang, X., Yu, P., & Ma, L. (2025). How and when generative AI use affects employee incremental and radical creativity: an empirical study in China. *European Journal of Innovation Management*. https://doi.org/10.1108/EJIM-04-2024-0466

Zhang, Y., Xu, F. Z., Feng, L., Shi, X., & Zhang, F. (2024). The power of a pledge: Exploring the relationship between sense of calling and innovative work behaviour in healthcare. *Creativity and Innovation Management*, 33 (3), 551–565. https://doi.org/10.1111/caim.12602

Zoppelletto A., Orlandi L.B., Zardini A., Rossignoli C., Kraus S. (2023) Organizational roles in the context of digital transformation: a micro-level perspective. *Journal of Business Research* 157, 113563. https://doi.org/10.1016/j.jbusres.2022.113563

2. Research Paper 1

Held, P., & Heubeck, T. (2025). GenAI and employee innovativeness: How employees' sensing capabilities and the capabilities to use and evaluate GenAI shape their innovative work behavior. *Digital Business*, 5 (2) 100149. https://doi.org/10.1016/j.digbus.2025.100149

Abstract

Innovation is critical for organizational success, with employees' innovative work behavior (IWB) forming a key microfoundation of firm-level innovation. While prior research has identified various antecedents of IWB, the role of generative AI (GenAI) remains underexplored. We address this gap by investigating how employees' capabilities to use and evaluate GenAI influence their IWB. Building on the dynamic capabilities view, we further explore how employees' capabilities to sense technological shifts shape the development of these GenAI capabilities and ultimately foster IWB. We test our model using survey data from 439 business consultants in Germany, Austria, and Switzerland, analyzed via partial least squares structural equation modeling (PLS-SEM). Our results show that employees' sensing capabilities promote both GenAI capabilities and directly enhance IWB. While employees' capability to evaluate GenAI promotes IWB, GenAI usage capability does not. Moreover, we identify a significant mediation pathway: employees' sensing capabilities enhance GenAI usage capability, which in turn enables GenAI evaluation capability and thereby fosters IWB. This study contributes to the IWB literature by exploring relevant yet understudied antecedents: employees' sensing capabilities and their capabilities to use and evaluate GenAI. Moreover, it extends emerging research on GenAI in innovation management by adopting a differentiated capability perspective and uncovering the distinct roles and interplay of employees' GenAI usage and evaluation capabilities.

Keywords

Innovative work behavior; Generative AI; dynamic capabilities; sensing; innovation management

Licensing Information

2.1. Introduction

Innovation is widely accepted as a crucial success factor for companies, as innovation is considered to be at the "heart of organizations' pursuit of long-term competitive advantage" (Roberts & Candi, 2024, p. 2). However, a recent Boston Consulting Group report reveals that 83% of companies view innovation as a top three priority, but only 3% are truly prepared to deliver on their innovation ambitions (Manly et al., 2024).

Against this backdrop, employees' innovative work behavior (IWB) has gained increasing attention among researchers and practitioners (Volery & Tarabashkina, 2021). IWB is conceptualized as a set of distinct yet interrelated behavioral activities of an employee—including idea exploration, generation, championing, and implementation—that collectively span all phases of the innovation process (De Jong & Den Hartog, 2010; Scott & Bruce, 1994; Kör et al., 2021). In other words, employees play a crucial role in driving organizational innovation (De Jong & Den Hartog, 2010; Mazzucchelli et al., 2019). Empirical studies found that employees' IWB is positively associated with organizational performance (Shanker et al., 2017) and firm-level innovation (Strobl et al., 2020). This view aligns with the microfoundations perspective, which conceptualizes individual-level actions—such as IWB—as fundamental building blocks of organizational-level outcomes like innovation and performance (Felin et al., 2015; Palmié et al., 2023; De Jong & Den Hartog, 2007).

Emerging generative AI (GenAI) technologies (e.g., ChatGPT, Dall-E, and Gemini) offer promising opportunities to enhance employees' IWB. GenAI technologies represent a powerful subcategory of AI (Schryen et al., 2025) and an advancement beyond traditional AI (Roberts & Candi, 2024). Specifically, GenAI technologies incorporate the ability to generate novel and meaningful content, such as text, images, and audio, based on underlying training data (Feuerriegel et al., 2024), renewing the interest in utilizing AI technologies as a tool for innovation (Piller et al., 2024).

Recent conceptual work emphasizes that GenAI is not intended to replace human creativity but to augment it (Bilgram et al., 2023). Previous studies show, for instance, that GenAI can promote employees' innovative behavior by augmenting work abilities (Yin et al., 2024), like solving problems in a novel and useful manner (Jia et al., 2024). For example, GenAI already synthesizes vast libraries of annotated medical scans that accelerate radiologists' anomaly-detection models, and it generates studio-quality product photos with tailored captions so e-commerce merchandisers can list new items without costly photo shoots

(Deloitte, 2024a). Moreover, individuals collaborating with GenAI show better creative performance than humans without GenAI support (Holzner et al., 2025). In co-creative settings, GenAI can support employees in defining problems, envisioning solutions, and subsequently validating these solutions (Grange et al., 2025). Most studies examining GenAI and its influence on creative outcomes and innovation frame GenAI as a human-GenAI co-creation process (e.g., Boussioux et al., 2024; Grange et al., 2025).

Understanding how GenAI affects individual-level IWB remains an underexplored area within this field, presenting a research gap we aim to address. Examining the influence of GenAI on employees' IWB is essential, as IWB represents a crucial success factor for companies (e.g., Shanker et al., 2017). Due to the complex and multifaceted nature of GenAI and building on a capabilities perspective, we incorporate two distinct GenAI constructs—GenAI usage capability and GenAI evaluation capability—following the AI literacy scale of Wang et al. (2023). GenAI usage capability "refers to the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently" (Wang et al., 2023, p. 4). In contrast, GenAI evaluation capability "refers to the ability to analyze, select and critically evaluate (Gen) AI applications and their outcomes" (Wang et al., 2023, p. 4). This argumentation leads to our first research question (RQ):

RQ 1. How do employees' capabilities to use and evaluate GenAI technologies shape their IWB?

Building on the dynamic capabilities view (Teece, 2007)—often used as a theoretical lens in innovation management (e.g., Akter et al., 2023; Hock-Doepgen et al., 2025; Ritala et al., 2024; Ferreira et al., 2020; Held et al., 2025)—we further argue that individual-level IWB in the digital age requires more than the capabilities to use and evaluate GenAI. While the dynamic capabilities view typically encompasses three core activities—sensing opportunities and threats, seizing opportunities, and transforming resources (Teece, 2007)—this study focuses specifically on individual sensing capabilities, conceptualized as employees' ability to detect and interpret shifts in the technological landscape and the market environment (Schoemaker et al., 2018; Harvey, 2022). We focus on sensing capabilities as they are considered particularly relevant to navigating emerging technologies (Zabel et al., 2023). These sensing capabilities allow for early insights into market changes and technological advancements (Teece, 2007; Harvey, 2022) and might form a relevant antecedent to the effective development of employees' GenAI usage and evaluation capabilities, as well as IWB.

Since employees likely first need to recognize the relevance and potential of GenAI, sensing capabilities provide the cognitive foundation upon which employees can build the required capabilities to leverage GenAI as a driver of IWB. Including employees' sensing capabilities is vital to investigating the antecedents of GenAI capabilities with the ultimate goal of leveraging IWB. We formulate our second and third RQ:

RQ 2. How do employees' sensing capabilities influence their capabilities to use and evaluate GenAI?

RQ 3. How do employees' sensing capabilities influence their IWB?

Drawing on individual-level dynamic capabilities and recent innovation management literature on GenAI, we hypothesize that employees' sensing capabilities promote both the capability to use (H1) and the capability to evaluate GenAI (H2). Further, we hypothesize that employees' sensing capabilities promote their IWB (H3). Next, we suggest that employees' GenAI usage capability and GenAI evaluation capability enhance their IWB (H4 and H5). Finally, we hypothesize that employees' GenAI usage capability promotes their GenAI evaluation capability (H6).

We test our hypotheses using partial least squares structural equation modeling (PLS-SEM) on a large-scale empirical sample of 439 business consultants from a leading global consultancy in Germany, Austria, and Switzerland. We selected this sample because the participating consultants already integrate GenAI into their daily work processes and work in different industries, so they have to deal with a broad and ever-changing range of problems and issues, and, therefore, require IWB.

Furthermore, the consulting industry is particularly affected by emerging GenAI technologies. Recent industry evidence shows that leading consultancies are already redesigning their entire client-delivery workflows around GenAI: McKinsey's 2025 Global AI Survey reports that 21% of professional-services firms have fundamentally reworked at least some workflows to deploy the technology (McKinsey, 2025). A Forbes article further states that GenAI is revolutionizing traditional consulting, as its tools deliver analytical and strategic-planning services with remarkable speed, efficiency, and cost-effectiveness (Minevich, 2024).

Our paper makes several valuable contributions to the literature. First, we contribute to IWB literature (e.g., De Jong & Den Hartog, 2010; Scott & Bruce, 1994; Volery & Tarabashkina, 2021; Kör et al., 2021). Our results demonstrate that employees' sensing capabilities promote their IWB. Employees' capability to use GenAI does not promote their IWB, but the capability to evaluate GenAI does. Therefore, our study complements previous studies regarding the antecedents of IWB (e.g., Gelaidan et al., 2024; Anser et al., 2021; AlEssa & Durugbo, 2022; Yuan & Woodman, 2010) by integrating individual sensing capabilities and an emerging and disruptive technology: GenAI.

Second, we contribute to the emerging literature on GenAI in innovation management (e.g., Chiarello et al., 2024; Cillo & Rubera, 2024; Kanbach et al., 2024; Roberts & Candi, 2024). While prior studies have highlighted the transformative potential of GenAI for creativity and innovation, recent reviews emphasize that empirical research in this domain remains fragmented (Holzner et al., 2025). Addressing this observation, our study adopts a capability perspective that explores the antecedents, mechanisms, and outcomes of two distinct but interrelated GenAI capabilities in the innovation context: GenAI usage capability and GenAI evaluation capability. This approach complements existing empirical studies that typically conceptualize GenAI as a single, undifferentiated construct (e.g., Cimino et al., 2025; Rana et al., 2024; Singh et al., 2024).

The remainder of this study provides the theoretical foundation (Chapter 2), derives the hypotheses (Chapter 3), details the methodology (Chapter 4), presents the empirical results (Chapter 5), and concludes with theoretical and practical implications, limitations, and suggestions for future research (Chapter 6).

2.2. Theoretical background

2.2.1. Innovative work behavior (IWB)

IWB is defined as "the intentional creation, introduction and application of new ideas within a work role, group or organization, in order to benefit role performance, the group, or the organization" (Janssen, 2000, p. 288). De Jong and Den Hartog (2010) further elaborate on IWB as a sequence of interrelated but distinct behavioral stages—idea exploration, idea generation, idea championing, and idea implementation—reflecting the whole span of the innovation process. In other words, IWB represents a multi-dimensional, overarching construct that captures all behaviors through which employees contribute to the innovation process (De Jong & Den Hartog, 2007). In simpler terms, in our study, we view IWB as the individual-level behavior of an employee. Importantly, this view distinguishes IWB from creativity, which typically focuses solely on generating novel ideas (Amabile, 1988; De Jong & Den Hartog, 2010). Therefore, we rely on the conceptualization by Kör et al. (2021), who position IWB as central to all organizational innovation efforts (see also Huhtala & Parzefall, 2007; Scott & Bruce, 1994). We view IWB as going beyond functional roles and argue that it is relevant for all company employees, not just the innovation departments.

The relevance of IWB stems from its demonstrated impact on a wide range of organizational outcomes. For instance, it has been linked to enhanced organizational performance (Shanker et al., 2017) and firm-level innovation (Strobl et al., 2020). These findings align with the broader microfoundations perspective, which states that individual-level actions—such as IWB—shape organizational-level outcomes (Felin et al., 2015; Palmié et al., 2023). Reflecting its increasing strategic importance, scholarly interest in IWB has grown substantially over the past decade, illustrated through various recent literature reviews (e.g., Farrukh et al., 2023; AlEssa & Durugbo, 2022).

Previous research has highlighted a broad set of individual and organizational (or contextual) factors that serve as antecedents to IWB (e.g., Yuan & Woodman, 2010). At the individual level, positive mood (Madrid et al., 2014), cultural intelligence (Afsar et al., 2021), or employee creativity (Volery & Tarabashkina, 2021) have been shown to enhance IWB.

Most research has focused on organizational antecedents for individual-level IWB as an outcome (Volery & Tarabashkina, 2021). These antecedents include servant leadership (Gelaidan et al., 2024), knowledge management infrastructure capabilities (Anser et al., 2021), team learning behaviors (Widmann & Mulder, 2018), or human resource management practices like feedback, autonomy, or training (Bos-Nehles et al., 2017). Moreover, perceived organizational support for innovation (Scott & Bruce, 1994), organizational climate (Volery & Tarabashkina, 2021), and the quality of leader-member relationships (Janssen & van Yperen, 2004) represent relevant organizational antecedents of IWB.

In summary, IWB is a multifaceted construct vital in fostering organizational innovation and performance (e.g., Strobl et al., 2020; Shanker et al., 2017). To fully leverage its potential, it is essential to understand which factors drive IWB. Against this backdrop, GenAI represents a promising but underexplored individual-level antecedent for IWB. Realizing GenAI's potential, however, likely requires that employees can identify and interpret technological developments and market changes—an ability captured by the concept of employees' sensing capabilities. These sensing capabilities may provide the cognitive foundation for developing GenAI usage and evaluation capabilities, which in turn can enable IWB. The following section introduces GenAI and its potential for innovation management.

2.2.2. Generative AI and its potential for innovation management

The release of ChatGPT in November 2022 brought GenAI to the forefront of AI discussions (Gartner, 2023). This tool quickly gained traction, reaching 100 million monthly active users within two months—a record as the fastest-growing consumer application in history (Reuters, 2023). We adopt the definition of Feuerriegel et al. (2024, p. 111) and refer to GenAI as "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data."

GenAI goes one step further than traditional AI as it can generate new data based on training data (Roberts & Candi, 2024); therefore, GenAI can be classified as a powerful subcategory of AI (Schryen et al., 2025). Moreover, GenAI is based on generative modeling, differentiating it from discriminative modeling (often used for data-driven decision support) by employing a machine learning architecture, such as a deep neural network (Feuerriegel et al., 2024; Ng & Jordan, 2001).

Figure 2.1 illustrates the procedural differences between discriminative and GenAI models, as conceptualized by Banh and Strobel (2023). Accordingly, discriminative AI models rely on existing data to determine boundaries and make classifications or decisions. This process is linear, proceeding from data input to boundary determination, ultimately reaching a specific conclusion. In contrast, GenAI models operate through an iterative cycle involving prompt input, creation, and generation of new, meaningful content. Here, the process is inherently creative, allowing for continuous refinement through specifying and generating cycles, which enables the model to produce novel outputs rather than merely categorizing existing data (Banh & Strobel, 2023).

A key feature of GenAI is its adaptability through prompting. Rather than retraining the model for specific tasks, users can steer GenAI's outputs by providing tailored instructions—so-called prompts—that define the desired format, tone, or objective (Liu et al., 2023). This mechanism enables a flexible application of pre-trained models across various use cases. Prompt engineering focuses on the systematic design of prompts to enhance the quality of generated outputs (Liu & Chilton, 2022). As a result, the interaction between users and GenAI takes the form of a co-creation process in which prompt design plays a central role in shaping the relevance and quality of the generated output (Feuerriegel et al., 2024).

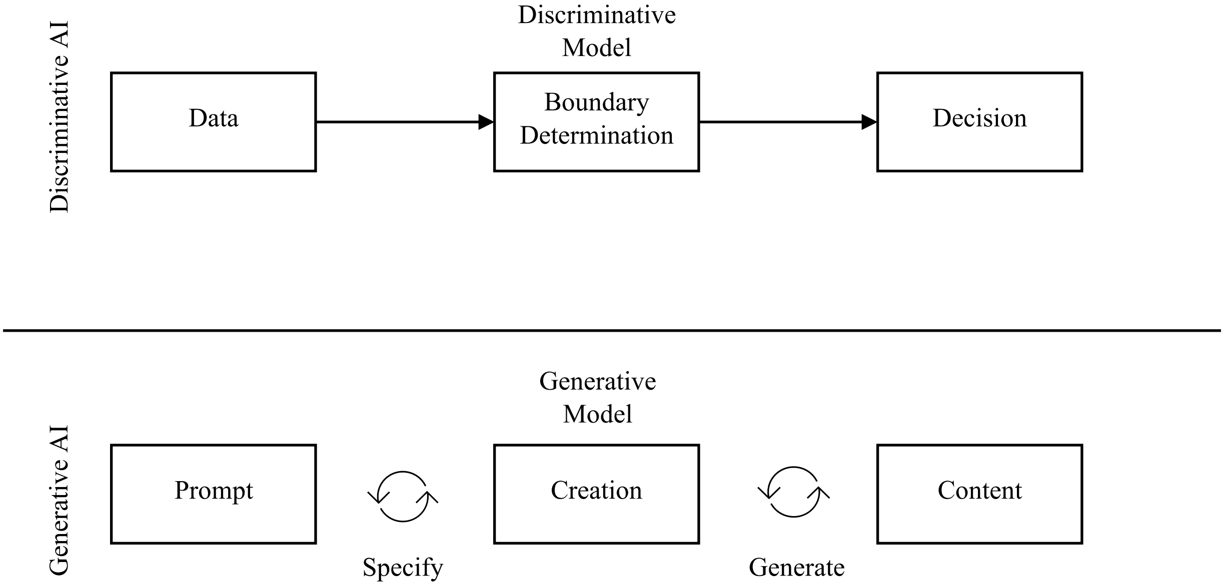


Figure 2.1 Procedural differences of discriminative AI and generative AI

Note: Own illustration based on Banh and Strobel (2023, p. 5)

From an innovation management perspective, there seems to be no limit to the presumed added value of these GenAI technologies. At the organizational level, recent studies indicate that GenAI could influence business model innovation (Kanbach et al., 2024; Teng et al., 2025), enhance ideation processes (Eisenreich et al., 2024), change consumer behavior and corresponding marketing strategies (Cillo & Rubera, 2024), foster digital supply chain innovation (Wang & Zhang, 2025a), and improve exploratory and exploitative innovation (Singh et al., 2024).

These examples infer that GenAI represents a disruptive innovation for companies. Consequently, there has been a substantial increase in research interest for innovation management researchers, evident from the rapidly increasing number of publications in this area (e.g., Akter et al., 2023; Chiarello et al., 2024; Haefner et al., 2023; Mariani & Dwivedi, 2024; Sedkaoui & Benaichouba, 2024; Chen & Chan, 2024).

Due to the significance of GenAI in corporate innovation management, most of these studies focus on the impact of GenAI on innovation management at the organizational level. However, this focus on firm-level innovation omits that innovation is critically dependent on individuals and their actions (Felin et al., 2015; Palmié et al., 2023).

2.2.3. Employees' GenAI usage and evaluation capabilities

Most of the current research in innovation management literature regarding GenAI is literature reviews with a focus on future research directions (e.g., Akter et al., 2023; Haefner et al., 2023; Mariani et al., 2023; Roberts & Candi, 2024; Sedkaoui & Benaichouba, 2024). However, more and more quantitative empirical studies are now being conducted on the subject (e.g., Cimino et al., 2025; Rana et al., 2024; Singh et al., 2024).

What is striking about these quantitative empirical studies is that they often choose a single construct to measure the GenAI component of their research model. Cimino et al. (2025) use a construct named "generative AI appropriation," which represents the process by which innovation managers adapt GenAI tools (such as ChatGPT) to their specific work requirements and integrate these tools into their workflows. Rana et al. (2024) utilize the construct "use of Generative AI," defined as the deployment of GenAI technology by organizations for various business functions, where it is leveraged to enhance organizational effectiveness and performance. Singh et al. (2024) utilize a construct called "adoption of GenAI," defined as organizations' integration and utilization of GenAI technologies to enhance performance through innovative outputs and efficiency gains.

While these studies offer essential empirical findings regarding GenAI in innovation management, we build on them using two different GenAI constructs. Thus, our study aims to differentiate further and break down GenAI in the application toward individual-level IWB. Adapted from the AI literacy scale introduced by Wang et al. (2023), we distinguish between the foundational GenAI capabilities of usage and evaluation.

First, we consider employees' GenAI usage capability, which "refers to the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently" (Wang et al., 2023, p. 4). This construct centers on operational proficiency, enabling users to engage with GenAI tools without requiring in-depth reflection. Beyond mere tool application, GenAI usage involves flexible adaptation to various requirements and efficient integration of different GenAI tools into workflows. Thus, we propose that GenAI usage capability allows employees to leverage technical tools and quickly become familiar with their functions.

Second, we include the construct employees' GenAI evaluation capability, which "refers to the ability to analyze, select and critically evaluate (Gen) AI applications and their outcomes" (Wang et al., 2023, p. 4). This construct emphasizes that users need reflective capabilities beyond handling technology developed through consistent engagement with GenAI. Given the "black-box" nature of AI models (Mueller et al., 2019), evaluative skills are essential for making informed decisions and critically scrutinizing the validity of generated content. For instance, critical thinking is pivotal when applying GenAI in complex decision-making contexts (Wang et al., 2023). Users who learn to identify both the strengths and limitations of GenAI outputs can tailor these results to the specific demands of their work context, optimizing outcomes accordingly.

In other words, GenAI usage capability is about applying the tools as they are in the absence of much critical thinking (Liu et al., 2025). In contrast, GenAI evaluation capability involves a deeper understanding and the cognitive ability to assess the quality and relevance of the GenAI-generated outputs.

2.2.4. Dynamic capabilities lens and employees' sensing capabilities

Dynamic capabilities refer to a "firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997, p. 516). The dynamic capabilities framework is widely used and recognized in management research (e.g., Eisenhardt & Martin, 2000; Schilke et al., 2018; Teece, 2007; Zollo & Winter, 2002) and explains how firms can achieve competitive advantage in dynamic environments characterized by innovation-driven competition (Teece, 2014).

Organizational capabilities can generally be distinguished into ordinary and dynamic capabilities (Winter, 2003). Ordinary capabilities encompass performing administrative, operational, and governance-related functions required to accomplish tasks (Teece, 2014). In contrast, dynamic capabilities are needed for strategic change and renewal (Agarwal & Helfat, 2009; Helfat et al., 2007) and enable companies to change the way they currently earn their living (Helfat & Winter, 2011). Dynamic capabilities include conducting acquisitions and new product development (Helfat & Winter, 2011) or business model design (Teece & Linden, 2017).

Dynamic capabilities are underpinned by three core activities: sensing opportunities and threats, seizing opportunities, and transforming resources (Teece, 2007). First, sensing capabilities refer to scanning the market, detecting shifts, and sensing market changes before the competition does, which is especially critical in turbulent environments (Schoemaker et al., 2018). After firms sense an opportunity, they must seize it through new products or services requiring investments in development and commercialization activity (Teece, 2007). A natural extension of sensing and seizing capabilities is the need to transform the organization in response to the realized opportunities. Specifically, transforming capabilities enable firms to continuously adapt by redesigning their internal structures and reshaping external relationships, ensuring they remain agile in dynamic environments (Day & Schoemaker, 2016).

GenAI is increasingly viewed through the lens of organizational capabilities (AL-khatib & Ramayah, 2024; Shore et al., 2024). However, due to the focus of dynamic capabilities theory on firm-level capabilities, this framework neglects the role of the individuals (i.e., managers and employees) and their capabilities behind the companies (Heubeck, 2023; Salvato & Vassolo, 2018). This criticism gave rise to the microfoundational research stream of dynamic capabilities (Adner & Helfat, 2003; Helfat & Martin, 2015; Heubeck, 2024). This research stream fundamentally states that competitive advantage at the firm level is created by the capabilities of individuals (Foss & Mazzelli, 2025; Felin et al., 2015).

Building on this micro-level logic, we shift the firm-level focus of existing research regarding GenAI to the individual level. In this vein, we argue that employees inherently use GenAI tools—for example, an individual user writes a ChatGPT prompt. Therefore, the GenAI capabilities of employees are critical for realizing and building firm-level GenAI capabilities. Thus, this view enriches recent firm-level research—which views GenAI through the lens of organizational capabilities (AL-khatib & Ramayah, 2024; Shore et al., 2024)—by focalizing individual-level GenAI capabilities: Employees' GenAI usage capability and GenAI evaluation capability.

We further investigate employees' sensing capabilities as antecedents for GenAI capabilities, as sensing capabilities are particularly relevant to navigating emerging technologies (Zabel et al., 2023). Sensing capabilities at the individual level encompass the ability of employees to detect and interpret shifts in the technological landscape, providing early insights into market changes and technological advances (Teece, 2007; Harvey, 2022). Thus, sensing capabilities are especially critical for digital transformation in general and new technologies in particular (Warner & Wäger, 2019). Given GenAI's potential for substantial technological and market disruptions, employees' capability to sense emerging opportunities and threats is critical in such an unpredictable environment. For example, employees can be involved in digital opportunity evaluation—a critical microfoundation of sensing capabilities—and assess the opportunities and risks of a new technology, leading to the decision whether to adopt it or not (Leso et al., 2024). Cross-industrial sensing, especially monitoring digital initiatives and technology adoption of employees in other industries, is a promising way to identify emerging technological trends and technology usage (Ellström et al., 2022). Thus, because GenAI represents an emerging technology landscape that needs to be explored by individuals, we focus on employees' sensing capabilities as facilitators of GenAI capabilities.

2.3. Hypothesis development

In the following section, we develop our hypotheses, with Figure 2.2 summarizing the research model.

According to Teece (2007), sensing capabilities involve scanning and monitoring technological developments and hypothesizing about the evolution of technologies, making them particularly relevant to navigating emerging technologies (Zabel et al., 2023). Specifically, employees' cognitive functions, such as perception and attention, help generate novel hypotheses and recognize trends (like GenAI) relevant to opportunities and threats, a process termed "generative sensing" (Dong et al., 2016; Helfat & Martin, 2015). More concretely, this involves digital scouting and digital scenario planning as an essential foundation for quickly making sense of unexpected trends (Warner & Wäger, 2019). Once a technology is identified as potentially important, it must be further probed and tested practically to gain a deeper understanding (Schoemaker et al., 2018).

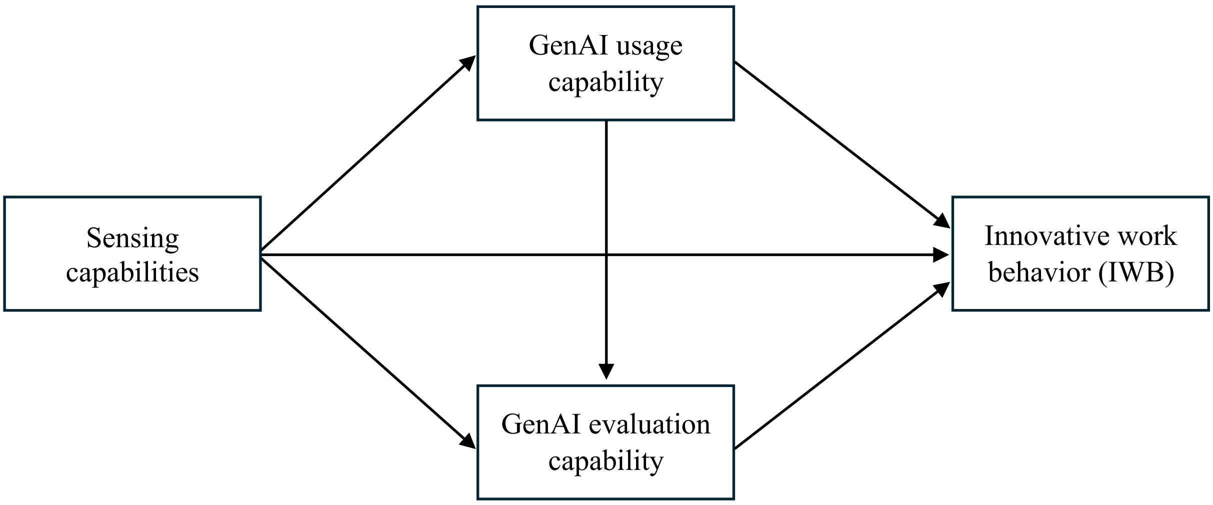


Figure 2.2 Research model

Source: Own illustration

Individuals with strong sensing capabilities can, therefore, identify novel technologies (like GenAI) at an earlier stage and develop a richer understanding of their potential use cases and value. We suggest that strong employees' sensing capabilities increase their capability to use and evaluate GenAI. Their information advantage—due to strong sensing capabilities—might enable them not only to recognize relevant application areas but also to critically assess the quality and usefulness of GenAI outputs. For instance, an employee with strong sensing capabilities may actively monitor discussions and updates about GenAI tools and thereby learn that specific models produce hallucinated or biased results. Such insights can inform prompting strategies or encourage a more cautious interpretation of generated content, enhancing GenAI usage and evaluation capability. Therefore, we state the following two hypotheses:

H1. Employees' sensing capabilities enhance their GenAI usage capability.

H2. Employees' sensing capabilities enhance their GenAI evaluation capability.

We further argue that employees' sensing capabilities enhance their IWB. Accordingly, IWB begins with identifying opportunities or problems that arise (De Jong & Den Hartog, 2010). Moreover, dissatisfaction with the status quo due to environmental changes is a relevant antecedent for IWB (Yuan & Woodman, 2010). This starting point closely aligns with the conceptualization of sensing capabilities to detect environmental shifts and opportunities (Teece, 2007). Sensing capability is a cognitive process through which environmental changes are perceived (Lin et al., 2016).

Previous studies found that sensing capabilities positively influence the performance of the initiation and implementation of innovation (Lin et al., 2016). One reason is that sensing capabilities are crucial to identifying a novel problem as a foundation for innovation (Lin et al., 2016; Birkinshaw et al., 2008). Furthermore, sensing capabilities improve product and process innovation (Alshanty & Emeagwali, 2019). One underlying mechanism here is that employees with stronger sensing capabilities can access and integrate a greater breadth of knowledge sources, which is associated with greater innovation success (Leiponen & Helfat, 2010).

Accordingly, we argue that employees' sensing capabilities provide a relevant antecedent for IWB, as they could enable employees to recognize change, formulate ideas, and initiate innovative action. Thus, we hypothesize:

H3. Employees' sensing capabilities enhance their IWB.

We further argue that employees' capabilities to use and evaluate GenAI promote their IWB. As GenAI-mediated innovation is increasingly conceptualized as a co-creative process (e.g., Grange et al., 2025), the quality and innovativeness of outcomes are not inherent to the technology itself but emerge through the co-creation with the user (Feuerriegel et al., 2024; Liu et al., 2023).

There are already plenty of suggested use cases of how GenAI can support IWB, including user journey mapping, idea generation, and prototyping (Bilgram & Laarmann, 2023), with GenAI augmenting employees' working abilities (Yin et al., 2024). Yet, these observed benefits are not automatic: users must be able to steer GenAI via prompt formulation and iterative specification to produce valuable results (Liu et al., 2023). As the prompting process is probabilistic and generative rather than deterministic, employees actively shape the generated output via a trial-and-error process and continuously specify their desired tasks as input prompts until their task is solved (Banh & Strobel, 2023).

Empirical studies further show that GenAI can support employees in defining problems, envisioning solutions, and testing these solutions (Grange et al., 2025). GenAI has also been found to influence individual-level creativity and innovation routines regarding speed, quality, and quantity for various tasks like creation planning or prototyping (Chu et al., 2025). Moreover, Zhang et al. (2025) found that integrating GenAI into everyday workflows enhances both incremental and radical innovation.

The interactive nature of GenAI also demands continuous evaluation of the generated content, especially given known limitations such as hallucination and bias (Feuerriegel et al., 2024). Users must critically assess which outputs are valid, implementable, and useful within their specific task context. This evaluative process is crucial for translating GenAI-generated outputs into concrete IWB.

Taken together, employees who possess strong capabilities to use and evaluate GenAI—by effectively utilizing and prompting the technology, steering its output, and critically evaluating its relevance—are better positioned to harness the technology's innovation potential. These capabilities enable employees to actively contribute to ideating and implementing novel solutions, thereby fostering IWB. Thus, we posit:

H4. Employees' GenAI usage capability enhances their IWB.

H5. Employees' GenAI evaluation capability enhances their IWB.

We further aim to investigate the nuanced mechanisms between both GenAI capabilities.

We argue that employees' GenAI usage capability is foundational for developing their GenAI evaluation capability. Following Wang et al. (2023), (Gen)AI usage capability refers to individuals' operational ability to interact with and apply (Gen)AI tools effectively to accomplish tasks. In contrast, (Gen)AI evaluation capability requires higher-order cognitive skills, including critically assessing (Gen)AI outputs and determining their appropriateness and reliability. Empirical validation of the AI literacy framework by Wang et al. (2023) demonstrates that these two capabilities are conceptually distinct yet interdependent, with operational competence being a prerequisite for reflective evaluation.

This interdependence is further supported by Liu et al. (2025), who position GenAI usage and GenAI evaluation both in the cognitive skill domain within their AI literacy framework. Furthermore, they see a hierarchical differentiation between both GenAI capabilities, with GenAI usage needing medium-order thinking skills and GenAI evaluation needing higher-order thinking skills. That suggests that GenAI usage capability is the precondition for GenAI evaluation capability.

The already described technical nature of GenAI systems reinforces this suggested relationship. GenAI operates on a generative rather than deterministic logic, requiring users to iteratively specify and refine prompts to produce useful content (Banh & Strobel, 2023). This trial-and-error process involves using and testing what prompts lead to the best output. In other words, the GenAI usage capability will likely lead to better GenAI evaluation capability. Taken together, we posit:

H6. Employees' GenAI usage capability enhances their GenAI evaluation capability.

2.4. Method

2.4.1. Data collection and sample

For the empirical validation of the research model, we surveyed business consultants located in Germany, Austria, and Switzerland from one of the leading consultancies worldwide. This internationally renowned consultancy operates globally in over 100 countries, with several 100,000 employees and a turnover of tens of billions of dollars per year.

We surveyed the strategy, consulting, and innovation units of this company. This sample is particularly suitable for our research, as these consultants already work with GenAI and integrate it into their work. Additionally, these consultants work across industries and have advised various projects and clients. Thus, these consultants must deal with ever-changing problems and client needs, which require them to incorporate IWB.

The region of Germany, Austria, and Switzerland offers a suitable context for our study as it is one of Europe's largest and most dynamic consulting markets. Germany alone generated almost 50 billion euros in consulting revenues in 2024 (BDU, 2024). Moreover, these three countries share a common business language and similar data protection regulations. Germany hosts the EU's largest pool of GenAI start-ups. It incorporates the second-highest share of AI-skilled workers among the OECD countries (McKinsey, 2023), making this region particularly fertile ground for examining how employees acquire GenAI usage and evaluation capabilities and translate them into IWB.

Surveying consultants in the context of digital transformation is also in line with similar established studies (e.g., Warner & Wäger, 2019). Consultants are critical in advising and implementing GenAI solutions across industries (Deloitte, 2024b). A recent report by the consultancy McKinsey (2024) highlights the significant adoption of AI among consulting firms, positioning them as leaders in deploying GenAI technologies. Accenture reported over three billion GenAI-driven bookings in recent years, showcasing consultants' extensive hands-on experience with this technology (Accenture, 2024). This substantial figure demonstrates that consultants are well-versed in the practical applications of GenAI, making them highly suitable for our research context.

We created the survey, including initial pre-tests between April and June 2024. The pre-tests were conducted with two professors, a doctoral student, and two target group consultants to ensure the survey was comprehensible. After the pre-tests and minor adjustments, the data collection phase finally occurred in July 2024. We contacted 1174 consultants via personalized mail containing a link to the online survey. In this way, we received 439 completed responses, which corresponds to a response rate of 37.4%. This response rate can be classified as very good and exceeds comparable research settings (e.g., Cimino et al., 2025). Table 2.1 shows the sample characteristics and demographic data of the respondents. To summarize, we have a well-balanced sample encompassing diverse experience levels across all industries.

Before starting with the data analysis, we tested for common method bias and non-response bias. We assessed common method bias by conducting Harman's single-factor test and defined the widely used value of < 50% acceptable (Harman, 1976; Podsakoff et al., 2003). Our data set showed a value of 25.39%, which indicates that common method bias is not a concern in our study. Furthermore, we compared data obtained at the beginning (first 33%) and at the end (final 33%) of the collected responses to conduct a non-response bias test. To identify significant differences, we performed a sample *t*-test on our constructs. We could not find any significant differences between early and late respondents, demonstrating that non-response bias is not a concern in this study.

Table 2.1 Sample characteristics.

Variable		No.	%
Gender	Female	184	41.9
	Male	253	57.6
	Non-binary	2	0.0
Education (highest level)	High School Diploma	17	3.8
	Bachelor’s Degree	71	16.1
	Master’s Degree/Diploma	315	71.8
	Doctorate	34	7.7
	Others	2	0.0
Work experience (in years)	Less than 1	16	0.4
	1–3	88	20.0
	3–5	71	16.2
	5–10	117	26.7
	More than 10	147	33.5
Company affiliation (in years)	Less than 1	100	22.8
	1–3	130	29.6
	3–5	62	14.1
	5–10	90	20.5
	More than 10	57	13.0
Career Level	Intern/Working Student	40	9.1
	Analyst	87	19.8
	Consultant	108	24.6
	Manager	91	20.7
	Senior Manager	57	13.0
	Principal	27	6.2
	Managing Director	29	6.6
Industry expertise (more than one answer possible)	Health and Public Sector	175	39.9
	Finance	188	42.8
	Communications and Media	118	26.9
	IT and Software	137	31.2
	Resources	109	24.8
	Consumer Goods	165	37.6
	Mobility and Automotive	188	42.8

Note: $N = 439$

Source: Own illustration

2.4.2. Variable measurements

All measurement items used in this study were extracted from well-researched and established scales (Harvey, 2022; Wang et al., 2023; De Jong & Den Hartog, 2010) and constructed using a 5-point Likert scale ranging from “Strongly Agree” to “Strongly Disagree.” Details of the constructs and their measurement items are summarized in table 2.7 in the Appendix.

To assess the construct of employees’ sensing capabilities, we used the scale of Harvey (2022)—an adapted form of Ancona and Caldwell (1992)—emphasizing the microfoundations of sensing capabilities as part of dynamic capabilities. This scale captures the environmental scanning activities of employees (i.e., on an individual level), focusing on their ability to observe technological trends, competitor activities, and market ideas. The measurement scale consists of four items.

To measure the constructs of GenAI usage capability and GenAI evaluation capability, we extracted the scale of the AI literacy framework of Wang et al. (2023). We modified it slightly by exchanging the original terminology “AI” with “GenAI.” GenAI usage capability is measured using three items, and GenAI evaluation capability is also measured using three items.

The construct of IWB was measured using the scale of De Jong and Den Hartog (2010), which is operationalized through four dimensions: idea exploration, idea generation, idea championing, and idea implementation. This scale consists of ten items that capture the full spectrum of employees’ IWB, from exploring new ideas to successfully implementing innovative solutions in their work. Although these dimensions reflect different aspects of the innovation process, De Jong and Den Hartog (2010) found only weak differences between the four dimensions, leading to a one-construct solution.

2.4.3. Model evaluation

We used structural equation modeling (SEM) and the statistical software SmartPLS 4 for the data analysis. Thereby, we oriented ourselves to the guidelines of Hair et al. (2022) and applied the partial least squares (PLS) path modeling method. PLS-SEM fits our research model as it is particularly well-suited for an explanation-prediction perspective (Hair & Sarstedt, 2021; Sarstedt & Danks, 2022), providing better predictive capabilities than covariance-based approaches (CB-SEM) (Hair et al., 2019).

Hair et al. (2019) highlight four key considerations when deciding whether PLS-SEM is appropriate: (1) data characteristics, (2) model characteristics, (3) model estimation, and (4) model evaluation. We systematically assessed our study against these four criteria and concluded that PLS-SEM is the most suitable technique. Compared with CB-SEM, which excels in confirmatory tests of compact theoretical models, PLS-SEM better serves our goal of jointly predicting and explaining the complex network of direct, indirect, and sequential effects in our research model (Hair et al., 2022). Moreover, PLS-SEM can estimate all relationships of all constructs in parallel (Becker et al., 2023). Therefore, we chose this technique to assess the relationships between sensing capabilities, GenAI capabilities, and individual-level IWB.

2.5. Results

2.5.1. Measurement model

To calculate the measurement model, we used the standard PLS-SEM algorithm. The quality criteria assessments are shown in Tables 2.2 and 2.3, including indicator reliability, composite reliability, convergent validity, and discriminant validity.

To assess the indicator reliability, we defined outer factor loading values of > 0.50 as acceptable. Although there is a general threshold value of > 0.708, loadings between 0.40 and 0.70 are also acceptable, and it is not always necessary to exclude items with factor loadings < 0.708 (Hair et al., 2022). For the constructs sensing capabilities, GenAI usage capability, and GenAI evaluation capability, all items exceeded the threshold value of 0.50. For the construct IWB, Item 1 (factor loading = 0.396) and Item 2 (factor loading = 0.451) were removed due to the low factor loading.

To assess internal consistency, we examined Cronbach's alpha and composite reliability. A Cronbach's alpha value of > 0.70 was defined as acceptable due to the exploratory nature of our research (Hair et al., 2014). In addition, a composite reliability value of > 0.70 was defined as sufficient (Hair et al., 2022). All constructs met those criteria. Therefore, we can state that internal consistency and composite reliability are not a concern in this study.

To assess convergent validity, we considered the average variance extracted (AVE) and defined acceptable values as AVE > 0.50 (Fornell & Larcker, 1981).

Table 2.2 Measurement model evaluation.

Construct and indicator	Factor loading	Composite reliability	AVE	Cronbach's α
Sensing capabilities		0.830	0.645	0.817
Sensing capabilities 1	0.749			
Sensing capabilities 2	0.848			
Sensing capabilities 3	0.765			
Sensing capabilities 4	0.847			
GenAI usage capability		0.734	0.631	0.703
GenAI usage capability 1	0.880			
GenAI usage capability 2^{R}	0.678			
GenAI usage capability 3	0.812			
GenAI evaluation capability		0.734	0.642	0.718
GenAI evaluation capability 1	0.705			
GenAI evaluation capability 2	0.847			
GenAI evaluation capability 3	0.843			
Innovative work behavior		0.846	0.475	0.840
Innovative work behavior 3	0.629			
Innovative work behavior 4	0.590			
Innovative work behavior 5	0.594			
Innovative work behavior 6	0.748			
Innovative work behavior 7	0.720			
Innovative work behavior 8	0.767			
Innovative work behavior 9	0.716			
Innovative work behavior 10	0.725			

Notes*:* $N = 439$; ^{R} = inversed item

Source: Own illustration

Furthermore, an AVE between 0.40 and 0.50 was also acceptable if Cronbach's alpha coefficient exceeded 0.60 (Fornell & Larcker, 1981). In Table 2.2 it is shown that the AVE for the constructs sensing capabilities, GenAI usage capability, and GenAI evaluation capability is clearly above the threshold value of 0.50. The AVE of 0.475 for the construct IWB is slightly below the threshold value 0.50. However, given that Cronbach's alpha value of 0.84 exceeds 0.60 and the composite reliability value is also more than sufficient (0.846), the marginally lower AVE value is unproblematic, and we can conclude that all of our constructs satisfy convergent validity (Fornell & Larcker, 1981). Treating AVE values that are marginally below 0.50 as acceptable in exploratory research is consistent with pertinent research in high-impact journals (e.g., Kumar et al., 2025; Lam et al., 2012; Tran & Thai, 2025).

To assess the discriminant validity of the constructs, we used the Heterotrait-Monotrait Ratio (HTMT) and defined a cut-off value of 0.85 (Henseler et al., 2015). Table 2.3 shows that all average correlations were below that cut-off value, supporting discriminant validity.

Table 2.3 Heterotrait-Monotrait Ratio.

	Constructs	1	2	3	4
1	GenAI evaluation capability				
2	GenAI usage capability	0.731			
3	IWB	0.421	0.290		
4	Sensing capabilities	0.292	0.256	0.493	

Source: Own illustration

2.5.2. Structural model

The next step was to assess the structural model. We first examined the variance inflation factors (VIF) to identify potential collinearity among the predictor constructs. As shown in Table 2.4, all VIF values remain below the critical threshold of 3, indicating that collinearity is not a concern in the structural model (Hair et al., 2019).

Table 2.4 Variance Inflation Factors.

	VIF
GenAI evaluation capability → IWB	1.411
GenAI usage capability → GenAI evaluation capability	1.042
GenAI usage capability → IWB	1.394
Sensing capabilities → GenAI evaluation capability	1.042
Sensing capabilities → GenAI usage capability	1.000
Sensing capabilities → IWB	1.065

Source: Own illustration

In the next step, we calculated the structural model utilizing the standard bootstrapping algorithm (5000 samples) and calculated R^2 values, path coefficients, and significance levels. We classified the significance levels as follows: extremely significant ($p < 0.001$), highly significant ($p < 0.01$), and significant ($p < 0.05$). Furthermore, we defined the sizes of the effects as strong ($\beta > 0.35$), moderate ($\beta > 0.15$), and weak ($\beta > 0.02$).

PLS path analysis of the research model showed that sensing capabilities explain 4.0% (0.040) of the variance of GenAI usage capability. Sensing capabilities and GenAI usage capability explain 29.1% (0.291) of the variance of GenAI evaluation capability together. Lastly, sensing capabilities, GenAI usage capability, and GenAI evaluation capability explain 23.7% (0.237) of the variance in IWB. Table 2.5 shows an overview of the hypothesis test results of structural modeling.

Table 2.5 Hypothesis test results.

Hypothesis	**β**	***p***	***t***	**Result**
H1. Sensing capabilities → GenAI usage capability	0.201	< 0.001	4.192	Supported
H2. Sensing capabilities → GenAI evaluation capability	0.127	0.003	2.985	Supported
H3. Sensing capabilities → IWB	0.356	< 0.001	7.668	Supported
H4. GenAI usage capability → IWB	0.028	0.566	0.574	Not Supported
H5. GenAI evaluation capability → IWB	0.242	< 0.001	5.039	Supported
H6. GenAI usage capability → GenAI evaluation capability	0.499	< 0.001	12.712	Supported

Source: Own illustration

Hypothesis 1 stated that employees' sensing capabilities promote their GenAI usage capability. Our data analysis supports this hypothesis, as sensing capabilities have an extremely significant, moderate positive effect on GenAI usage capability ($\beta = 0.201$, $p < 0.001$).

Hypothesis 2 predicted that employees' sensing capabilities are positively related to their GenAI evaluation capability. The analysis shows that Hypothesis 2 can be accepted due to a highly significant, weak positive effect of sensing capabilities on GenAI evaluation capability ($\beta = 0.127$, $p = 0.003$).

Hypothesis 3 states that employees' sensing capabilities promote their IWB. This hypothesis can be accepted due to the extremely significant, strong positive effect of sensing capabilities on IWB ($\beta = 0.356$, $p < 0.001$).

Hypothesis 4 proposed a positive influence of employees' GenAI usage capability on their IWB. Although the coefficient is positive, this hypothesis is rejected due to statistical insignificance ($\beta = 0.028$, $p = 0.566$).

Hypothesis 5 predicted that employees' GenAI evaluation capability promotes their IWB. This hypothesis can be accepted due to an extremely significant, moderate positive effect of GenAI evaluation capability on IWB ($\beta = 0.242$, $p < 0.001$).

Hypothesis 6 posits that employees' GenAI usage capability promotes their GenAI evaluation capability. The analysis supports this hypothesis due to the extremely significant and strong, positive effect of GenAI usage capability on GenAI evaluation capability (β = 0.499, p < 0.001). All direct effects are also illustrated in Figure 2.3.

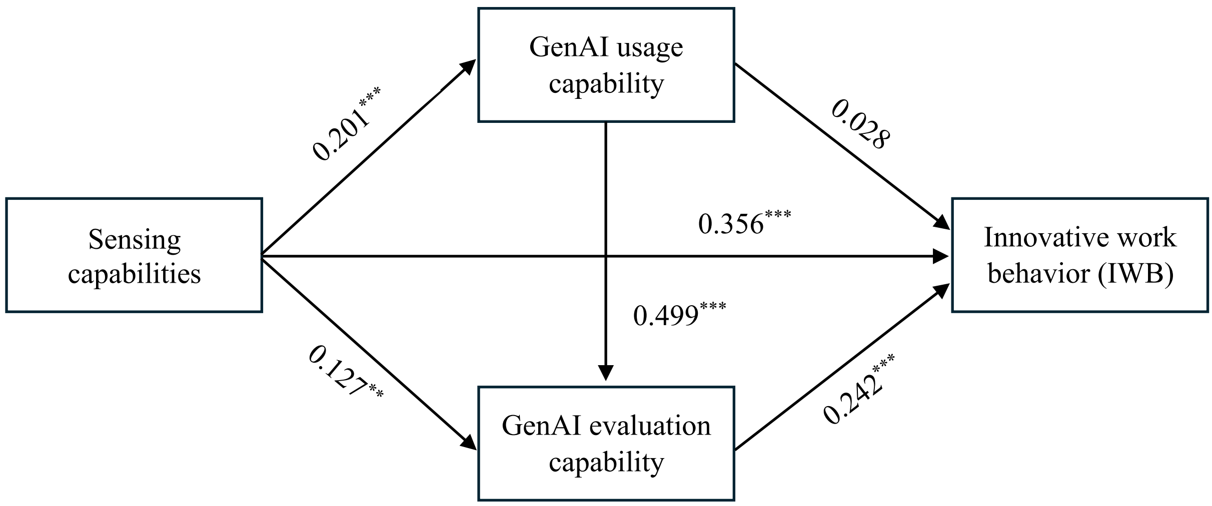


Figure 2.3 Research model with path results (**p < 0.01, ***p < 0.001).

Source: Own illustration

2.5.3. Mediation effects

The analysis also reveals several significant indirect effects within the model, which are also illustrated in Table 2.6. First, the path from sensing capabilities → GenAI usage capability → GenAI evaluation capability demonstrates an extremely significant indirect effect (β = 0.10, p < 0.001). This finding indicates that GenAI usage capability is a significant mediator between sensing capabilities and GenAI evaluation capability.

Further, the indirect effect from GenAI usage capability → GenAI evaluation capability → IWB is also extremely significant and positive (β = 0.121, p < 0.001), highlighting the role of GenAI evaluation capability in mediating the relationship between GenAI usage capability and IWB.

However, the path from sensing capabilities → GenAI usage capability → IWB shows a non-significant indirect effect (β = 0.006, p = 0.582). This nonfinding suggests that while sensing capabilities may influence GenAI usage capability, there is no sufficient relationship between GenAI usage capability and IWB.

In contrast, the indirect effect of sensing capabilities → GenAI evaluation capability → IWB is positive and highly significant (β = 0.031, *p* = 0.011). This finding implies that the capability to evaluate GenAI mediates the relationship between sensing capabilities and IWB.

Finally, the complete mediation path (sensing capabilities → GenAI usage capability → GenAI evaluation capability → IWB) is positive and significant (β = 0.024, *p* = 0.005), indicating that this complete mediation chain has a substantial indirect effect on IWB. Thus, the results demonstrate that employees' sensing capabilities drive IWB through improved GenAI usage capability and subsequent improved GenAI evaluation capability.

Table 2.6 Indirect effects.

Indirect effects	***β***	***p***	***t***
Sensing capabilities → GenAI usage capability → GenAI evaluation capability	0.100	< 0.001	3.867
GenAI usage capability → GenAI evaluation capability→ IWB	0.121	< 0.001	4.474
Sensing capabilities → GenAI usage capability → IWB	0.006	0.582	0.550
Sensing capabilities → GenAI evaluation capability → IWB	0.031	0.011	2.534
Sensing capabilities → GenAI usage capability → GenAI evaluation capability → IWB	0.024	0.005	2.827

Source: Own illustration

2.6. Discussion

Considering the widely accepted view that innovation is crucial for organizational success and the recently observed discrepancy between innovation prioritization and readiness (Manly et al., 2024), the question arises of how organizations can promote their innovativeness. This study focuses on employees' IWB, a key microfoundation of organizational-level innovation (De Jong & Den Hartog, 2010; Scott & Bruce, 1994; Shanker et al., 2017).

Specifically, we investigate the antecedents of employees' IWB. We address a research gap regarding how GenAI technologies influence employees' IWB by examining two distinct capabilities—GenAI usage and evaluation capabilities—based on the AI literacy framework by Wang et al. (2023). Building on the dynamic capabilities view (Teece, 2007), we further introduce employees' sensing capabilities as foundational antecedents to both GenAI capabilities and IWB. We conducted a PLS-SEM analysis using a large-scale empirical sample of 439 business consultants to test our model and hypotheses.

The findings reveal that employees' sensing capabilities enhance both GenAI capabilities—usage and evaluation (H1 and H2)—and directly foster their IWB (H3). Further, we found that the employees' capability to use GenAI does not enhance their IWB (H4), but the capability to evaluate GenAI does (H5). Finally, we found that employees' capability to use GenAI enhances their capability to evaluate GenAI (H6).

The most unexpected result is our null finding for H4. This finding might indicate that operational proficiency in GenAI is, by itself, insufficient to stimulate employees' IWB. Recent studies allow us to suggest why. Lee et al. (2025) report that when knowledge workers feel "confident" merely using GenAI, their critical-thinking effort drops and ideas converge on conventional solutions, an effect they refer to as mechanized convergence. Complementing this, large-scale experiments show that individuals with low (Gen)AI literacy are actually more receptive to (Gen)AI because they imbue the technology with an aura of "magic," which in turn suppresses reflective scrutiny (Tully et al., 2025). In other words, basic usage skills can lull employees into accepting the model's first plausible answer. In contrast, the evaluation dimension, which was conceived in the recent scale validation by Liu et al. (2025) as the peak of GenAI competence, provides users with the cognitive tools to recognize superficiality, iteratively provide new prompts, and integrate domain knowledge. Our data, therefore, suggest that without this higher-order evaluative layer, GenAI usage capability may plateau—or even restrain—true innovation.

In addition, our findings reveal significant indirect effects that highlight the pathways through which employees' sensing capabilities enhance IWB. Specifically, we demonstrated that employees' sensing capabilities positively influence both GenAI capabilities—usage and evaluation—with GenAI evaluation capability subsequently driving IWB. This indirect effect pathway highlights that sensing capabilities facilitate an employee's evaluative engagement with GenAI, thereby serving as an essential antecedent to leveraging GenAI's full potential in fostering IWB. Additionally, while employees' GenAI usage capability positively influences the GenAI evaluation capability, it does not directly lead to IWB. This nuanced result suggests that the capability to "simply" use and apply GenAI tools is insufficient to drive IWB; rather, the critical evaluation—as a higher-order thinking skill—of GenAI outputs contributes to IWB.

Moreover, the complete mediation chain (sensing capabilities → GenAI usage capability→ GenAI evaluation capability → IWB) demonstrates a statistically significant effect, underscoring the interconnected nature of these constructs. This pathway suggests the critical role of employees' capability to use and evaluate GenAI as mediators that convert sensing capabilities into individual-level IWB. However, the indirect effect associated with the complete mediation chain is comparatively small (β = 0.024). Although this coefficient attains statistical significance, its magnitude suggests a modest contribution to the explained variance in IWB, thereby limiting its independent managerial relevance. A comparison with the other indirect paths reinforces this interpretation: the GenAI usage capability → GenAI evaluation capability → IWB pathway is considerably stronger (β = 0.121), the sensing capabilities → GenAI evaluation capability → IWB link is also stronger (β = 0.031), and the direct sensing capabilities → IWB effect remains substantially greater (β = 0.356). Consequently, organizations should regard GenAI usage capability primarily as a preparatory stage that facilitates the development of GenAI evaluation capability, while prioritizing resource allocations toward enhancing employees' sensing capabilities and, above all, their capability to evaluate GenAI outputs, since these elements yield the most pronounced gains in IWB.

2.6.1. Theoretical contributions

Grounded in a concise capability architecture, we link individual sensing capabilities, drawn from the dynamic capabilities framework, with GenAI usage and evaluation capabilities, derived from the AI-literacy literature, to explain how employees transform emerging digital tools into IWB. Our study makes several valuable contributions to the literature.

First, we contribute to IWB literature (e.g., Volery & Tarabashkina, 2021; De Jong & Den Hartog, 2010; Scott & Bruce, 1994; Kör et al., 2021). Our results demonstrate that employees' sensing capabilities promote IWB. The capability of employees to use GenAI does not facilitate their individual-level IWB, but the GenAI evaluation capability does. Therefore, our study complements previous studies regarding the antecedents of IWB, including servant leadership (Gelaidan et al., 2024), positive mood (Madrid et al., 2014), cultural intelligence (Afsar et al., 2021), or employee creativity (Volery & Tarabashkina, 2021).

While prior research has predominantly focused on organizational antecedents of IWB (Volery & Tarabashkina, 2021), our study applies a dynamic, cognitively grounded capability perspective, addressing so far highly understudied antecedents: employees' sensing capabilities and their capabilities to use and evaluate GenAI. By distinguishing between different GenAI-related capabilities and highlighting the foundational role of sensing capabilities, we provide a more nuanced understanding of how employees translate technological potential into IWB.

Thus, we answer recent calls for empirically studying individual-level dynamic capabilities in the context of GenAI (Heubeck & Held, 2025).

Second, we contribute to the emerging literature on GenAI and its creative potential in the broader innovation management context (e.g., Chiarello et al., 2024; Cillo & Rubera, 2024; Kanbach et al., 2024; Roberts & Candi, 2024; Sedkaoui & Benaichouba, 2024; Singh et al., 2024). While prior studies have highlighted the transformative potential of GenAI for creativity and innovation, recent reviews emphasize that empirical research in this domain remains fragmented (Holzner et al., 2025).

Against this backdrop, our study adopts a capability perspective that explores the antecedents, mechanisms, and outcomes of two distinct but interrelated GenAI capabilities of employees in the innovation context: GenAI usage capability and GenAI evaluation capability. In line with previous studies, we frame GenAI and its potential benefits as a result of a human-GenAI co-creation process (e.g., Boussioux et al., 2024; Grange et al., 2025). Our study and its capability perspective complement previous studies by highlighting the central role of human capabilities in realizing the creative potential of GenAI technologies. We examine how employees' sensing capabilities serve as cognitive antecedents that enable the development of these GenAI capabilities and how, in turn, these capabilities shape IWB. We also explore the mechanisms between GenAI usage and evaluation capabilities.

This approach complements existing studies that typically conceptualize GenAI as a single, undifferentiated construct (e.g., Cimino et al., 2025; Rana et al., 2024; Singh et al., 2024). Finally, our study extends a growing body of research applying the dynamic capabilities lens to GenAI (e.g., AL-Khatib & Ramayah, 2024; Shore et al., 2024) by offering a fine-grained microfoundational view of how individual-level capabilities can be developed and mobilized to unlock GenAI's innovative potential in everyday work.

2.6.2. Practical contributions

Our study contains essential practical implications for companies and managers aiming to enhance the IWB of their employees by leveraging employees' dynamic sensing capabilities and GenAI capabilities. While we emphasize throughout our study that our findings should be interpreted in context, given that the data were collected in Germany, Austria, and Switzerland, we argue that the following practical implications are nonetheless transferable to other countries with a similar level of technological maturity.

Our study showed that employees' sensing capabilities (i.e., the ability to scan the environment and collect and filter new information) enhance IWB (i.e., make employees more innovative). In addition, employees' sensing capabilities facilitate employees' GenAI usage and evaluation capabilities of GenAI. Therefore, companies should devote considerable resources to increasing their employees' sensing capabilities. Concrete measures include, for example, regularly sending employees to conferences, seminars, and trade shows (Khan et al., 2020), where they can observe new trends, exchange knowledge, and build professional networks. Another instrument is the effective monitoring of competitor activities like changes in product offerings or prices (Helfat & Raubitschek, 2018). Complementing these initiatives, firms could establish weekly "tech-radar" sessions in which cross-functional teams review recent patent filings, start-up funding rounds, and specialist blogs, assessing their relevance for ongoing projects; an AI-powered monitoring platform that curates weak signals into personalized newsfeeds would further embed trend sensing into employees' daily routines.

Furthermore, our study showed that employees' GenAI usage capability does not affect their IWB, while employees' capability to evaluate GenAI outputs critically enhances their IWB. Against the backdrop that GenAI is often framed through a human-GenAI co-creation process (e.g., Boussioux et al., 2024; Grange et al., 2025), this perspective implies that the output of GenAI is dependent on the capabilities of the employee interacting with the technology. Thus, companies should focus primarily on increasing employees' evaluation skills concerning GenAI outcomes to leverage GenAI effectively. Effective ways of achieving this are creating suitable training formats and upskilling initiatives, highlighting the strengths and weaknesses of GenAI to understand its underlying functioning (Pinski et al., 2023). For example, firms could offer scenario-based micro-workshops in which employees diagnose hallucinations and bias in GenAI outputs and discuss the ethical trade-offs of deploying such content in client work. In parallel, organizations might develop a living "prompt-engineering handbook" that pairs effective prompt templates with evaluation checklists, ensuring that users move beyond basic tool operation toward rigorous, critical appraisal of GenAI suggestions.

Finally, our study shows that GenAI is generally a complex and multi-layered construct. We demonstrate this by differentiating between employees' GenAI usage capability and GenAI evaluation capability. Through this nuanced approach, we create an awareness for managers and companies to consider that the realized potential of GenAI is not certain and that the "simple" capability to apply and use the technology is not sufficient. The value of GenAI for individual-level IWB is unlocked through employees' capability to critically evaluate the output, highlighting the crucial role that humans still play.

2.6.3. Limitations and future research

As with any other study, this study has several limitations that open avenues for future research. First, the cross-sectional nature of our data limits the ability to make strong causal inferences. Although we developed our hypotheses based on robust theoretical foundations and tested them using PLS-SEM, future studies could employ longitudinal designs or experimental methods.

Second, our data are based on self-reported measures, which may be subject to social desirability and common method bias. Although we conducted Harman's single-factor test and took procedural precautions to mitigate such biases, self-report data cannot fully capture the richness and behavioral nuance of how employees interact with GenAI in real-world contexts. Future research could triangulate survey data with behavioral or usage data (e.g., log files from GenAI systems) or adopt mixed-method designs to enrich the findings.

Third, while consultants represent an ideal population for studying GenAI in high-paced, dynamic, and innovative settings, the generalizability of our findings to other industries or occupational groups may be limited. Consultants typically operate in project-based structures with high digital affinity, which may not reflect the broader workforce. These contextual levers amplify both the development of GenAI capabilities and the translation of those capabilities into IWB. The pattern may diverge in domains with stricter regulatory oversight or lower digital intensity. In healthcare, for instance, stringent data-protection rules could reduce GenAI usage capability yet increase the salience of GenAI evaluation capability as clinicians must scrutinize GenAI outputs for liability reasons. In public administration, limited autonomy and bureaucratic procedures might dampen the entire capability–IWB chain, whereas in education, moderate autonomy but high ethical scrutiny could shift emphasis toward GenAI evaluation skills. As Deloitte's (2024a) cross-industry scan of innovative GenAI use cases underscores, the innovation potential of GenAI varies strongly across industries. Future studies could replicate our model in other professional contexts (e.g., manufacturing, public sector, or healthcare) to test the boundary conditions of our findings.

Fourth, because our sample comes from Germany, Austria, and Switzerland—countries embedded in a strong European regulatory framework such as general data protection regulations—employees' GenAI perceptions are likely filtered through strict data privacy and ethical evaluation requirements. Future research could investigate how varying levels of AI regulation impact the relationship between GenAI capabilities and innovation, a topic of growing importance for international business (e.g., Wang & Zhang, 2025b).

Fifth, although we differentiated GenAI capabilities into usage and evaluation dimensions based on a validated scale, GenAI remains an evolving phenomenon with diverse application contexts. Future research should explore additional facets of GenAI-related competencies—such as prompt engineering proficiency, ethical awareness, or collaboration fluency in human-AI teams—and examine their interplay with innovation-related outcomes.

Finally, our study focuses on individual-level sensing capabilities as antecedents of GenAI capabilities and IWB. In line with the original scale of Harvey (2022) and broader dynamic capabilities literature (e.g., Teece, 2007), we conceptualize these sensing capabilities as broad and general higher-order capabilities. Future research could extend that view and examine how GenAI can support individuals with their sensing capabilities (e.g., digital AI-supported dashboards to recognize new technological trends).

2.7. Appendix

Table 2.7 Measurement scales.

Construct	Item
Sensing capabilities	S1: I look for what competing firms are doing.
	S2: I scan the environment for market ideas/expertise.
	S3: I collect technical information/ideas from individuals outside my firm.
	S4: I scan the environment for technical ideas/expertise.
GenAI usage capability	U1: I can skillfully use GenAI applications to help me with my daily work.
	U2: It is usually hard for me to learn to use a new GenAI application.[R]
	U3: I can use GenAI applications to improve my work efficiency.
GenAI evaluation capability	E1: I can evaluate the capabilities and limitations of a GenAI application after using it for a while.
	E2: I can choose a proper solution from various solutions provided by GenAI.
	E3: I can choose the most appropriate GenAI application from a variety for a particular task.
Innovative work behavior	I1: I pay attention to issues that are not part of my daily work.*
	I2: I wonder how things can be improved.*
	I3: I search out new working methods, techniques or instruments.
	I4: I generate original solutions for problems.
	I5: I find new approaches to execute tasks.
	I6: I make important organizational members enthusiastic for innovative ideas.
	I7: I attempt to convince people to support an innovative idea.
	I8: I systematically introduce innovative ideas into work practices.
	I9: I contribute to the implementation of new ideas.
	I10: I put effort in the development of new things.

[R] = inversed scale; * = Removed due to low factor loading

Source: Own illustration

2.8. References

Accenture. (10/2024). Accenture and NVIDIA lead enterprises into era of AI. https://newsroom.accenture.com/news/2024/accenture-and-nvidia-lead-enterprises-into-era-of-ai (last accessed 19 June 2025)

Adner, R., & Helfat, C. E. (2003). Corporate effects and dynamic managerial capabilities. *Strategic Management Journal*, 24 (10), 1011–1025. https://doi.org/10.1002/smj.331

Afsar, B., Al-Ghazali, B. M., Cheema, S., & Javed, F. (2021). Cultural intelligence and innovative work behavior: the role of work engagement and interpersonal trust. *European Journal of Innovation Management*, 24 (4), 1082–1109. https://doi.org/10.1108/EJIM-01-2020-0008

Agarwal, R., & Helfat, C. E. (2009). Strategic renewal of organizations. *Organization Science*, 20 (2), 281–293. https://doi.org/10.1287/orsc.1090.0423

Akter, S., Hossain, M. A., Sajib, S., Sultana, S., Rahman, M., Vrontis, D., & McCarthy, G. (2023). A framework for AI-powered service innovation capability: Review and agenda for future research. *Technovation*, 125, 102768. https://doi.org/10.1016/j.technovation.2023.102768

AlEssa, H. S., & Durugbo, C. M. (2022). Systematic review of innovative work behavior concepts and contributions. *Management Review Quarterly*, 72 (4), 1171–1208. https://doi.org/10.1007/s11301-021-00224-x

Alshanty, A. M., & Emeagwali, O. L. (2019). Market-sensing capability, knowledge creation and innovation: The moderating role of entrepreneurial-orientation. *Journal of Innovation & Knowledge*, 4 (3), 171–178. https://doi.org/10.1016/j.jik.2019.02.002

AL-khatib, A. w., & Ramayah, T. (2024). Artificial intelligence ‐ based dynamic capabilities and circular supply chain: Analyzing the potential indirect effect of frugal innovation in retailing firms. *Business Strategy and the Environment*, 34 (1), 830–848 https://doi.org/10.1002/bse.4018

Amabile, T. M. (1988). A model of creativity and innovation in organizations. Research in organizational behavior. *Research in Organizational Behavior,*, *10*.

Ancona DG & Caldwell DF (1992) Bridging the boundary: External activity and performance in organizational teams. *Administrative Science Quarterly* 37 (4), 634–665.

Anser, M. K., Yousaf, Z., Khan, A., & Usman, M. (2021). Towards innovative work behavior through knowledge management infrastructure capabilities: Mediating role of functional flexibility and knowledge sharing. *European Journal of Innovation Management*, 24 (2), 461–480. https://doi.org/10.1108/EJIM-09-2019-0250

Banh, L., & Strobel, G. (2023). Generative artificial intelligence. *Electronic Markets*, 33 (63). https://doi.org/10.1007/s12525-023-00680-1

BDU (2024) Facts & figures zum consultingmarkt 2024 https://www.bdu.de/media/355573/facts-figures-vorjahr.pdf (last accessed 2 August 2025)

Becker, J.-M., Cheah, J.-H., Gholamzade, R., Ringle, C. M, & Sarstedt, M. (2023). PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management*, 35 (1), 321–346. https://doi.org/10.1108/IJCHM-04-2022-0474

Bilgram, V., & Laarmann, F. (2023). Accelerating innovation with generative AI: AI-augmented digital prototyping and innovation methods. *IEEE Engineering Management Review*, 51 (2), 18–25. https://doi.org/10.1109/EMR.2023.3272799

Birkinshaw, J., Hamel, G., & Mol, M. J. (2008). Management innovation. *Academy of management Review*, 33 (4), 825–845. https://doi.org/10.5465/amr.2008.34421969

Bos-Nehles, A., Renkema, M., & Janssen, M. (2017). HRM and innovative work behaviour: A systematic literature review. *Personnel review*, 46 (7), 1228–1253. https://doi.org/10.1108/PR-09-2016-0257

Boussioux, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem-solving. *Organization Science*, 35 (5), 1589–1607. https://doi.org/10.1287/orsc.2023.18430

Chen, Z., & Chan, J. (2024). Large language model in creative work: The role of collaboration modality and user expertise. *Management Science*, 70 (12), 9101–9117. https://doi.org/10.1287/mnsc.2023.03014

Chiarello, F., Giordano, V., Spada, I., Barandoni, S., & Fantoni, G. (2024). Future applications of generative large language models: A data-driven case study on ChatGPT. *Technovation*, 133, 103002. https://doi.org/10.1016/j.technovation.2024.103002

Chu, W., Baxter, D., & Liu, Y. (2025). Exploring the impacts of generative AI on artistic innovation routines. *Technovation*, 143, 103209. https://doi.org/10.1016/j.technovation.2025.103209

Cillo, P., & Rubera, G. (2024). Generative AI in innovation and marketing processes: A roadmap of research opportunities. *Journal of the Academy of Marketing Science*. Advance online publication. https://doi.org/10.1007/s11747-024-01044-7

Cimino, A., Felicetti, A. M., Corvello, V., Ndou, V., & Longo, F. (2025). Generative artificial intelligence (AI) tools in innovation management: a study on the appropriation of ChatGPT by innovation managers. *Management Decision.* 63 (10), 3431–3453 https://doi.org/10.1108/MD-10-2023-1968

Day, G. S., & Schoemaker, P. J. (2016). Adapting to fast-changing markets and technologies. *California Management Review*, 58 (4), 59–77. https://doi.org/10.1525/cmr.2016.58.4.59

De Jong, J., & Den Hartog, D. (2007). How leaders influence employees' innovative behaviour. *European Journal of Innovation Management*, 10 (1), 41–64. https://doi.org/10.1108/14601060710720546

De Jong, J., & Den Hartog, D. (2010). Measuring innovative work behaviour. *Creativity and Innovation Management*, 19 (1), 23–36. https://doi.org/10.1111/j.1467-8691.2010.00547.x

Deloitte (2024a). Generative AI and the future of work https://www.deloitte.com/global/en/services/consulting/research/generative-ai-and-the-future-of-work.html (last accessed 31 July 2025)

Deloitte. (2024b). Now decides next: Moving from potential to performance. https://www2.deloitte.com/us/en/pages/consulting/articles/state-of-generative-ai-in-enterprise.html (last accessed 19 June 2025)

Dong, A., Garbuio, M., & Lovallo, D. (2016). Generative sensing: A design perspective on the microfoundations of sensing capabilities. *California Management Review*, 58 (4), 97–117. https://doi.org/10.1525/cmr.2016.58.4.97

Ellström, D., Holtström, J., Berg E., Josefsson C. (2022) Dynamic capabilities for digital transformation. J Strat Manag, 15(2), 272–286. https://doi.org/10.1108/JSMA-04-2021-0089

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, 21, 1105–1121.

Eisenreich, A., Just, J., Gimenez-Jimenez, D., & Füller, J. (2024). Revolution or inflated expectations? Exploring the impact of generative AI on ideation in a practical sustainability context. *Technovation*, 138, 103123. https://doi.org/10.1016/j.technovation.2024.103123

Farrukh, M., Meng, F., Raza, A., & Wu, Y. (2023). Innovative work behaviour: the what, where, who, how and when. *Personnel Review*, 52 (1), 74–98. https://doi.org/10.1108/PR-11-2020-0854

Felin, T., Foss, N. J., & Ployhart, R. E. (2015). The microfoundations movement in strategy and organization theory. *The Academy of Management Annals*, 9 (1), 575–632. https://doi.org/10.1080/19416520.2015.1007651

Ferreira, J., Coelho, A., & Moutinho, L. (2020). Dynamic capabilities, creativity and innovation capability and their impact on competitive advantage and firm performance: The moderating role of entrepreneurial orientation. *Technovation*, 92-93, 102061. https://doi.org/10.1016/j.technovation.2018.11.004

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, 66 (1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18 (1), 39. https://doi.org/10.2307/3151312

Foss, N. J., & Mazzelli, A. (2025). Bringing managers and management back into strategy: Interfaces and dynamic managerial capabilities. *Journal of Business Research*, 186, 114947. https://doi.org/10.1016/j.jbusres.2024.114947

Gartner. (2023). What's new in artificial intelligence from the 2023 Gartner Hype Cycle: Innovations in and around generative AI dominate and have transformative impact. https://www.gartner.com/en/articles/what-s-new-in-artificial-intelligence-from-the-2023-gartner-hype-cycle. (last accessed 19 June 2025)

Gelaidan, H. M., Al-Swidi, A. K., & Al-Hakimi, M. A. (2024). Servant and authentic leadership as drivers of innovative work behaviour: the moderating role of creative self-efficacy. *European Journal of Innovation Management*, 27 (6), 1938–1966. https://doi.org/10.1108/EJIM-07-2022-0382

Grange, C., Demazure, T., Ringeval, M., Bourdeau, S., & Martineau, C. (2025). The Human-GenAI Value Loop in Human-Centered Innovation: Beyond the Magical Narrative. *Information Systems Journal*. 0: 1–23 https://doi.org/10.1111/isj.12602

Haefner, N., Parida, V., Gassmann, O., & Wincent, J. (2023). Implementing and scaling artificial intelligence: A review, framework, and research agenda. *Technological Forecasting and Social Change*, 197, 122878. https://doi.org/10.1016/j.techfore.2023.122878

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th).

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (Third edition). SAGE.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31 (1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., & Sarstedt, M. (2021). Explanation plus prediction—The logical focus of project management research. *Project Management Journal*, 52 (4), 319–322. https://doi.org/10.1177/8756972821999945

Harman, H. H. (1976). Modern factor analysis*, 3rd* . University of Chicago press.

Harvey, J.-F. (2022). Microfoundations of sensing capabilities: From managerial cognition to team behavior. *Strategic Organization*, 147612702211429. https://doi.org/10.1177/14761270221142959

Held, P., Heubeck, T., & Meckl, R. (2025). Boosting SMEs' digital transformation: the role of dynamic capabilities in cultivating digital leadership and digital culture. *Review of Managerial Science*, 1–29. https://doi.org/10.1007/s11846-025-00919-5

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh H, Teece D.J., Winter. S. G. (2007). Dynamic capabilities: understanding strategic change in organizations. Blackwell Publishing, Oxford.

Helfat, C. E., & Martin, J. A. (2015). Dynamic managerial capabilities. *Journal of Management*, 41 (5), 1281–1312. https://doi.org/10.1177/0149206314561301

Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy*, 47 (8), 1391–1399. https://doi.org/10.1016/j.respol.2018.01.019

Helfat, C. E., & Winter, S. G. (2011). Untangling dynamic and operational capabilities: Strategy for the (n)ever‐changing world. *Strategic Management Journal*, 32 (11), 1243–1250. https://doi.org/10.1002/smj.955

Henseler, J., Ringle, C. M. & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43 (1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Heubeck, T. (2023). Managerial capabilities as facilitators of digital transformation? Dynamic managerial capabilities as antecedents to digital business model transformation and firm performance. *Digital Business*, 3 (1), 100053. https://doi.org/10.1016/j.digbus.2023.100053

Heubeck, T. (2024). Looking back to look forward: A systematic review of and research agenda for dynamic managerial capabilities. *Management Review Quarterly*, 74 (4), 2243–2287. https://doi.org/10.1007/s11301-023-00359-z

Heubeck, T., & Held, P. (2025). Management capabilities in the age of generative artificial intelligence (GenAI): A conceptual framework and future research directions. In J. Liebowitz (Ed.), *Achieving Digital Transformation through Analytics and AI* (pp. 131–153). World Scientific. https://doi.org/10.1142/13939

Hock-Doepgen, M., Heaton, S., Clauss, T., & Block, J. (2025). Identifying microfoundations of dynamic managerial capabilities for business model innovation. *Strategic Management Journal*, 46 (2), 470-501. https://doi.org/10.1002/smj.3663

Holzner, N., Maier, S., & Feuerriegel, S. (2025). Generative AI and Creativity: A Systematic Literature Review and Meta-Analysis. *arXiv preprint arXiv:2505.17241*. https://doi.org/10.48550/arXiv.2505.17241

Huhtala, H., & Parzefall, M.-R. (2007). A review of employee well-being and innovativeness: An opportunity for a mutual benefit. *Creativity and Innovation Management*, 16 (3), 299–306. https://doi.org/10.1111/j.1467-8691.2007.00442.x

Janssen, O. (2000). Job demands, perceptions of effort ‐ reward fairness and innovative work behaviour. *Journal of Occupational and Organizational Psychology*, 73 (3), 287–302. https://doi.org/10.1348/096317900167038

Janssen, O., & van Yperen, N. W. (2004). Employees' goal orientations, the quality of leader-member exchange, and the outcomes of job performance and job satisfaction. *Academy of Management Journal*, 47 (3), 368–384. https://doi.org/10.5465/20159587

Jia, N., Luo, X., Fang, Z., & Liao, C. (2024). When and how artificial intelligence augments employee creativity. *Academy of Management Journal*, 67 (1), 5–32. https://doi.org/10.5465/amj.2022.0426

Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2024). The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*, 18 (4), 1189–1220. https://doi.org/10.1007/s11846-023-00696-z

Khan, O., Daddi, T., & Iraldo, F. (2020). Microfoundations of dynamic capabilities: Insights from circular economy business cases. *Business Strategy and the Environment*, 29 (3), 1479–1493. https://doi.org/10.1002/bse.2447

Kör, B., Wakkee, I., & van der Sijde, P. (2021). How to promote managers' innovative behavior at work: Individual factors and perceptions. *Technovation*, 99, 102127. https://doi.org/10.1016/j.technovation.2020.102127

Kumar, A., Shankar, A., Hollebeek, L. D., Behl, A., & Lim, W. M. (2025). Generative artificial intelligence (GenAI) revolution: A deep dive into GenAI adoption. *Journal of Business Research*, 189, 115160. https://doi.org/10.1016/j.jbusres.2024.115160

Lam, L. W. (2012). Impact of competitiveness on salespeople's commitment and performance. *Journal of business research*, 65 (9), 1328–1334. https://doi.org/10.1016/j.jbusres.2011.10.026

Lee, H. P., Sarkar, A., Tankelevitch, L., Drosos, I., Rintel, S., Banks, R., & Wilson, N. (2025, April). The impact of generative AI on critical thinking: Self-reported reductions in cognitive effort and confidence effects from a survey of knowledge workers. In *Proceedings of the 2025 CHI conference on human factors in computing systems* (pp. 1-22).

Leiponen, A., & Helfat, C. E. (2010). Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic management journal*, 31 (2), 224–236. https://doi.org/10.1002/smj.807

Leso B. H., Cortimiglia M. N., Ghezzi A., Minatogawa V. (2024) Exploring digital transformation capability via a blended perspective of dynamic capabilities and digital maturity: a pattern matching approach. *Review of Managerial Science* 18 (4),1149–1187. https://doi.org/10.1007/s11846-023-00692-3

Lin, H.-F., Su, J.-Q., & Higgins, A. (2016). How dynamic capabilities affect adoption of management innovations. *Journal of Business Research*, 69 (2), 862–876. https://doi.org/10.1016/j.jbusres.2015.07.004

Liu, M., Zhang, L. J., & Zhang, D. (2025). Enhancing student GAI literacy in digital multimodal composing through development and validation of a scale. *Computers in Human Behavior*, 166, 108569. https://doi.org/10.1016/j.chb.2025.108569

Liu, V., & Chilton, L. B. (2022, April). Design guidelines for prompt engineering text-to-image generative models. In *Proceedings of the 2022 CHI conference on human factors in computing systems* (pp. 1–23). https://doi.org/10.1145/3491102.3501825

Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., & Neubig, G. (2023). Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ACM Computing Surveys*, 55 (9), 1–35. https://doi.org/10.1145/3560815

Madrid, H. P., Patterson, M. G., Birdi, K. S., Leiva, P. I., & Kausel, E. E. (2014). The role of weekly high-activated positive mood, context, and personality in innovative work behavior: A multilevel and interactional model. *Journal of Organizational Behavior*, 35 (2), 234–256. https://doi.org/10.1002/job.1867

Manly, J., Ringel M, MacDougall A., Harnoss J., Wolke-Perten J., Backler W., Gjerstad K., Kimura R., &Viner B.(2024) Most Innovative Companies 2024: Innovation Systems Need a Reboot. Boston Consulting Group. https://www.bcg.com/publications/2024/innovation-systems-need-a-reboot (last accessed 10 June 2025)

Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research*, 175, 114542. https://doi.org/10.1016/j.jbusres.2024.114542

Mariani, M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation*, 122, 102623. https://doi.org/10.1016/j.technovation.2022.102623

Mazzucchelli, A., Chierici, R., Abbate, T., & Fontana, S. (2019). Exploring the microfoundations of innovation capabilities. Evidence from a cross-border R&D partnership. *Technological Forecasting and Social Change*, 146, 242–252. https://doi.org/10.1016/j.techfore.2019.06.003

McKinsey (2023) Effects of GenAI on the German labor market https://www.mckinsey.de/news/presse/wie-genai-die-arbeitswelt-in-deutschland-veraendert (last accessed 2 August 2025)

McKinsey. (2024). The state of AI in early 2024: Gen AI adoption spikes and starts to generate value. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai (last accessed 19 June 2025)

McKinsey (2025): The state of AI: How organizations are rewiring to capture value. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai (last accessed 31 July 2025)

Minevich, M. (2024). GenAI revolution is reshaping the future of traditional consulting https://www.forbes.com/sites/markminevich/2024/04/26/gen-ai-revolution-is-reshaping-the-future-of-traditional-consulting/ (last accessed 31 July 2025)

Mueller, S. T., Hoffman, R. R., Clancey, W., Emrey, A., & Klein, G. (2019). *Explanation in Human-AI Systems: A Literature Meta-Review, Synopsis of Key Ideas and*

Publications, and Bibliography for Explainable AI. https://doi.org/10.48550/arXiv.1902.01876

Ng, A., Jordan, M. (2001). On discriminative vs. generative classifiers: A comparison of logistic regression and naive bayes. *Advances in Neural Information Processing Systems*, *14*.

Palmié, M., Rüegger, S., & Parida, V. (2023). Microfoundations in the strategic management of technology and innovation: Definitions, systematic literature review, integrative framework, and research agenda. *Journal of Business Research*, 154, 113351. https://doi.org/10.1016/j.jbusres.2022.113351

Piller, F. T., Srour, M., & Marion, T. J. (2024). Generative AI, innovation, and trust. *The Journal of Applied Behavioral Science*, 60 (4), 613–622. https://doi.org/10.1177/00218863241285033

Pinski, M., Adam, M., & Benlian, A. (2023). AI knowledge: improving AI delegation through human enablement. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1–17). ACM. https://doi.org/10.1145/3544548.3580794

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88 (5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rana, N. P., Pillai, R., Sivathanu, B., & Malik, N. (2024). Assessing the nexus of Generative AI adoption, ethical considerations and organizational performance. *Technovation*, *135*, 103064. https://doi.org/10.1016/j.technovation.2024.103064

Reuters. (2023). ChatGPT sets record for fastest-growing user base - analyst note. https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/ (last accessed 19 June 2025)

Ritala, P., Aaltonen, P., Ruokonen, M., & Nemeh, A. (2024). Developing industrial AI capabilities: An organisational learning perspective. *Technovation*, 138, 103120. https://doi.org/10.1016/j.technovation.2024.103120

Roberts, D. L., & Candi, M. (2024). Artificial intelligence and innovation management: Charting the evolving landscape. *Technovation*, 136, 103081. https://doi.org/10.1016/j.technovation.2024.103081

Salvato, C., & Vassolo, R. (2018). The sources of dynamism in dynamic capabilities. *Strategic Management Journal*, 39 (6), 1728–1752. https://doi.org/10.1002/smj.2703

Sarstedt, M., & Danks, N. P. (2022). Prediction in HRM research–A gap between rhetoric and reality. *Human Resource Management Journal*, 32 (2), 485–513. https://doi.org/10.1111/1748-8583.12400

Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. *The Academy of Management Annals*, 12 (1), 390–439. https://doi.org/10.5465/annals.2016.0014

Schoemaker, P. J. H., Heaton, S., & Teece, D. (2018). Innovation, dynamic capabilities, and leadership. *California Management Review*, 61 (1), 15–42. https://doi.org/10.1177/0008125618790246

Schryen, G., Marrone, M., & Yang, J. (2025). Exploring the scope of generative AI in literature review development. *Electronic Markets*, 35 (13). https://doi.org/10.1007/s12525-025-00754-2

Scott, S. G., & Bruce, R. A. (1994). Determinants of innovative behavior: A path model of individual innovation in the workplace. *Academy of Management Journal*, 37 (3), 580–607. https://doi.org/10.2307/256701

Sedkaoui, S., & Benaichouba, R. (2024). Generative AI as a transformative force for innovation: a review of opportunities, applications and challenges. *European Journal of Innovation Management.* Advance online publication. https://doi.org/10.1108/EJIM-02-2024-0129

Shanker, R., Bhanugopan, R., Van der Heijden, B. I., & Farrell, M. (2017). Organizational climate for innovation and organizational performance: The mediating effect of innovative work behavior. *Journal of vocational behavior*, 100, 67–77. https://doi.org/10.1016/j.jvb.2017.02.004

Shore, A., Tiwari, M., Tandon, P., & Foropon, C. (2024). Building entrepreneurial resilience during crisis using generative AI: An empirical study on SMEs. *Technovation*, 135, 103063. https://doi.org/10.1016/j.technovation.2024.103063

Singh, K., Chatterjee, S., & Mariani, M. (2024). Applications of generative AI and future organizational performance: The mediating role of explorative and exploitative innovation and the moderating role of ethical dilemmas and environmental dynamism. *Technovation*, 133, 103021. https://doi.org/10.1016/j.technovation.2024.103021

Strobl, A., Matzler, K., Nketia, B. A., & Veider, V. (2020). Individual innovation behavior and firm-level exploration and exploitation: how family firms make the most of their managers. Review of Managerial Science, 14 (4), 809–844. https://doi.org/10.1007/s11846-018-0309-9

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28 (13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J. (2014). The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. *Academy of Management Perspectives*, 28 (4), 328–352. https://doi.org/10.5465/amp.2013.0116

Teece, D. J., & Linden, G. (2017). Business models, value capture, and the digital enterprise. *Journal of Organization Design*, *6* (1). https://doi.org/10.1186/s41469-017-0018-x

Teece, D. J., Pisano, G., Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal* 18 (7), 509–533. http://www.jstor.org/stable/3088148

Teng, D., Ye, C., & Martinez, V. (2025). Gen-AI's effects on new value propositions in business model innovation: Evidence from information technology industry. *Technovation*, 143, 103191. https://doi.org/10.1016/j.technovation.2025.103191

Tran, M.-L., Thai, H.-C.V. (2025). Future-ready strategies: dynamic managerial capabilities, digitalization, and green product innovation in building firm resilience. *Business Ethics, the Environment & Responsibility* 0: *1*–24 https://doi.org/10.1111/beer.70007

Tully, S. M., Longoni, C., & Appel, G. (2025). Lower artificial intelligence literacy predicts greater AI receptivity. *Journal of Marketing*, 00222429251314491. https://doi.org/10.1177/00222429251314491

Volery, T., & Tarabashkina, L. (2021). The impact of organisational support, employee creativity and work centrality on innovative work behaviour. *Journal of Business Research*, 129, 295-303. https://doi.org/10.1016/j.jbusres.2021.02.049

Wang, B., Rau, P.-L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology*, 42 (9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

Wang, S., & Zhang, H. (2025a). Generative artificial intelligence and internationalization green innovation: Roles of supply chain innovations and AI regulation for SMEs. *Technology in Society*, 82, 102898. https://doi.org/10.1016/j.techsoc.2025.102898

Wang, S., & Zhang, H. (2025b). Promoting sustainable development goals through generative artificial intelligence in the digital supply chain: Insights from Chinese tourism SMEs. Sustainable Development, 33 (1), 1231-1248. https://doi.org/10.1002/sd.3152

Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52 (3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001

Widmann, A., & Mulder, R. H. (2018). Team learning behaviours and innovative work behaviour in work teams. *European Journal of Innovation Management*, 21 (3), 501–520. https://doi.org/10.1108/EJIM-12-2017-0194

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, 24 (10), 991–995. https://doi.org/10.1002/smj.318

Yin, M., Jiang, S., & Niu, X. (2024). Can AI really help? The double-edged sword effect of AI assistant on employees' innovation behavior. *Computers in Human Behavior*, 150, 107987. https://doi.org/10.1016/j.chb.2023.107987

Yuan, F., & Woodman, R. W. (2010). Innovative behavior in the workplace: The role of performance and image outcome expectations. *Academy of Management Journal*, 53 (2), 323–342. https://doi.org/10.5465/AMJ.2010.49388995

Zabel, C., O'Brien, D., & Natzel, J. (2023). Sensing the metaverse: The microfoundations of complementor firms' dynamic sensing capabilities in emerging-technology ecosystems. *Technological Forecasting and Social Change*, 192, 122562. https://doi.org/10.1016/j.techfore.2023.122562

Zhang, X., Yu, P., & Ma, L. (2025). How and when generative AI use affects employee incremental and radical creativity: an empirical study in China. *European Journal of Innovation Management*. https://doi.org/10.1108/EJIM-04-2024-0466

Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization Science*, 13 (3), 339–351. https://doi.org/10.1287/orsc.13.3.339.2780

3. Research Paper 2

Held, P., Heubeck, T., & Meckl, R. (2025). The influence of individuals' capability to use generative AI on their idea generation: The mediating role of cognitive information-processing styles *European Journal of Innovation Management*. 28 (10), 5376–5399 https://doi.org/10.1108/EJIM-06-2025-0711

Abstract

Purpose – This study investigates how individuals' capability to use generative artificial intelligence (GenAI) influences their idea generation and explores the cognitive mechanisms underlying this relationship. Drawing on cognitive experiential theory, which posits that individuals rely on two distinct and stable information processing styles (rational and experiential), this study examines how these styles mediate the link between GenAI usage capability and idea generation and all underlying relationships between these constructs.

Design/methodology/approach – This study employs a quantitative research design based on survey data from 399 business consultants located in Germany, Austria, and Switzerland at a leading global consultancy. Partial least squares structural equation modeling (PLS-SEM) is applied to test the hypothesized structural relationships.

Findings – The findings demonstrate that (1) individuals' capability to use GenAI enhances their idea generation; (2) individuals' capability to use GenAI influences both information processing styles; (3) rational information processing style enhances idea generation and not experiential information processing; (4) significant mediation effect of individuals' tendency to rely on the rational system that translates GenAI usage capability into idea generation.

Originality/value – This study enriches GenAI research in innovation management by identifying individuals' capability to use GenAI as a critical antecedent of idea generation. This capability perspective complements recent studies focusing on the extent, frequency, or purpose of GenAI usage and its influence on creative outputs.

Keywords

Innovation management; idea generation; generative AI; generative AI usage; AI capability; cognitive experiential theory

Statement Green Open Access

The following chapter contains an author accepted manuscript (AAM) version of the article:

Held, P., Heubeck, T., & Meckl, R. (2025). The influence of individuals' capability to use generative AI on their idea generation: The mediating role of cognitive information-processing styles *European Journal of Innovation Management*. 28 (10), 5376–5399 https://doi.org/10.1108/EJIM-06-2025-0711

3.1. Introduction

Generative artificial intelligence (GenAI) represents a disruptive innovation that offers enormous economic potential across various business functions within a company (e.g., Kanbach et al., 2024; Chen & Chan, 2024; Fosso Wamba et al., 2024). Unlike traditional AI, which primarily focuses on data analysis, pattern recognition, and predictions (Roberts & Candi, 2024), GenAI *generates* original and creative content (Banh & Strobel, 2023).

This *generative* ability has sparked renewed interest in using AI technologies as a tool for innovation (Piller et al., 2024), also illustrated through the significant research interest at the intersection of GenAI and innovation management (e.g., Chiarello et al., 2024; Cimino et al., 2025; Mariani & Dwivedi, 2024; Vitellaro et al., 2025; Sedkaoui & Benaichouba, 2024). Particularly, GenAI's impact on idea generation, a central aspect of organizational life (Vandenbosch et al., 2006), where novel ideas serve as "the lifeblood of successful innovations" (Berg, 2016, p. 433), has been extensively studied (e.g., Bouschery et al., 2023; Boussioux et al., 2024; Eisenreich et al., 2024; Meincke et al., 2024). Specifically, GenAI can facilitate idea generation by enabling users to explore extensive solution and problem spaces, drawing on vast and diverse knowledge bases and supporting the combination of existing knowledge elements to identify novel connections and insights (Bouschery et al., 2023; Boussioux et al., 2024).

Much of this research frames GenAI's role through human–GenAI collaboration (e.g., Bankins et al., 2024; Boussioux et al., 2024; Choudhary et al., 2023)—that is, on the individual level of, for example, employees or managers. This perspective emphasizes human intelligence and GenAI's joint creative potential. Yet, despite the growing body of research emphasizing human–GenAI collaboration, surprisingly little attention has been given to individuals' capability to use GenAI. GenAI usage capability, understood as "the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently" (Wang et al., 2022, p. 4), is likely a critical antecedent to realizing the potential benefits of human–GenAI collaboration. Thus, this capabilities view offers a valuable perspective within innovation management.

However, existing studies often conceptualize GenAI usage in terms of frequency, extent, or purpose (e.g., Zhang et al., 2025) or treat GenAI as a uniform intervention (e.g., Eisenreich et al., 2024; Meincke et al., 2024). These conceptualizations of GenAI usage neglect interindividual differences in users' capability to engage with GenAI technology. By assuming a homogeneous level of user competence, these studies overlook that the creative value derived from GenAI may depend on individuals' capability to use the technology. This is surprising given that interacting with GenAI systems inherently requires the formulation of structured input prompts—a process central to how generative models produce relevant and high-quality output (Banh & Strobel, 2023; Feuerriegel et al., 2024). To realize the innovation potential of human–GenAI collaboration, it is essential to understand whether and how individuals' capability to use GenAI influences their idea generation. To address this gap, we pose our first research question (RQ):

RQ 1. To what extent does an individual's capability to use GenAI foster their idea generation?

While individuals' capability to use GenAI may provide the foundation for generating ideas, idea generation is fundamentally a cognitive process (Paulus & Brown, 2007; Garbuio & Lin, 2021), originating in the mind of an individual (Amabile, 1983; Campbell, 1960). Building on this perspective, it is relevant not only to determine whether individuals have the capability to use GenAI but also to determine the cognitive mechanisms through which this capability translates into idea generation.

Epstein's cognitive experiential theory[12] is a suitable theoretical lens to investigate this mechanism (Epstein, 1973, 2003, 2014). Rooted in psychology, the cognitive experiential theory is a dual-process theory stating that humans process information (e.g., GenAI-generated output text) through two distinct cognitive systems: the *experiential system*—an intuitive, emotion-driven process relying on associative memory—and the *rational system*—a deliberate, analytical process guided by logic and reasoning (Epstein, 1973, 2010; Kahneman, 2011).

The relative influence of each system on a given behavior, like idea generation, is shaped by the individual (Epstein, 2014). In other words, individuals differ in their preference regarding their information processing mode (i.e., experiential or rational). While some individuals are more inclined toward the rational system, others rely more on the experiential system.

The experiential and rational information processing systems are crucial for idea generation, as they foster complementary cognitive operations that collectively enhance creativity (Baldacchino et al., 2023; Eling et al., 2015). The experiential system is vital for idea generation because it facilitates intuitive judgments and associative memory, enabling the spontaneous emergence of novel ideas (Bălău et al., 2019; Epstein, 2003). Conversely, the rational system is essential for idea generation as it enables problem structuring and deductive

[12] The theory was originally introduced by Epstein as cognitive experiential self-theory but was later shortened to cognitive experiential theory. Today, both terms are used interchangeably in research.

reasoning (Luoma & Martela, 2021; Marques et al., 2022), supporting the development of new ideas.

Including cognitive experience theory in our study context is valuable as it helps to understand which information processing system is the main driver for promoting idea generation. We, thus, formulate our second RQ:

RQ 2. To what extent does an individual's tendency to rely on experiential and rational information processing systems promote their idea generation?

Although information processing styles are generally regarded as relatively stable preferences, they are not entirely fixed (Epstein, 2003). Repeated engagement with external structures—such as GenAI tools—can modulate these preferences and become functionally integrated into cognitive processes (Reiser, 2004; Clark & Chalmers, 1998). Thus, individuals process information not in isolation but instead in close coupling with their environment (Hollan et al., 2000). We propose that as individuals develop GenAI usage capability, GenAI becomes an integral component of their approach to understanding problems and generating solutions, thereby shaping their tendency to rely on information processing styles. We pose our third RQ:

RQ 3. To what extent does an individual's capability to use GenAI influence their tendency to rely on experiential and rational information processing systems?

We use partial least squares structural equation model (PLS-SEM) analysis on a large-scale sample of 399 consultants from a leading global consultancy in the DACH region (Germany, Austria, Switzerland) to test our research model. We chose this sample because the consultants in our study already use GenAI in their daily work and operate across a wide range of industries, thereby covering a broad spectrum of application contexts and problem types relevant to GenAI-supported idea generation. As GenAI is a relatively new phenomenon, the consultants likely differ in their capability to use the technology.

Our study makes several significant theoretical contributions to existing innovation management literature studying GenAI (e.g., Cimino et al., 2025; Mariani & Dwivedi, 2024; Roberts & Candi, 2024; Vitellaro et al., 2025; Sedkaoui & Benaichouba, 2024). First, our findings demonstrate that individuals' capability to use GenAI promotes their idea generation. Therefore, we extend previous research results highlighting this technology's enormous potential for idea generation (e.g., Eisenreich et al., 2024; Meincke et al., 2024). We enrich the research field by highlighting a critical, yet previously overlooked, perspective on GenAI and its potential for idea generation: the individuals' capability to use the technology. Therefore, we complement studies investigating the frequency, extent, or purpose of GenAI usage for creative outcomes like idea generation (e.g., Zhang et al., 2025). This extension is essential as it underscores that the creative value derived from GenAI is not solely a function of the technology itself but critically depends on the human's capability to engage with it effectively. Our study also addresses an observation by Holzner et al. (2025), which shows that empirical research on GenAI and the potential for creative outcomes such as idea generation remains fragmented and has predominantly focused on academic settings, while business professionals are vastly underrepresented.

Second, our findings show relevant underlying cognitive mechanisms in the interaction of individuals' GenAI capability and idea generation. Specifically, by building on cognitive experiential theory, we demonstrate that (1) individuals' capability to use GenAI promotes tendencies to rely on both information processing styles; (2) only the tendency to rely on rational information processing promotes idea generation, but conversely not experiential information processing; and (3) the tendency to rely on rational processing mediates the GenAI usage capability–idea generation link. Our findings thus extend previous research on cognitive styles and idea generation (e.g., Baldacchino et al., 2023; Eling et al., 2015; Yeo et al., 2024). In contrast to earlier studies that emphasize the experiential system as particularly relevant for idea generation (e.g., Bălău et al., 2019), our research finds no support for this link in the context of GenAI. Instead, our results indicate the tendency to rely on rational information processing as the key mediator in the context of GenAI usage capability and idea generation.

3.2. Theoretical background

3.2.1. GenAI and individuals' GenAI usage capability

GenAI represents a powerful subcategory of AI (Schryen et al., 2025), with the introduction of applications such as ChatGPT, Dall-E, and Gemini driving the augmentation of human capabilities (Hermann & Puntoni, 2024). GenAI is defined as "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data" (Feuerriegel et al., 2024, p. 111). While GenAI may seem like a recent breakthrough, it is built on decades of research. The development of the technology dates back to the 1950s and 1960s with early statistical language models, which have since evolved through advancements in deep learning and neural networks (Susarla et al., 2023). The recent breakthrough in GenAI can be attributed to four key factors: (1) the massive scaling of computational power; (2) advancements in model architecture; (3) the ability to pre-train models on vast amounts of unlabeled data; and (4) refinements in training techniques (Brynjolfsson et al., 2023).

Within the domain of GenAI, Large Language Models (LLMs), exemplified by the rise of OpenAI's ChatGPT, are the most prominent class. LLMs serve as versatile tools that facilitate the execution of diverse linguistic tasks across a broad range of applications (Susarla et al., 2023; Hermann & Puntoni, 2024). These models are built on transformer architecture, which utilizes self-attention mechanisms to process text sequences, making it particularly effective for capturing long-range dependencies within language data (Vaswani et al., 2017). Generative pre-trained transformers (GPTs) are designed to generate original content by predicting the next word in a sequence based on the context provided (Vaswani et al., 2017). This predictive ability is made possible through extensive pretraining on vast, diverse datasets encompassing billions of words across multiple domains (Banh & Strobel, 2023; Brynjolfsson et al., 2023). Pretraining allows GPTs to internalize complex linguistic patterns, enabling them to generate text that is both syntactically coherent and semantically meaningful (Susarla et al., 2023).

GenAI's generative capabilities make it highly relevant for creative processes (e.g., Chen & Chan, 2024; Liu et al., 2023; Magni et al., 2024). GenAI's ability to produce novel outputs and adapt to diverse contexts positions it as a disruptive tool for unlocking new opportunities in areas such as idea generation (Bouschery et al., 2023; Piller et al., 2024).

A key feature of GPTs is their adaptability, especially through prompting. Prompting is a crucial mechanism in GenAI, enabling pre-trained models to adapt to new tasks with minimal or no additional training by using carefully crafted instructions provided by users to guide output generation (Liu et al., 2023). Building on this, the interaction between humans and GenAI is increasingly characterized by co-creative processes, in which user input through prompts shapes the generated outputs and thereby contributes to the model's performance (Feuerriegel et al., 2024).

GenAI models produce probabilistic rather than deterministic outputs, as they rely on probability distributions shaped by the underlying language model and the specific input prompts used (Liu et al., 2023). Thus, the same prompt can produce different yet equally valid results each time, while different prompts can also lead to the same outcome. This makes prompt formulation a trial-and-error process, where rephrasing and tweaking keywords help refine the final output (Banh & Strobel, 2023).

To capture the user-side variability in these interactions, we draw on the concept of GenAI usage capability, which we define as "the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently" (Wang et al., 2022, p. 4). This construct originates from the broader notion of AI literacy and reflects both the technical and cognitive skills required to interact effectively with GenAI. In other words, we argue that an effective GenAI outcome is not simply a product of the algorithm's capacity but hinges on the user's ability to guide, interpret, and refine the model's responses. GenAI does not think or decide—it responds to what the user provides. Much like a skilled interviewer elicits insightful answers by asking the right questions, it is the competent user who unlocks the creative potential of the model.

3.2.2. Idea generation

Idea generation, the initial step in the broader idea journey—which includes the phases of idea generation, elaboration, championing, and implementation—involves creating novel and useful ideas that form the foundation for further development and implementation (Perry-Smith & Mannucci, 2017). In this sense, ideas are "discrete, or enumerated, descriptions of solutions to a problem posed" (Kornish & Hutchison-Krupat, 2017, p. 634). This problem can be implicit or explicit (Mannucci & Perry-Smith, 2022). For instance, a marketing manager could persistently be interested in the competition's campaigns (i.e., implicit problem) or could design a campaign to enhance brand awareness (i.e., explicit problem). Combining and reorganizing information and existing concepts, idea generation can solve these problems (Amabile, 1983; Jong & Hartog, 2010).

At its core, idea generation is a cognitive process grounded in psychology (Paulus & Brown, 2007). In other words, idea generation occurs within the individual's mind (Amabile, 1983; Campbell, 1960). This underlines the critical role of the individual creator in the idea-generation phase (Mannucci & Perry-Smith, 2022). Although ideas can be generated in a team (e.g., Harvey, 2014; Mannucci, 2017), cognitive processes at the individual level play a fundamental role in the origin of ideas (Rietzschel et al., 2010).

However, individual idea generation benefits from social contexts facilitating collaboration and knowledge sharing (Amabile et al., 1996; Mannucci & Perry-Smith, 2022; Woodman et al., 1993). Empirical evidence further highlights that exposure to others' ideas can stimulate originality in idea generation (Wang et al., 2018). From a firm's perspective, there are several ways to foster idea generation actively and systematically. For example, firms can utilize formally planned activities, such as brainstorming, or informal activities, such as extra free time for employees, to ideate. Additionally, they can seek to close gaps in the existing innovation portfolio or generally foster idea generation through market scouting and technology (Gurtner & Reinhardt, 2016).

The relevance of idea generation and novel ideas for firms is widely accepted in the literature (e.g., Girotra et al., 2010; Gurtner & Reinhardt, 2016; Ng et al., 2022; Wang et al., 2024). Novel ideas are described as "the lifeblood of successful innovations" (Berg, 2016, p. 433) and as a central aspect of organizational life (Vandenbosch et al., 2006). Idea generation is considered essential for the innovation process, as it begins with an idea, and all subsequent phases and the ultimate success depend on the initial idea (Kornish & Ulrich, 2014; Toubia & Netzer, 2017). Further, idea generation is crucial for the designing and marketing of new products and marketing strategies (Toubia, 2006).

Therefore, we argue that idea generation is a critical driver of organizational success and represents a cognitive process in an individual's mind. Understanding whether and how individuals' GenAI usage capability can influence and enhance this process and uncovering the underlying mechanisms is valuable and will be further examined in the following sections.

3.2.3. Cognitive experiential theory

Cognitive experiential theory, first introduced by Epstein (1973), has significantly developed since its introduction (Epstein, 1994, 2003, 2014). Over time, numerous researchers have expanded and adapted this theory (e.g., Sloman, 1996; Strack & Deutsch, 2004). Generally, the cognitive experiential theory is often considered part of the broader family of dual-process theories (e.g., Kahneman, 2003), according to which humans possess two independent yet interactive cognitive systems for processing information: the experiential (intuitive) system and the rational (analytical) system (Epstein, 2003, 2014).

The experiential system, also known as "System 1," operates automatically, associatively, and affect-laden, often functioning beneath the threshold of conscious awareness (Epstein, 2010; Epstein et al., 1996; Kahneman, 2011). Evolutionary in origin, this system is shared with other species and is critical in enabling rapid, adaptive responses to environmental stimuli (Epstein, 1994). Driven by emotions, the experiential system learns effortlessly from experience and encodes these lessons automatically (Epstein, 2003). As a result, individuals often experience the outputs of this system as a sense of "just knowing" without a clearly identifiable rational basis (Kahneman, 2011; Kahneman & Klein, 2009). By quickly scanning memory for analogous past experiences, this system retrieves associated emotional cues to inform decision-making, relying on prior outcomes as a guide (Epstein, 2014).

In contrast, the rational system, "System 2," operates with deliberation, relying on logic and systematic reasoning to process information and guide decision-making (Epstein et al., 1996; Evans & Stanovich, 2013). Functioning as an inferential mechanism, it adheres to established rules of reasoning and evidence, reflecting its relatively recent emergence in evolutionary terms (Epstein, 2003). In its controlled and rule-governed nature, the rational system is characterized by deliberate monitoring and systematic analysis designed to address complex problems (Kahneman, 2003). This system operates more slowly and demands more cognitive resources (Epstein, 2010; Kahneman, 2011). Often described as a verbal reasoning system, it depends heavily on language and abstract symbols, such as words and numbers, to perform its functions (Epstein, 2014). Table 3.1 provides a comparative overview of the key attributes of the experiential and rational systems.

The experiential and rational systems have unique value and significance, and neither is inherently superior to the other (Epstein, 2014). Instead, research suggests that individuals capable of flexibly integrating both systems, depending on the situational demands, tend to excel in navigating complex decision environments (Bakken et al., 2024). The interaction of both systems and their balance derive optimal outcomes across diverse organizational contexts (Luoma & Martela, 2021). Operating in parallel, these systems interact bidirectionally, engaging in competitive, cooperative, or collaborative dynamics (Hodgkinson & Sadler-Smith, 2018). The relative influence of each system on a given behavior or decision is shaped by the individual and the specific situational context (Epstein, 2014). While some individuals are more inclined toward the rational system, others may rely more heavily on the experiential system. In addressing complex and analytical problems, the rational system plays a dominant role, whereas emotional responses are predominantly governed by the experiential system (Epstein, 2014).

A compelling example of a competitive situation involving the parallel execution of the two systems during information processing is as follows: Imagine a manager confronted with the challenging decision of implementing layoffs during financial hardship.

Table 3.1 Comparison of the attributes of experiential and rational information processing.

Experiential system	Rational system
Solves problems in living by what was automatically learned from experience	Solves problems by conscious reasoning
Nonverbal: Encodes information often in images	Verbal: Encodes information in abstract symbols, including words and numbers
Emotional	Affect free
Associative connections between stimuli, responses, and outcomes	Cause-and-effect relations among stimuli, responses, and outcomes
Behavior mediated by automatic representations of events and feelings	Behavior mediated by conscious appraisal of events
Holistic	Analytic
Effortless and minimally demanding cognitive resources	Effortful and demanding cognitive resources
Rapid processing: Oriented toward immediate action; impulsive	Slower processing and capable of long-delayed action
Self-evidently valid: Experiencing is believing	Requires validation by logic and evidence

Source: Adapted from Epstein (2014, p. 12)

The manager's rational system underscores the necessity of reducing the workforce to stabilize the company and secure its survival, drawing upon precise financial data to support this course of action. Simultaneously, the experiential system triggers empathy and concern for the well-being of employees and their families, resulting in a conflict between logical analysis and emotional response. This tension is often described as a struggle between "head and heart" (Lieberman, 2002).

From an innovation management perspective, cognitive experiential theory provides valuable implications for understanding human behavior in work-related contexts. For instance, intuition, a core aspect of the experiential system, has been found essential for fostering creativity, entrepreneurial thinking, and innovation, which are central to business success (Baldacchino et al., 2023). Intuitive processing allows leaders and employees to effectively draw on past experiences and implicit knowledge to navigate uncertainty and complexity across various organizational settings, including professional service contexts such as healthcare (Calabretta et al., 2017; Marques et al., 2022). The rational system, in contrast, empowers employees to adopt deliberate and systematic approaches to problem-solving and conflict resolution (Cerni et al., 2014). By integrating the logical structure of this system, businesses can strengthen decision-making processes, minimize errors, and better align actions with organizational goals (Armstrong et al., 2012; Cerni et al., 2014). While situational demands may activate either system, individuals differ in their dispositional tendency to rely more strongly on experiential or rational processing (Epstein et al., 1996).

3.3. Hypotheses development

In this section, we develop our research hypotheses, resulting in the research model depicted in Figure 3.1.

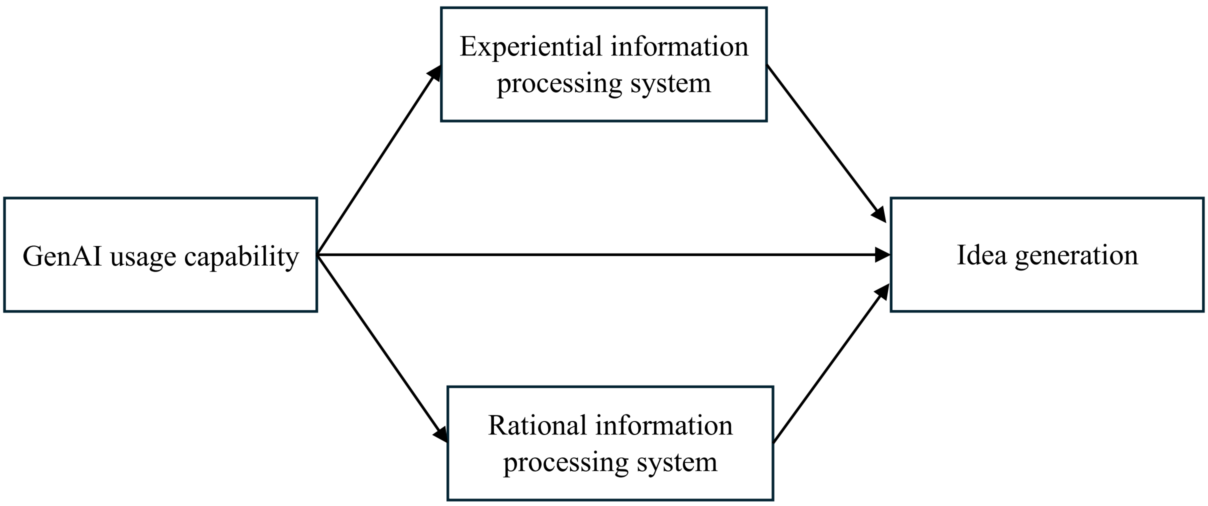


Figure 3.1 Research model
Source: Own illustration

We argue that an individual's capability to use GenAI fosters their idea generation. GenAI, guided by human interactions like prompt refinement, can enhance creative problem-solving by navigating larger problem spaces and expanding the range and quality of potential solutions (Bouschery et al., 2023; Boussioux et al., 2024). Moreover, GenAI supports the generation of novel ideas by identifying connections between seemingly unrelated pieces of information and presenting them as coherent and structured suggestions (Lee & Chung, 2024). This human–GenAI collaboration is characterized by co-creative processes in which user input through prompts influences the generated outputs (Feuerriegel et al., 2024). In other words, the quality of GenAI-supported outcomes fundamentally depends on the user's ability to apply and exploit (Gen-)AI tools effectively (Wang et al., 2022). Thus, the user's capability directly influences the effectiveness of using GenAI. GenAI technologies may further support individuals in idea generation by handling convergent thinking tasks, freeing cognitive capacity for divergent, creative thinking (Grilli & Pedota, 2024). Moreover, individuals can expand the diversity of their idea outputs by combining their judgment and the technologies' generative ability (Meincke et al., 2024). Furthermore, GenAI can amplify individuals' idea generation by enhancing content and context awareness, supporting the exploration of different solution pathways during idea generation (Sundberg & Holmström, 2024; Holmström & Carroll, 2025). GenAI supports individuals in overcoming cognitive blind spots by leveraging extensive datasets and generating novel combinations of ideas, which humans might overlook due to cognitive biases (Joosten et al., 2024). However, the outcome quality of GenAI systems is inherently shaped by the user's ability to prompt, interpret, and refine model interactions (Banh & Strobel, 2023).

Additionally, the application of GenAI in early innovation phases has been shown to reduce resource-related barriers and improve accessibility, enabling individuals to generate ideas more efficiently and effectively (Bilgram & Laarmann, 2023). Further, Haase and Hanel (2023) demonstrate that GenAI can match human creative outputs by recombining knowledge into novel ideas, particularly for everyday tasks. This suggests that individuals' GenAI usage capability enhances their idea-generation output beyond typical cognitive limitations. Therefore, we hypothesize:

H1. Individuals' capability to use GenAI fosters their idea generation.

We further hypothesize that both information processing systems—the experiential and the rational—promote individuals' idea generation. This argumentation is based on the view that idea generation is fundamentally a cognitive process (Paulus & Brown, 2007; Campbell, 1960). Cognitive experiential theory posits that individuals differ in their stable preferences for processing information stimuli (e.g., GenAI output), either intuitively via the experiential system or analytically via the rational system (Epstein, 2003, 2014). These styles contribute differently but complementarily to idea generation and creativity, fostering distinct cognitive operations (e.g., Baldacchino et al., 2023; Eling et al., 2015; Moore et al., 2014).

The experiential system facilitates intuitive judgments and associative memory, allowing novel ideas to emerge spontaneously (Bălău et al., 2019). Additionally, it promotes divergent thinking by bypassing rigid cognitive constraints and supporting rapid pattern recognition (Epstein, 2003; Marques et al., 2022). Intuitive processing is particularly valuable in early-stage idea generation, where flexibility, associative recombination of information, and spontaneous insight are essential (Sowden et al., 2015). This process allows individuals to access implicit knowledge and emotionally charged cues from experience, which fosters originality and fluency in idea generation. Empirical studies show that individuals relying on intuitive processing often generate more original solutions than those guided solely by analytical reasoning (Gonçalves & Cash, 2021). Likewise, experienced entrepreneurs frequently draw on emotionally charged insights to identify opportunities in uncertain environments (Baldacchino et al., 2023).

The rational system, in contrast, contributes to idea generation by enabling problem structuring, causal reasoning, and deductive hypothesis building—cognitive operations that directly support creative output (Luoma & Martela, 2021; Marques et al., 2022). Especially in organizational settings marked by complexity and resource constraints, individuals use analytical strategies such as logical decomposition and scenario modeling to articulate potential innovations (Calabretta et al., 2016). Rational cognitive styles have been found to promote intrapreneurial idea initiation through goal-directed reasoning (Marques et al., 2022). Entrepreneurs applying structured search and analytical decomposition tend to generate more feasible and high-quality ideas, particularly when building on domain-specific expertise (Gemmell et al., 2012). Analytical processing further shapes idea generation by guiding attention, identifying constraints, and enabling the logical recombination of knowledge (Hodgkinson & Sadler-Smith, 2018). These capabilities are especially relevant when idea generation depends on abstraction, rule-based inference, and conceptual coherence (Luoma & Martela, 2021).

In sum, while experiential cognition may trigger spontaneous idea generation, the rational system enables structured exploration and concept formation through deliberate, rule-based reasoning. Based on this argumentation, we formulate the following hypotheses:

H2a. Individuals' tendency to process information intuitively promotes idea generation.

H2b. Individuals' tendency to process information rationally promotes idea generation.

While information processing styles are typically conceptualized as relatively stable preferences, they are not entirely fixed (Epstein, 2003). These stable traits can be modulated through repeated engagement with external structures that shape cognitive activity (Reiser, 2004). Such external structures can be tools and artifacts situated in the environment—ranging from notebooks to computational systems like GenAI tools—and become functionally integrated into human cognitive processes (Clark & Chalmers, 1998). Individuals do not process information in isolation but form tightly coupled cognitive systems with their environments (Hollan et al., 2000). In this context, GenAI tools represent a particularly dynamic form of such an environment that actively shapes how users engage with information. Developing the capability to use GenAI effectively means interacting with it as a cognitive partner that continuously structures and simplifies mental tasks. Hollan et al. (2000) note that such external scaffolding can shape individuals' thinking, particularly when the interaction becomes routine and goal-directed.

GenAI systems support cognitive processes such as learning and reflection by providing users context-specific guidance and tailored feedback that helps them internalize new knowledge (Alavi et al., 2024). We argue that when individuals become skilled in using these systems, GenAI can become a regular part of understanding problems and developing solutions, supporting and gradually shaping their preferred ways of processing information.

For instance, individuals who primarily rely on rational-analytical strategies and learn to interact fluently with systems that produce intuitive, associative outputs may adapt behaviorally and become more confident and cognitively fluent in intuitive modes of thinking. Conversely, individuals with intuitive inclinations might be encouraged by tools that require logical prompt engineering or reward structured iteration to increasingly engage in analytical strategies. In both cases, the repeated use of GenAI in cognitively demanding tasks may act as a stabilizing influence, reinforcing the internalization of alternative processing routines.

Empirical evidence shows that skilled use of GenAI can shift users' cognitive focus from task execution toward reflective evaluation and oversight, altering how attention and effort are distributed in cognitive tasks (Lee et al., 2025). This suggests that the capability to use GenAI may not only affect situational thinking but could also, over time, influence more stable preferences in how individuals process information. Theoretically, repeated interaction with GenAI in problem-solving contexts can gradually internalize the tool's reasoning patterns and representational structures (Malloy & Gonzalez, 2024). Building on this, we argue that developing the capability to use GenAI proficiently may reshape individuals' dominant cognitive strategies by embedding external reasoning formats into their habitual processing routines.

Thus, the capability to use GenAI is not just a matter of performance optimization; it may gradually shape the cognitive scaffolding through which individuals perceive, interpret, and solve problems. When used skillfully, GenAI systems may influence how information is processed more generally, potentially altering users' dominant cognitive inclinations. We, thus, hypothesize:

H3a. Individuals' capability to use GenAI promotes their tendency to process information intuitively.

H3b. Individuals' capability to use GenAI promotes their tendency to process information rationally.

3.4. Method

3.4.1. Data collection and sample

To validate the research model empirically, we conducted a survey involving consultants from a leading global consultancy within the DACH region (Germany, Austria, Switzerland). This globally recognized firm operates in more than 100 countries, employs several hundred thousand professionals, and achieves annual revenues in the tens of billions of dollars.

Our study focused on this company's strategy, consulting, and innovation divisions. Despite operating under shared corporate protocols, consultants in this firm work across heterogeneous industries and project types and exhibit substantial dispersion in GenAI-related skills and usage patterns, providing the necessary variance to test our theorized mechanisms empirically. As the needs of the clients of the consultants are constantly changing (e.g., new regulations, new technologies, new business models, new products, new competitors), the problems are also very diverse, continually evolving, and the consultants need to generate new ideas. They are confronted with new problems on a day-to-day basis.

Moreover, studying consultants in the context of digital transformation, which also entails GenAI, aligns closely with established approaches in prior research (e.g., Warner & Wäger, 2019; Williams & van Triest, 2023). Consultants are essential in facilitating the adoption and implementation of GenAI solutions across industries (Deloitte, 2024). Industry analyses further highlight that consulting firms have positioned themselves as leaders in adopting and deploying GenAI technologies (McKinsey, 2024a). Accenture reported generating over three billion dollars in bookings from GenAI-driven initiatives in recent years, underscoring the extensive practical experience consultants have gained with this transformative technology (Accenture, 2024). These findings demonstrate that consultants are theoretically knowledgeable and possess substantial hands-on expertise, further validating their relevance as subjects for our research.

The survey design and preliminary testing phase occurred between April and June 2024. To ensure clarity and validity, pre-tests were carried out with two professors, a doctoral researcher, and two consultants representative of the target group. After minor refinements to the survey, we conducted the data collection in July 2024. We distributed personalized email invitations containing a survey link to 1,032 consultants, ultimately receiving 399 completed responses (response rate 38.7%). Table 3.2 provides an overview of the sample's demographics, illustrating a balanced distribution across industries and experience levels.

Table 3.2 Sample characteristics.

Variable		**No.**	**%**
Gender	Female	167	41.9
	Male	230	57.6
	Non-binary	2	0.0
Education (highest level)	High School Diploma	10	2.5
	Bachelor's Degree	48	12.0
	Master's Degree/Diploma	306	76.7
	Doctorate	34	8.5
	Others	1	0.0
Work experience (in years)	Less than 1	5	1.3
	1–3	64	16.0
	3–5	67	16.8
	5–10	116	29.1
	More than 10	147	36.9
Company affiliation (in years)	Less than 1	63	15.8
	1–3	127	31.8
	3–5	62	15.5
	5–10	90	22.6
	More than 10	57	14.3
Career Level	Analyst	87	21.8
	Consultant	108	27.1
	Manager	91	22.8
	Senior Manager	57	14.3
	Principal	27	6.8
	Managing Director	29	7.3
Industry expertise	Health and Public Sector	162	40.6
	Finance	175	43.9
(more than one answer possible)	Communications and Media	113	28.3
	IT and Software	127	31.8
	Resources	105	26.3
	Consumer Goods	153	38.3
	Mobility and Automotive	176	44.1

Note: $N = 399$
Source: Own illustration

3.4.2. Variable measurements

The measurement items utilized in this study were carefully derived from well-validated and widely recognized scales (Wang et al., 2022; Epstein et al., 1996; Jong & Hartog, 2010). These items were designed using a 5-point Likert scale, with response options ranging from 1, indicating "Strongly Agree," to 5, representing "Strongly Disagree." A comprehensive summary of the constructs and their corresponding measurement items is provided in table 3.9 in the Appendix.

To assess the construct GenAI usage capability, we extracted and slightly modified a similar construct from the AI literacy scale proposed by Wang et al. (2022). GenAI usage capability is defined as "the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently" (Wang et al., 2022, p. 4). It is measured by three items, which determine an individual's perceived ability to use GenAI applications effectively, their ease or difficulty in learning to use new GenAI tools, and their ability to use these applications to increase work efficiency.

We used the scale of Epstein et al. (1996) to measure the constructs experiential information processing system and rational information processing system. Both constructs were measured with five items each. The experiential system captures individuals' dispositional tendency to rely on automatic, intuitive, and affectively influenced processes, emphasizing heuristic-based and context-specific approaches driven by associative memory. The rational system reflects individuals' dispositional propensity to engage in deliberate, analytical, and logical reasoning, characterized by abstract principles and systematic information processing.

To measure the construct idea generation, we utilized the five proposed items of Jong and Hartog (2010) as part of their broader conceptualization of innovative work behavior (IWB). This dimension captures an early phase of the innovation process by reflecting an individual's actions to combine and reorganize information to produce novel and useful solutions, including new products, services, or improvements in work processes. We deliberately focused on the idea generation dimension—rather than the complete IWB construct—because we aim to investigate how GenAI tools can support in early creative phases of innovation processes (e.g., Eisenreich et al., 2024; Meincke et al., 2024). By isolating idea generation as the relevant outcome variable, we ensure a conceptually aligned and theoretically meaningful assessment of how GenAI usage capability translates into innovation-related performance.

3.4.3. Model evaluation

We used structural equation modeling (SEM) to analyze the data and conducted our calculations using the statistical software SmartPLS 4. Our approach closely followed the guidelines of Hair et al. (2022), applying the partial least squares (PLS) path modeling approach. The selection of PLS-SEM for our analysis is driven by its suitability for research approaches that emphasize both explanation and prediction (Gudergan et al., 2025; Hair & Sarstedt, 2021; Sarstedt & Danks, 2022). Further, PLS-SEM combines the strengths of exploratory and confirmatory research (Sharma et al., 2024). PLS-SEM demonstrates significant advantages over covariance-based structural equation modeling by offering enhanced predictive capabilities and greater flexibility, particularly in exploratory research contexts (Hair et al., 2019). Additionally, PLS-SEM facilitates the simultaneous estimation of all relationships among constructs, enabling a comprehensive examination of complex models (Becker et al., 2023). For this study, PLS-SEM is particularly well-suited to assess the intricate relationships between individuals' GenAI usage capability, the experiential and rational information processing systems, and idea generation. By estimating direct and indirect effects, PLS-SEM provides robust insights into the underlying mechanisms that connect these constructs.

3.5. Results

3.5.1. Measurement model

We applied the standard PLS-SEM algorithm to calculate the measurement model. The evaluation of quality criteria encompassed indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, following the procedure of Hair et al. (2022). The results of these assessments are presented in Tables 3.3 and 3.4.

In the first step, we assessed indicator reliability. A common rule of thumb is a value of > 0.708 for the external loadings of the indicators. However, values between 0.4 and 0.7 can also be sufficient, and these indicators should only be excluded if the deletion leads to an increase in internal consistency or convergent validity (Hair et al., 2022). The outer loadings for the construct GenAI usage capability all exceeded 0.708.

Table 3.3 Measurement model evaluation.

Construct and indicator	Factor loading	Composite reliability	Cronbach's α	AVE
GenAI usage capability		0.727	0.711	0.628
GenAI usage capability 1	0.841			
GenAI usage capability 2^R	0.784			
GenAI usage capability 3	0.750			
Experiential information processing		0.883	0.883	0.608
Experiential information processing 1	0.776			
Experiential information processing 2	0.678			
Experiential information processing 3	0.816			
Experiential information processing 4	0.874			
Experiential information processing 5	0.743			
Rational information processing		0.762	0.760	0.582
Rational information processing 1^R	0.779			
Rational information processing 2^R	0.799			
Rational information processing 3	0.764			
Rational information processing 4	0.705			
Idea generation		0.769	0.763	0.514
Idea generation 1	0.624			
Idea generation 2	0.737			
Idea generation 3	0.779			
Idea generation 4	0.736			
Idea generation 5	0.699			

Notes: N = 399; ^{R} = inversed item
Source: Own illustration

For the construct experiential information processing, the second outer loading of 0.678 is minimally below the limit value but in the range of 0.4 and 0.7 and, therefore, acceptable. For the construct rational information processing, all outer loadings exceed 0.7, except for the fifth indicator, which we removed (outer loading of 0.294). The construct idea generation has three outer loadings above 0.708, and Item 1 (outer loading of 0.624) and Item 5 (outer loading of 0.699) are minimally below the value of 0.708 but in the range of 0.4–0.7 and, therefore, acceptable. We can state that indicator reliability is consequently ensured in our model.

Next, we evaluated the internal consistency reliability. We examined the composite reliability and Cronbach's alpha to determine the internal consistency reliability. For both, we set the usual target value of > 0.7 (Hair et al., 2022). All our constructs exceed 0.7. Hence, we can state that our model's internal consistency and reliability are assured.

We examined the average variance extracted (AVE) as a key metric to evaluate convergent validity. An AVE value exceeding 0.50 was established as the acceptable threshold, ensuring that the constructs demonstrate sufficient shared variance with their indicators (Hair et al., 2022). All constructs surpass this 0.50 benchmark, indicating that convergent validity is not a concern in our measurement model.

Last, we assessed the discriminant validity of the constructs by utilizing the Heterotrait-Monotrait Ratio (HTMT). We use the widely used cut-off value of 0.85 (Henseler et al., 2015). Table 3.4 contains the HTMT and illustrates that every value is below 0.85, indicating that discriminant validity is ensured for our measurement model.

Table 3.4 Heterotrait-Monotrait Ratio.

	Constructs	1	2	3	4
1	Experiential information processing				
2	GenAI usage capability	0.153			
3	Idea generation	0.138	0.315		
4	Rational information processing	0.093	0.140	0.501	

Source: Own illustration

3.5.2. Structural model

After evaluating the measurement model, we assessed the structural model. In the first step, we calculated the variance inflation factor (VIF) to check for potential collinearity issues among the predictor constructs. The VIF values presented in Table 3.5 indicate that none exceeds the threshold of 3, confirming the absence of collinearity issues in the structural model (Hair et al., 2019).

Table 3.5 Variance Inflation Factors.

	VIF
Rational information processing → Idea generation	1.014
Experiential information processing → Idea generation	1.017
GenAI usage capability → Rational information processing	1.000
GenAI usage capability → Experiential information processing	1.000
GenAI usage capability → Idea generation	1.028

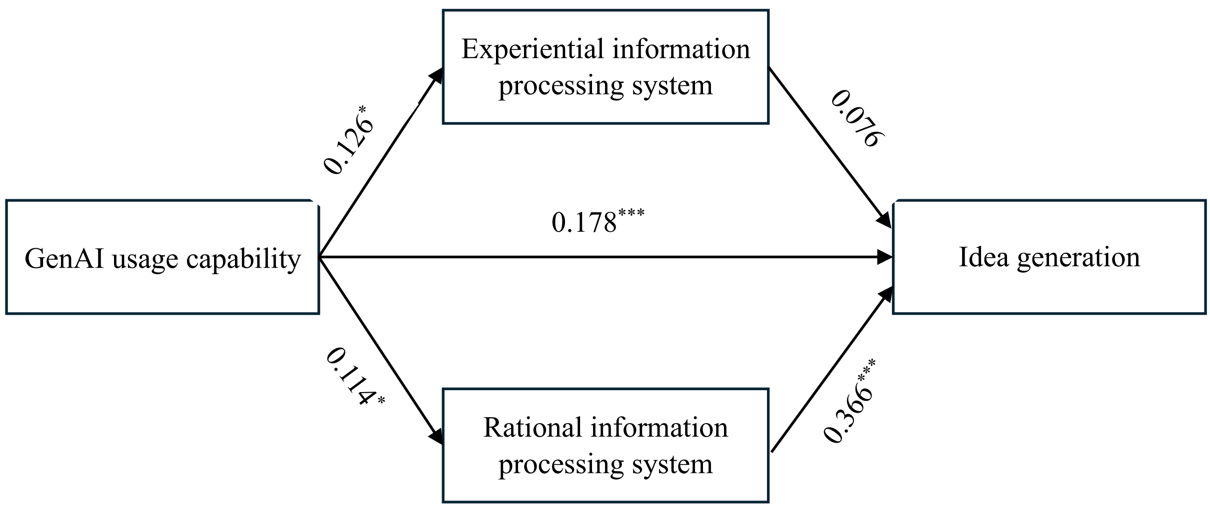
Source: Own illustration

In the subsequent phase of our analysis, we applied the standard bootstrapping algorithm with 5,000 resamples to estimate the structural model. This approach allowed us to assess R^2 values, path coefficients, and corresponding significance levels. To interpret the significance levels, we categorized the *p*-values as follows: results were considered extremely significant when $p \leq 0.001$, highly significant when $p \leq 0.01$, and significant when $p \leq 0.05$. Table 3.6 provides an overview of path coefficients and corresponding significance levels, which are also illustrated in Figure 3.2. In addition, Table 3.7 summarizes the hypothesis test results.

Table 3.6 Direct effects.

Direct effects	**β**	***p***	***t***
GenAI usage capability → Experiential information processing	0.126	0.019	2.338
GenAI usage capability → Rational information processing	0.114	0.026	2.231
GenAI usage capability → Idea generation	0.178	0.001	3.270
Experiential information processing → Idea generation	0.076	0.143	1.465
Rational information processing → Idea generation	0.366	< 0.001	6.933

Source: Own illustration



Notes: *p < 0.05, **p < 0.01, ***p < 0.001.

Figure 3.2 Research model with path coefficients.

Source: Own illustration

Table 3.7 Hypothesis test results.

	Hypothesis	Result
H1.	Individuals' capability to use GenAI fosters their idea generation.	Supported
H2a.	Individuals' tendency to process information intuitively promotes idea generation.	Rejected
H2b.	Individuals' tendency to process information rationally promotes idea generation.	Supported
H3a.	Individuals' capability to use GenAI promotes their tendency to process information intuitively.	Supported
H3b.	Individuals' capability to use GenAI promotes their tendency to process information rationally.	Supported

Source: Own illustration

The results of the path analysis reveal nuanced insights into the relationship between GenAI usage capability and both information processing systems. Specifically, the analysis indicates that the capability to use GenAI accounts for 1.6% of the variance observed in the experiential information processing system, demonstrating a modest but measurable impact. Similarly, GenAI usage capability explains 1.3% of the variance within the rational information processing system, suggesting its role in influencing both information processing systems. The

R^2 values of the mediators are relatively low, which is expected when modeling cognitive processes influenced by various contextual and individual factors. More importantly, their inclusion increases the R^2 of the final dependent variable (idea generation) from 7.3% to 19.2%, demonstrating their substantive role in the explanatory model and their contribution to understanding the relationship between GenAI usage capability and idea generation.

3.5.3. Mediation effects

Our mediation analysis demonstrates a significant indirect effect of individuals' GenAI usage capability on idea generation via the tendency to rely on rational information processing (β = 0.042, p = 0.038). In contrast, the indirect effect through the tendency to rely on experiential information processing is not significant (β = 0.010, p = 0.242). These results highlight that only rational information processing mediates the relationship between individuals' GenAI usage capability and idea generation in our model. Table 3.8 summarizes the indirect effects.

Table 3.8 Indirect effects.

Indirect effects	**β**	***p***	***t***
GenAI usage capability → Rational information processing → Idea generation	0.042	0.038	2.070
GenAI usage capability → Experiential information processing → Idea generation	0.010	0.242	1.170

Source: Own illustration

3.6. Discussion

This study investigates how individuals' capability to use GenAI influences their idea generation, a core activity in innovation management. Addressing a critical gap in current research, we shift the focus from general usage metrics (frequency, extent, or purpose) to individuals' capability to skillfully engage with GenAI technology. Drawing on cognitive experiential theory, we further examine the cognitive mechanisms that underlie the relationship between GenAI usage capability and idea generation.

Our analysis is based on survey data from 399 business consultants located in Germany, Austria, and Switzerland at a leading global consultancy. We analyzed the data using PLS-SEM. Our findings mainly confirmed our theoretically grounded hypotheses. Specifically, we found that individuals' capability to use GenAI improves their idea generation (H1). We further found that (1) individuals' capability to use GenAI promotes tendencies to rely on both information processing styles (H2a and H2b); (2) only the tendency to rely on rational information processing promotes idea generation, not experiential information processing (H3a and H3b); and (3) the tendency to rely on rational processing mediates the GenAI usage capability–idea generation link.

These findings offer novel insights into the intersection of GenAI usage capability, cognitive information processing styles, and idea generation. As theoretically expected, individuals with higher levels of GenAI usage capability have improved idea generation, supporting the notion that technical and cognitive proficiency in interacting with GenAI tools is essential to unlock their creative potential. Notably, our findings reveal an asymmetry in the role of the two cognitive systems. While prior research frequently underscores the relevance of intuitive, associative processing for creativity and idea generation (e.g., Bălău et al., 2019; Epstein, 2003), our results suggest that in the specific context of GenAI-supported idea generation, rational information processing plays the more decisive role in driving idea generation based on GenAI usage capability.

3.6.1. Theoretical contributions

Our study offers several significant theoretical contributions to the growing body of innovation management literature in the context of GenAI (e.g., Cimino et al., 2025; Mariani & Dwivedi, 2024; Roberts & Candi, 2024; Vitellaro et al., 2025). Most notably, we provide empirical evidence that individuals' capability to use GenAI promotes their idea generation. This finding allows us to expand existing studies emphasizing GenAI's immense potential to foster idea generation (e.g., Eisenreich et al., 2024; Meincke et al., 2024). We enrich the research field by highlighting a critical, yet previously overlooked, perspective on GenAI and its creative potential for idea generation: the individuals' capability to use the technology. Therefore, we complement studies investigating GenAI usage's frequency, extent, or purpose for creative outcomes like idea generation (e.g., Zhang et al., 2025). This perspective adds depth to understanding how GenAI contributes to idea generation, emphasizing that its creative value is closely linked to human capabilities rather than being an automatic byproduct of the technology itself. Moreover, our research directly responds to the observation of Holzner et al. (2025), who emphasize that existing empirical literature on GenAI and its potential for creative outcomes, such as idea generation, is not only fragmented but also predominantly focused on data from academic settings. By shifting the focus to business consultants—a group largely underrepresented in prior research—we help close this gap and contribute to a more comprehensive understanding of GenAI's role in real-world innovation contexts.

Second, we found relevant underlying cognitive mechanisms in the link between individuals' GenAI usage capability and idea generation. Drawing on cognitive experiential theory, we provide evidence for a more nuanced understanding of this relationship. Specifically, our results show that (1) individuals' capability to use GenAI promotes their tendencies to rely on both information processing styles; (2) only the tendency to rely on rational information processing promotes idea generation, not experiential information processing; and (3) the tendency to rely on rational processing mediates the GenAI usage capability–idea generation link.

These findings extend existing research on cognitive styles and their role in idea generation (e.g., Baldacchino et al., 2023; Eling et al., 2015). Whereas prior studies have often emphasized the value of experiential thinking for idea generation (e.g., Bălău et al., 2019), our results present a different picture within the context of GenAI usage capability and idea generation. Contrary to earlier assumptions, the experiential system does not appear to be a significant driver of idea generation in this setting. Instead, our evidence highlights a stronger reliance on rational information processing as the decisive factor, positioning it as the key cognitive path through which GenAI usage capability translates into idea generation.

3.6.2. Practical contributions

Our findings have practical implications that can help companies and consultants ensure a targeted approach to GenAI. First, our results demonstrate that an individual's capability to use GenAI promotes their idea generation. In other words, the creative value of GenAI critically depends on the human capability to engage with it effectively. That means companies should invest in their employees and support them in systematically building their GenAI usage capability. A key lever for this is training in prompt engineering—the ability to formulate clear and targeted instructions that guide GenAI systems. As McKinsey (2024b) notes, effective prompts benefit from defined roles ("You are a consultant…"), clear output formats, and iterative refinement. These simple but powerful techniques help users get more accurate and helpful responses, turning GenAI into a productive support tool. To enable such upskilling at scale, companies can rely on established programs such as the Fraunhofer Institute's compact online course[13] “Prompting für generative KI,” which introduces essential prompting strategies through hands-on examples. Structured offerings like this can help organizations anchor GenAI’s competence in everyday workflows and unlock its innovation potential through user proficiency.

Second, our study contributes to building a deeper understanding of the cognitive mechanisms underlying GenAI-supported idea generation. From a managerial perspective, this knowledge is essential for unlocking the full creative value of GenAI technologies. We show that individuals’ capability to use GenAI directly enhances their idea generation and increases their tendency to rely on experiential and rational information processing systems. However, only the rational system—characterized by deliberate, analytical thinking—was found to promote idea generation in the GenAI context. From a practical perspective, it suggests that organizations should consider the psychological dimensions of GenAI use—how people think, reason, and process information when interacting with these systems. Understanding GenAI as part of a human–technology cognitive system can help organizations approach its implementation more holistically and recognize that meaningful outcomes rely not only on access to powerful tools but also on the cognitive information processing styles of those who use them.

3.6.3. Limitations and future research

Our study faces some limitations that open avenues for future research. First, as a result of our quantitative survey approach, our data was collected at a single point in time. This limits the validity of the results. Future studies could further explore temporal developments through longitudinal or experimental designs.

Second, the reliance on self-reported data may introduce biases such as common method variance or social desirability. Although we conducted established diagnostic tests, which did not indicate problematic bias, such risks can never be entirely excluded. Future research could strengthen measurement validity by combining self-assessments with behavioral indicators or third-party evaluations.

[13] Frauenhofer Institute: Prompt Engineering - Techniken für Generative KI https://www.bigdata-ai.fraunhofer.de/de/data-scientist/schulungssuche/KompakteinstiegPromptingFuerGenerativeKI.html (last accessed 02 June 2025)

Third, the consultants in our sample likely work on client issues that are at least partially pre-structured, limiting the possibility for genuine problem identification, which could restrict the generalizability of our findings to contexts with more open-ended problem spaces.

Fourth, as our data come from consultants working for a single global consultancy with formalized hiring and quality-assurance protocols, unobserved firm-level standardization may attenuate individual variability, limiting the generalizability of our findings to organizations with less codified problem-solving routines.

Fifth, this study concentrates on cognitive information processing styles as mediating mechanisms. Although this lens offers explanatory value, other psychological or contextual variables, such as individual learning orientation or situational task complexity, may also influence how GenAI usage capability affects idea generation and deserve further attention.

Finally, this study focuses exclusively on the idea-generation phase and does not consider subsequent stages of the innovation process. However, recent research shows that transformer-based language models, such as those used in GenAI applications, can support individuals in generating, evaluating, and prioritizing large sets of ideas (Just et al., 2024). Future research could, therefore, extend our model by examining how individuals' GenAI usage capability influences later phases of the innovation process, such as idea evaluation.

3.7. Appendix

Table 3.9 Measurement scales

Construct	Item
GenAI usage capability	U1: I can skillfully use GenAI applications to help me with my daily work.
	U2: It is usually hard for me to learn to use a new GenAI application.[R]
	U3: I can use GenAI applications to improve my work efficiency.
Experiential information processing system	E1: I trust my initial feelings about people.
	E2: I believe in trusting my hunches.
	E3: My initial impressions of people are almost always right.
	E4: When it comes to trusting people, I can usually rely on my "gut feelings."
	E5: I can usually feel when a person is right or wrong even if I can't explain how I know.
Rational information processing system	R1: I don't like to have to do a lot of thinking.[R]
	R2: I try to avoid situations that require thinking in depth about something.[R]
	R3: I prefer to do something that challenges my thinking abilities rather than something that requires little thought.
	R4: I prefer complex to simple problems.
	R5: Thinking hard and for a long time about something gives me little satisfaction.[1]
Idea generation	I1: I search out new working methods, techniques or instruments.
	I2: I generate original solutions for problems.
	I3: I create new ideas.
	I4: I find new approaches to execute tasks.
	I5: I mobilize support for innovative ideas.

Notes: [R] = inversed; [1] = Removed due to low outer loading of indicator < 0.50
Source: Own illustration

3.8. References

Accenture. (2024). Accenture fiscal 2024 annual report. https://www.accenture.com/content/dam/accenture/final/accenture-com/a-com-custom-component/iconic/document/Accenture-Fiscal-2024-Annual-Report.pdf (last accessed 17 February 2025)

Alavi, M., Leidner, D. E., & Mousavi, R. (2024). Knowledge management perspective of generative artificial intelligence. *Journal of the Association for Information Systems*, 25 (1), 1–12. https://doi.org/10.17705/1jais.00859

Amabile, T. M. (1983). The social psychology of creativity: A componential conceptualization. *Journal of Personality and Social Psychology*, 45 (2), 357–376. https://doi.org/10.1037/0022-3514.45.2.357

Amabile, T. M., Conti, R., Coon, H., Lazenby, J., & Herron, M. (1996). Assessing the work environment for creativity. *Academy of Management Journal*, 39 (5), 1154–1184. https://doi.org/10.5465/256995

Armstrong, S. J., Cools, E., & Sadler-Smith, E. (2012). Role of cognitive styles in business and management: reviewing 40 years of research. *International Journal of Management Reviews*, 14 (3), 238–262. https://doi.org/10.1111/j.1468-2370.2011.00315.x

Bakken, B. T., Hansson, M., & Hærem, T. (2024). Challenging the doctrine of “non-discerning” decision-making: Investigating the interaction effects of cognitive styles. *Journal of Occupational and Organizational Psychology*, 97 (1), 209–232. https://doi.org/10.1111/joop.12467

Bălău, G., Faems, D., & van der Bij, H. (2019). Team experiential cognitive style and team performance: The moderating impact of workplace setting. *Creativity and Innovation Management*, 28 (3), 343–354. https://doi.org/10.1111/caim.12319

Baldacchino, L., Ucbasaran, D., & Cabantous, L. (2023). Linking experience to intuition and cognitive versatility in new venture ideation: A dual-process perspective. *Journal of Management Studies*, 60 (5), 1105–1146. https://doi.org/10.1111/joms.12794

Banh, L., & Strobel, G. (2023). Generative artificial intelligence. *Electronic Markets*, 33 (63), 1–17. https://doi.org/10.1007/s12525-023-00680-1

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior*, 45 (2), 159–182. https://doi.org/10.1002/job.2735

Becker, J.-M., Cheah, J.-H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023). PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management*, 35 (1), 321–346. https://doi.org/10.1108/IJCHM-04-2022-0474

Berg, J. M. (2016). Balancing on the creative highwire: Forecasting the success of novel ideas in organizations. *Administrative Science Quarterly*, 61 (3), 433–468. https://doi.org/10.1177/0001839216642211

Bilgram, V., & Laarmann, F. (2023). Accelerating innovation with generative AI: AI-augmented digital prototyping and innovation methods. *IEEE Engineering Management Review*, 51 (2), 18–25. https://doi.org/10.1109/EMR.2023.3272799

Bouschery, S. G., Blazevic, V., & Piller, F. T. (2023). Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models. *Journal of Product Innovation Management*, 40 (2), 139–153. https://doi.org/10.1111/jpim.12656

Boussioux, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem-solving. *Organization Science*, 35 (5), 1589–1607. https://doi.org/10.1287/orsc.2023.18430

Brynjolfsson, E., Li, D., & Raymond, L. (2023). Generative AI at Work. (No. w31161). National Bureau of Economic Research. https://doi.org/10.3386/w31161

Calabretta, G., Gemser, G., & Wijnberg, N. M. (2017). The interplay between intuition and rationality in strategic decision making: A paradox perspective. *Organization Studies*, 38 (3-4), 365–401. https://doi.org/10.1177/0170840616655483

Campbell, D. T. (1960). Blind variation and selective retention in creative thought as in other knowledge processes. *Psychological Review*, 67, 380–400. https://doi.org/10.1037/h0040373

Cerni, T., Curtis, G. J., & Colmar, S. H. (2014). Cognitive-experiential leadership model: How leaders' information-processing systems can influence leadership styles, influencing tactics, conflict management, and organizational outcomes. *Journal of Leadership Studies*, 8 (3), 26–39. https://doi.org/10.1002/jls.21335

Chen, Z., & Chan, J. (2024). Large language model in creative work: The role of collaboration modality and user expertise. *Management Science*, 70 (12), 9101–9117 https://doi.org/10.1287/mnsc.2023.03014

Chiarello, F., Giordano, V., Spada, I., Barandoni, S., & Fantoni, G. (2024). Future applications of generative large language models: A data-driven case study on

ChatGPT. *Technovation*, 133, 103002. https://doi.org/10.1016/j.technovation.2024.103002

Choudhary, V., Marchetti, A., Shrestha, Y. R., & Puranam, P. (2023). Human-AI ensembles: when can they work? *Journal of Management*, 51 (2), 536-569. https://doi.org/10.1177/01492063231194968

Cimino, A., Felicetti, A. M., Corvello, V., Ndou, V., & Longo, F. (2025). Generative artificial intelligence (AI) tools in innovation management: a study on the appropriation of ChatGPT by innovation managers. *Management Decision.* 63 (10), *3431*–3453 https://doi.org/10.1108/MD-10-2023-1968

Clark, A., & Chalmers, D. (1998). The extended mind. *analysis*, 58 (1), 7–19.

Deloitte. (08/2024). Now decides next: Moving from potential to performance. https://www2.deloitte.com/us/en/pages/consulting/articles/state-of-generative-ai-in-enterprise.html (last accessed 17 February 2025)

Eisenreich, A., Just, J., Gimenez-Jimenez, D., & Füller, J. (2024). Revolution or inflated expectations? Exploring the impact of generative AI on ideation in a practical sustainability context. *Technovation*, *138*, 103123. https://doi.org/10.1016/j.technovation.2024.103123

Eling, K., Langerak, F., & Griffin, A. (2015). The performance effects of combining rationality and intuition in making early new product idea evaluation decisions. *Creativity and innovation management*, 24 (3), 464–477.

Epstein, S. (1973). The self-concept revisited. Or a theory of a theory. *The American Psychologist*, 28 (5), 404–416. https://doi.org/10.1037/h0034679

Epstein, S. (1994). Integration of the cognitive and the psychodynamic unconscious. *The American Psychologist*, 49 (8), 709–724. https://doi.org/10.1037/0003-066X.49.8.709

Epstein, S. (2003). Cognitive-experiential self-theory of personality. In I. B. Weiner (Ed.), *Handbook of Psychology* (pp. 159–184). Wiley. https://doi.org/10.1002/0471264385.wei0507

Epstein, S. (2010). Demystifying intuition: What it is, what it does, and how it does it. *Psychological Inquiry*, 21 (4), 295–312. https://doi.org/10.1080/1047840X.2010.523875

Epstein, S. (2014). Cognitive-experiential theory: An integrative theory of personality. Oxford University Press.

Epstein, S., Pacini, R., Denes-Raj, V., & & Heier, H. (1996). Individual differences in intuitive–experiential and analytical–rational thinking styles. *Journal of Personality and Social Psychology* 71 (2), 390–405.

Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science* 8 (3), 223–241. https://doi.org/10.1177/1745691612460685

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, 66 (1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, 62 (16), 5676–5696. https://doi.org/10.1080/00207543.2023.2294116

Garbuio, M., & Lin, N. (2021). Innovative idea generation in problem finding: Abductive reasoning, cognitive impediments, and the promise of artificial intelligence. *Journal of Product Innovation Management*, 38 (6), 701–725. https://doi.org/10.1111/jpim.12602

Gemmell, R. M., Boland, R. J., & Kolb, D. A. (2012). The socio–cognitive dynamics of entrepreneurial ideation. *Entrepreneurship Theory and Practice*, 36 (5), 1053–1073. https://doi.org/10.1111/j.1540-6520.2011.00486.x

Girotra, K., Terwiesch, C., & Ulrich, K. T. (2010). Idea generation and the quality of the best idea. *Management Science*, 56 (4), 591–605. https://doi.org/10.1287/mnsc.1090.1144

Gonçalves, M., & Cash, P. (2021). The life cycle of creative ideas: Towards a dual-process theory of ideation. *Design Studies*, *72*, 100988. https://doi.org/10.1016/j.destud.2020.100988

Grilli, L., & Pedota, M. (2024). Creativity and artificial intelligence: A multilevel perspective. *Creativity and Innovation Management*, 33 (2), 234–247. https://doi.org/10.1111/caim.12580

Gudergan, S. P., Moisescu, O. I., Radomir, L., Ringle, C. M., & Sarstedt, M. (2025). Special issue editorial: Advanced partial least squares structural equation modeling (PLS-SEM) applications in business research. *Journal of Business Research*, *188*, 115087. https://doi.org/10.1016/j.jbusres.2024.115087

Gurtner, S., & Reinhardt, R. (2016). Ambidextrous idea generation—antecedents and outcomes *Journal of Product Innovation Management*, 33 (S1), 34–54. https://doi.org/10.1111/jpim.12353

Haase, J., & Hanel, P. H. (2023). Artificial muses: Generative artificial intelligence chatbots have risen to human-level creativity. *Journal of Creativity*, 33 (3), 100066. https://doi.org/10.1016/j.yjoc.2023.100066

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (Third edition). SAGE.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31 (1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., & Sarstedt, M. (2021). Explanation plus prediction—the logical focus of project management research. *Project Management Journal*, 52 (4), 319–322. https://doi.org/10.1177/8756972821999945

Harvey, S. (2014). Creative synthesis: Exploring the process of extraordinary group creativity. *The Academy of Management Review*, 39 (3), 324–343. https://doi.org/10.5465/amr.2012.0224

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43 (1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hermann, E., & Puntoni, S. (2024). Artificial intelligence and consumer behavior: From predictive to generative AI. *Journal of Business Research*, 180, 114720. https://doi.org/10.1016/j.jbusres.2024.114720

Hodgkinson, G. P., & Sadler-Smith, E. (2018). The dynamics of intuition and analysis in managerial and organizational decision making. *Academy of Management Perspectives*, 32 (4), 473–492. https://doi.org/10.5465/amp.2016.0140

Hollan, J., Hutchins, E., & Kirsh, D. (2000). Distributed cognition: toward a new foundation for human-computer interaction research. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 7 (2), 174–196. https://doi.org/10.1145/353485.353487

Holmström, J., & Carroll, N. (2025). How organizations can innovate with generative AI. *Business Horizons.* 68 (5), 559–573. https://doi.org/10.1016/j.bushor.2024.02.010

Holzner, N., Maier, S., & Feuerriegel, S. (2025). Generative AI and creativity: A systematic literature review and meta-analysis. *arXiv preprint arXiv:2505.17241*.

Jong, J. de, & Hartog, D. den (2010). Measuring innovative work behaviour. *Creativity and Innovation Management*, 19 (1), 23–36. https://doi.org/10.1111/j.1467-8691.2010.00547.x

Joosten, J., Bilgram, V., Hahn, A., & Totzek, D. (2024). Comparing the ideation quality of humans with generative artificial intelligence. *IEEE Engineering Management Review*, 52 (2), 153–164. https://doi.org/10.1109/EMR.2024.3353338

Just, J., Hutter, K., & Füller, J. (2024). Catching but a glimpse?—Navigating crowdsourced solution spaces with transformer-based language models. *Creativity and Innovation Management* 33 (4), 718–741. https://doi.org/10.1111/caim.12612

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *The American Economic Review* 93 (5), 1449–1475. http://www.jstor.org/stable/3132137

Kahneman, D. (2011). Thinking, fast and slow (First paperback edition). Psychology/economics. Farrar Straus and Giroux.

Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: A failure to disagree. *The American Psychologist*, 64 (6), 515–526. https://doi.org/10.1037/a0016755

Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2024). The GenAI is out of the bottle: Generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*, 18 (4), 1189–1220. https://doi.org/10.1007/s11846-023-00696-z

Kornish, L. J., & Hutchison-Krupat, J. (2017). Research on idea generation and selection: Implications for management of technology. *Production and Operations Management*, 26 (4), 633–651. https://doi.org/10.1111/poms.12664

Kornish, L. J., & Ulrich, K. T. (2014). The importance of the raw idea in innovation: Testing the sow's ear hypothesis. *Journal of Marketing Research*, 51 (1), 14–26. https://doi.org/10.1509/jmr.12.0401

Lee, B. C., & Chung, J. J. (2024). An empirical investigation of the impact of ChatGPT on creativity. *Nature Human Behaviour*, 8 (10), 1906–1914. https://doi.org/10.1038/s41562-024-01953-1

Lee, H. P., Sarkar, A., Tankelevitch, L., Drosos, I., Rintel, S., Banks, R., & Wilson, N. (2025, April). The impact of generative AI on critical thinking: Self-reported reductions in cognitive effort and confidence effects from a survey of knowledge workers. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (pp. 1-22). https://doi.org/10.1145/3706598.3713778

Lieberman, J. D. (2002). Head over the heart or heart over the head? Cognitive experiential self-theory and extralegal heuristics in juror decision making. *Journal of Applied Social Psychology,* 32 (12), 2526–2553. https://doi.org/10.1111/j.1559-1816.2002.tb02755.x

Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., & Neubig, G. (2023). Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ACM Computing Surveys*, 55 (9), 1–35. https://doi.org/10.1145/3560815

Luoma, J., & Martela, F. (2021). A dual-processing view of three cognitive strategies in strategic decision making: Intuition, analytic reasoning, and reframing. *Long Range Planning*, 54 (3), 102065. https://doi.org/10.1016/j.lrp.2020.102065

Magni, F., Park, J., & Chao, M. M. (2024). Humans as creativity gatekeepers: Are we biased against AI creativity? *Journal of Business and Psychology*, 39 (3), 643–656. https://doi.org/10.1007/s10869-023-09910-x

Malloy, T., & Gonzalez, C. (2024). Applying generative artificial intelligence to cognitive models of decision making. *Frontiers in Psychology*, *15*, 1387948. https://doi.org/10.3389/fpsyg.2024.1387948

Mannucci, P. V. (2017). Drawing snow white and animating Buzz Lightyear: Technological toolkit characteristics and creativity in cross-disciplinary teams. *Organization Science*, 28 (4), 711–728. https://doi.org/10.1287/orsc.2017.1141

Mannucci, P. V., & Perry-Smith, J. E. (2022). "Who are you going to call?" Network activation in creative idea generation and elaboration. *Academy of Management Journal*, 65 (4), 1192–1217. https://doi.org/10.5465/amj.2019.0333

Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research*, 175, 114542. https://doi.org/10.1016/j.jbusres.2024.114542

Marques, C. S., Lopes, C., Braga, V., Ratten, V., & Santos, G. (2022). Intuition and rationality in intrapreneurship and innovation outputs: The case of health professionals in primary health care. *International Entrepreneurship and Management Journal*, 18 (2), 579–602. https://doi.org/10.1007/s11365-021-00761-7

McKinsey (2024a). The state of AI in early 2024: Gen AI adoption spikes and starts to generate value. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai (last accessed 17 February 2025)

McKinsey (2024b). What is prompt engineering? https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-prompt-engineering (last accessed 2 June 2025)

Meincke, L., Girotra, K., Nave, G., Terwiesch, C., & Ulrich, K. T. (2024). Using large language models for idea generation in innovation. *The Wharton School Research Paper*, https://doi.org/10.2139/ssrn.4526071

Moore, D., Sauder, J., & Jin, Y. (2014, August). "A Dual-Process Analysis of Design Idea Generation." Proceedings of the ASME 2014 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. Volume 7: 2nd Biennial International Conference on Dynamics for Design; 26th International Conference on Design Theory and Methodology. Buffalo, New York, USA. August 17–20, 2014. V007T07A017. ASME. https://doi.org/10.1115/DETC2014-34657

Ng, T. W. H., Shao, Y., Koopmann, J., Wang, M., Hsu, D. Y., & Yim, F. H. K. (2022). The effects of idea rejection on creative self-efficacy and idea generation: Intention to remain and perceived innovation importance as moderators. *Journal of Organizational Behavior*, 43 (1), 146–163. https://doi.org/10.1002/job.2567

Paulus, P. B., & Brown, V. R. (2007). Toward more creative and innovative group idea generation: A cognitive-social-motivational perspective of brainstorming. *Social and Personality Psychology Compass*, 1 (1), 248–265. https://doi.org/10.1111/j.1751-9004.2007.00006.x

Perry-Smith, J. E., & Mannucci, P. V. (2017). From creativity to innovation: The social network drivers of the four phases of the idea journey. *The Academy of Management Review*, 42 (1), 53–79. https://doi.org/10.5465/amr.2014.0462

Piller, F. T., Srour, M., & Marion, T. J. (2024). Generative AI, innovation, and trust. *The Journal of Applied Behavioral Science*, 60 (4), 613–622. https://doi.org/10.1177/00218863241285033

Reiser, B. J. (2004). Scaffolding complex learning: The mechanisms of structuring and problematizing student work. *The Journal of the Learning Sciences* 13 (3), 273–304.

Rietzschel, E. F., Nijstad, B. A., & Stroebe, W. (2010). The selection of creative ideas after individual idea generation: Choosing between creativity and impact. *British Journal of Psychology,* 101 (Pt 1), 47–68. https://doi.org/10.1348/000712609X414204

Roberts, D. L., & Candi, M. (2024). Artificial intelligence and innovation management: Charting the evolving landscape. *Technovation*, *136*, 103081. https://doi.org/10.1016/j.technovation.2024.103081

Sarstedt, M., & Danks, N. P. (2022). Prediction in HRM research–A gap between rhetoric and reality. *Human Resource Management Journal*, 32 (2), 485–513. https://doi.org/10.1111/1748-8583.12400

Schryen, G., Marrone, M., & Yang, J. (2025). Exploring the scope of generative AI in literature review development. *Electronic Markets*, 35 (1). https://doi.org/10.1007/s12525-025-00754-2

Sedkaoui, S., & Benaichouba, R. (2024). Generative AI as a transformative force for innovation: a review of opportunities, applications and challenges. *European Journal of Innovation Management*. https://doi.org/10.1108/EJIM-02-2024-0129

Sharma, P. N., Sarstedt, M., Ringle, C. M., Cheah, J.-H., Herfurth, A., & Hair, J. F. (2024). A framework for enhancing the replicability of behavioral MIS research using prediction oriented techniques. *International Journal of Information Management*, 78, 102805. https://doi.org/10.1016/j.ijinfomgt.2024.102805

Sloman, S. A. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin*, 119 (1), 3–22. https://doi.org/10.1037/0033-2909.119.1.3

Sowden, P., Pringle, A., & Gabora, L. (2015). The shifting sands of creative thinking: Connections to dual process theory. *Thinking & Reasoning,* 21 (1), 40–60. https://doi.org/10.1080/13546783.2014.885464

Strack, F., & Deutsch, R. (2004). Reflective and impulsive determinants of social behavior. *Personality and Social Psychology Review 8*(3), 220–247. https://doi.org/10.1207/s15327957pspr0803_1

Sundberg, L., & Holmström, J. (2024). Innovating by prompting: How to facilitate innovation in the age of generative AI. *Business Horizons*, 67 (5), 561–570. https://doi.org/10.1016/j.bushor.2024.04.014

Susarla, A., Gopal, R., Thatcher, J. B., & Sarker, S. (2023). The Janus effect of generative AI: charting the path for responsible conduct of scholarly activities in information systems. *Information Systems Research*, 34 (2), 399–408. https://doi.org/10.1287/isre.2023.ed.v34.n2

Toubia, O. (2006). Idea generation, creativity, and incentives. *Marketing Science*, 25 (5), 411–425. https://doi.org/10.1287/mksc.1050.0166

Toubia, O., & Netzer, O. (2017). Idea generation, creativity, and prototypicality. *Marketing Science*, 36 (1), 1–20. https://doi.org/10.1287/mksc.2016.0994

Vandenbosch, B., Saatcioglu, A., & Fay, S. (2006). Idea management: A systemic view *Journal of Management Studies*, 43 (2), 259–288. https://doi.org/10.1111/j.1467-6486.2006.00590.x

Vaswani, A., Shazeer, N. M., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems*, 30. 31st Conference on Neural Information Processing Systems.* CA, USA: Long Beach.

Vitellaro, F., Schifilliti, V., Buratti, N., & Cesaroni, F. (2025). I won't become obsolete! Exploring the acceptance and use of GenAI by marketing professionals. *European Journal of Innovation Management.* https://doi.org/10.1108/EJIM-04-2024-0471

Wang, B., Rau, P.-L. P., & Yuan, T. (2022). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology*, 42 (9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

Wang, K., Nickerson, J., & Sakamoto, Y. (2018). Crowdsourced idea generation: The effect of exposure to an original idea. *Creativity and Innovation Management*, 27 (2), 196–208. https://doi.org/10.1111/caim.12264

Wang, T., Qi, T., Zhou, X., & Xin, X. (2024). Idea generation performance in open innovation communities: The role of user interaction. *Information & Management*, 61 (3), 103930. https://doi.org/10.1016/j.im.2024.103930

Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52 (3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001

Williams, C., & van Triest, S. (2023). Understanding performance in professional services for innovation intermediation: Technology consultants vs. management consultants. *Technovation*, *126*, 102824. https://doi.org/10.1016/j.technovation.2023.102824

Woodman, R. W., Sawyer, J. E., & Griffin, R. W. (1993). Toward a theory of organizational creativity. *The Academy of Management Review*, 18 (2), 293–321. https://doi.org/10.2307/258761

Yeo, G. B., Celestine, N. A., Parker, S. K., To, M. L., & Hirst, G. (2024). A neurocognitive framework of attention and creativity: Maximizing usefulness and novelty via directed and undirected pathways. *Journal of Organizational Behavior*, 45 (6), 912–934. https://doi.org/10.1002/job.2787

Zhang, X., Yu, P., & Ma, L. (2025). How and when generative AI use affects employee incremental and radical creativity: an empirical study in China. *European Journal of Innovation Management*. https://doi.org/10.1108/EJIM-04-2024-0466

4. Research Paper 3

Held, P., Heubeck, T., & Meckl, R. (2025). GenAI at work: How explorative GenAI usage and regulatory focus shape professionals' innovative work behavior *Currently under review in a scientific journal*

Abstract

Generative AI (GenAI) adoption is widespread among professionals, yet its influence on their innovative work behavior (IWB) is not sufficiently explored. Building on March's exploration–exploitation logic and regulatory focus theory, we examine whether GenAI adoption enhances IWB and the potential underlying mechanisms. We surveyed 339 German professionals and analyzed the data utilizing partial least squares structural equation modeling (PLS-SEM). Findings show that professionals' GenAI adoption encourages both explorative and exploitative GenAI usage. However, only explorative GenAI usage translates into higher IWB; exploitative GenAI usage and mere GenAI adoption leave IWB unchanged. A promotion focus strengthens both explorative GenAI usage and IWB, whereas a prevention focus weakens IWB without affecting usage choices. This study advances IWB research by disentangling GenAI adoption from the type of usage, demonstrating that the benefits of GenAI hinge on how professionals deploy it. It also extends regulatory focus theory by showing that motivational orientation shapes professionals' IWB and explorative GenAI usage.

Keywords

Generative AI; Explorative GenAI usage; Exploitative GenAI usage; Regulatory focus theory; Promotion focus; Prevention focus; Exploration and exploitation; Innovative work behavior

5. Book Chapter: Management Capabilities in the Age of GenAI

Heubeck, T., & Held, P. (2025). Management capabilities in the age of generative artificial intelligence (GenAI): A conceptual framework and future research directions. In J. Liebowitz (Ed.), Achieving Digital Transformation through Analytics and AI (pp. 131–153). World Scientific. https://doi.org/10.1142/13939

Abstract

The rapid proliferation of generative artificial intelligence (GenAI), characterized by tools like ChatGPT, represents a transformative shift in strategic decision-making and business operations. GenAI's unprecedented potential, including its ability to generate novel content and its projected contribution to global GDP growth, necessitates the adaptation of managerial capabilities. This paper explores the intersection of GenAI and the theory of dynamic managerial capabilities (DMCs), focusing on the four dimensions of DMCs: human capital, social capital, cognition, and emotions. It proposes an extended DMC framework tailored to the GenAI era, highlighting the reciprocal relationship between GenAI and managerial capabilities. GenAI enhances DMCs by expanding knowledge synthesis and fostering innovation, while effective managerial capabilities amplify the responsible and creative deployment of GenAI. The study underscores the ethical and social implications of GenAI, including bias, trust, and workforce impacts, calling for principled managerial approaches and ethical guidelines. Future research avenues include developing GenAI literacy frameworks, examining its emotional influence on managers, and identifying strategic decision-making scenarios where GenAI offers maximum value. The findings emphasize the urgency for leaders to adapt to GenAI's disruptive potential, ensuring their organizations remain competitive while fostering innovation and aligning with societal values. The era of GenAI presents challenges and opportunities, demanding proactive and informed leadership to navigate its complexities and unlock its transformative promise.

6. Research Paper 4

Held, P., Heubeck, T., & Meckl, R. (2025). Boosting SMEs' digital transformation: the role of dynamic capabilities in cultivating digital leadership and digital culture. *Review of Managerial Science*, 1-29. https://doi.org/10.1007/s11846-025-00919-5

Abstract

Digital transformation is crucial for the competitiveness of small and medium-sized enterprises (SMEs), yet many SMEs struggle with its implementation. Although digital leadership and digital culture are two established facilitators of digital transformation, their antecedents remain highly understudied. Drawing on the dynamic capabilities framework, we hypothesize that dynamic capabilities promote digital leadership and digital culture in SMEs. Our empirical study builds on questionnaire data from 98 SMEs located in Southern Germany. The findings support the enabling role of dynamic capabilities, indicating that dynamic capabilities enhance digital leadership and digital culture. Contrary to our expectations, the hypothesized mediation effects between dynamic capabilities, digital leadership, and digital culture were not supported, indicating that the translation mechanisms between digital leadership and digital culture might be less direct and straightforward than previously presumed. Thus, dynamic capabilities emerge as critical, yet separate, enablers of digital leadership and digital culture. By positioning dynamic capabilities as antecedents rather than outcomes, this study provides a novel perspective on central enablers of digital transformation, extending dynamic capabilities theory into this context. Overall, our findings offer important implications for facilitating SMEs' digital transformation, highlighting dynamic capabilities as essential for fostering digital leadership and digital culture. Despite its significance, our study faces some limitations that hinder the generalizability of our findings, including relatively small sample size or specific sample context. Future research should replicate and extend our analyses using larger and more diverse samples.

Keywords Digital culture, Digital leadership, Digital transformation, Dynamic capabilities, Small and medium-sized enterprises

6.1. Introduction

Digital transformation has become a popular topic in business research (Kraus et al., 2021) as it represents a profound technological change that affects all levels of a company (Nadkarni & Prügl, 2021; Pfister & Lehmann, 2023). This change introduces new processes that fundamentally reshape how a company operates and creates value (Kraus et al., 2022). As a result, digital transformation has become vital for enhancing firm performance in today's competitive business landscape (Malodia et al., 2023).

However, implementing digital transformation in small and medium-sized enterprises (SMEs) is associated with difficulties (Gyamerah et al., 2025). Most SMEs have fallen behind due to their specific characteristics. For instance, SMEs face inherent resource scarcity (Eller et al., 2020) and have limited capabilities to scale their business model (Galli-Debicella, 2021). In addition, SMEs often lack a holistic understanding of digital transformation, as their leaders tend to perceive it as a onetime project rather than an ongoing organization-wide change process (Zoppelletto et al., 2023).

Consequently, research suggests that SMEs rely on a successful digital transformation to stay competitive (Skare et al., 2023; Pfister & Lehmann, 2023). Through the adoption and strategic integration of technologies, SMEs can improve their operational efficiency (Koporcic et al., 2025). Therefore, SMEs must actively embrace the current trends in digitalization (Kallmuenzer et al., 2025), which represents an essential component of digital transformation.

Although technology is necessary for successful digital transformation (Vial, 2019), other enablers must also be considered (Dörr et al., 2023; Saihi et al., 2023). Consequently, alongside the technological dimension, a human dimension needs to be incorporated (Nadkarni & Prügl, 2021). Notably, there is growing consensus in the literature on the importance of establishing digital leadership (e.g., Brunner et al., 2023; Cortellazzo et al., 2019; Huang et al., 2023; Gyamerah et al., 2025) and cultivating digital culture (e.g., Butt et al., 2024; Weritz et al., 2020; Ghafoori et al., 2024) to achieve successful digital transformation in an organization.

Accordingly, digital leaders select, promote, and enable the effective use of technologies among their employees (Op ´t Roodt et al., 2025). Their leadership introduces the necessary mindset needed for the transformational process (Konopik et al., 2022). Moreover, digital leaders play a critical role in shaping the strategic direction for digital transformation and in ensuring that digital initiatives are effectively aligned with the organization's core business objectives (Canhoto et al., 2021; Singh et al., 2020). Furthermore, digital leadership promotes a trust-based organizational culture that supports collaboration and enables individuals to thrive in the digital age (Tigre et al., 2023).

Organizational culture affects various aspects of an organization during digital transformation (Ghafoori et al., 2024), including technology adoption (Dasgupta & Gupta, 2019; Jackson, 2011). Digital transformation requires a digital mindset and subsequent cultural change (Fitzgerald et al., 2014). Thus, digital culture is crucial for the success of digital transformation (Warner & Wäger, 2019; Weritz et al., 2020).

Consequently, one critical challenge for SMEs lies in effectively leveraging digital leadership and digital culture to boost digital transformation. Against this backdrop, the *dynamic capabilities framework* provides a fitting theoretical lens, as it encompasses a firm's ability to sense opportunities, seize identified opportunities, and transform resources (Teece, 2007; Teece et al., 1997). Several studies highlight the importance of dynamic capabilities in the digital context (e.g., Matarazzo et al., 2021; Mikalef & Gupta, 2021; Warner & Wäger, 2019; Weritz et al., 2024; Soluk & Kammerlander, 2021), resulting in a dedicated research stream for the interplay of dynamic capabilities and digital transformation (Kraus et al., 2022; Abbad & Rowe, 2024).

However, there is insufficient knowledge about the interplay of both enablers—digital leadership and digital culture—with the dynamic capabilities framework. Recent research either conceptualizes digital leadership as a dynamic capability itself (e.g., Konopik et al., 2022) or highlights its role in fostering dynamic capabilities for digital transformation (e.g., Huang et al., 2023; Gyamerah et al., 2025). While these studies illustrate the crucial role of digital leadership in promoting dynamic capabilities, they do not explore vice versa how dynamic capabilities—as a crucial organizational foundation—can enhance digital leadership.

In examining the interplay between digital culture and dynamic capabilities, digital culture is frequently conceptualized as a moderator that facilitates the translation of dynamic capabilities into organizational outcomes (e.g., An et al., 2024). However, Warner and Wäger (2019) challenge this perspective by emphasizing that the process of building dynamic capabilities in the context of digital transformation itself initiates an ongoing strategic renewal, including the renewal of organizational culture. Nevertheless, research has not yet examined whether dynamic capabilities can actively promote and shape digital culture.

To the best of our knowledge, there is a lack of quantitative empirical research on how dynamic capabilities influence digital leadership and digital culture in the context of SMEs' digital transformation. We depart from previous research by positioning dynamic capabilities as an *antecedent*—not as an outcome—of digital leadership and digital culture. This perspective offers a new angle on well-established and validated constructs of digital transformation research and highlights the enabling role of dynamic capabilities in digital transformation, as suggested by previous research (e.g., Heubeck, 2023; Fachrunnisa et al., 2020; Warner & Wäger, 2019). Specifically, we aim to contribute to the literature by answering the following two research questions:

RQ 1. To what extent do dynamic capabilities promote digital culture and digital leadership in the context of SMEs' digital transformation?

RQ 2. What are the interdependencies between digital leadership and digital culture in the context of dynamic capabilities within SMEs' digital transformation?

Drawing on dynamic capabilities literature, we hypothesize that dynamic capabilities foster both digital leadership and digital culture in SMEs. We also explore potential mediation effects between these factors to better understand the underlying mechanisms. We tested our hypotheses on a sample of primary questionnaire data from 98 SMEs in Southern Germany and found general support for the facilitating role of dynamic capabilities for digital culture and digital leadership. Despite our theoretical expectations, we found no support for a mediation relationship between dynamic capabilities, digital culture, and digital leadership.

Our study makes two central theoretical contributions. First, we offer a conceptual extension by proposing that dynamic capabilities act as organizational building blocks that precede and enable the development of digital leadership and digital culture. While prior research often positions digital leadership and digital culture as facilitators (e.g., Gyamerah et al., 2025; Huang et al., 2023) or moderators (e.g., An et al., 2024) of dynamic capabilities, we complement this view by reversing the perspective: dynamic capabilities, understood as higher-order routines (Winter, 2003), provide the structural and cognitive foundations from which these transformation-enabling constructs can emerge. This theoretical shift helps better understand how organizations actively construct the conditions necessary for digital transformation (Leso et al., 2024).

Second, we contribute to a more differentiated view of how dynamic capabilities shape the socio-organizational foundations of digital transformation by showing that digital leadership and digital culture emerge as distinct, non-interdependent outcome paths. Contrary to our theoretical expectations—and to prevailing assumptions of sequential or mediating relationships (e.g., Cortellazzo et al., 2019; Butt et al., 2024)—our findings reveal that both constructs are directly influenced by dynamic capabilities but do not causally affect one another. This suggests that leadership and culture reflect parallel manifestations of adaptive capacity rather than components of a linear process. Particularly in SMEs, where change is often informal and context-driven (Zoppelletto et al., 2023), this dual-path perspective refines existing assumptions by accounting for the non-hierarchical, emergent nature of capability-driven digital transformation (Schoemaker et al., 2018; Warner & Wäger, 2019).

6.2. Theory

6.2.1. The role of digital leadership within SMEs' digital transformation

In line with Müller et al. (2024), who focus on the role of business leaders in digital transformations, we adopt the perspective of "leadership as a social influence process" (Banks et al., 2022, p. 1). This perspective emphasizes "the activities of an organized group in its efforts toward goal setting and goal achievement" (Stogdill, 1950, p. 4). Against this backdrop, we view digital leadership as "an emerging construct that broadly encompasses leading both the transition and the organization in a digital environment" (Hossain et al., 2025, p. 3).

Digital leaders drive organizational change by leveraging digital technologies and combining technical expertise with their strategic vision (McCarthy et al., 2022; Cortellazzo et al., 2019). In other words, they unite both technology and business competencies (Hossain et al., 2025) and effectively coordinate various digital transformation initiatives (Singh et al., 2020).

Moreover, digital leaders promote the digital vision both internally and externally (Benitez et al., 2022). They mobilize digital transformation initiatives by living and communicating the company's mission throughout the workforce (Porfírio et al., 2021). As such, digital leadership represents a socio-technological phenomenon across multiple organizational levels (Schuster et al., 2023). By fostering a culture of experimentation and readiness for change, digital leaders prepare the workforce for digital transformation (Konopik et al., 2022). They also guide decisions on which technologies to adopt and how quickly they should be implemented (Porfírio et al., 2021). Further, they act as role models with regard to ethical behavior in digital transformation contexts (Cortellazzo et al., 2019).

Digital leaders require a broad set of digital, business, and strategic leadership skills (Benitez et al., 2022). Müller et al. (2024) elaborate this further by identifying three core competencies—technical, business, and people-oriented—embedded in four archetypal competency portfolios: (1) the challenger, who excels in exploring market innovation, (2) the bricoleur, who supports operational efficiency, (3) the organizer, who ensures active stakeholder involvement, and (4) the competitor, who enhances competitive positioning. This framework underscores that effective digital leadership should be context-specific and dynamically adjusted to the complexities of digital transformation.

Furthermore, with regard to digital skills, Op ’t Roodt et al. (2025) emphasize three core competencies of digital leaders: (1) digital interaction, defined as effectively selecting and utilizing digital media appropriate to situational needs; (2) digital openness, described as leaders’ enthusiasm and receptiveness towards embracing technological innovations; and (3) digital role modeling, characterized by leaders providing guidance and establishing clear frameworks for their teams’ digital media usage.

Additionally, successful digital transformation necessitates flexible organizational structures for continuous adaptation and requires leaders to have digital transformation awareness (understanding digital dynamics), digital transformation acceleration (rapid implementation of digital initiatives), and digital transformation harmonization (effective integration of digital activities) (Hanelt et al., 2021).

In sum, digital leadership emerges as both a driving force (Malodia et al., 2023; Müller et al., 2024) and a key enabler for digital transformation (Leso et al., 2024). Thereby, leadership factors such as strategy, culture, and talent development were found to be more critical to digital transformation than technological issues (Kane et al., 2019). This is especially true for SMEs, where decision-making tends to be leader-centric, resulting in the conclusion that a successful digital transformation is closely tied to the skills of the digital leader (Gyamerah et al., 2025). Moreover, digital transformation is frequently initiated by the entrepreneurs themselves (Li et al., 2018). This infers that SMEs must leverage digital leadership to facilitate digital transformation.

6.2.2. The role of digital culture within SMEs’ digital transformation

Another crucial enabler for successful digital transformation is digital culture (Saihi et al., 2023; Ghafoori et al., 2024). In line with previous research, we define digital culture as an organizational culture that encompasses the shared values, beliefs, and behavioral patterns that enable and support digital transformation (Upadhyay & Kumar, 2020; An et al., 2024).

Digital culture fosters virtual collaboration and actively supports the development of employees by nurturing their capabilities to remain competitive in the digital environment (Grover et al., 2022). It is tightly interconnected with technology, data, and innovation, aiming to foster flexibility, agility, and creativity within organizations operating in digital environments (An et al., 2024).

Moreover, digital culture affects various aspects of an organization during digital transformation (Ghafoori et al., 2024). It is characterized by openness to change, agility, and a commitment to continuous learning (Hartl & Hess, 2017). A strong emphasis on "testing before implementing" reflects the values of experimentation and iterative learning in the deployment of digital technologies (Butt et al., 2024). In this context, digital culture fosters digital transformation by embedding a start-up mindset and the acceptance of failures, supporting organizational reinvention toward a shared future purpose, and encouraging individuals to try again with the same passion after setbacks (Butt et al., 2024).

Successful digital transformation depends on cultivating a digital mindset and fostering a corresponding cultural change (Fitzgerald et al., 2014). Digital culture shapes how individuals perceive and accept digital technologies by influencing core beliefs related to usefulness, ease of use, social expectations, and support structures—making culture a critical antecedent to successful digital technology adoption (Dasgupta & Gupta, 2019). When organizational values are widely shared, the organization is better equipped to adopt new technologies effectively (Jackson, 2011).

In addition, a data-driven culture strongly influences both product and process innovation, thereby enhancing the firm's competitiveness within the industry (Chatterjee et al., 2024), which is essential for successfully navigating the challenges of digital transformation. Digital culture also fosters the digitalization of organizational processes (Proksch et al., 2024). However, a control-oriented organizational culture can hinder digital transformation by obstructing the openness and creativity required for digital innovation (Müller et al., 2019).

Diverse cultural backgrounds within the workforce influence how organizations adopt and manage digital technologies (Wang & Esperança, 2023). Therefore, digital transformation should not replace existing cultural values; instead, it should serve to renew and build upon the foundational elements of culture and further develop them (Warner & Wäger, 2019).

Overall, digital culture functions as a crucial enabler of digital transformation in SMEs (Leso et al., 2024; Isensee et al., 2020). Given the informal and bottom-up character of digital transformation in SMEs, change is often promoted by peer-driven initiatives that encourage a digital mindset and support the development of a digital culture through supportive and non-judgmental engagement with employees (Zoppelletto et al., 2023). A risk-averse organizational culture is a key barrier to successful digitalization in SMEs (Kallmuenzer et al., 2025). This indicates that SMEs must establish a digital culture to facilitate digital transformation.

6.2.3. Dynamic capabilities as a theoretical lens for digital transformation

Dynamic capabilities have emerged as a pivotal theoretical framework in strategic management, particularly suited for analyzing how businesses adapt to rapid environmental changes (e.g., Teece, 2007; Peteraf et al., 2013; Schilke et al., 2018; Eisenhardt & Martin, 2000). Company capabilities can be divided into two broad categories: dynamic and ordinary (Teece, 2014; Winter, 2003). Accordingly, the ordinary "capability is ordinary in the sense of maintaining the status quo" (Helfat & Winter, 2011, p. 1244). This implies that they are primarily concerned with routine administrative, operational, and governance functions (Teece, 2014).

On the contrary, there are dynamic capabilities that are geared toward strategic change (Helfat & Winter, 2011) and are defined as "the capacity of an organization to purposefully create, extend, and modify its resource base" (Helfat et al., 2007, p. 1). In line with the resource-based view, dynamic capabilities can serve as strategic resources that are valuable, rare, and difficult to imitate, thereby contributing to competitive advantage (Peteraf et al., 2013; Gupta et al., 2024).

Dynamic capabilities can be categorized into three core activities: sensing opportunities and threats, seizing opportunities, and transforming resources (Teece, 2007). These three core activities play a vital role in guiding how firms adapt, although they often remain hidden from external observers (Schoemaker et al., 2018). *Sensing* refers to a firm's ability to systematically scan, interpret, and learn from its environment in order to identify emerging technological and market opportunities as well as potential threats (Teece, 2007). *Seizing* captures the capability to mobilize resources and invest in new products or services, enabling the firm to capitalize on identified opportunities through effective value creation (Teece, 2007, 2014). *Transforming* refers to the firm's capacity to continuously renew, recombine, and reconfigure its tangible and intangible assets (Teece, 2007).

Since digital transformation represents a massive and rapid change—strategically within the company and in the environment—dynamic capabilities seem to be a suitable theoretical lens for our research. In this vein, several studies have investigated the interplay between dynamic capabilities and digital transformation in similar contexts (Warner & Wäger, 2019; Matarazzo et al., 2021; Heubeck, 2023; Cannas, 2023; Orero-Blat et al., 2025), resulting in a distinct research stream that combines digital transformation and dynamic capabilities. Kraus et al. (2022) identify dynamic capabilities as one of five dominant themes in the digital transformation literature related to business and management. In their recent literature review, Abbad and Rowe (2024) further confirm the timeliness of dynamic capabilities by proposing a process model that sequentially articulates three categories of digital transformation capabilities: digital sensing, digital seizing, and digital reconfiguring. The same breakdown is made by Leso et al. (2024), who identify five thematic fields of action for digital transformation regarding the microfoundations of sensing, seizing, and reconfiguring capabilities: (1) designing and managing transformation, (2) promoting digital value propositions, (3) acting in digital business ecosystems, and (4) systematizing structural change. They also specify a fifth category containing supporters and enablers of digital transformation, including digital leadership and digital culture.

Thus, we can conclude that dynamic capabilities play a crucial role in digital transformation as they provide a framework for understanding how organizations adapt, innovate, and maintain competitive advantage in a rapidly changing digital world (Teece, 2018). This is relevant as particularly SMEs need to adapt to this new digital reality (Gonçalves et al., 2024).

6.3. Hypotheses development

In dynamic and digitally evolving environments, SMEs must continuously adapt to remain competitive (Canhoto et al., 2021). Against this background, organizational structures must be flexible and favor separate business units, agile forms, and dedicated digital functions (Verhoef et al., 2021). In this context, dynamic capabilities— defined as a firm's ability to sense opportunities and threats, seize those opportunities, and reconfigure its resource base accordingly—are essential organizational routines that enable strategic change (Teece, 2007). While dynamic capabilities are often discussed as generic enablers of adaptation (e.g., Helfat & Winter, 2011), we argue that in the specific context of SMEs undergoing digital transformation, they serve a more foundational role: dynamic capabilities function as the *organizational building blocks* for developing two established facilitators of digital transformation—digital leadership and digital culture.

We position dynamic capabilities as higher-order, organization-wide routines (Winter, 2003) that precede and enable the formation of specialized digital competencies. In this sense, dynamic capabilities are not merely mechanisms for change but are the very conditions under which digital leadership and digital culture can emerge. Dynamic capabilities often emerge from and build upon historically embedded routines and organizational memory (Zollo & Winter, 2002). As such, dynamic capabilities are cumulative and path-dependent, drawing from a firm's unique experience base and past adaptation mechanisms (Eisenhardt & Martin, 2000; Teece et al., 1997).

Because of this historically rooted nature, dynamic capabilities—though adaptive—tend to stabilize around established schemas and processes (Zollo & Winter, 2002). They evolve slowly over time and often carry an organization's legacy ways of sensing, interpreting, and responding to change (Eisenhardt & Martin, 2000). In contrast, we view digital leadership and digital culture as more fluid and future-oriented forces. They are not merely adaptations of past competencies but rather involve a deliberate break or reorientation of the firm's strategic mindset and cultural identity in light of emerging digital realities. They challenge embedded routines and usher in new values like agility, experimentation, and customer-centricity (Zoppelletto et al., 2023; Tigre et al., 2023).

Digital leadership integrates strategic, technological, and interpersonal competencies to guide organizations through digital transformation by promoting a clear digital vision and fostering change readiness (Hossain et al., 2025). It involves context-specific skills such as digital interaction, openness to innovation, and role modeling (Op 't Roodt et al., 2025). In SMEs, where leadership is often centralized, digital leadership is a key enabler of successful digital transformation (Gyamerah et al., 2025).

Building on this, we argue that dynamic capabilities may play a foundational role in the development of digital leadership. Specifically, we suggest that the sensing and seizing dimensions of dynamic capabilities could help SME leaders recognize the strategic relevance of digital technologies, articulate a coherent digital vision, and mobilize organizational efforts around them. Furthermore, reconfiguring capabilities may support leaders in adapting internal structures and processes, thereby enabling the implementation of digital initiatives and reinforcing leadership legitimacy during transformation processes. We state our first hypothesis (see Fig. 6.1 for the research model) as follows:

H1. Dynamic capabilities foster digital leadership within SMEs.

Digital culture encompasses the shared values, norms, and behavioral patterns that support openness to technological change, promote agility and experimentation, and foster a continuous learning mindset across the organization (Upadhyay & Kumar, 2020; Hartl & Hess, 2017; An et al., 2024). It shapes how individuals perceive, adopt, and engage with digital technologies and is therefore considered a critical enabler of successful digital transformation, particularly in SME contexts where informal, bottom-up processes dominate (Dasgupta & Gupta, 2019; Zoppelletto et al., 2023; Leso et al., 2024).

Building on this conceptualization, we argue that dynamic capabilities may catalyze the emergence of digital culture in SMEs undergoing digital transformation. In particular, we suggest that the transformation dimension of dynamic capabilities—which involves the ongoing renewal of organizational resources, structures, and routines—provides the structural and cognitive conditions under which a digital mindset and corresponding cultural patterns can evolve. Warner and Wäger (2019) offer empirical support for this view by demonstrating that digital transformation, as a process driven by dynamic capabilities, often results in a strategic renewal that explicitly includes changes in organizational culture. Their findings show that firms engaging in digital transformation through dynamic capabilities ultimately refresh their internal culture by fostering digital values, practices, and ways of thinking. Accordingly, we propose that dynamic capabilities not only facilitate adaptation on a structural and strategic level but also actively promote the development of digital culture as part of a broader transformation process. Therefore, we propose the following hypothesis:

H2. Dynamic capabilities foster digital culture within SMEs.

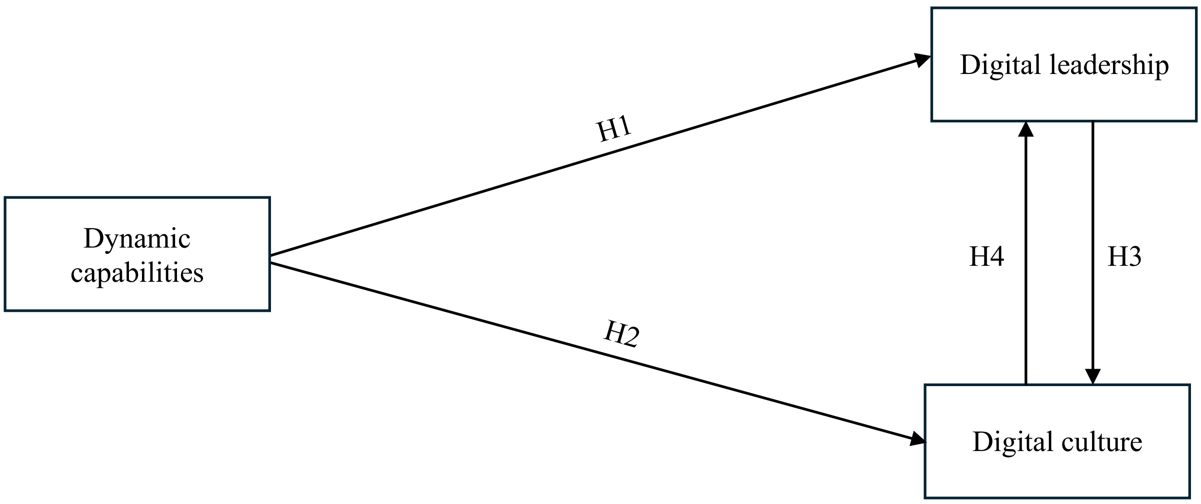


Figure 6.1 Research Model

Source: Own illustration

Beyond the independent effects of dynamic capabilities on digital leadership and digital culture, we argue that these two constructs may also interact, suggesting a potential mediation mechanism through which one construct channels the effects of dynamic capabilities onto the other. While digital leadership and digital culture are often treated as parallel enablers of digital transformation (e.g., Konopik et al., 2022; Leso et al., 2024), extant literature also points to significant interdependencies between them (e.g., Porfírio et al., 2021).

On the one hand, digital leadership may foster the emergence of digital culture by shaping shared values, guiding behavioral norms, and providing direction throughout the digital transformation process. Digital leaders promote a digital vision, act as role models, and foster a culture of experimentation and openness to change (Porfírio et al., 2021; Cortellazzo et al., 2019). They influence how employees perceive and engage with technology, thereby setting the tone for organizational learning and adaptability (Op ’t Roodt et al., 2025; Müller et al., 2024). Particularly in SMEs, where leaders hold significant sway over organizational values and practices, leadership actions can be expected to shape cultural dynamics more directly (Gyamerah et al., 2025). From this perspective, digital leadership may represent a transmission mechanism through which dynamic capabilities translate into a supportive digital culture. Thus, we hypothesize:

H3. Digital leadership mediates the relationship between dynamic capabilities and digital culture.

Conversely, a pre-existing or evolving digital culture may enable or reinforce digital leadership. A culture characterized by openness to technological change, continuous learning, and a tolerance for failure creates an environment in which digital leaders can more easily exercise their roles (Ghafoori et al., 2024; Butt et al., 2024). Such a culture legitimizes visionary leadership, encourages risk-taking, and facilitates the acceptance of transformative agendas (Fitzgerald et al., 2014; Dasgupta & Gupta, 2019). In particular, shared digital mindsets can lower resistance to change and increase alignment with leadership initiatives aimed at digital innovation and organizational transformation (Zoppelletto et al., 2023; An et al., 2024). In this view, digital culture may act as a facilitating mechanism that enhances the effectiveness of digital leadership as an outcome of dynamic capabilities. Therefore, we suggest the following hypothesis:

H4. Digital culture mediates the relationship between dynamic capabilities and digital leadership.

6.4. Method

6.4.1. Data collection and sample

For the empirical test of the research model, we surveyed SMEs from a southern German region in Baden-Wuerttemberg. The official SME report of the state of Baden-Wuerttemberg 2021 shows the essential importance of SMEs for this federal state (MW BW, 2021). A structural analysis by the Institute for SME Research at the University of Mannheim describes that in 2019, over 99% of companies in Baden-Wuerttemberg were defined as SMEs, employing half of all employees (MW BW, 2021). Furthermore, the report highlights the challenges regarding SMEs' digital transformation, making this region suitable for our study.

The questionnaire, including initial pre-tests, was created between February and April 2024. It was part of a larger, more practically focused study of SMEs in this region and was developed in collaboration with another research team. After the pilot phase and questionnaire adjustments, the data collection phase finally occurred in May 2024. In cooperation with a local bank, the managing directors of 952 companies were contacted by letter, which contained a link to the online survey (we used QuestionPro as a survey tool). To determine an appropriate sample size for our analysis, we conducted an a priori power analysis using the software G*Power 3 (Faul et al. 2007). Based on the assumptions of an F-test for linear multiple regression (fixed model), with an expected high effect size ($f^2 = 0.35$), a significance level of $\alpha = 0.05$, and a statistical power of 0.95, the calculated minimum required sample size was 70 participants.

We received 168 responses, from which 104 were completed (response rate: 10.9%). The response rate aligns with those reported in prior research using similar survey-based approaches (e.g., Hernández-Linares et al., 2024; Heubeck & Meckl, 2022). We then removed one conspicuous response in which the participant ticked the first box for each question. In addition, we removed five responses, as these were companies with a turnover of more than 50 million and, thus, were no longer SMEs. As a result, we obtained 98 usable responses from SMEs, which is suitable for our study. Table 6.1 shows the sample characteristics, including demographic data of the SMEs.

Several methods and tests were used to avoid common method bias. First, various pre-tests were conducted with three research assistants, two professors, and three target group entrepreneurs to ensure the questions' comprehensibility and clarity (MacKenzie & Podsakoff, 2012). Second, the social desirability bias was minimized by an introductory text in the study, which ensured that no personal data of the participants was collected via the questionnaire and that no identification of individual respondents was possible. During the data analysis, we also conducted common method and non-response bias tests (see Chap. 6.4.3).

Table 6.1 Sample characteristics

Variable			%
Industry	Manufacturing	26	26.5
	Services	72	73.5
Employees	0–9	32	32.7
	10–49	44	44.9
	50–249	18	18.4
	250–499	4	4.1
Firm age (in years)	0–10	17	17.3
	11–20	22	22.4
	21–50	31	31.6
	>50	28	28.6
Revenue (in Mio €)	≤ 0.5	15	15.3
	0.5–2	27	27.6
	2–10	35	35.7
	10–50	21	21.4
Management position (respondent)	CEO and/or owner	79	80.6
	Other members of the board	6	6.1
	Manager	10	10.2
	Employee	3	3.1

Note: $N = 98$

Source: Own illustration

6.4.2. Variable measurements

For the measurement items, we used well-researched and accepted scales (Kump et al., 2019; Rossmann, 2018) and constructed using a 5-point Likert scale ranging from 1 “strongly agree” to 5 “strongly disagree.” Details of the constructs and their measurement items are shown in Table 6.5 in the appendix.

To measure the independent variable, dynamic capabilities, we used the dynamic capabilities scale of Kump et al. (2019), which is based on Teece (2007). Using the sensing, seizing, and transforming capacities proposed by Teece (2007), a total of 14 items were assessed (five for sensing, four for seizing, and five for transforming).

We required a German translation of the original scale for our survey, which was conducted in German. To obtain this, we reached out to the authors of the original scale, who provided us with their validated German translation.

To measure the dependent variables, *digital leadership* and *digital culture*, we used the scale of Rossmann (2018), who proposed a conceptualization and measurement model for firms' digital maturity by deriving eight dimensions for measuring digital maturity. These eight dimensions are required capabilities to achieve digital maturity. Two of these dimensions are leadership capability and culture capability, each measured by four items. As the original study relates to the digital context, these two constructs are termed digital culture and digital leadership in our study. The original scale was in English. We applied the back-translation methodology here and translated the statements into German.

Digital leadership and digital culture are dependent variables that may be influenced by other factors. Based on previous research in similar contexts, we included several control variables. We controlled for two variables for SMEs' size: number of employees and revenue (Kellermanns et al., 2012; Malodia et al., 2023). We further controlled for company age and the company's industry (Zahra et al., 2006; Chesbrough & Rosenbloom, 2002; Weritz et al., 2024). In addition, we controlled for the management level, asking the person completing the questionnaire what position they held in the company (Heubeck & Meckl, 2022).

6.4.3. Statistical procedure

We used IBM SPSS Statistics for the data analysis. First, we constructed the variables for dynamic capabilities, digital leadership, and digital culture using a principal component factor analysis. For an optimal allocation of the items, we applied a varimax rotation. We excluded missing values listwise. For assessing the basic eligibility of the data for factor analysis, we conducted Bartlett's test of sphericity and measured the sampling adequacy criterion (MSA) as well as the Kaiser-Meyer-Olkin (KMO) criterion (Hair et al., 2014). We only formed a factor if it comprised at least three variables, each with factor loadings exceeding 0.30 (Hair et al., 2014). To determine the number of extracted factors, we used the Kaiser-Guttman (KG) criterion, the scree test (Thompson, 2004), and the latent root criterion, which specifies factor loadings of > 0.40 and eigenvalues of at least 1 (Gower, 1966). The quality criteria were assessed using Cronbach's alpha for reliability, the average variance extracted (AVE), and the Fornell-Larcker ratio (FLR) for validity. Cronbach's alpha values of > 0.60 were defined as acceptable for reliability due to the exploratory nature of our research (Hair et al., 2014). Acceptable variability was defined as an AVE of > 0.50 and an FLR < 1 (Fornell & Larcker, 1981). In addition, an AVE between 0.40 and 0.50 counted as acceptable validity if Cronbach's alpha coefficient also exceeded 0.60 (Fornell & Larcker, 1981).

We tested for common method bias by conducting Harman's single factor test and defined the often-used value of < 50% as acceptable (Harman, 1976; Podsakoff et al., 2003). Our analysis revealed a single-factor variance of 32.87%, which is well below the commonly accepted threshold, indicating that common method bias is unlikely to be a concern in our study. Furthermore, to conduct a non-response bias test, we compared data obtained at the beginning (33%) and at the end (33%) of the collection period. To identify significant differences, we performed a sample t-test on our constructs. None of the variables showed a statistically significant difference between the two groups since all p-values exceeded 0.05. These results indicate that non-response bias is unlikely to pose a significant issue in our study. To test our hypotheses, we used multiple regression analysis. Thereby, we defined the significance levels as extremely significant ($p \leq 0.001$), highly significant ($p \leq 0.01$), and significant ($p \leq 0.05$). Besides, we defined the strength of the effects as strong ($b > 0.35$), moderate ($b > 0.15$), and weak ($b > 0.02$) (Cohen 1988).

Our research model proposes that dynamic capabilities foster digital leadership (H1) and digital culture (H2). Furthermore, it posits that digital leadership is a strengthening mediator in the direct positive relationship between dynamic capabilities and digital culture (H3). Conversely, it suggests that digital culture is a strengthening mediator in the direct positive relationship between dynamic capabilities and digital leadership (H4). Specifically, we tested Hypotheses 1 and 2 (i.e., direct effects) through regression analysis based on factor analysis. We tested Hypotheses 3 and 4 (i.e., the indirect effects) through regression analysis employing the bootstrapping method using Hayes' (2021) PROCESS macro for SPSS. The confidence intervals were calculated based on 5000 bootstrap samples, with standard errors adjusted using heteroscedasticity-robust inference HC4 (Cribari-Neto). For mediation to be established, the independent variable needs to have a significant effect on the mediator, and the mediator needs to have a significant effect on the dependent variable (Baron & Kenny, 1986).

6.5. Results

6.5.1. Measurement model

We conducted a principal components factor analysis with all items and constructs. The Bartlett test of sphericity was highly significant for all factors ($p < 0.001$). The KMO and MSA criteria confirmed these findings to confirm the basic data eligibility for factor analysis. Table 6.2 summarizes the results of the factor analysis. We made two modifications to the dynamic capabilities measurement scale and the three sub-dimensions: sensing, seizing, and transforming. Specifically, the third sensing item and the fourth seizing item were excluded due to a low factor loading (< 0.400). No other modifications were necessary for the subdimensions. All sub-dimensions met the criteria explained above. The final factor for dynamic capabilities was extracted, comprising the three sub-dimensions mentioned.

Table 6.2 Factor analysis results

Factor	Item	Std. FL
Sensing (KMO = 0.757; $p < 0.001$; AVE = 0.570; FLR = 0.508; α = 0.738; $N = 98$)	Sensing 1	0.727
	Sensing 2	0.789
	Sensing 4	0.671
	Sensing 5	0.823
Seizing (KMO = 0.655; $p < 0.001$; AVE = 0.590; FLR = 0.271; α = 0.629; $N = 98$)	Seizing 1	0.760
	Seizing 2	0.758
	Seizing 3	0.786
Transforming (KMO = 0.734; $p < 0.001$; AVE = 0.512; FLR = 0.534; α = 0.773; $N = 98$)	Transforming 1	0.682
	Transforming 2	0.729
	Transforming 3	0.808
	Transforming 4	0.706
	Transforming 5	0.642
Dynamic capabilities (KMO = 0.720; $p < 0.001$; AVE = 0.739; FLR = 0.531; α = 0.864; $N = 98$)	Sensing	0.860
	Seizing	0.867
	Transforming	0.851
Digital leadership (KMO = 0.675; $p < 0.001$; AVE=0.735; FLR = 0.644; α = 0.815; $N = 98$)	Digital Leadership 1	0.849
	Digital Leadership 4	0.814
	Digital Culture 2	0.906
Digital culture (KMO = 0.664; $p < 0.001$; AVE = 0.504; FLR = 0.549; α = 0.662; $N = 98$)	Digital Culture 1	0.785
	Digital Culture 3	0.675
	Digital Culture 4	0.644
	Digital Leadership 3	0.728

Notes: α = Cronbach's alpha; AVE = Average variance extracted; FLR = Fornell-Larcker ratio; KMO = Kaiser-Meyer-Olkin; N = Sample size; p = Significance value for the Bartlett test of sphericity; Std. FL = Standardized factor loadings
Source: Own illustration

We then analyzed composite factors for both digital leadership and culture constructs. Three factors could be extracted here. Subsequently, we removed the second item of digital leadership, as it strongly loaded on a third unrelated factor. After removing this item, we extracted two factors. In contrast to the measurement scale we used, the first factor, digital leadership, consisted of the items DL1, DL4, and DC2. The second factor, digital culture, consisted of the items DC1, DC3, DC4, and DL3.

6.5.2. Bivariate and regression results

In the next step, we calculated the correlations listed in Table 6.3. The regression analysis results can be found in the appendix (Tables 6.6, 6.7, 6.8) and are summarized in Figure 6.2. An overview of the results of the hypotheses tests is presented in Table 6.4.

Table 6.3 Bivariate results

	Variable	1	2	3	4	5	6	7	8
1	Dynamic capabilities	1							
2	Digital leadership	0.415^{***}	1						
3	Digital culture	0.506^{***}	0.218^{*}	1					
4	Company age	–0.147	0.104	–0.026	1				
5	Company size	0.006	–0.152	–0.044	0.200^{*}	1			
6	Revenue	–0.038	–0.064	–0.051	0.354^{***}	0.733^{***}	1		
7	Management position	0.128	–0.084	0.228^{*}	0.147	0.383^{***}	0.408^{***}	1	
8	Industry	–0.088	–0.020	0.021	0.131	–0.010	0.105	0.305^{**}	1

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$; $^{*}p < 0.05$; $N = 98$

Source: Own illustration

Hypothesis 1 stated that SMEs' dynamic capabilities are positively related to digital leadership. Our data analysis supports Hypothesis 1, as we found an extremely significant, strong effect of dynamic capabilities on digital leadership ($b = 0.460$, $p < 0.001$).

Hypothesis 2 predicted that SMEs' dynamic capabilities of a company are positively related to digital culture. Our data analysis shows that Hypothesis 2 can be accepted due to dynamic capabilities' extremely significant, strong effect on digital culture ($b = 0.475$, $p < 0.001$).

Hypothesis 3 posited that digital leadership mediates the relationship between dynamic capabilities and digital culture. The analysis showed that digital leadership has a positive but statistically insignificant effect on digital culture ($b = 0.017$, $p = 0.867$), an initial indication that there is no mediator effect. The indirect effect of dynamic capabilities on digital culture via digital leadership is positive but statistically insignificant ($b = 0.080$, 95% CI: − 0.871, 0.138). Therefore, Hypothesis 3 is rejected.

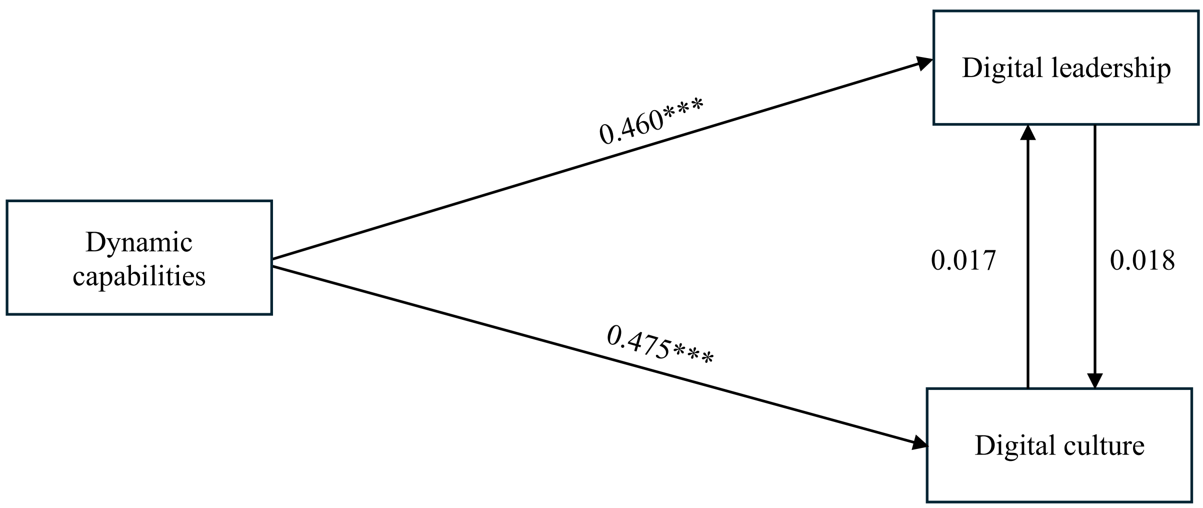


Figure 6.2 Research Model with regression effects, N = 98, *** p < 0.001

Source: Own illustration

Hypothesis 4 stated that digital culture mediates the relationship between dynamic capabilities and digital leadership. The analysis showed that digital leadership has a positive but statistically insignificant effect on digital culture ($b = 0.018$, $p = 0.867$), an initial indication against a mediating effect. The indirect effect of dynamic capabilities on digital leadership via digital culture is positive but statistically insignificant (b = 0.089, 95% CI: − 0.115, 0.113), leading to the rejection of Hypothesis 4.

Table 6.4 Summary of hypothesis test results

Hypothesis		Results
H1	Dynamic capabilities foster digital leadership within SMEs.	Supported
H2	Dynamic capabilities foster digital culture within SMEs.	Supported
H3	Digital leadership mediates the relationship between dynamic capabilities and digital culture.	Not supported
H4	Digital culture mediates the relationship between dynamic capabilities and digital leadership.	Not supported

Source: Own illustration

6.6. Discussion

This study set out to explore how dynamic capabilities—positioned as antecedents— foster two established enablers of SMEs' digital transformation: digital leadership and digital culture. Drawing on the dynamic capabilities framework, we positioned these capabilities not as outcomes but as foundational routines that actively shape the socio-organizational conditions of digital transformation. Our findings provide empirical support for this core assumption: dynamic capabilities significantly foster both digital leadership and digital culture. This reinforces the theoretical proposition that sensing, seizing, and transforming capabilities do not merely accompany digital change but serve as higher-order enablers that structure and activate firm-level readiness for digital transformation.

At the same time, our results challenge some prevailing assumptions about the interdependence of digital leadership and digital culture. While prior work has often implied interdependent or aligned relationships between digital leadership and digital culture (e.g., Cortellazzo et al., 2019; Butt et al., 2024), we could not confirm such interdependence in our data. Instead, our analysis suggests distinct outcome paths, each directly influenced by dynamic capabilities. In other words, our findings reveal that both constructs are directly influenced by dynamic capabilities but do not causally affect one another. Rather than contradicting the transformation logic, this finding refines it by suggesting that leadership and culture constitute complementary—yet structurally distinct—manifestations of adaptive capacity. Especially in SME contexts—characterized by informal structures and bottom-up processes (Zoppelletto et al., 2023)—parallel development paths may be more realistic than tightly coupled, hierarchical relationships.

6.6.1. Theoretical contributions

Our study makes two important theoretical contributions. First, our study offers a significant conceptual extension to the existing literature by reconfiguring the role of dynamic capabilities in the context of digital transformation. Prior research predominantly portrays digital leadership as a dynamic capability itself (e.g., Konopik et al., 2022) or as a facilitator of dynamic capabilities (e.g., Gyamerah et al., 2025; Huang et al., 2023). Respectively, digital culture is seen as a moderator that facilitates the translation of dynamic capabilities into outcomes (e.g., An et al., 2024). In contrast, we extend this understanding by a change in the perspective, proposing that dynamic capabilities as higher-order organizational building blocks can precede and enable the emergence of digital leadership and digital culture rather than being shaped by them.

Drawing on the dynamic capabilities framework (Teece, 2007; Helfat et al., 2007; Winter, 2003), we conceptualize sensing, seizing, and transforming not only as mechanisms of strategic adaptation but also as foundational capacities that structure the firm's ability to develop context-specific transformation competencies. In this view, dynamic capabilities serve as meta-level routines that orchestrate the formation of lower-level organizational phenomena such as digital leadership behavior or digital cultural orientations. This understanding aligns with the notion of dynamic capabilities as "higher-order capabilities" (Winter, 2003) that provide the scaffolding upon which more granular competencies can emerge.

By positioning dynamic capabilities as organizational building blocks for digital leadership and digital culture, our study responds to recent calls to better understand how firms can actively construct transformation-enabling conditions (Leso et al., 2024; Abbad & Rowe, 2024). Especially in the SME context, where informal structures and bottom-up processes dominate (Zoppelletto et al., 2023), the interpretation of dynamic capabilities as building blocks for digital leadership and digital culture offers valuable theoretical refinement. It highlights that SMEs should not treat leadership and culture as isolated levers but as outcomes of more deeply rooted organizational routines that evolve over time through accumulated adaptation experiences (Zollo & Winter, 2002; Eisenhardt & Martin, 2000).

Second, our study contributes to a more differentiated understanding of how dynamic capabilities influence the socio-organizational foundations of digital transformation by revealing that digital leadership and digital culture operate as distinct and non-interdependent outcome paths. Contrary to prior assumptions that suggest a sequential or mediating relationship—where digital leadership fosters a digital culture or vice versa (e.g., Cortellazzo et al., 2019; Butt et al., 2024)—our findings indicate that both constructs are directly shaped by dynamic capabilities, but they do not mediate each other's effects.

This result suggests that in SMEs' digital transformation contexts, there is not a linear progression from dynamic capabilities to digital leadership to digital culture or from dynamic capabilities from digital culture to digital leadership. Instead, we propose that digital leadership and digital culture should be conceptualized as parallel expressions of the firm's dynamic transformation capacity, each activated through distinct mechanisms of dynamic capabilities.

In this light, our study advances a non-hierarchical, non-sequential model of digital transformation in SMEs—one that reflects the emergent, iterative, and often non-linear dynamics inherent in organizational adaptation processes (Schoemaker et al., 2018; Warner & Wäger, 2019).

By introducing this dual-path perspective, we extend current theory in two important ways. First, we challenge over-simplified assumptions of causality between digital leadership and digital culture in digital transformation contexts, which may overlook alternative configurations or mutual independence. Second, we highlight the strategic versatility of dynamic capabilities: they enable multiple, parallel channels of digital transformation, not just singular pathways. This insight opens the door for future research to explore contingent patterns of capability deployment and transformation logic—especially in organizations facing structural constraints but high adaptive potential, such as SMEs.

6.6.2. Practical contributions

Our findings have several practical contributions, which can be used for concrete recommendations for SMEs undergoing digital transformation. Accordingly, our first practical contribution is that SMEs should actively strengthen the three core dimensions of dynamic capabilities—sensing, seizing, and transforming—through targeted practices.

To enhance sensing capabilities, SMEs should establish mechanisms for systematically monitoring technological trends, competitor activity, and customer needs. This includes integrating digital dashboards to visualize real-time data and detect weak signals (Schoemaker et al., 2013) or engaging in cross-industry trend scouting (Ellström et al., 2022).

To strengthen seizing capabilities, SMEs should create structures that enable "probe-and-learn experimentation," including experiments and rapid prototyping (Day & Schoemaker, 2016). A concrete action would be the establishment of a digital innovation lab, where employees can experiment with minimum viable products (Warner & Wäger, 2019).

To develop transforming capabilities, SMEs should join a digital ecosystem to interact with multiple external partners (Warner & Wäger, 2019). Another action here is to decompose digital transformation into specified projects and prioritize these projects in alignment with the digital strategy (Ellström et al., 2022). Finally, SMEs can hire external digital experts, such as chief digital officers or consultants, to redesign internal structures and improve digital maturity (Warner & Wäger, 2019).

Our second practical implication arises from the finding that our data did not support the theorized mediation effects between digital leadership and digital culture. Our results indicate that—at least within the SME context—these elements may develop more independently than expected.

For practitioners, this implies that digital leadership and digital culture should not be treated as automatically reinforcing. Instead, both areas may require separate, targeted interventions. Leadership development initiatives, for instance, should not rely on cultural change as a natural byproduct. Likewise, efforts to foster a digital culture may not, by themselves, lead to strong leadership behavior. SMEs should, therefore, consider pursuing complementary but distinct strategies for both domains—each with its own set of tools, responsibilities, and timelines—to more effectively build the socio-organizational basis for digital transformation.

6.6.3. Limitations and future research

Like any research, our study faces several inherent limitations that can serve as starting points for future research. First, we focused on SMEs from a specific region in Southern Germany. It is important to acknowledge the limitations in terms of generalizability, particularly across different organizational and cultural contexts. As a first step, further studies could be carried out in other regions in Germany to make generalizable statements for Germany. In a second step, this could be extended to other countries to examine the extent to which cultural factors or the region’s technological maturity play a role.

Another limitation concerns the relatively small sample size, which may affect the statistical power of our analyses and increase the risk of estimation bias. Although we conducted an a priori power analysis using G*Power and confirmed that the sample size was sufficient to detect large effects with high confidence, the limited number of observations may still constrain the ability to identify more subtle or indirect relationships. Moreover, smaller samples can reduce the robustness and generalizability of the findings. Future research should, therefore, replicate and extend our analyses with larger and more diverse samples to strengthen the external validity of the results.

A further methodological limitation concerns potential endogeneity. Our model assumes that dynamic capabilities precede and shape digital leadership and digital culture. However, based on cross-sectional data, we cannot entirely exclude reverse causality or omitted variable bias. It is conceivable that digital leadership and culture also contribute to developing dynamic capabilities—a direction supported by other strands of research (e.g., Gyamerah et al., 2025; Huang et al., 2023). Yet, our study does not reject this inverse relationship. Instead, we offer a theoretically motivated shift in perspective. While much of the existing literature conceptualizes digital leadership and digital culture as antecedents or moderators of dynamic capabilities, we propose the reverse view and argue that dynamic capabilities act as higher-order foundations from which these constructs emerge. Nevertheless, future studies should use longitudinal or quasi-experimental designs to test for reciprocal relationships and better account for endogeneity.

Moreover, the non-significant mediation effects may also reflect limitations in measurement precision, as two items showed partial construct overlap in the factor analysis. While conceptually robust, this empirical convergence could have diluted statistical power to detect indirect effects. Nonetheless, these results do not weaken our theoretical model; instead, they point to the need for more granular investigation into the mechanisms linking dynamic capabilities, digital leadership, and digital culture.

Next, our study did not measure digital transformation as a construct in our model. Since the promotional effect of digital leadership and digital culture has already been established in the literature by numerous studies (Brunner et al., 2023; Ghafoori et al., 2024; Schuster et al., 2023), we decided to make this the fundamental assumption of our study. However, future research could measure the exact strength of these effects, especially in comparison to other enablers such as technical infrastructure or digital readiness. This could be particularly helpful for practitioners, as SMEs would have a kind of priority list and could allocate their limited budget in a value-adding way.

Finally, we only looked at dynamic capabilities on the organizational level. Previous research (Heubeck, 2024; Helfat & Martin, 2015) argues that firm-level capabilities are sometimes too abstract and difficult to grasp. Thus, studying dynamic capabilities at an individual level might make sense in the context of digital transformation. For example, Scuotto et al. (2021) found that individual digital capabilities are crucial for a company facing market changes. In other words, future research could investigate the role of individuals in developing digital culture and digital leadership.

6.7. Appendix

Table 6.5 Questionnaire items derived from Kump et al. (2019) and Rossmann (2018)

Construct	**Item**
Sensing	SE1 Our company knows the best practices in the market
	SE2 Our company is up-to-date on the current market situation
	SE3 Our company systematically searches for information on the current market situation*
	SE4 As a company, we know how to access new information
	SE5 Our company always has an eye on our competitors' activities
Seizing	SZ1 Our company can quickly relate to new knowledge from the outside
	SZ2 We recognize what new information can be utilized in our company
	SZ3 Our company is capable of turning new technological knowledge into process and product innovation
	SZ4 Current information leads to the development of new products and services*
Transforming	T1 By defining clear responsibilities, we successfully implement plans for changes in our company
	T2 Even when unforeseen interruptions occur, change projects are seen through consistently in our company
	T3 Decisions on planned changes are pursued consistently in our company
	T4 In the past, we have demonstrated our strengths in implementing changes
	T5 In our company, change projects can be put into practice alongside the daily business
Digital leadership	DL1 Our executives support the implementation of the digital strategy
	DL2 The digital strategy is only implemented in individual functional areas (inverse)**
	DL3 The culture of leadership in our firm is based on transparency, cooperation and decentralized decision-making processes
	DL4 The digital strategy of our firm has an influence on the task and role profiles of executives
Digital culture	DC1 Decisions within our firm are transparent to our own employees
	DC2 Digitization has an impact on the decision-making agility of our firm
	DC3 In day-to-day business, employees and executives exchange information about the digital transformation of our firm
	DC4 Continuous change is part of our corporate culture

*Removed due to low factor loading; **Removed due to high factor loading on an unrelated factor

Source: Own illustration

Table 6.6 Regression results: Direct effects hypotheses with dependent variable digital leadership

Digital Leadership	**Model 1**				**Model 2**				**Model 3**			
	b	**β**	***se***	**VIF**	***b***	**β**	***se***	**VIF**	***b***	**β**	***se***	**VIF**
Study variables												
Dynamic capabilities					0.469***	0.469***	0.094	1.066	0.460***	0.460***	0.108	1.399
Digital culture									0.018	0.018	0.109	1.432
Control variables												
Company age	0.044	0.134	0.036	1.163	0.066*	0.199*	0.033	1.184	0.066*	0.198*	0.033	1.203
Company size	-0.256	-0.210	0.187	2.286	-0.251	-0.206	0.167	2.286	-0.249	-0.205	0.168	2.296
Revenue	0.063	0.062	0.163	2.492	0.090	0.089	0.145	2.496	0.091	0.090	0.146	2.506
Management position	-0.048	-0.038	0.150	1.354	-0.176	-0.139	0.029	1.403	-0.181	-0.143	0.140	1.476
Industry	-0.010	-0.035	0.032	1.148	0.008	0.026	0.029	1.166	0.008	0.026	0.029	1.166
Constant	0.266		0.333		0.170		0.297		0.171		0.299	
R^2	0.046				0.252				0.252			
P	0.496				< 0.001				< 0.001			

Notes: b = regression coefficient, β = standardized regression coefficient, N = sample size, p = significance value, R^2 = coefficient of determination, se = standard error, VIF = variance inflation factor, $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $N = 98$

Source: Own illustration

Table 6.7 Regression results: Direct effects hypotheses with dependent variable digital culture

Digital Culture	**Model 1**				**Model 2**				**Model 3**			
	b	**β**	***se***	**VIF**	***b***	**β**	***se***	**VIF**	***b***	**β**	***se***	**VIF**
Study variables												
Dynamic capabilities					0.483^{***}	0.483^{***}	0.090	1.066	0.475^{***}	0.475^{***}	0.103	1.360
Digital leadership									0.017	0.017	0.102	1.337
Control variables												
Company age	-0.003	-0.009	0.036	1.163	0.020	0.059	0.032	1.184	0.018	0.055	0.033	1.237
Company size	-0.107	-0.880	0.183	2.286	-0.102	-0.084	0.161	2.286	-0.098	-0.081	0.164	2.343
Revenue	-0.111	-0.110	0.159	2.492	-0.084	-0.083	0.140	2.496	-0.085	-0.084	0.141	2.506
Management position	0.417	0.329	0.147	1.354	0.285	0.225	0.131	1.403	0.288^{*}	0.228^{*}	0.133	1.429
Industry	-0.020	–0.068	0.031	1.148	-0.001	-0.005	0.028	1.166	-0.002	-0.005	0.028	1.167
Constant	0.057		0.326		-0.042		0.287		–0.045		0.289	
R^2	0.083				0.302				0.302			
P	0.149				< 0.001				< 0.001			

Notes: b = regression coefficient, β = standardized regression coefficient, N = sample size, p = significance value, R^2 = coefficient of determination, se = standard error, VIF = variance inflation factor, $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $N = 98$

Source: Own illustration

Table 6.8 Bootstrapping regression results

Indirect effect	*b*	*se*	Confidence interval		
			Lower	**Upper**	**Level**
Dynamic capabilities → Digital leadership → Digital culture	0.080	0.0562	-0.871	0.138	95%
Dynamic capabilities → Digital culture → Digital leadership	0.089	0.0569	-0.115	0.113	95%

Notes: *se* = Standard error, *b* = coefficient, *N* = Sample size; $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; number of bootstrap samples = 5000, bootstrap inference for model coefficients, *N* = 98

Source: Own illustration

6.8. References

Abbad H., Rowe F. (2024) Understanding dynamic capabilities for digital transformation: a literature review and future research directions. In: 1st International conference on digital transformation society, DTS 2024, Naples, Italy

An M., Lin J., Luo X. (2024) The impact of human AI skills on organizational innovation: the moderating role of digital organizational culture. *Journal of Business Research* 182, 114786. https://doi.org/10.1016/j.jbusres.2024.114786

Banks G.C., Dionne S.D., Mast M.S., Sayama H. (2022) Leadership in the digital era: a review of who, what, when, where, and why. *The Leadership Quarterly* 33 (5), 101634. https://doi.org/10.1016/j.leaqua.2022.101634

Baron R.M., Kenny D.A. (1986) The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology* 51 (6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Benitez J., Arenas A., Castillo A., Esteves J. (2022) Impact of digital leadership capability on innovation performance: the role of platform digitization capability. *Information & Management* 59 (2),103590. https://doi.org/10.1016/j.im.2022.103590

Brunner T.J.J., Schuster T., Lehmann C. (2023) Leadership's long arm: the positive influence of digital leadership on managing technology-driven change over a strengthened service innovation capacity. *Frontiers in Psychology* 14, 988808. https://doi.org/10.3389/fpsyg.2023.988808

Butt A., Imran F., Helo P., Kantola J. (2024) Strategic design of culture for digital transformation. *Long Range Planning* 57 (2), 102415. https://doi.org/10.1016/j.lrp.2024.102415

Canhoto A.I., Quinton S., Pera R., Molinillo S., Simkin L. (2021) Digital strategy aligning in SMEs: a dynamic capabilities perspective. *The Journal of Strategic Information Systems* 30 (3), 101682. https://doi.org/10.1016/j.jsis.2021.101682

Cannas R. (2023) Exploring digital transformation and dynamic capabilities in agrifood SMEs. *Journal of Small Business Management* 61 (4), 1611–1637. https://doi.org/10.1080/00472778.2020.1844494

Chatterjee S., Chaudhuri R., Vrontis D. (2024) Does data-driven culture impact innovation and performance of a firm? An empirical examination. *Annals of Operations Research* 333 (2), 601–626. https://doi.org/10.1007/s10479-020-03887-z

Chesbrough H., Rosenbloom R.S. (2002) The role of the business model in capturing value from innovation: evidence from Xerox Corporation's technology spin-off companies. *Industrial and Corporate Change* 11 (3), 529– 555. https://doi.org/10.1093/icc/11.3.529

Cohen J. (1988) Statistical power analysis for the behavioral sciences. L. Erlbaum Associates, Hillsdale

Cortellazzo L., Bruni E., Zampieri R. (2019) The role of leadership in a digitalized world: a review. *Frontiers in Psychology* 10, 1938. https://doi.org/10.3389/fpsyg.2019.01938

Dasgupta S., Gupta B. (2019) Espoused organizational culture values as antecedents of internet technology adoption in an emerging economy. *Information & Management* 56 (6), 103142. https://doi.org/10.1016/j.im.2019.01.004

Day G.S., Schoemaker P.J. (2016) Adapting to fast-changing markets and technologies. *California Management Review* 58 (4), 59–77. https://doi.org/10.1525/cmr.2016.58.4.59

Dörr L., Fliege K., Lehmann C., Kanbach D.K., Kraus S. (2023) A taxonomy on influencing factors towards digital transformation in SMEs. *Journal of Small Business Strategy* 33 (1), 53–69. https://doi.org/10.53703/001c.66283

Eisenhardt K.M., Martin J.A. (2000) Dynamic capabilities: what are they? *Strategic Management Journal* 21 (10–11), 1105–1121

Eller R., Alford P., Kallmünzer A., Peters M. (2020) Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. *Journal of Business Research* 112, 119–127. https://doi.org/10.1016/j.jbusres.2020.03.004

Ellström D., Holtström J., Berg E., Josefsson C. (2022) Dynamic capabilities for digital transformation. *Journal of Strategy and Management* 15 (2), 272–286. https://doi.org/10.1108/JSMA-04-2021-0089

Fachrunnisa O., Adhiatma A., Lukman N., Majid M.N.A. (2020) Towards SMEs' digital transformation: the role of agile leadership and strategic flexibility. *Journal of Small Business Strategy* 30 (3), 65–85

Faul F., Erdfelder E., Lang A.G., Buchner A. (2007) G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods* 3P(2), 175–191. https://doi.org/10.3758/BF03193146

Fitzgerald M., Kruschwitz N., Bonnet D., Welch M. (2014) Embracing digital technology: a new strategic imperative. *MIT Sloan Management Review* 55, 1–12

Fornell C., Larcker D.F. (1981) Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18 (1), 39–50. https://doi.org/10.2307/3151312

Galli-Debicella A. (2021) How SMEs compete against global giants through sustainable competitive advantages. *Journal of Small Business Strateg*y 31 (5), 13–21. https://doi.org/10.53703/001c.29812

Ghafoori A., Gupta M., Merhi M.I., Gupta S., Shore A.P. (2024) Toward the role of organizational culture in data-driven digital transformation. *International Journal of Production Economics* 271, 109205. https://doi.org/10.1016/j.ijpe.2024.109205

Gonçalves M.P., Ferreira F.A., Dabić M., Ferreira J.J. (2024) "Navigating through the digital swamp": assessing SME propensity for online marketplaces. *Review of Managerial Sci*ence 18 (9), 2583–2612. https://doi.org/10.1007/s11846-023-00704-2

Gower J.C. (1966) Some distance properties of latent root and vector methods used in multivariate analysis. *Biometrika* 53 (3/4), 325–338. https://doi.org/10.2307/2333639

Grover V., Tseng S.L., Pu W. (2022) A theoretical perspective on organizational culture and digitalization. *Information & Management* 59 (4), 103639. https://doi.org/10.1016/j.im.2022.103639

Gupta N., Sardana D., Lee R. (2024) Dynamic capabilities that matter for business failure versus survival. *Industrial Marketing Management* 116, 40–50. https://doi.org/10.1016/j.indmarman.2023.11.004

Gyamerah S., Afshari L., Asante D. (2025) Digital transformation in the SME context: the nexus between leadership, digital capabilities and digital strategy. *International Small Business Journal: Researching Entrepreneurship* 43 (3), 303–328. https://doi.org/10.1177/02662426251314108

Hair J.F., Black W.C., Babin B.J., Anderson R.E. (2014) Multivariate data analysis, 7th edn. Pearson Education, Upper Saddle River

Hanelt A., Bohnsack R., Marz D., Antunes Marante C. (2021) A systematic review of the literature on digital transformation: insights and implications for strategy and organizational change. *Journal of Management Stud*ies 58 (5), 1159–1197. https://doi.org/10.1111/joms.12639

Harman H.H. (1976) Modern factor analysis. University of Chicago Press

Hartl E., Hess T. (2017) The role of cultural values for digital transformation: insights from a Delphi study. In: Proceedings of the 23rd Americas conference on information systems (AMCIS 2017)

Helfat C.E., Finkelstein S., Mitchell W., Peteraf M., Singh H., Teece D.J., Winter S.G. (2007) Dynamic capabilities: understanding strategic change in organizations. Blackwell Publishing, Oxford

Helfat C.E., Martin J.A. (2015) Dynamic managerial capabilities: review and assessment of managerial impact on strategic change. *Journal of Management* 41 (5), 1281–1312. https://doi.org/10.1177/0149206314561301

Helfat C.E., Winter S.G. (2011) Untangling dynamic and operational capabilities: strategy for the (n)ever changing world. *Strategic Management Journal* 32 (11), 1243–1250. https://doi.org/10.1002/smj.955

Hernández-Linares R., López-Fernández M.C., García-Piqueres G., Pina e Cunha M., Rego A. (2024) How knowledge-based dynamic capabilities relate to firm performance: the mediating role of entrepreneurial orientation. *Review of Managerial Science* 18 (10), 2781–2813. https://doi.org/10.1007/s11846-023-00691-4

Heubeck T. (2024) Looking back to look forward: a systematic review of and research agenda for dynamic managerial capabilities. *Management Review Quarterly* 74, 2243–2287. https://doi.org/10.1007/s11301-023-00359-z

Heubeck T. (2023) Managerial capabilities as facilitators of digital transformation? Dynamic managerial capabilities as antecedents to digital business model transformation and firm performance. *Digital Business* 3 (1), 100053. https://doi.org/10.1016/j.digbus.2023.100053

Heubeck T., Meckl R. (2022) Antecedents to cognitive business model evaluation: a dynamic managerial capabilities perspective. *Review of Managerial Science* 16 (8), 2441–2466. https://doi.org/10.1007/s11846-021-00503-7

Hossain S., Fernando M., Akter S. (2025) Digital leadership: towards a dynamic managerial capability perspective of artificial intelligence-driven leader capabilities. *Journal of Leadership & Organizational Studies* 32 (2), 189–208. https://doi.org/10.1177/15480518251319624

Huang J.Y.H., Jiang R., Chang J.Y.T. (2023) The effects of transformational and adaptive leadership on dynamic capabilities: digital transformation projects. *Project Management Journal* 54 (4), 428–446. https://doi.org/10.1177/87569728231165896

Isensee C., Teuteberg F., Griese K.-M., Topi C. (2020) The relationship between organizational culture, sustainability, and digitalization in SMEs: a systematic review. *Journal of Cleaner Production* 275, 122944. https://doi.org/10.1016/j.jclepro.2020.122944

Jackson S. (2011) Organizational culture and information systems adoption: a three-perspective approach. *Information and Organization* 21 (2), 57–83. https://doi.org/10.1016/j.infoandorg.2011.03.003

Kallmuenzer A., Mikhaylov A., Chelaru M., Czakon W. (2025) Adoption and performance outcome of digitalization in small and medium-sized enterprises. *Review of Managerial Science* 19, 2011–2038. https://doi.org/10.1007/s11846-024-00744-2

Kane G.C., Phillips A.N., Copulsky J., Andrus G. (2019) How digital leadership is(n't) different. *MIT Sloan Management Review* 60 (3), 34–39

Kellermanns F.W., Eddleston K.A., Sarathy R., Murphy F. (2012) Innovativeness in family firms: a family influence perspective. *Small Business Economics* 38 (1), 85–101. https://doi.org/10.1007/s11187-010-9268-5

Konopik J., Jahn C., Schuster T., Hoßbach N., Pflaum A. (2022) Mastering the digital transformation through organizational capabilities: a conceptual framework. *Digital Business* 2 (2), 100019. https://doi.org/10.1016/j.digbus.2021.100019

Koporcic N., Kukkamalla P.K., Markovic S., Maran T. (2025) Resilience of small and medium-sized enterprises in times of crisis: an umbrella review. *Review of Managerial Science* https://doi.org/10.1007/s11846-025-00883-0

Kraus S., Durst S., Ferreira J.J., Veiga P., Kailer N., Weinmann A. (2022) Digital transformation in business and management research: an overview of the current status quo. *International Journal of Information Management* 63, 102466. https://doi.org/10.1016/j.ijinfomgt.2021.102466

Kraus S., Schiavone F., Pluzhnikova A., Invernizzi A.C. (2021) Digital transformation in healthcare: analyzing the current state-of-research. *Journal of Business Research* 123, 557–567. https://doi.org/10.1016/j.jbusres.2020.10.030

Kump B., Engelmann A., Kessler A., Schweiger C. (2019) Toward a dynamic capabilities scale: measuring organizational sensing, seizing, and transforming capacities. *Industrial and Corporate Change* 28 (5), 1149–1172. https://doi.org/10.1093/icc/dty054

Leso B.H., Cortimiglia M.N., Ghezzi A., Minatogawa V. (2024) Exploring digital transformation capability via a blended perspective of dynamic capabilities and digital maturity: a pattern matching approach. *Review of Managerial Science* 18 (4), 1149–1187. https://doi.org/10.1007/s11846-023-00692-3

Li L., Su F., Zhang W., Mao J.-Y. (2018) Digital transformation by SME entrepreneurs: a capability perspective. *Information Systems Journal* 28 (6), 1129–1157. https://doi.org/10.1111/isj.12153

MacKenzie S.B., Podsakoff P.M. (2012) Common method bias in marketing: causes, mechanisms, and procedural remedies. *Journal of Retailing* 88 (4), 542–555. https://doi.org/10.1016/j.jretai.2012.08.001

Malodia S., Mishra M., Fait M., Papa A., Dezi L. (2023) To digit or to head? Designing digital transformation journey of SMEs among digital self-efficacy and professional leadership. *Journal of Business Research* 157, 113547. https://doi.org/10.1016/j.jbusres.2022.113547

Matarazzo M., Penco L., Profumo G., Quaglia R. (2021) Digital transformation and customer value creation in Made in Italy SMEs: a dynamic capabilities perspective. *Journal of Business Research* 123, 642–656. https://doi.org/10.1016/j.jbusres.2020.10.033

McCarthy P., Sammon D., Alhassan I. (2022) Digital transformation leadership characteristics: a literature analysis. *Journal of Decision Systems* 32 (1), 79–109. https://doi.org/10.1080/12460125.2021.1908934

Mikalef P., Gupta M. (2021) Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management* 58 (3), 103434. https://doi.org/10.1016/j.im.2021.103434

Müller S.D., Konzag H., Nielsen J.A., Sandholt H.B. (2024) Digital transformation leadership competencies: a contingency approach. *International Journal of Information Management* 75, 102734. https://doi.org/10.1016/j.ijinfomgt.2023.102734

Müller S.D., Obwegeser N., Glud J.V., Johildarson G. (2019) Digital innovation and organizational culture: the case of a Danish media company. *Scandinavian Journal of Information Systems* 31 (2), 3–34

MW BW (2021) Mittelstandsbericht des Landes Baden-Württemberg 2021. https://www.baden-wuerttemberg.de/de/service/presse/pressemitteilung/pid/mittelstandsbericht-2021-fuer-die-jahre-2015-bis-2020-veroentlicht-1 Accessed 15 August 2024

Nadkarni S., Prügl R. (2021) Digital transformation: a review, synthesis and opportunities for future research. *Management Review Quarterly* 71 (2), 233–341. https://doi.org/10.1007/s11301-020-00185-7

Op ´t Roodt H., Bracht E.M., van Dick R., Hernandez Bark A.S. (2025) Navigating through the digital workplace: measuring leader digital competence. *Journal of Business and Psychology* 40 (1), 179–205. https://doi.org/10.1007/s10869-024-09947-6

Orero-Blat M., Palacios-Marqués D., Leal-Rodríguez A.L., Ferraris A. (2025) Beyond digital transformation: a multi-mixed methods study on big data analytics capabilities and innovation in enhancing organizational performance. *Review of Managerial Science* 19 (2), 649–685. https://doi.org/10.1007/s11846-024-00768-8

Peteraf M., Di Stefano G., Verona G. (2013) The elephant in the room of dynamic capabilities: bringing two diverging conversations together. *Strategic Management Journal* 34 (12), 1389–1410. https://doi.org/10.1002/smj.2078

Pfister P., Lehmann C. (2023) Measuring the success of digital transformation in German SMEs. *Journal of Small Business Strategy* 33(1), 1–19. https://doi.org/10.53703/001c.39679

Podsakoff P.M., MacKenzie S.B., Lee J.-Y., Podsakoff N.P. (2003) Common method biases in behavioral research: a critical review of the literature and recommended remedies. *The Journal of Applied Psychology* 88(5), 879– 903. https://doi.org/10.1037/0021-9010.88.5.879

Porfírio J.A., Carrilho T., Felício J.A., Jardim J. (2021) Leadership characteristics and digital transformation. *Journal of Business Research* 124, 610–619. https://doi.org/10.1016/j.jbusres.2020.10.058

Proksch D., Rosin A.F., Stubner S., Pinkwart A. (2024) The influence of a digital strategy on the digitalization of new ventures: the mediating effect of digital capabilities and a digital culture. *Journal of Small Business Management* 62 (1), 1–29. https://doi.org/10.1080/00472778.2021.1883036

Rossmann A. (2018) Digital maturity: conceptualization and measurement model [paper presentation]. In: Thirty Ninth International Conference on Information Systems, San Francisco, p 1–9

Saihi A., Ben-Daya M., As'ad R. (2023) Underpinning success factors of maintenance digital transformation: a hybrid reactive Delphi approach. *International Journal of Production Economics* 255, 108701. https://doi.org/10.1016/j.ijpe.2022.108701

Schilke O., Hu S., Helfat C.E. (2018) Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. *Academy of Management Annals* 12 (1), 390–439. https://doi.org/10.5465/annals.2016.0014

Schoemaker P.J.H., Heaton S., Teece D.J. (2018) Innovation, dynamic capabilities, and leadership. *California Management Review* 61(1), 15–42. https://doi.org/10.1177/0008125618790246

Schoemaker P.J.H., Day G.S., Snyder S.A. (2013) Integrating organizational networks, weak signals, strategic radars and scenario planning. *Technological Forecasting and Social Change* 80 (4), 815–824. https://doi.org/10.1016/j.techfore.2012.10.020

Schuster T., Brunner T.J.J., Schneider M.H.G., Lehmann C., Kanbach D.K. (2023) Leading in the digital age: Conceptualising digital leadership and its influence on service innovation performance. *International Journal of Innovation Management* 27 (6), 2350031. https://doi.org/10.1142/S1363919623500317

Scuotto V., Nicotra M., Del Giudice M., Krueger N., Gregori G.L. (2021) A microfoundational perspective on SMEs' growth in the digital transformation era. *Journal of Business Research* 129, 382–392. https://doi.org/10.1016/j.jbusres.2021.01.045

Singh A., Klarner P., Hess T. (2020) How do chief digital officers pursue digital transformation activities? The role of organization design parameters. *Long Range Planning* 53 (3), 101890. https://doi.org/10.1016/j.lrp.2019.07.001

Skare M., de Las Mercedes Obesso M., Ribeiro-Navarrete S. (2023) Digital transformation and European small and medium enterprises (SMEs): a comparative study using digital economy and society index data. *International Journal of Information Management* 68, 102594. https://doi.org/10.1016/j.ijinfomgt.2022.102594

Soluk J., Kammerlander N. (2021) Digital transformation in family-owned Mittelstand firms: a dynamic capabilities perspective. *European Journal of Information Systems* 30 (6), 676–711. https://doi.org/10.1080/0960085X.2020.1857666

Stogdill R.M. (1950) Leadership, membership and organization. *Psychological Bulletin* 47 (1), 1–14. https://doi.org/10.1037/h0053857

Teece D.J. (2007) Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal* 28 (13), 1319–1350. https://doi.org/10.1002/smj.640

Teece D.J. (2014) The foundations of enterprise performance: dynamic and ordinary capabilities in an (economic) theory of firms. *Academy of Management Perspectives* 28 (4), 328–352. https://doi.org/10.5465/amp.2013.0116

Teece D.J. (2018) Business models and dynamic capabilities. *Long Range Planning* 51 (1), 40–49. https://doi.org/10.1016/j.lrp.2017.06.007

Teece D.J., Pisano G., Shuen A. (1997) Dynamic capabilities and strategic management. *Strategic Management Journal* 18 (7), 509–533

Thompson B. (2004) Exploratory and confirmatory factor analysis: understanding concepts and applications. American Psychological Association, Washington

Tigre F.B., Curado C., Henriques P.L. (2023) Digital leadership: a bibliometric analysis. *Journal of Leadership & Organizational Studies* 30 (1), 40–70. https://doi.org/10.1177/15480518221123132

Upadhyay P., Kumar A. (2020) The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance. *International Journal of Information Management* 52, 102100. https://doi.org/10.1016/j.ijinfomgt.2020.102100

Verhoef P.C., Broekhuizen T., Bart Y., Bhattacharya A., Qi Dong J., Fabian N., Haenlein M. (2021) Digital transformation: a multidisciplinary reflection and research agenda. *Journal of Business Research* 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vial G. (2019) Understanding digital transformation: a review and a research agenda. *The Journal of Strategic Information Systems* 28(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

Wang S., Esperança J.P. (2023) Can digital transformation improve market and ESG performance? Evidence from Chinese SMEs. *Journal of Cleaner Production* 419, 137980. https://doi.org/10.1016/j.jclepro.2023.137980

Warner K.S., Wäger M. (2019) Building dynamic capabilities for digital transformation: an ongoing process of strategic renewal. *Long Range Planning* 52 (3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001

Weritz P., Braojos J., Matute J. (2020) Exploring the antecedents of digital transformation: dynamic capabilities and digital culture aspects to achieve digital maturity. In: Americas conference on information systems (AMCIS)

Weritz P., Braojos J., Matute J., Benitez J. (2024) Impact of strategic capabilities on digital transformation success and firm performance: theory and empirical evidence.

European Journal of Information Systems. https://doi.org/10.1080/0960085X.2024.2311137

Winter S.G. (2003) Understanding dynamic capabilities. *Strategic Management Journal* 24(10), 991–995. https://doi.org/10.1002/smj.318

Zahra S.A., Sapienza H.J., Davidsson P. (2006) Entrepreneurship and dynamic capabilities: a review, model and research agenda. *Journal of Management Studies* 43 (4), 917–955. https://doi.org/10.1111/j.1467-6486.2006.00616.x

Zollo M., Winter S.G. (2002) Deliberate learning and the evolution of dynamic capabilities. *Organization Science* 13(3), 339–351. https://doi.org/10.1287/orsc.13.3.339.2780

Zoppelletto A., Orlandi L.B., Zardini A., Rossignoli C., Kraus S. (2023) Organizational roles in the context of digital transformation: a micro-level perspective. *Journal of Business Research* 157, 113563. https://doi.org/10.1016/j.jbusres.2022.113563

7. Conclusion

7.1. Summary of findings and theoretical implications

The central research goal of this cumulative dissertation was to investigate to what extent and in which way GenAI shapes the IWB and idea generation—as core early stage innovation activity—of employees and professionals. This objective is relevant as GenAI adoption is already widespread among employees at the workplace (Ernst & Young, 2024) and employee-level innovation represents a fundamental microfoundation of firm-level outcomes like innovation (Jong & Hartog, 2010; Mazzucchelli et al., 2019; Strobl et al., 2020) and organizational performance (Shanker et al., 2017). Hence, from a managerial perspective, understanding whether GenAI enhances employee-level innovation is critical, given its potential for firms' overall innovative capacity. Therefore, the first research question was derived:

RQ I. To what extent and in which way does GenAI shape employee innovativeness?

Three research papers collectively show that GenAI is not an automatic "innovation booster." Instead, GenAI's innovative value depends on how employees and professionals engage with it and which capabilities and motivational orientations they bring into the co-creative human–GenAI process.

The first research paper demonstrates that employees' sensing capabilities—conceptualized as an individual-level dynamic capability—directly foster IWB and indirectly do so by enabling GenAI-related capabilities. Importantly, the paper disentangles GenAI usage capability and GenAI evaluation capability. While employees' GenAI evaluation capability positively affects their IWB, GenAI usage capability alone does not; rather, it matters through a sequential pathway in which GenAI usage capability enables GenAI evaluation capability, which then translates into IWB. This capabilities perspective and the resulting findings refine current research at the interface of GenAI and innovation management that often treats GenAI as a single construct (e.g., Cimino et al., 2025; Rana et al., 2024; Singh et al., 2024), contribute to the literature stream of IWB antecedents (e.g., Gelaidan et al., 2024; Madrid et al., 2014; Volery & Tarabashinka, 2021; Yuan & Woodman, 2010) and provide one possible explanation why prior findings on GenAI and creativity are mixed and fragmented (Holzner et al., 2025).

The second research paper complements the first paper by focusing on idea generation as a core early-stage innovation activity. The findings confirm that individuals' GenAI usage capability increases idea generation. However, the underlying cognitive mechanism is asymmetric: Individuals' GenAI usage capability strengthens both their experiential and rational information processing tendencies, yet only rational information processing drives idea generation and mediates this relationship. The paper therefore extends Epstein's cognitive experiential theory (Epstein, 1973, 2003, 2014) into the GenAI context and challenges prior studies that have often emphasized the value of experiential thinking for idea generation (e.g., Bălău et al., 2019) by illustrating that in the context of GenAI the experiential system does not appear to be a significant driver of idea generation. It further complements previous studies investigating GenAI's potential for idea generation (e.g., Eisenreich et al., 2024; Meincke et al., 2024) by integrating a capability perspective highlighting the crucial role of the user competence.

The third research paper adds a motivational and GenAI usage-pattern perspective. It shows that professionals' mere adoption of GenAI does not enhance their IWB. Instead, explorative GenAI usage—using GenAI for novelty-oriented activities such as searching for new possibilities, renewing products, services or processes, and learning new skills—promotes IWB, whereas exploitative GenAI usage does not. Regulatory focus (see Higgins, 2012; Higgins & Pinelli, 2020) further shapes these effects: promotion focus fosters IWB and stimulates explorative GenAI use, while prevention focus dampens IWB. Theoretically, this advances March's (1991) exploration–exploitation logic by specifying GenAI as a tool that can support both types of work activities, but with innovation benefits emerging only when GenAI is used for explorative work activities. The paper also contributes to the research stream of regulatory focus theory by indicating that promotion focus is a significant psychological antecedent of explorative GenAI usage.

Taken together, RQ I is answered as follows: GenAI can foster employee innovativeness in professional work contexts, but not automatically. For IWB, benefits emerge when employees develop GenAI evaluation capability, which is enabled by GenAI usage capability and supported by broader sensing capabilities; mere adoption or operational use of GenAI alone does not increase their IWB. For idea generation, GenAI usage capability is effective primarily through a strengthened reliance on rational (as opposed to experiential) information processing. Moreover, GenAI contributes to IWB mainly when used exploratively, a pattern fostered by promotion focus. Overall, GenAI-driven innovativeness is thus contingent on human capabilities, usage patterns, cognitive information processing, and motivational orientations rather than technology per se.

These findings specify *how* GenAI can translate into employee innovativeness. Yet, they also point to a broader, organization-level condition: the innovative potential of GenAI is likely to remain latent if employees do not adopt the technology or lack an enabling context to develop the required capabilities. Responding to this managerial and theoretical issue, the dissertation complements the individual level perspective with an organizational lens and examines the firm-level foundations that foster human-centered conditions of digital transformation, namely digital leadership and digital culture. Hence, the second research question was postulated:

RQ II. What organizational foundations can foster digital leadership and digital culture?

The fourth research paper examines which organizational foundations help SMEs build digital leadership and cultivate a digital culture—two widely acknowledged facilitators of digital transformation. Drawing on the dynamic capabilities framework (Teece, 2007), the paper argues that SMEs' ability to sense opportunities, seize them, and continuously transform their structures should provide the organizational foundation from which digital leadership and digital culture can emerge. Empirically, the study reveals a clear pattern: dynamic capabilities foster both digital leadership and digital culture in SMEs, whereas the two human-related enablers do not unfold in a straightforward sequential or mutually reinforcing way. In other words, SMEs with stronger dynamic capabilities are better able to develop digital leadership and cultivate digital culture—yet leadership and culture appear as distinct, parallel outcomes rather than a linear cause–and–effect chain.

These findings imply two central theoretical contributions. First, the dissertation extends dynamic capabilities theory into the socio-organizational domain of digital transformation by reversing the dominant causal framing in prior work. Instead of treating digital leadership and digital culture mainly as preconditions or facilitators of dynamic capabilities (e.g., Konopik et al., 2022; Gyamerah et al., 2025; Huang et al., 2023), the paper positions dynamic capabilities as organizational building blocks that precede and enable both constructs. This reframing highlights that firms do not only "use" leadership and culture to transform digitally; instead, adaptive higher-order routines are what allow such digital leadership and digital cultural orientations to form in the first place.

Second, the results refine digital transformation research—particularly in SME contexts—by challenging assumptions of a hierarchical or mediating relationship between leadership and culture (e.g., Cortellazzo et al., 2019; Butt et al., 2024). The evidence suggests that both may develop independently of each other.

Taken together, RQ II is answered as follows: dynamic capabilities constitute a crucial organizational foundation for building the human side of digital transformation, as they directly foster both digital leadership and a digital culture. However, these enablers do not automatically translate into one another; instead, they represent parallel outcomes rooted in the firm's higher-order routines. Although research paper 4 addresses digital technologies more broadly than GenAI specifically, its results still provide implicit insights into how firms can create human-centered conditions that facilitate the adoption, diffusion, and effective use of emerging technologies such as GenAI.

7.2. Practical implications

The empirical findings of this dissertation yield practical implications that help managers leverage GenAI in ways that strengthen their employees' IWB and idea generation, which represent important microfoundations of firm-level innovation.

The first important finding is that GenAI represents a potentially powerful tool to enhance employees' IWB and idea generation, but not by mere operational use or adoption of the technology. Across the papers, a consistent message emerges: The value of GenAI for innovative outcomes depends on the specific employee capabilities and the type of work activities for which GenAI is used.

The first implication concerns employee-level capability development. The first research paper demonstrates that GenAI usage capability alone does not increase employees' IWB. In contrast GenAI evaluation capability does, and usage primarily serves as an antecedent of GenAI evaluation capability. For managers, this means that GenAI initiatives should be designed around two explicit learning goals. One goal is to ensure that employees can use GenAI proficiently; the other—and more critical one—is to ensure that employees build a deeper understanding and the cognitive ability to assess the quality and relevance of GenAI-generated outputs. Specifically, firms should complement prompt engineering trainings with evaluation-focused upskilling formats that train employees to recognize the typical weaknesses of GenAI (e.g., hallucinatory content, superficial reasoning, biased suggestions) and to validate outputs against their domain knowledge before acting on them.

The same paper highlights that employees' sensing capabilities directly increase IWB and simultaneously facilitate the development of both GenAI usage and evaluation capabilities. Thus, managers should invest in opportunity-recognition routines that systematically strengthen employees' external scanning. Concrete measures, which are also described in more detail in the paper, include sending employees to conferences and trade shows, monitoring competitor activities, and establishing recurring "tech-radar" sessions that translate weak signals into actionable opportunity spaces.

A second set of implications relates to the potential of GenAI for idea generation. The second research paper demonstrates that individuals' GenAI usage capability fosters idea generation and identifies prompt engineering as a scalable mechanism to build this capability. Hence, firms can support employees in systematically developing GenAI usage capability through structured prompting training. Importantly, the second research paper also shows that the GenAI usage capability–idea generation link is mediated only by rational, not experiential, information processing. Since employees differ in their cognitive processing tendencies, managers should be aware of that fact. They may consider these tendencies when allocating people to tasks in the context of idea generation and GenAI. This does not imply that people who rely mainly on the experiential information processing system cannot generate ideas. Still, it does show that, in the GenAI context, analytical engagement is the path through which GenAI usage capability translates into enhanced idea generation.

A third set of implications addresses how GenAI should be embedded into daily work to foster professionals' IWB. The third research paper finds no positive effect of GenAI adoption on IWB; only explorative GenAI usage increases IWB, while exploitative usage does not influence IWB. Accordingly, managers should introduce GenAI with explicit explorative use cases (e.g., searching for alternative solutions, reframing challenges, experimenting with novel approaches) rather than expecting innovation gains from efficiency-oriented use alone. The third research paper further shows that promotion focus fosters explorative GenAI use and IWB, whereas prevention focus dampens IWB. This implies that managers can consider motivational orientations when composing project teams for GenAI-supported exploration, because promotion-focused members are more likely to engage in the usage pattern that empirically drives IWB.

Ultimately, the organizational-level evidence suggests that building general dynamic capabilities create an organizational foundation that is fruitful for building digital leadership and cultivating a digital culture, both important antecedents of digital transformation. The paper derives concrete managerial steps: Companies should strengthen sensing, seizing, and transforming capabilities through systematic trend and customer monitoring, probe-and-learn experimentation (e.g., rapid prototyping), and continuous adaptation of structures and partnerships. Because digital leadership and digital culture do not automatically reinforce each other, firms might address both deliberately: digital leadership development to guide technology-driven change, and digital cultural initiatives that sustain openness, experimentation, and learning. Although this research paper examines digital technologies in general, these routines implicitly represent the human-centered conditions under which the adoption and competent use of GenAI can scale.

In sum, this dissertation provides managers with an evidence-based roadmap: build employees' GenAI usage capability for idea generation, but prioritize GenAI evaluation capability for IWB; strengthen employees' sensing capability as an upstream driver of IWB and GenAI capabilities; steer GenAI toward explorative work activities; account for cognitive and motivational differences in task allocation and team staffing; and embed GenAI rollout in building organizational dynamic capabilities as fundamental building blocks of digital leadership and digital culture, which are essential antecedents of a successful digital transformation.

7.3. Limitations and avenues for future research

This dissertation is accompanied by several limitations, which provide avenues for future research. The following section will elaborate on these limitations. The limitations of the individual papers will not be repeated here, as they have already been discussed in detail in the respective sections; instead, aggregated and overarching limitations are highlighted against the backdrop of the entire dissertation.

First and foremost, the empirical evidence across the papers is rooted in quantitative, self-administered questionnaire data collected at a single point in time and in a specific institutional and cultural context, namely Germany and the broader DACH region. While this approach enables large-scale theory testing and comparability across studies, it limits causal inference, cannot fully rule out common-method or social-desirability biases, and primarily captures GenAI-related capabilities and usage as perceived rather than enacted behavior. In addition, focusing on DACH-based samples of consultants, professionals, and SMEs provides contextual depth for a region in which GenAI and technology in general have diffused rapidly, yet it might constrain the transferability of the findings to other cultural, regulatory, or industry environments. Future research may therefore benefit from methodological and contextual pluralism by complementing survey-based testing with qualitative designs (e.g., interviews, ethnographies) and with experiments or quasi-experiments that isolate causal mechanisms, as well as with behavioral or digital-trace indicators (e.g., tool logs or prompt histories) that reduce reliance on self-reports. Cross-cultural and cross-industry replications beyond the DACH region would further help to identify boundary conditions and refine the capabilities-based explanation developed in this thesis.

Second, the dissertation intentionally conceptualizes GenAI predominantly as an enabling augmentation technology that strengthens employees' IWB and idea generation. This focus is theoretically consistent with the dissertation's microfoundations logic. However, an emerging body of work indicates that human–GenAI collaboration may also entail adverse consequences for innovation. Recent evidence suggests a "double-edged sword" effect of AI assistance: advanced AI can increase creative self-efficacy and thereby foster AI-enabled innovation behavior, while simultaneously triggering STARA[14]-related threat appraisals and job-insecurity perceptions that suppress innovation behavior (Yin et al., 2024). In a related vein, repeated LLM use has been linked to cognitive offloading and the accumulation of "cognitive debt", implying reduced critical engagement and potential deskilling over time (Kosmyna et al., 2025). Against this backdrop, future research should more explicitly integrate both enabling and constraining pathways of GenAI into innovative outcomes, for instance by jointly theorizing capability-building and threat or technostress mechanisms and by examining organizational safeguards (e.g., training, GenAI readiness, job redesign) that allow firms to leverage innovation potentials without undermining employee autonomy or psychological safety.

Third, the dissertation captures GenAI effects at a comparatively early stage of diffusion and organizational appropriation, shortly after the breakthrough of tools such as ChatGPT and the rapid emergence of comparable applications (e.g., Midjourney, Gemini, Perplexity). While the timing provides valuable first-order insights into employees' GenAI-related capabilities and the translation into IWB, it also implies that observed relationships may partly reflect novelty effects and implicitly assume stable or increasing marginal benefits. As GenAI use becomes routinized and task portfolios adjust, benefits may plateau, shift in nature, or even reverse if overreliance and cognitive debt accumulate. Longitudinal panel studies, multi-wave field research, and diffusion-sensitive process designs are thus required to trace temporal trajectories, test for diminishing returns or tipping points, and examine whether early capability gains translate into durable innovation microfoundations.

[14] STARA awareness refers to the extent to which employees feel that their jobs can be replaced by smart technology.

Fourth, innovation outcomes are assessed through the IWB construct, a well-established multistage construct in innovation management (e.g., Jong & Hartog, 2010; Kör et al., 2021; Volery & Tarabashkina, 2021), which aligns with the dissertation's focus on employee-level microfoundations. Yet, IWB captures engagement in innovation-related behavior rather than the novelty, usefulness, or economic relevance of the resulting ideas, and it aggregates several innovation stages (idea exploration, idea generation, idea championing and idea implementation) into a single measure. Consequently, the dissertation cannot determine whether GenAI-driven increases in IWB translate into higher-quality or more radical outputs, nor can it distinguish between stage-specific effects. Future research should therefore complement IWB with direct indicators of idea quality (e.g., expert ratings or usefulness measures), separate incremental from radical outcomes, and model GenAI's differential influence across IWB phases, ideally linking individual-level GenAI practices to team- and firm-level innovation performance.

Finally, and relatedly, the dissertation treats GenAI largely as a homogeneous technology class. This abstraction is appropriate for theory development at the level of capabilities (GenAI usage capability, GenAI evaluation capability) but overlooks the increasing heterogeneity of the GenAI ecosystem. Different tools and foundation models vary substantially in modality, transparency, controllability, domain specialization, embedded governance, and interaction affordances.

7.4. Concluding remarks

Concluding this cumulative dissertation, it is essential to revisit its two overarching goals and the broader scholarly conversation in which they are situated. The rapid diffusion of GenAI has created both substantial expectations and considerable uncertainty about its implications for innovation in organizations. Against this backdrop, this thesis aimed to advance innovation-management and digital-transformation research by developing and empirically examining a multi-level capabilities perspective on how GenAI translates into employee innovativeness and which organizational foundations enable digital leadership and digital culture, two important drivers of digital transformation. Across the included studies, the dissertation reinforces a central, integrative conclusion: GenAI does not constitute an automatic lever for employee innovativeness but unfolds its value only through human capabilities in a human–GenAI co-creation process. At the individual level, the thesis clarifies that GenAI's innovation potential is contingent on employees' capabilities and their cognitive and motivational conditions, thereby contributing to microfoundational explanations of innovation in the GenAI age. At the organizational level, the dissertation further demonstrates that dynamic capabilities represent a critical foundation of digital transformation in SMEs, as they foster the development of digital leadership and digital culture—two human-centered enablers that shape how technologies are adopted, routinized, and scaled in everyday work.

Taken together, this thesis presents a coherent account of GenAI-enabled innovation as a socio-technical achievement, characterized by powerful technology on one side and decisive human and organizational capabilities on the other.

7.5. References

Bălău, G., Faems, D., & van der Bij, H. (2019). Team experiential cognitive style and team performance: The moderating impact of workplace setting. *Creativity and Innovation Management*, 28 (3), 343–354. https://doi.org/10.1111/caim.12319

Butt A., Imran F., Helo P., Kantola J. (2024) Strategic design of culture for digital transformation. *Long Range Planning* 57 (2),102415. https://doi.org/10.1016/j.lrp.2024.102415

Cimino, A., Felicetti, A. M., Corvello, V., Ndou, V., & Longo, F. (2025). Generative artificial intelligence (AI) tools in innovation management: a study on the appropriation of ChatGPT by innovation managers. *Management Decision.* 63 (10) 3431–3453 https://doi.org/10.1108/MD-10-2023-1968

Cortellazzo L., Bruni E., Zampieri R. (2019) The role of leadership in a digitalized world: a review. *Frontiers in Psychology* 10, 1938. https://doi.org/10.3389/fpsyg.2019.01938

Eisenreich, A., Just, J., Gimenez-Jimenez, D., & Füller, J. (2024). Revolution or inflated expectations? Exploring the impact of generative AI on ideation in a practical sustainability context. *Technovation*, 138, 103123. https://doi.org/10.1016/j.technovation.2024.103123

Epstein, S. (1973). The self-concept revisited. Or a theory of a theory. *The American Psychologist*, 28 (5), 404–416. https://doi.org/10.1037/h0034679

Epstein, S. (2003). Cognitive-experiential self-theory of personality. In I. B. Weiner (Ed.), *Handbook of Psychology* (pp. 159–184). Wiley. https://doi.org/10.1002/0471264385.wei0507

Epstein, S. (2014). Cognitive-experiential theory: An integrative theory of personality. Oxford University Press.

Ernst and Young. (2024). The EY 2024 Work Reimagined Survey [Press release]. https://www.ey.com/en_gl/insights/workforce/work-reimagined-survey (last accessed 21 November 2025)

Gelaidan, H. M., Al-Swidi, A. K., & Al-Hakimi, M. A. (2024). Servant and authentic leadership as drivers of innovative work behaviour: the moderating role of creative self-efficacy. *European Journal of Innovation Management*, 27 (6), 1938–1966. https://doi.org/10.1108/EJIM-07-2022-0382

Gyamerah S., Afshari L., Asante D. (2025) Digital transformation in the SME context: the nexus between leadership, digital capabilities and digital strategy. *International Small*

Business Journal: Researching Entrepreneurship 43 (3), 303–328. https://doi.org/10.1177/02662426251314108

Higgins, E. T. (2012). *Regulatory focus theory.* 1, 483–504. Handbook of theories of social psychology.

Higgins, E. T., & Pinelli, F. (2020). Regulatory Focus and Fit Effects in Organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, 7 (1), 25–48. https://doi.org/10.1146/annurev-orgpsych-012119-045404

Holzner, N., Maier, S., & Feuerriegel, S. (2025). Generative AI and Creativity: A Systematic Literature Review and Meta-Analysis. *arXiv preprint arXiv:2505.17241*. https://doi.org/10.48550/arXiv.2505.17241

Huang J.Y.H., Jiang R., Chang J.Y.T. (2023) The effects of transformational and adaptive leadership on dynamic capabilities: digital transformation projects. *Project Management Journal* 54 (4), 428–446. https://doi.org/10.1177/87569728231165896

Jong, J. de, & Hartog, D. den (2010). Measuring Innovative Work Behaviour. *Creativity and Innovation Management*, 19 (1), 23–36. https://doi.org/10.1111/j.1467-8691.2010.00547.x

Konopik J., Jahn C., Schuster T., Hoßbach N., Pflaum A. (2022) Mastering the digital transformation through organizational capabilities: a conceptual framework. *Digital Business* 2, 100019. https://doi.org/10.1016/j.digbus.2021.100019

Kosmyna, N., Hauptmann, E., Yuan, Y. T., Situ, J., Liao, X. H., Beresnitzky, A. V., Braunstein, I. & Maes, P. (2025). Your brain on chatgpt: Accumulation of cognitive debt when using an ai assistant for essay writing task. arXiv preprint arXiv:2506.08872. https://doi.org/10.48550/arXiv.2506.08872

Kör, B., Wakkee, I., & van der Sijde, P. (2021). How to promote managers' innovative behavior at work: Individual factors and perceptions. *Technovation,* 99, 102127. https://doi.org/10.1016/j.technovation.2020.102127

Madrid, H. P., Patterson, M. G., Birdi, K. S., Leiva, P. I., & Kausel, E. E. (2014). The role of weekly high-activated positive mood, context, and personality in innovative work behavior: A multilevel and interactional model. *Journal of Organizational Behavior*, 35 (2), 234–256. https://doi.org/10.1002/job.1867

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2 (1), 71–87. https://doi.org/10.1287/orsc.2.1.71

Mazzucchelli, A., Chierici, R., Abbate, T., & Fontana, S. (2019). Exploring the microfoundations of innovation capabilities. Evidence from a cross-border R&D

partnership. *Technological Forecasting and Social Change*, 146, 242–252. https://doi.org/10.1016/j.techfore.2019.06.003

Meincke, L., Girotra, K., Nave, G., Terwiesch, C., & Ulrich, K. T. (2024). Using large language models for idea generation in innovation. *The Wharton School Research Paper*, https://doi.org/10.2139/ssrn.4526071

Rana, N. P., Pillai, R., Sivathanu, B., & Malik, N. (2024). Assessing the nexus of Generative AI adoption, ethical considerations and organizational performance. *Technovation*, 135, 103064. https://doi.org/10.1016/j.technovation.2024.103064

Shanker, R., Bhanugopan, R., van der Heijden, B. I., & Farrell, M. (2017). Organizational climate for innovation and organizational performance: The mediating effect of innovative work behavior. *Journal of Vocational Behavior*, 100, 67–77. https://doi.org/10.1016/j.jvb.2017.02.004

Singh, K., Chatterjee, S., & Mariani, M. (2024). Applications of generative AI and future organizational performance: The mediating role of explorative and exploitative innovation and the moderating role of ethical dilemmas and environmental dynamism. *Technovation*, 133, 103021. https://doi.org/10.1016/j.technovation.2024.103021

Strobl, A., Matzler, K., Nketia, B. A., & Veider, V. (2020). Individual innovation behavior and firm-level exploration and exploitation: how family firms make the most of their managers. *Review of Managerial Science*, 14 (4), 809–844. https://doi.org/10.1007/s11846-018-0309-9

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28 (13), 1319–1350. https://doi.org/10.1002/smj.640

Volery, T., & Tarabashkina, L. (2021). The impact of organisational support, employee creativity and work centrality on innovative work behaviour. *Journal of Business Research,* 129, 295–303. https://doi.org/10.1016/j.jbusres.2021.02.049

Yin, M., Jiang, S., & Niu, X. (2024). Can AI really help? The double-edged sword effect of AI assistant on employees' innovation behavior. *Computers in Human Behavior*, 150, 107987. https://doi.org/10.1016/j.chb.2023.107987

Yuan, F., & Woodman, R. W. (2010). Innovative behavior in the workplace: The role of performance and image outcome expectations. *Academy of Management Journal*, 53 (2), 323–342. https://doi.org/10.5465/AMJ.2010.49388995