Exploring Productivity Gains from GenAI-Enabled Virtual Assistants: A Configurational Study of a Multifaceted Phenomenon

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Niklas Rieger (born Preiss)
Sheffield Hallam University, Sheffield, United Kingdom of Great Britain and Northern Ireland
niklas.j.preiss@student.shu.ac.uk

Enterprises increasingly embed generative AI–enabled virtual assistants (VA) into enterprise productivity software to improve digital work and performance. Evidence indicates that productivity gains (PG) are a multifaceted phenomenon of organized complexity shaped by interdependent organizational, technological, and human factors. Drawing on established IS lenses, this paper develops a theory-driven model of when and how VA-enabled enterprise productivity software yields PG. This paper deductively derives a research model specifying four IS theory-based conjunctural factors, and articulates equifinal pathways that enable or inhibit PG. To evaluate necessity and sufficiency, the paper outlines an expert interview-based fuzzy-set Qualitative Comparative Analysis research design. The contributions are threefold: (i) defining VA-enabled PG within enterprise productivity software as a multifaceted phenomenon; (ii) introducing a configurational research model; and (iii) extending IS business-value theorizing to AI-augmented digital work through set-theoretic reasoning and theory-driven propositions for empirical validation. The model clarifies when VA enhance enterprise performance and offers a testable roadmap for research on human–AI collaboration.

Keywords:
generative AI,
virtual assistants,
enterprise productivity software,
productivity gains,
configurational theory

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1 Introduction

Generative artificial intelligence (GenAI)–powered virtual assistants (VA) are rapidly becoming integral components of enterprise productivity software and are expected to transform the nature of knowledge work (Brynjolfsson et al., 2025; Cambon et al., 2023; Edelman et al., 2023). Commercially available examples, such as Microsoft 365 Copilot and Google Workspace Gemini, exemplify this new class of artificial intelligence (AI)-augmented productivity tools. These VA integrate large language models (LLMs) and multimodal AI capabilities, spanning text, voice, and image, to extend the functionality of traditional productivity applications. Embedding advanced generative and reasoning features directly into core applications (e.g., Word, Excel, PowerPoint) enables content generation, data analysis, summarization, and communication within the respective enterprise productivity software (Bano et al., 2025; Microsoft Corporation, 2023; Vorvoreanu et al., 2025). Early empirical evidence indicates that these tools can yield substantial productivity benefits (Bano et al., 2025; Vorvoreanu et al., 2025). Recent advances in GenAI, and applications built on them, have been hypothesized to deliver step-changes in labor productivity at historically significant scale (Brynjolfsson et al., 2025; Edelman et al., 2023). Initial experiments and field studies corroborate these expectations: GenAI users complete tasks faster and with higher quality than control groups (Cambon et al., 2023; Noy & Zhang, 2023). Despite this promise, realizing productivity gains (PG) from VA cannot be assumed. IS research has long grappled with understanding how IT adoption translates into PG, a debate known as the IT productivity paradox (Brynjolfsson, 1993). This paradox raises the research question:

Under what combinations of organizational, functional, and human factors do GenAI-enabled VA embedded in enterprise productivity software yield PG?

This overarching question is addressed through three sub-questions: (I) How can VA-enabled PG be conceptualized as a multifaceted phenomenon? (II) Which theory-grounded organizational, technological, and human factors combine to produce or inhibit PG? (III) What configurational propositions can guide empirical fsQCA validation? The systematic review by Preiss & Westner (2025a) highlights those gaps, showing that while digital assistant technologies (DAT) hold strong potential to reshape organizational performance and strategy, empirical research remains scarce. DAT are primarily conversational systems, such as chatbots, voice agents, and intelligent assistants, that leverage machine learning, natural language processing or GenAI, to retrieve information, perform routine tasks, and support decision-making (Preiss & Westner, 2025b). Existing studies emphasize short-term, task-level effects, neglect longitudinal adoption trajectories, and rarely employ established IS theories, resulting in limited theoretical integration and ambiguous findings (Preiss & Westner, 2025a). This gap is particularly salient given the IT productivity paradox, which highlights that technological potential does not automatically translate into realized organizational performance (Brynjolfsson, 1993). Addressing it in the GenAI context requires research that considers not only direct productivity effects but also the configurational interplay of organizational, technological, and human factors over time, thereby capturing equifinal pathways to IT-enabled innovation (Coreynen et al., 2017; Parida et al., 2019; Sjödin et al., 2019). To address this gap, I propose a theory-driven configurational model explaining how GenAI-enabled VA embedded in enterprise productivity software generate PG (hereafter, for readability, "VA-enabled PG"; the full term is used when needed for clarity). The remainder of this paper (1) conceptualizes VA-enabled PG and motivates a configurational perspective; (2) specifies a research model grounded in the core building blocks of configurational theorizing, theoretical multiplicity, factorial logic, and combinatorial logic (Park et al., 2020) and develops initial propositions; and (3) discusses expected contributions and outlines an empirical fsQCA.

2 Theoretical Background: PG as a Configurational Phenomenon

Previous research shows that organizations' ability to realize PG from IT adoption is an important antecedent of business-value creation, competitive performance and broader business transformation (Acharya, 2023; Melville et al., 2004; Storey et al., 2016). In recent years, enterprises have increasingly integrated GenAI-enabled VA into their enterprise productivity software to streamline operations and enhance service delivery (Brynjolfsson et al., 2025; Peng et al., 2023a). VA already play a central role in administrative work (adopted by 37.7% of businesses) and nearly 10% of organizations use them to improve operational workflows (Dutta, 2025). Explaining the mechanisms behind such PG has therefore become highly relevant. Prior IS research suggests that PG accomplished through GenAI-enabled VA constitutes a multifaceted phenomenon that must be analyzed from organizational, technological, and human perspectives (Maharaj et al., 2024; Schmidhuber et al., 2021; Todericiu, 2025). This multifaceted nature underscores the importance of applying insights from established IS theories to maximize the gains of new technologies. As the review by Preiss & Westner (2025a) found, prior studies on DAT have drawn on frameworks such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), Task–Technology Fit (TTF) or the IS Success Model. Recent work reflects a growing recognition that aligning technology with user needs, task requirements, and organizational context, guided by established IS theories, is essential for realizing the full productivity benefits of VA (Amarilli et al., 2023; Chan & Reich, 2007). Accordingly, contemporary studies on DAT increasingly emphasize real-world PG and tangible outcomes as key measures of success (Afroogh et al., 2025; Celis et al., 2025; Song et al., 2025). Beyond efficiency, quality, and output, additional benefits, including reduced cognitive load, improved well-being, accelerated workplace learning, and enhanced decision quality also sustain PG (Preiss & Westner, 2025a; Tarafdar et al., 2019). PG refers to measurable, attributable gains, such as shorter cycle times, lower error rates, higher throughput, or lower cost in the efficiency, quality, or output arising from the use of VA in enterprise productivity software that leverages expertise, data, collaboration, and AI (Dwivedi et al., 2021; Fang et al., 2025; Noy & Zhang, 2023). These gains are typically contingent on combinations of factors rather than single causes (Park et al., 2020; Ragin & Fiss, 2008). Prior IS research shows that the effects of IT capabilities differ in combination compared to isolation (Chen et al., 2020), and that the joint influence of user acceptance (UTAUT/TAM), TTF (Goodhue & Thompson, 1995), and information/system quality (DeLone & McLean, 2014) conditions whether VA yield PG when integrated into productivity software. This points to conjunctural causation, where specific combinations of organizational, technological, and human factors generate gains (Coreynen et al., 2017; Ragin & Fiss, 2008). IS business-value research identifies multiple paths to achieving PG (Melville et al., 2004; Rai et al., 2012). Early empirical studies on GenAI-enabled tools reinforce this. Noy & Zhang (2023) find that productivity effects vary by task type, while Cambon et al. (2023) show that contextual factors such as collaboration mode and data integration moderate VA effectiveness. These findings underscore equifinality and motivate a configurational, set-theoretic approach (Park et al., 2020; Rihoux & Ragin, 2009). Several factors exhibit asymmetric effects. High TTF appears to function as a foundational/near-necessary enabler of PG, while its absence often precludes gains (Goodhue & Thompson, 1995; Jeyaraj, 2022; Jeyaraj et al., 2006). By contrast, managerial support or training can amplify productivity when present, but their absence does not always fully preclude improvements (Boonstra, 2013; Thong et al., 1996). Such asymmetries further support configurational theorizing that accommodates both enabling and inhibiting mechanisms (Coreynen et al., 2017; Sjödin et al., 2019). Given these diverse outcomes, I argue that VA-enabled PG is a configurational phenomenon: specific combinations of organizational (Business–IT Alignment (BIA); Top Management Support (TMS)), behavioral (Adoption and Change Enablement (ACE)), and technological/task (TTF) factors jointly determine success (Fiss, 2011; Park et al., 2020; Ragin & Fiss, 2008).

2.1 Defining PG from VA-enabled Enterprise Productivity Software

Organizations seeking PG from DAT face a complex phenomenon that resists explanation by any single theoretical lens (Aral et al., 2012; Benbya et al., 2020; Sarker et al., 2019). Research on IT-enabled PG shows that success is best understood through multiple, interrelated perspectives and emerges when organizational, technological, and human dimensions are considered jointly (Aral et al., 2012; Brachten et al., 2021; Brosig, 2021). VA-enabled PG is defined as organizationally relevant improvements in knowledge-work performance attributable to GenAI-enabled VA over approximately 6–12 months after rollout (Freeman et al., 2024; Sirmon et al., 2007; Vahter & Vadi, 2024). For example, Fang et al. (2025, p. 28) found that a chatbot "can deliver measurable productivity improvements with comparable inputs". Organizations adopt these tools not only for experimentation but also with explicit expectations of realizing PG. Although PG arises from individual and team work practices, the configurational model is calibrated at the organizational level. Accordingly, PG is conceptualized as an organizational-level set indicating whether an organization achieves sustained, substantively meaningful PG from VA-supported knowledge work. Consistent with the organizational unit of analysis, all four factors are conceptualized as organizational-level factors. Although ACE and TTF operate at the user–task interface, they are treated as organizational factors, reflected in aggregated user experiences and workflow integration. The four factors are deliberately specified as complementary and minimally overlapping: BIA captures strategic use-case clarity and business linkage; TTF denotes the degree to which VA capabilities fit target tasks or use cases; ACE comprises user-proximal enablement activities (e.g., training, communication, process adaptation); and TMS denotes top-management legitimation, resourcing, and governance of VA initiatives.

Building on established IS theories, these factors are introduced in section 3, where their theoretical grounding, construct definitions, and indicators are developed in detail. Together, they form a focused yet sufficiently rich set of organizational factors that provides a basis for theorizing configurational "causal recipes" for PG (Park et al., 2020). Accordingly, a configurational perspective, operationalized through methods such as fsQCA, is appropriate to capture three essential ideas: equifinality (multiple viable pathways to PG), conjunctural causality (combinations of factors that jointly produce outcomes), and causal asymmetry (configurations leading to PG need not mirror those leading to its absence) (Pappas & Woodside, 2021; Park et al., 2020). This perspective is particularly relevant for GenAI-based VA, where stochastic model behavior, hallucinations, grounding in organizational knowledge, and privacy/compliance constraints jointly shape realized PG (Acharya, 2023; Bano et al., 2025; Peng et al., 2023b).

3 Research Model and Methods

The four factors draw on IS theories with extensive meta-analytic and review support in IT adoption and business-value research: strategic alignment (Chan & Reich, 2007; Coltman et al., 2015), task–technology fit (Goodhue & Thompson, 1995; Jeyaraj, 2022), technology acceptance (Balakrishnan et al., 2024; Davis, 1985; Venkatesh et al., 2003), and top management support (Boonstra, 2013; Jeyaraj et al., 2023). The structured literature review by Preiss & Westner (2025a) found that, across 61 articles, only four explicitly employed IS theories, underscoring both a gap in theoretical integration and the relevance of these established foundations for the VA context. The four constructs were deductively selected to ensure complementary coverage of organizational (BIA, TMS), behavioral (ACE), and technological/task (TTF) dimensions. VA-enabled PG depends on how organizational, technological, and human factors combine. FsQCA will be suitable for empirical testing (Brosig, 2021; Pappas & Woodside, 2021). Factors and outcomes are conceptualized as sets. Standard notation is used. Prior IS research suggests that the four factors capture complementary yet interdependent conditions influencing how organizations realize PG (Park et al., 2020; Schneider & Wagemann, 2012). Each is modeled as a graded set that combines conjuncturally with the others to explain differences in PG, representing a distinct facet of the broader phenomenon rather than a single net-effect predictor. Each factor is modeled as a condition that reflects differences within a given variable, i.e., every condition distinguishes between two or more types of the same variable (Schneider & Wagemann, 2012).

BIA is rooted in the Strategic Alignment Model (Henderson & Venkatraman, 1993) and IS business-value research (Chan & Reich, 2007; Melville et al., 2004). BIA captures the degree to which IT initiatives are synchronized with organizational objectives, business processes, and performance metrics. High BIA is present when organizations articulate prioritized VA use cases, connect them to core processes and KPIs, and integrate VA initiatives into business planning (Chan & Reich, 2007; Coltman et al., 2015). Low BIA (~BIA) reflects ad hoc pilots or deployments disconnected from core workflows (Kopper et al., 2020). In organizations exhibiting high BIA, VA are purposefully applied to improve customer responsiveness, reduce coordination costs, or accelerate information processing, for example (Abdellatif et al., 2022; Andrade & Moazeni, 2023; Bird & Lotfi, 2024). In the context of GenAI-enabled VA, BIA is particularly critical. Empirical and practitioner reports show that many organizations are stuck in prolonged "pilot phases," with widespread GenAI experimentation but only a small fraction of use cases delivering measurable business value (Alsheiabni et al., 2019; Hansen et al., 2024). Without such alignment, VA usage tends to remain opportunistic and scattered, making it unlikely that local gains add up to organization-level PG.

TTF posits that technology delivers performance impacts only when its functionalities align with the requirements of users' tasks (Goodhue & Thompson, 1995). For GenAI-enabled VA, TTF comprises functional fit (Bano et al., 2025; Peng et al., 2023b), information quality and reliability, including hallucination risk and error patterns (Helal et al., 2025; Liu et al., 2025) or workflow integration, such as embedding into productivity software or ticketing systems (Acharya, 2023). High TTF is typically present when VA provide accurate, contextually grounded, and timely assistance for key knowledge-work tasks, within the organization's data and security constraints (Bano et al., 2025). Low TTF (~TTF) can reflect missing capabilities, poor grounding in organizational data, limited context, or misaligned integration that generates rework and distrust (Gebauer et al., 2010; Helal et al., 2025). The IS Success Model (DeLone & McLean, 1992, 2014) further serves as a complementary theoretical foundation for this factor, extending the TTF argument by explaining how fit translates into realized outcomes. LLMs are stochastic and prone to hallucinations, plausible but nonfactual content, which raise fundamental concerns about reliability and trust (Huang et al., 2025). These properties mean that VA outputs may be helpful in some tasks but hazardous in others unless suitably constrained (Brynjolfsson et al., 2025). Emerging empirical work in IS and management shows that PG from GenAI tools are highly task contingent: productivity improvements are largest for tasks where AI knowledge and capabilities align with work demands, and much smaller or even negative when this alignment is weak (Brynjolfsson et al., 2025). Studies of human–AI collaboration likewise find that organizing work based on TTF standards is crucial for realizing PG (Przegalinska et al., 2025).

ACE reflects the behavioral and organizational mechanisms that translate technological potential into realized value. Drawing from TAM (Davis, 1985), the UTAUT (Venkatesh et al., 2003), and organizational change theory (Lapointe & Rivard, 2005), this factor captures the organization's ability to facilitate employee adoption and adapt work practices around new technologies. In this model, ACE refers to user-proximal mechanisms that support the adoption, routinization, and effective use of VA. It includes activities such as communication about VA capabilities, limitations, and appropriate use or user training and coaching (e.g., prompt design, verification strategies). High ACE means organizations actively onboard users, provide ongoing support, and adapt workflows based on feedback (Alter, 2018; Söllner et al., 2025). In contrast, low ACE (~ACE) denotes resistance to change, lack of managerial communication, or insufficient training, barriers that undermine integrating VA and attenuate PG (Lapointe & Rivard, 2005; Venkatesh et al., 2003). GenAI-enabled VA require active, skillful use, including formulating effective prompts, interpreting probabilistic outputs, and integrating those outputs into existing work routines. Empirical studies and large surveys indicate that, even when GenAI tools are technically available, adoption and value often remain limited because employees do not see clear, localized use cases, feel uncertain about how to use the tools, or fear making mistakes (Söllner et al., 2025). Recent work on the responsible use of GenAI stresses the need for training, guidelines, and human-in-the-loop oversight to ensure that workers understand both the capabilities and the limitations of GenAI tools (Söllner et al., 2025). Without user-centered enablement, organizations risk either shadow AI usage that bypasses controls or underutilization of enterprise-grade VA solutions (Silic et al., 2025).

TMS captures legitimation and resourcing of VA initiatives at the top-management level. Grounded in organizational control and IT implementation research (Boonstra, 2013; Thong et al., 1996), TMS denotes the extent to which senior executives actively champion, resource, and monitor IT and especially AI initiatives. In the case of VA, strong TMS ensures that the technology is institutionally legitimized, adequately funded, and integrated into strategic and operational priorities. High TMS is typically present when senior executives articulate a VA vision, set expectations for productivity improvements, allocate budgets and staff, and integrate VA initiatives into governance structures (Boonstra, 2013; Jeyaraj et al., 2023). Low TMS (~TMS) can occur when VA initiatives lack sponsorship, remain side projects, or are constrained by ambiguous mandates and limited resources (Korzyński et al., 2024). In the GenAI context, TMS is critical for two main reasons. First, GenAI introduces new risk, security, and compliance exposures, such as data leakage, inadvertent disclosure of personal or confidential information, and violations of regulations. Enterprise evidence shows that employees often paste sensitive data into public GenAI tools via unmanaged accounts, creating serious compliance and security risks without proper governance and technical controls (Dong et al., 2024; Korzyński et al., 2024; J. Yang et al., 2024). Second, GenAI programs usually begin as broad experimentation but must be refocused on a few high-value, feasible use cases once firms understand the technology's strengths and limits. Such strategic reprioritization, and the associated decisions on budgets, data access, and risk appetite, requires active TMS (Korzyński et al., 2024).

4 Configurational Propositions

Building on the factors defined in the previous section, this section develops the combinatorial logic that links BIA, TTF, ACE, and TMS to VA-enabled PG. In line with Park et al. (2020), this final step articulates causal recipes that explain how the selected factors, modeled as fuzzy-set conditions, jointly produce the outcome PG. Moving beyond factorial logic, causality is treated as conjunctural and equifinal: distinct configurations of conditions can yield the same outcome in complex, nonlinear settings (Ragin & Fiss, 2008). Moreover, multiple distinct combinations, or equifinal pathways, may lead to the same outcome, underscoring the complex and nonlinear nature of IT-enabled PG (Fiss, 2011; Park et al., 2020). Figure 1 presents the proposed research model, which explains how organizational-level conditions combine to produce PG. The paper advances with theoretically grounded propositions that specify how configurations of BIA, TMS, ACE, and TTF lead to PG. Each is stated in Boolean notation and provides the groundwork for fsQCA validation (Kohtamäki et al., 2019; Shulman, 2008). Building on Brosig et al. (2022), a set-theoretic ontology is adopted, emphasizing causal asymmetry: the presence and absence of PG may arise from different configurations. Propositions are framed as truth-table configurations, conjunctions expected to be sufficient for PG, enabling empirical evaluation via fsQCA consistency and coverage (Schneider & Wagemann, 2012). This configurational approach extends IT-performance frameworks (Melville et al., 2004; Wade & Hulland, 2004) by foregrounding interactive effects among the four factors. It advances digital business-value theory toward a complexity-sensitive account of GenAI's impact, where adaptive human–AI collaboration resists explanation by isolated capabilities.

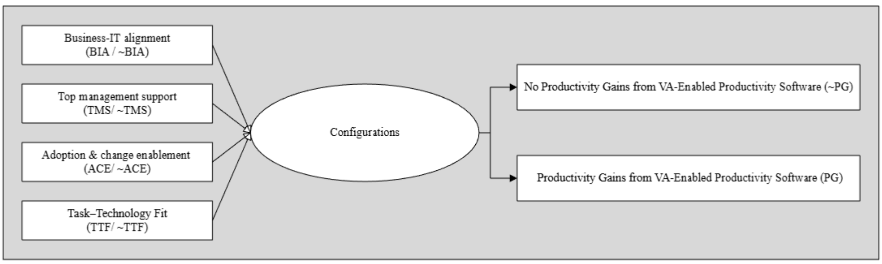

Figure 1: Preliminary research model on VA-enabled PG
Source: Own

4.1 Potential Foundational Conditions

Prior IS research suggests that certain conditions frequently behave as foundational enablers of PG, irrespective of other contextual factors (Brynjolfsson & Hitt, 2000; Melville et al., 2004). Both BIA and TTF are expected to be foundational enabling conditions for PG. In set-theoretic terms, PG cases are expected to be near-subsets of high-BIA and high-TTF; that is, BIA and TTF may behave approximately as necessary conditions. Future studies can test whether PG is consistently a subset of BIA and TTF using standard necessity consistency and coverage indicators, rather than imposing necessity ex ante (Ragin & Fiss, 2008; Schneider & Wagemann, 2012). This approach helps avoid premature claims of necessity and enhances the transparency of empirical validation. While necessary factors indicate factors that must be present for PG to occur, they do not reveal how outcomes materialize.

Configurational theorizing therefore extends to sufficiency analysis, which examines how distinct combinations of factors jointly produce PG. This step recognizes the asymmetrical nature of causality: the presence of a factor may be essential but not, by itself, sufficient. The following propositions thus specify equifinal configurations of BIA, TMS, ACE, and TTF that together form alternative, sufficient pathways to PG. These are empirical expectations, not hard constraints; necessity will be assessed via fsQCA rather than assumed ex ante.

Potential Condition C1 (PG → BIA) expects that organizations with high VA-enabled PG will almost always exhibit high BIA. In other words, PG cases are likely to be (near-)subsets of the set of BIA cases. Strategic alignment between IT and business objectives ensures that digital initiatives are directed toward organizationally relevant use cases and that technological resources are purposefully applied to value-creating activities (Chan & Reich, 2007; Coltman et al., 2015). Without such alignment, IT efforts, including VA deployment, tend to become fragmented and fail to yield sustainable productivity improvements (Kopper et al., 2020; Silic et al., 2025). Hence, high BIA is expected to act as a foundational enabling condition for realizing PG. Potential Condition C2 (PG → TTF) posits that organizations with high VA-enabled PG will almost always exhibit high TTF. Consistent with Goodhue & Thompson's (1995) foundational model, productivity improvements arise only when technological features align with the cognitive and procedural demands of users' tasks. Without sufficient fit, even well-supported and strategically aligned systems fail to translate into tangible PG (Gebauer et al., 2010; Gebauer & Ginsburg, 2006). Therefore, TTF is expected to function as an enabling condition for realizing PG.

4.2 Potential Causal Configurations for PG

Proposition P1 (BIA*TMS*TTF→PG) is characterized by (high) BIA, (strong) TMS, and (high) TTF. Indeed, meta-analytic evidence shows TMS drives IT assimilation, which in turn yields business-value. Jeyaraj et al. (2023) find that strong executive backing significantly boosts IT adoption and its ultimate impact on PG. Combined with a well-fitted VA (high TTF), these factors suggest a "leadership-driven" path to productivity. Proposition P2 (BIA*ACE*TTF→PG) is the alternative configuration of (high) BIA, (extensive) ACE, and (high) TTF suggesting a user-centered success route. Ifinedo (2008) found that business vision is a significant factor in achieving success, which suggests that clarity of vision and business context matter for technology initiatives (part of change management). These configurations reflect equifinality: organizations may achieve PG via BIA, TMS, and TTF (P1) or via BIA, TTF, and ACE (P2).

4.3 Potential Causal Configurations for Limited PG

Proposition P3 (~BIA*TTF→~PG) states that with high TTF, organizations with low BIA are expected to fail to realize substantial PG. Without clear linkage to core processes and goals, VA use remains fragmented and its effects difficult to aggregate (Jeyaraj et al., 2023). Proposition P4 (BIA*~TTF→~PG) states that organizations with high BIA but ~TTF are expected to experience limited or absent PG. Strategically chosen use cases may nonetheless underperform if VA functionality, information quality, or grounding in organizational data are insufficient (Freeman et al., 2024). Proposition P5 (BIA*TTF*~TMS*~ACE→~PG) indicates a situation where initiatives are aligned (BIA) and VA are technically capable (TTF), but weak TMS and weak ACE are expected to prevent PG. VA use remains sporadic or shadow-like and does not translate into sustained PG.

5 Discussion and Conclusion

VA-enabled PG is conceptualized as a multifaceted outcome of organized complexity. By shifting from a variance-based logic to a configurational perspective, we contribute to IS business-value theory in three ways. First, we provide a definition of PG that accounts for the multifaceted nature of GenAI-driven impact. Second, we introduce a parsimonious model of four interdependent factors (BIA, TTF, ACE, and TMS) that captures the "causal recipes" of VA-enabled work. Finally, the proposed equifinal propositions (P1–P5) offer a robust theoretical foundation for fsQCA validation. These insights provide immediate utility for practitioners seeking to move GenAI initiatives towards more sustained organizational PG. To empirically validate the theorized propositions, a multi-stage fsQCA study is proposed. By identifying necessary and sufficient conditions through truth table analysis, this design will reveal the causal asymmetries inherent in GenAI adoption, specifically how the absence of one factor may necessitate different configurations of the remaining conditions to achieve the same level of PG. As a conceptual paper, the propositions represent testable expectations rather than confirmed findings; this limitation is inherent to the theory-building stage of configurational research (Park et al., 2020) and is addressed through the outlined fsQCA design. By combining configurational reasoning with set-theoretic analysis, the model extends IS business-value theory to the GenAI era and offers a foundation for future empirical research on how VA factor sets jointly determine organizational performance.

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