Exploring the influence of generative artificial intelligence on job satisfaction in SMEs: insights from managers

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Abstract

Purpose – This study aims to investigate the impact of “generative artificial intelligence (GenAI)”on managerial job satisfaction in “small and medium-sized manufacturing enterprises (SMEs)”, with a specific focus on work quality and decision-making effectiveness.

Design/methodology/approach – Grounded in the “unified theory of acceptance and use of technology (UTAUT)” and the “expectation-confirmation model (ECM)”, this study also incorporates additional constructs such as ethical use, perceived GenAI value, and available resources. A survey of 163 SME managers was analyzed using “partial least squares structural equation modeling (PLS-SEM)”.

Findings – The findings revealed that security and privacy, ethical use, perceived GenAI value and available resources significantly enhance managerial job satisfaction. In contrast, ease of use, expectation confirmation and social influence were not statistically significant. Additionally, job satisfaction positively influences both work quality and decision-making effectiveness.

Practical implications – Results offer guidance for SME managers, developers and policymakers seeking to maximize the benefits of GenAI adoption and boost managerial job satisfaction. Organizations should strengthen data protection measures and establish ethical GenAI governance frameworks to build trust and accountability, while policymakers can support these efforts through clear national standards. Enhancing infrastructure, providing targeted training and ensuring equitable access to resources help managers integrate GenAI confidently. Aligning GenAI initiatives with employee well-being and professional development fosters engagement. Developers can embed secure, transparent and user-centered features to enhance reliability. Collectively, these actions support sustainable GenAI use that improves satisfaction and decision-making.

Originality/value – This study is original in its focus on managerial-level outcomes of GenAI adoption within manufacturing SMEs a perspective largely overlooked in existing literature. Unlike prior research that centers on technological performance or firm-level benefits, this study investigates the individual manager’s experience, integrating underexplored constructs such as ethical use and perceived GenAI value. It also offers novel theoretical empirical evidence to an emerging research area and provides a practical framework to inform GenAI adoption strategies in resource-constrained SME environments.

Keywords Generative artificial intelligence, Job satisfaction, Work quality, Decision-making effectiveness

Paper type Research article

1. Introduction

The adoption of artificial intelligence (AI) tools is reshaping business practices across industries (Emon and Khan, 2025). Generative AI (GenAI) represents one of the most transformative advancements, enabling AI models to create novel forms of content including

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narratives, visual designs, and conceptual responses based on patterns extracted from training data (Md *et al.*, 2025). Expanding across all sectors, GenAI tools are increasingly being used in manufacturing "small and medium-sized enterprises (SMEs)" for product development, report writing, process automation, and decision support (Rajaram and Tinguely, 2024). One key outcome of such technology interaction is job satisfaction, which plays an important role in determining employee performance, organizational commitment, and sustained engagement with technology (Rahaman and Uddin, 2022; Guenther *et al.*, 2025). For managerial roles in particular, this satisfaction is closely tied to how effectively technology supports core responsibilities, especially decision-making and work quality (Alzadjali and Ahmad, 2024). As Judge *et al.* (2001) explained, job satisfaction arises when individuals perceive that their job outcomes, such as effectiveness, autonomy, or success, meet or exceed expectations. In managerial contexts, satisfaction is closely associated with the extent to which technologies improve decision-making effectiveness and work quality (Alzadjali and Ahmad, 2024). GenAI can support these outcomes by generating faster insights, automating repetitive tasks, and assisting complex decision processes (Salazar and Kunc, 2025).

Literature shows that actual technology usage and its perceived benefits, such as improved performance and efficiency, are closely linked to user satisfaction and continued use (Odoom *et al.*, 2017; Isaac *et al.*, 2019). Despite the increasing adoption of GenAI in enterprises (Jalil *et al.*, 2024; Ijaz Baig and Yadegaridehkordi, 2025), much of the existing work has focused on enterprise innovation performance, team productivity, and operational efficiency, leaving a clear gap in understanding its effects at the managerial level (Zhang *et al.*, 2025, 2026). Limited research has addressed how GenAI influences managerial satisfaction, work quality, and decision-making in manufacturing SMEs, where managers are actively involved in complex operational decisions. Furthermore, evidence from fields such as cybersecurity (e.g. Maulita and Hayadi, 2025) shows that AI-enabled analytics influence key organizational outcomes, including estimating financial losses and supporting risk-informed decisions. This highlights that AI's impact extends far beyond simple ease of use.

To address this gap, the present study investigates how the actual use of GenAI tools influences managerial job satisfaction in manufacturing SMEs and how this satisfaction subsequently affects work quality and decision-making effectiveness. The "Unified Theory of Acceptance and Use of Technology (UTAUT)" and the "Expectation-Confirmation Model (ECM)" are selected as the theoretical bases, enabling the inclusion of organizational and technological factors such as security and privacy, GenAI expectation confirmation, ethical use of GenAI, resource availability, and perceived GenAI value. Data is collected from managers in Malaysian manufacturing SMEs and analyzed using "Partial Least Squares Structural Equation Modeling (PLS-SEM)". The empirical findings reveal that security and privacy, perceived GenAI value, and available organizational resources significantly enhance managerial job satisfaction, while ethical use significantly strengthens expectation confirmation. In contrast, commonly emphasized technology adoption drivers perceived ease of use, expectation confirmation, and social influence do not demonstrate significant effects in explaining job satisfaction in this context. These results are theoretically meaningful because they confirm that, in SME managerial environments, satisfaction with GenAI is driven less by traditional usability or social influence mechanisms and more by structural and governance-related assurances surrounding the technology. In other words, contrary to conventional technology acceptance assumptions, usability and peer influence do not appear to be the primary drivers of managerial satisfaction with GenAI; instead, security, ethical safeguards, perceived value, and organizational resource support play more decisive roles. Results also offer practical implications for SME managers, GenAI developers, and policymakers by stressing the need to match GenAI with employee expectations, ensure support and training, and enhance task relevance and decision-making. These insights can guide strategic decisions to maximize the positive impact of GenAI on workforce satisfaction and productivity.

This study is original in its focus on managerial-level outcomes of GenAI adoption within manufacturing SMEs, a perspective that has been largely overlooked in existing literature. Unlike prior research that primarily focuses on technological performance or firm-level benefits, this study examines the experiences of individual managers and incorporates less explored constructs such as ethical use and the perceived value of GenAI. By refining assumptions about the drivers of GenAI adoption, the study extends the UTAUT and ECM frameworks in post-adoption contexts and offers a practical framework to guide post-adoption outcomes of GenAI use within organizations. This study is structured as follows: Section 2 presents the literature review, followed by the theoretical foundation in Section 3. Section 4 outlines the methodology, while Section 5 reports the results. Sections 6 and 7 discuss the findings and their implications, respectively. Section 8 concludes the study, and Section 9 outlines its limitations and future research directions.

2. Literature review

GenAI in SMEs has become an emerging research frontier, reflecting the growing recognition of its transformative potential across industries. As digital technologies increasingly shape the competitive landscape, GenAI offers SMEs new opportunities to enhance capabilities in areas such as innovation, customer personalization, resilience, and digital value creation (Rajaram and Tinguely, 2024). Studies on GenAI adoption use different analytical strategies, including single-channel, multi-modal fusion, and hybrid AI-driven approaches (Arafah *et al.*, 2025). Single-channel methods offer simplicity and stability, making them suitable when data are limited. Multi-modal techniques integrate diverse data sources, providing richer insights but often requiring higher data quality and resources. In some cases, they may not outperform simpler methods, particularly in SME contexts with resource or data constraints. Warmayana *et al.* (2025), similarly, highlighted contextual factors shape analytical outcomes. This emphasized the need for more critical examination of methodological choices in understanding GenAI's impact on managerial satisfaction and decision-making in SMEs. Recent studies examine the role of GenAI in supporting these outcomes through various theoretical lenses, contributing to an understanding of its strategic relevance in SME contexts. For instance, Wang and Zhang (2025) applied the "Resource-Based View" and "Dynamic Capabilities Theory" to examine the integration of GenAI into digital supply chains to enhance Environmental, Social, and Governance (ESG) performance in Chinese tourism SMEs. Their empirical analysis of 429 firms highlights GenAI's role in fostering innovation and collaboration, key drivers of ESG outcomes, while also emphasizing the influence of customer involvement in shaping these effects.

Shore *et al.* (2024) adopted Organizational Information Processing Theory to assess GenAI's contribution to entrepreneurial resilience. Based on data from 87 French SMEs, their study positions entrepreneurial orientation as a foundational capability and GenAI as a higher-order capability that together enhance resilience in turbulent markets. The findings also illustrate the influence of external market conditions on the effectiveness of GenAI-supported strategies. Jalil *et al.* (2024) examined GenAI's impact on digital value creation within SMEs, emphasizing the role of technology orientation in facilitating this transformation. Drawing on the "Technology Organization Environment (TOE)" framework and survey data from 335 Malaysian SMEs, the study underscores the importance of a forward-looking technological posture in balancing GenAI for business growth. Building on this, Almashawreh *et al.* (2024) investigate key technological and organizational factors that shape GenAI integration within Jordanian SMEs. Their findings, based on 364 firms, identify elements such as IT knowledge, digital infrastructure, managerial support, and incentive structures as critical in maximizing the effectiveness of AI-driven initiatives. In a conceptual contribution, Abrokwah-Larbi (2023) proposes a framework grounded in "Dynamic Capabilities Theory", presenting GenAI as an enabler of customer personalization through mechanisms such as deep learning and smart data, with the Internet of Things serving as a moderating factor. This framework links

GenAI with enhanced marketing outcomes, including value co-creation, interactive engagement, and customer loyalty elements essential to long-term competitiveness in digitally driven markets. The summary of the studies and their associated details are provided in Table 1.

Although research on GenAI adoption and the factors shaping its organizational implementation is expanding, often guided by frameworks such as the TOE model and "Dynamic Capabilities theory", the effects of GenAI use on employee-related outcomes, especially job satisfaction, are still not well understood. There is limited empirical evidence on the relationship between GenAI adoption and job satisfaction within the context of SMEs. Job satisfaction is widely recognized as a critical determinant of employee retention, performance, and organizational commitment (Judge *et al.*, 2001). Although the impact of information technology adoption on job satisfaction has been examined in earlier literature (Sweis, 2010; Islam, 2011), the unique characteristics and implications of GenAI necessitate more research in this context. Understanding how the integration of GenAI affects employee satisfaction is therefore essential. Exploring this relationship from a managerial perspective can provide valuable insights into how GenAI influences organizational dynamics and employee morale, ultimately guiding more effective and responsible implementation strategies.

3. Theoretical foundation

The UTAUT, introduced by Venkatesh *et al.* (2003), provides a comprehensive framework for explaining users form intentions and engagement with technology. It has been applied in many domains and expanded to assess the outcomes of technology use within organizations, including user satisfaction (Maillet *et al.*, 2015). UTAUT covers several constructs including

Table 1. GenAI and SME related studies

Author	Context	Theory	Data collection	Data analysis	Constructs
Wang and Zhang (2025)	GenAI and digital supply chains in tourism SMEs	Resource-Based View, Dynamic Capabilities Theory	Survey of 429 international SMEs in China	Empirical analysis	"GenAI (e.g. ChatGPT) innovation, collaboration, environmental, social, and governance performance, Customer involvement"
Shore *et al.* (2024)	Use of Gen AI by SMEs	Organizational Information Processing Theory	87 useable responses from SMs in France	Variance-based Structural Equation Modeling (WarpPLS 7.0)	"GenAI use, entrepreneurial orientation, entrepreneurial resilience, market turbulence"
Jalil *et al.* (2024)	AI adoption intention and digital value creation for SME	Technology-Organization-Environment	Survey of 335 SME owners in Malaysia (self-administered/ online questionnaires)	Structural Equation Modeling	"Intention to adopt AI, technology orientation, digital value creation"
Almashawreh *et al.* (2024)	Factors influencing AI adoption in SME	Technology–Organization–Environment	Survey of 364 SME owner in Jordan	Structural Equation Modeling	"AI adoption, employee IT knowledge, IT infrastructure, managerial commitment, training initiatives, reward systems"
Abrokwah-Larbi (2023)	Use of Gen AI by SMEs	Dynamic Capabilities Theory	Theoretical study; Literature review-based	Conceptual analysis; Research propositions	"Customer personalization, generative artificial intelligence, deep learning, smart data, internet of things, interactive marketing, value co-creation, consumer loyalty"

"performance expectancy", "effort expectancy", "social influence", "security and privacy concerns", and "perceived value" capture anticipatory beliefs regarding the usefulness, ease, and social relevance of technology prior to or during adoption (Venkatesh *et al.*, 2003).

By contrast, the ECM, proposed by Oliver (1980), focuses on post-adoption evaluation. Expectation confirmation refers to the cognitive process through which users compare initial expectations with actual experiences of technology use. Satisfaction increases when expectations are met or exceeded, and decreases when expectations are disconfirmed (Mamun *et al.*, 2020). Conceptually, expectation confirmation differs from UTAUT constructs: while performance expectancy and perceived value are forward-looking judgments about anticipated utility, expectation confirmation is a reconsidering assessment of whether those expectations were fulfilled. In this study, expectation confirmation was hypothesized to directly influence satisfaction, consistent with ECM's positioning of satisfaction as the immediate outcome of expectation-experience alignment (Oliver, 1980).

Ethical considerations have become an increasingly important focus in GenAI-related studies, particularly regarding fairness, transparency, and accountability (Radwan and Mcginty, 2024). By integrating UTAUT and ECM with ethical considerations, this study offers a comprehensive framework through which SMEs can better understand the determinants of employee satisfaction in GenAI adoption. The research model is presented in Figure 1.

3.1 Hypothesis development

Security and privacy involve protecting sensitive organizational and personal information from unauthorized access or misuse (Hasani *et al.*, 2023). In GenAI-enabled SMEs, strong security and privacy measures are important for building user trust and acceptance (Rajaram and Tinguely, 2024). Employees feel more confident and satisfied when their data and communications are secure (Bitrián *et al.*, 2024; Pratama and Prastyo, 2024). Conversely, security breaches or weak privacy controls can harm employees' perceptions of the work environment, leading to dissatisfaction and resistance (Bhargava *et al.*, 2021). Therefore, ensuring robust security and privacy practices can enhance job satisfaction by reducing concerns over data vulnerability.

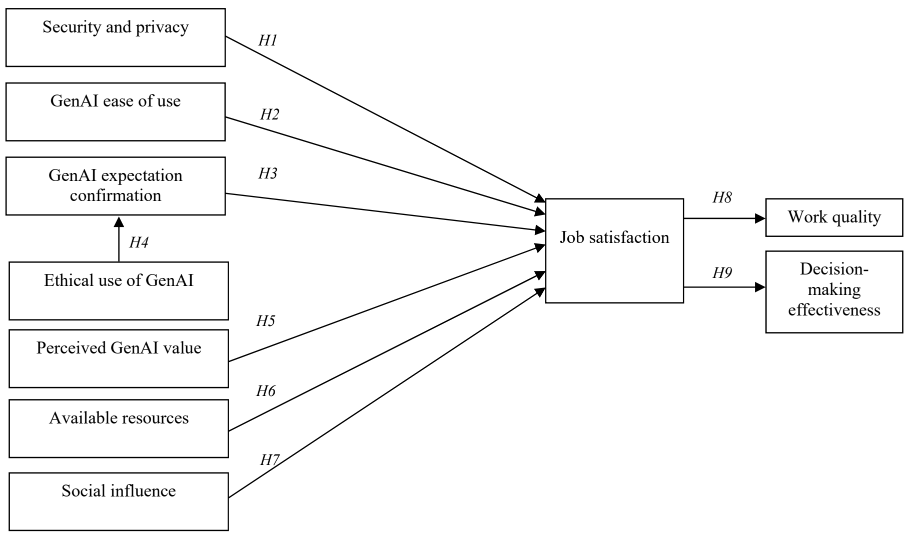

Figure 1. Research model

H1. Security and privacy are positively related to job satisfaction.

Ease of use refers to "the degree to which a user believes that utilizing a particular technology will be free of effort" (Venkatesh *et al.*, 2003). In the GenAI context, ease of use reflects not only interface simplicity but also the clarity and predictability of AI outputs, as well as the cognitive effort required to iteratively prompt and refine responses (Wei and Pardo, 2022). Unlike traditional enterprise systems, GenAI tools generate probabilistic outputs that may vary across similar prompts, introducing uncertainty and increasing cognitive load during interaction. This implies that ease of use in GenAI extends beyond interface usability to include cognitive effort, output interpretability, and response predictability. Accordingly, employees who perceive GenAI tools as requiring minimal effort to generate accurate and actionable outputs are more likely to experience higher job satisfaction (Manresa *et al.*, 2024). Therefore, ease of use is expected to be particularly important in shaping positive employee outcomes in GenAI contexts.

H2. GenAI ease of use is positively related to job satisfaction.

Expectation confirmation refers to "the degree to which users' initial expectations are met after interacting with technology" (Huang and Yu, 2023). In the GenAI context, fulfilling employees' expectations regarding functionality, and usability can strengthen satisfaction with both the technology and work environment (Manresa *et al.*, 2024). Positive expectation confirmation enhances trust, reduces cognitive dissonance, and fosters positive emotional responses (Shahin Sharifi and Rahim Esfidani, 2014). When GenAI meets or exceeds expectations, employees are more likely to report higher satisfaction with their job tasks (Huang and Yu, 2023). Thus, successful expectation confirmation can significantly improve job satisfaction.

H3. GenAI expectation confirmation is positively related to job satisfaction.

Ethical use of GenAI involves the responsible, fair, transparent, and unbiased deployment of AI technologies within organizations (Rana *et al.*, 2024). Adherence to ethical practices fosters alignment between employees' values and organizational behavior, enhancing positive perceptions (Shafik, 2024). Ethical compliance confirms users' initial expectations about fairness and responsibility during GenAI use, reinforcing positive outcomes (Söllner *et al.*, 2025). Therefore, ethical GenAI use is expected to foster higher levels of expectation confirmation.

H4. Ethical use of GenAI is positively related to GenAI expectation confirmation.

Perceived value refers to "the users' evaluation of the benefits and worth of a technology relative to the cost or effort involved" (Venkatesh *et al.*, 2003). In the GenAI context, perceived value includes the usefulness, efficiency, support, and competitive advantages AI tools offer to employees (Manresa *et al.*, 2024). When employees see GenAI systems as meaningfully contributing to their tasks and work goals, their job satisfaction increases (Lin *et al.*, 2019). Conversely, low perceived value can lead to dissatisfaction by complicating work (Khan *et al.*, 2025). Thus, enhancing GenAI's perceived value is critical for fostering a positive work environment.

H5. Perceived GenAI value is positively related to job satisfaction.

Available resources refer to the accessibility of necessary tools, infrastructure, technical support, and organizational capabilities required for the effective use of new technologies (Venkatesh *et al.*, 2003). In GenAI implementations, resource availability includes training, leadership support, infrastructure, and troubleshooting access (Bitrián *et al.*, 2024). Adequate resources boost employees' confidence, efficiency, and satisfaction (Bhargava *et al.*, 2021), while insufficient support can cause frustration, delays, and dissatisfaction (Huang and Yu, 2023). Thus, ensuring resource availability is critical to improving employee experiences with GenAI.

H6. Available resources are positively related to job satisfaction.

Social influence refers to "the extent to which individuals perceive that important others believe they should use a particular system or technology" (Venkatesh *et al.*, 2003). In GenAI context, social influence can arise from coworkers, supervisors, culture, or industry norms (Fandrejewska, 2025). Positive peer support and leadership endorsement can boost employees' confidence, acceptance, and satisfaction (Hasani *et al.*, 2023). Observing broad organizational acceptance encourages employees to integrate GenAI tools, enhancing job satisfaction (Dwivedi *et al.*, 2025). Thus, social influence is expected to shape employee satisfaction with GenAI.

H7. Social influence is positively related to job satisfaction.

Work quality refers to the standard of an employee's output, including aspects such as accuracy, creativity, and productivity (Susanto *et al.*, 2023). Job satisfaction has been widely recognized as a critical determinant of work quality, as satisfied employees are more engaged and committed to delivering high performance (Sypniewska *et al.*, 2023). In GenAI-enabled workplaces, improvements in job satisfaction are driven by factors such as ease of use, security, and perceived value can translate into better work outcomes (Zhang *et al.*, 2025, 2026). Satisfied employees are more likely to fully engage, show greater attention to detail, and innovate, thereby improving work quality (Ahn *et al.*, 2025).

H8. Job satisfaction is positively related to work quality.

Decision-making effectiveness refers to "the ability to make timely, accurate, and beneficial choices that positively impact organizational goals" (Wang and Byrd, 2017). Job satisfaction has been linked to cognitive performance, emotional stability, and confidence, all of which are critical for effective decision-making (Ali and Anwar, 2021). Satisfied employees in GenAI-driven organizations interpret insights better, collaborate more, and make smarter decisions (Söllner *et al.*, 2025). High satisfaction levels reduce stress and cognitive overload, leading to clearer judgment and improved decision outcomes (Van Der Westhuizen *et al.*, 2012).

H9. Job satisfaction is positively related to decision-making effectiveness.

The research model consists of nine hypotheses (H1-H9) capturing the proposed relationships, as illustrated in Figure 1.

4. Methodology

This study is predictive, as the model aims to assess how multiple exogenous constructs contribute to predicting job satisfaction and its downstream outcomes, work quality and decision-making effectiveness. Quantitative research design was used to test the hypotheses and examine the relationships among the variables. PLS-SEM was employed as an analytical approach, as it is well suited for prediction-oriented research and focuses on maximizing the explained variance of endogenous constructs. PLS-SEM was selected for its strong predictive capabilities and suitability for analyzing complex cause-and-effect relationships (Hair and Alamer, 2022). In addition, PLS-SEM helps minimize variance and reduce bias in parameter estimates (Hair *et al.*, 2019). Data analysis was conducted using SmartPLS software (Version 3.0).

4.1 Measurement of items

This study employed a structured questionnaire to gather data from manufacturing SMEs in Malaysia. The questionnaire was designed based on ten key constructs, incorporating a total of thirty-eight items, as summarized in Appendix 1. These constructs are Security and Privacy (SP), GenAI Ease of Use (EOU), GenAI Expectation Confirmation (GEC), Ethical Use of GenAI (EUG), Perceived GenAI Value (PGV), Available Resources (AR), Social Influence (SI), Job Satisfaction (JS), Work Quality (WQ), and Decision-Making Effectiveness (DME).

The items were adapted from prior validated studies (e.g. Gupta *et al.*, 2020; Thong *et al.*, 2006; Isaac *et al.*, 2019; Kašparová, 2023) and modified to fit the specific context of GenAI application in the Malaysian manufacturing sector. Each construct was operationalized through multiple items measured on a five-point Likert scale ranging from “strongly disagree” (1) to “strongly agree” (5).

4.2 Data collection and sample size

This study focused on managers working in SMEs’ manufacturing. The respondents included individuals in managerial roles who are directly involved in technology adoption and decision-making within their organizations. Their perspectives were essential for grasping the impact of GenAI on job satisfaction, work quality, and decision-making effectiveness in the manufacturing sector. Manufacturing SMEs represent an essential component of Malaysia’s economy, contributing significantly to GDP, employment, and technological innovation (Ijaz Baig and Yadegaridehkordi, 2025). This study specifically targeted employees from manufacturing SMEs that had already implemented GenAI tools in their daily operations. Therefore, purposive sampling was employed to ensure that only relevant respondents with direct experience using GenAI were included. To verify eligibility, a screening question was placed at the beginning of the questionnaire: “Are you currently using GenAI tools in your work processes?” Only those who confirmed active GenAI usage were allowed to proceed with the full survey. An online questionnaire was developed using Microsoft Forms and distributed via email and LinkedIn outreach to employees across multiple SME clusters. The contact information for manufacturing SMEs was retrieved from the SME Corporation Malaysia directory (https://smecorp.gov.my/) and relevant industrial association listings. A total of 163 complete and valid responses were collected. Hair *et al.* (2013) recommended that “the minimum sample size should be at least ten times the highest number of structural paths pointing to any construct in the model”. The sample size of 163 meets the recommendations for PLS-SEM analysis (Hair *et al.*, 2019). Thus, the sample obtained is appropriate for the study’s analysis requirements.

4.3 Demographic data

According to the demographic profile (Table 2), the gender composition comprised 99 males (60.73%) and 64 females (39.26%). Regarding age distribution, respondents were categorized as follows: 18–30 years (36 individuals, 22.08%), 31–42 years (60 individuals, 36.08%), 43–55 years (53 individuals, 32.51%), and 55–67 years and above (14 individuals, 8.58%). In terms of educational attainment, the majority of respondents held an undergraduate degree (94 individuals, 57.66%), followed by graduate-level qualifications (39 individuals, 23.92%) and diploma or short-course certifications (30 individuals, 18.40%). Concerning the manufacturing sector, respondents were engaged in various industries, including food and beverage equipment (35 individuals, 21.47%), plastic products (24 individuals, 14.72%), textiles and apparel (21 individuals, 12.88%), paper and paper products (19 individuals, 11.65%), pharmaceuticals and medical devices (17 individuals, 10.42%), wood materials/furniture and fixtures (16 individuals, 9.81%), non-metallic and mineral products such as cement, glass, and ceramics (16 individuals, 9.81%), and chemicals and chemical products (15 individuals, 9.20%).

5. Results

5.1 Measurement model

“Factor loading” (FL), Cronbach’s alpha (CA), and “composite reliability” (CR) served as measures to assess construct reliability. According to Hair and Alamer (2022), FL, CA, and CR values should exceed 0.7. This criterion was met in the study, with FL values ranging from 0.795 to 0.949, and both CA and CR surpassing the 0.7 threshold, confirming reliability as shown in

Table 2. Respondents demographics ($n = 163$)

Items	Categories	Frequency	Percentage
Gender	Male	99	60.73
	Female	64	39.26
Age	18–30	36	22.08
	31–42	60	36.08
	43–55	53	32.51
	55–67 above	14	8.58
Educational level	Undergraduate	94	57.66
	Graduate	39	23.92
	Diploma/Short course	30	18.40
Manufacturing sector	Plastic products	24	14.72
	Wood materials/furniture and fixtures	16	9.81
	Food and beverage equipment	35	21.47
	Pharmaceuticals and medical devices	17	10.42
	Textiles and apparel	21	12.88
	Paper and paper products	19	11.65
	Chemicals and chemical products	15	9.20
	Non-metallic and mineral products (e.g. cement, glass, ceramics)	16	9.81

Table 3. "Convergent validity" was evaluated through the extraction of "average variance" (AV). AV values exceeding 0.5 for each variable demonstrate satisfactory convergent validity. Discriminant validity was assessed using the "Fornell-Larcker criterion" (FLC), "cross-loadings" (CL), and "heterotrait-monotrait" (HTMT) ratio. FLC compares AV with squared correlations between variables, demonstrating sufficient discriminant validity (Table 4). HTMT analysis, depicted in Table 5, indicates values below the recommended threshold of 1, affirming discriminant validity. The CL results are provided Appendix 2.

5.2 Structural model

5.2.1 Collinearity assessment. The first step in evaluating the structural model is to assess potential collinearity among the predictor constructs. Variance Inflation Factor (VIF) values were examined to detect possible multicollinearity, as VIF reflects the extent to which the variance of a predictor is inflated due to its correlation with other predictors (Hair and Alamer, 2022). Excessive multicollinearity may distort path coefficients and reduce the stability of the structural model estimates. According to Hair and Alamer (2022), tolerance values above 0.20 and VIF values below 5.0 indicate that collinearity is not a serious concern.

In this study, the VIF values range from 1.00 to 2.561. The highest VIF value is observed for PGV = 2.561, followed by SP = 2.348 and GEC = 2.304. Other constructs, including AR = 1.771, SI = 1.109, and EOU = 1.096, also remain well below the recommended threshold. Since all VIF values are substantially below the cut-off value of 5.0, the results indicate that multicollinearity is not a concern in this study. Therefore, all predictor constructs were retained for subsequent structural model analysis. In addition, the VIF values were also examined to assess potential common method bias (CMB) using the full collinearity approach. According to the criterion proposed by Kock (2015), VIF values below 3.3 indicate that common method bias is unlikely to threaten the validity of the results. As all VIF values in this study range between 1.00 and 2.561, they remain well below this threshold, suggesting that common method bias is not a significant concern.

5.2.2 Hypothesis testing. The structural model was utilized to test the hypotheses, adopting a 95% confidence level as suggested by (Hair *et al.*, 2019). Table 6 and Figure 2 present the hypothesis testing results, outlining the path coefficients (β) and their corresponding p-values. The H1 ($\beta = 0.137$, $p = 0.040$), H4 ($\beta = 0.626$, $p = 0.000$), H5 ($\beta = 0.326$, $p = 0.000$), H6

Table 3. Reliability and convergent validity

Constructs	Items	Factor loading (FL)	Cronbach's alpha (CA)	Composite reliability (CR)	Average variance extracted (AV)
Available resources (AR)	AR1	0.970	0.933	0.952	0.833
	AR2	0.892			
	AR3	0.948			
	AR4	0.833			
Decision-making effectiveness (DME)	DME1	0.850	0.838	0.892	0.674
	DME2	0.876			
	DME3	0.731			
	DME4	0.820			
GenAI ease of use (EOU)	EOU1	0.865	0.879	0.915	0.729
	EOU2	0.874			
	EOU3	0.851			
	EOU4	0.825			
Ethical use of GenAI (EUG)	EUG1	0.908	0.949	0.963	0.866
	EUG2	0.932			
	EUG3	0.935			
	EUG4	0.948			
GenAI expectation confirmation (GEC)	GEC1	0.790	0.795	0.879	0.709
	GEC2	0.881			
	GEC3	0.852			
Job satisfaction (JS)	JS1	0.967	0.930	0.950	0.828
	JS2	0.834			
	JS3	0.946			
	JS4	0.887			
Perceived GenAI value (PGV)	PGV1	0.934	0.924	0.946	0.815
	PGV2	0.843			
	PGV3	0.897			
	PGV4	0.934			
Social influence (SI)	SI1	0.926	0.846	0.896	0.685
	SI2	0.757			
	SI3	0.858			
	SI4	0.755			
Security and privacy (SP)	SP1	0.911	0.881	0.926	0.808
	SP2	0.911			
	SP3	0.873			
Work quality (WQ)	WQ1	0.909	0.897	0.928	0.765
	WQ2	0.786			
	WQ3	0.865			
	WQ4	0.930			

($\beta = 0.383$, $p = 0.000$), H8 ($\beta = 0.720$, $p = 0.000$), and H9 ($\beta = 0.680$, $p = 0.000$) shows significant relationship. Therefore, Hypotheses H1, H4, H5, H6, H8, and H9 were accepted. However, H2 ($\beta = 0.028$, $p = 0.262$), H3 ($\beta = 0.057$, $p = 0.213$) and H7 ($\beta = 0.036$, $p = 0.260$) were presenting insignificant relationships. Therefore, hypotheses H2, H3, and H7 were rejected. The R^2 metric serves as a measure of the model's overall integrity. In this study, the R^2 values for are as follows: JS = 0.594, DME = 0.463, WQ = 0.518 and GEC = 0.391. According to Chin (1998), an R^2 exceeding 0.33 indicates a significant model. Thus, the R^2 values for proposed model are deemed significant.

5.2.3 Effect size (f^2). The effect size (f^2) was computed to measure the impact of each predictor on the endogenous constructs (Cohen, 1988; Hair and Alamer, 2022). According to Cohen, f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. In this study, AR ($f^2 = 0.25$) and PGV ($f^2 = 0.22$) exhibit medium effect sizes, while EUG ($f^2 = 0.48$) shows a large effect size, indicating a substantial influence on JS and

Table 4. Fornell-Larcker criterion

	AR	DME	EOU	EUG	GEC	JS	PGV	SI	SP	WQ
Available resources	0.912									
Decision-making effectiveness	0.663	0.821								
GenAI ease of use	0.435	0.517	0.931							
Ethical use of GenAI	0.273	0.255	0.113	0.854						
GenAI expectation confirmation	0.556	0.621	0.626	0.157	0.842					
Job satisfaction	0.668	0.680	0.641	0.227	0.588	0.910				
Perceived GenAI value	0.541	0.597	0.741	0.195	0.706	0.671	0.903			
Social influence	0.574	0.560	0.694	0.198	0.647	0.620	0.700	0.899		
Security and privacy	0.274	0.084	0.098	0.160	0.163	0.155	0.127	0.227	0.827	
Work quality	0.710	0.798	0.443	0.416	0.484	0.720	0.510	0.429	0.168	0.874

Table 5. Heterotrait-monotrait ratio (HTMT)

	AR	DME	EOU	EUG	GEC	JS	PGV	SI	SP	WQ
Available resources										
Decision-making effectiveness	0.742									
Ethical use of GenAI	0.449	0.573								
GenAI ease of use	0.305	0.292	0.117							
GenAI expectation confirmation	0.640	0.765	0.701	0.183						
Job satisfaction	0.701	0.763	0.679	0.240	0.673					
Perceived GenAI value	0.563	0.673	0.792	0.200	0.816	0.712				
Security and privacy	0.623	0.650	0.749	0.214	0.765	0.677	0.774			
Social influence	0.305	0.104	0.109	0.182	0.189	0.167	0.140	0.253		
Work quality	0.772	0.910	0.456	0.477	0.555	0.773	0.533	0.464	0.190	

GEC. SP ($f^2 = 0.03$) demonstrates a small effect on JS, suggesting a modest contribution. In contrast, EOU ($f^2 = 0.001$), GEC ($f^2 = 0.005$), and SI ($f^2 = 0.002$) show negligible effects, indicating a limited impact on JS. Additionally, JS exerts large effects on both WQ ($f^2 = 0.63$) and DME ($f^2 = 0.56$), highlighting its critical role in enhancing employees' performance outcomes when using GenAI tools.

5.2.4 Predictive relevance Q^2. Predictive relevance of the structural model was assessed using the blindfolding procedure in SmartPLS. The cross-validated redundancy measure (Q^2) was examined to determine the model's predictive capability for endogenous constructs. According to Hair and Alamer, 2022, Q^2 values greater than zero indicate that the model has predictive relevance. In this study, all endogenous constructs exhibit positive Q^2 values. Specifically, DME = 0.286 and GEC = 0.257 demonstrate moderate predictive relevance, while JS = 0.456 and WQ = 0.366 indicate strong predictive relevance. These results suggest that the structural model has satisfactory predictive capability.

6. Discussion

This study aimed to assess the actual impact of GenAI adoption on managerial job satisfaction, work quality, and decision-making effectiveness within the manufacturing SME sector.

Table 6. Path coefficients and hypotheses testing

Hypotheses	Path coefficients (β)	Sample mean	Standard deviation (STDEV)	*p*-values	Status	Decision
H1: Security and privacy → Job satisfaction	0.137	0.138	0.078	0.040	$p < 0.05$	Accepted
H2: GenAI ease of use → Job satisfaction	0.028	0.034	0.041	0.262	$p > 0.05$	Rejected
H3: GenAI expectation confirmation → Job satisfaction	0.057	0.058	0.072	0.213	$p > 0.05$	Rejected
H4: Ethical use of GenAI → GenAI expectation confirmation	0.626	0.627	0.061	0.000	$p < 0.05$	Accepted
H5: Perceived GenAI value → Job satisfaction	0.326	0.327	0.093	0.000	$p < 0.05$	Accepted
H6: Available resources → Job satisfaction	0.383	0.375	0.074	0.000	$p < 0.05$	Accepted
H7: Social influence → Job satisfaction	0.036	0.021	0.056	0.260	$p > 0.05$	Rejected
H8: Job satisfaction → Work quality	0.720	0.719	0.043	0.000	$p < 0.05$	Accepted
H9: Job satisfaction → Decision-making effectiveness	0.680	0.681	0.055	0.000	$p < 0.05$	Accepted

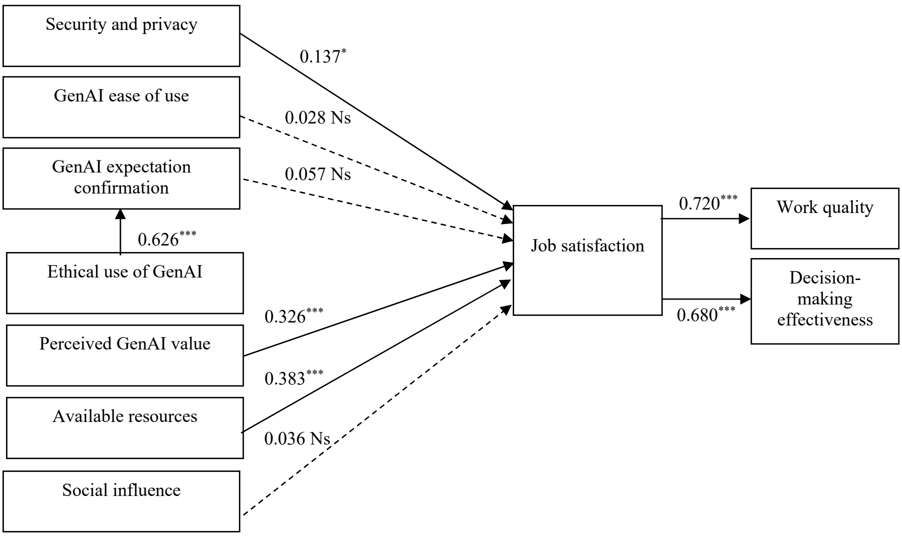

Figure 2. Hypotheses results

Security and privacy were found to positively influence job satisfaction. These considerations are especially critical in the manufacturing sector, where proprietary designs, production processes, and client data require strong protection. This result may be attributed to the fact that robust security and privacy measures enhance employee confidence and trust in GenAI systems, thereby increasing job satisfaction. This finding aligns with Dehghanpouri *et al.* (2020), who emphasized the role of trust and privacy in enhancing job satisfaction.

The results showed that GenAI's ease of use did not significantly affect job satisfaction. The distinctive nature of GenAI as a probabilistic, iterative, and cognitively demanding technology requires theoretical framing beyond traditional IT logics. Although user-friendliness is often emphasized in technology adoption models (Venkatesh *et al.*, 2003), GenAI interactions involve prompting, interpreting non-deterministic outputs, and managing cognitive load. This helps explain why ease of use was not significant: the challenge lies less in interface simplicity and more in the cognitive interaction required to harness GenAI effectively. Employees in the manufacturing sector may prioritize functional effectiveness, reliability, and security over simplicity (Asiaei and Ab. Rahim, 2019). This can be further explained through task routinization: once GenAI becomes embedded in standardized workflows, usability concerns diminish, as employees focus on reliable task execution rather than interface simplicity. Moreover, prior studies have shown that transformational leadership and organizational climate influence technology adoption behaviors (Hamid *et al.*, 2022; Yadulla *et al.*, 2024). Therefore, organizational factors such as leadership style, workplace culture, and managerial expectations may shape employees' perceptions of ease of use, thereby weakening its direct impact on job satisfaction.

GenAI expectation confirmation was not significantly associated with job satisfaction. This finding suggests that although employees' expectations regarding GenAI functionality may be met, expectation fulfillment alone is insufficient to enhance satisfaction. In manufacturing environments, employees are likely to place greater emphasis on the practical performance and operational benefits of technologies than on comparisons between initial expectations and actual outcomes (Thorley *et al.*, 2021). This interpretation is supported by the significant effect of perceived GenAI value on job satisfaction. One possible explanation is that perceived value may effectively subsume expectation confirmation in the context of GenAI. Prior research suggests that users' evaluations tend to evolve from expectation-based assessments toward broader judgments of value and utility over time (Bhattacherjee, 2001; Gursoy *et al.*, 2019). Consequently, employees may incorporate the fulfillment of expectations into their overall assessment of GenAI value, reducing the distinct explanatory role of expectation confirmation. In this sense, satisfaction may be driven less by whether GenAI meets initial expectations and more by the tangible benefits and ongoing utility that employees derive from its use (Dubey and Sahu, 2021). An alternative explanation is that expectation confirmation influences job satisfaction indirectly through perceived value rather than exerting a direct effect. Although this relationship was not examined in the current study, it represents a promising direction for future research. Overall, the findings suggest that in post-adoption GenAI contexts, employees prioritize the continued value generated by the technology over retrospective evaluations of expectation fulfillment. This helps explain why perceived value emerged as a significant predictor of job satisfaction, whereas expectation confirmation did not.

On the other hand, results demonstrated a significant correlation between ethical use of GenAI and GenAI expectation confirmation. Ethical use, including transparency and responsible AI practices, reinforces employees' trust in technology, making it more likely that their expectations are met (Yadulla *et al.*, 2024; Tripathi and Kumar, 2025). In the manufacturing sector, where trust in systems and organizational practices is paramount, ethical use serves as a foundation for aligning user expectations with actual system performance, as also suggested by (Niu and Mvondo, 2024). The findings of H5 revealed that perceived GenAI value positively influences job satisfaction. Employees who recognize clear value in GenAI, such as operational efficiency and better production planning experience higher job satisfaction. Perceived value translates into tangible improvements in work outcomes, aligning with the findings of Dubey and Sahu (2021), who emphasized the role of perceived technology value in promoting satisfaction.

Similarly, the availability of resources had a significant positive impact on job satisfaction. Adequate technical support, training, infrastructure, and management backing are essential for effective GenAI adoption in manufacturing SMEs (Rajaram and Tinguely, 2024). When these supporting conditions are present, employees feel empowered, leading to greater satisfaction. This finding confirms the work of Asamani *et al.* (2025) who emphasized that organizational support structures significantly influence technology satisfaction. Contrary to expectations, the findings for H7 indicate that social influence does not significantly affect job satisfaction. This result may be explained by the assumptions of the UTAUT framework regarding the voluntariness of technology use. In contexts where technology adoption is voluntary, social influence is more likely to shape user attitudes and outcomes. However, in SME environments where the use of GenAI may be managerial-driven or mandated, the role of social influence may become less salient, as employees are expected to use the technology regardless of peer or social pressures. Meanwhile, in the SME manufacturing context, employees may prioritize personal experience, system performance, and management directives over peer opinions when evaluating GenAI tools (Rajaram and Tinguely, 2024). Moreover, the emphasis on operational efficiency and security over social conformity could explain the insignificant role of social influence (Ijaz Baig and Yadegaridehkordi, 2025). Similar observations were reported by Li *et al.* (2024) found that social influence diminishes in environments where functional outcomes are prioritized. Furthermore, the structured nature of work in manufacturing SMEs often leaves limited scope for peer influence in shaping technology-related attitudes. Employees typically follow established procedures and focus on task efficiency, relying more on proven system performance and managerial support than on colleagues' opinions when adopting new technologies (Rajaram and Tinguely, 2024). Furthermore, the results showed that job satisfaction significantly enhanced work quality. In SME contexts, job satisfaction significantly enhances work quality (Mustafa *et al.*, 2021). When employees are content-driven by meaningful tasks and relieved from repetitive work through GenAI, they tend to engage more deeply (Md *et al.*, 2025). This leads to fewer errors and higher-quality outputs (Maamari and Osta, 2021). This finding is consistent with the broader literature emphasizing the link between job satisfaction and employee performance (Dhamija *et al.*, 2019). Finally, the results showed that job satisfaction significantly impacted decision-making effectiveness. In the manufacturing environment, where rapid and accurate decisions are important, GenAI tools support employees by providing data-driven insights (Rajaram and Tinguely, 2024). This pattern reflects managerial accountability structures: in SME contexts, employees are held responsible for performance outcomes rather than conformity to peer attitudes, which explains why governance-related factors outweigh social influence. When employees are satisfied with these tools, they are more likely to trust and effectively use them in decision-making processes, leading to improved outcomes (Carayannis *et al.*, 2024). This aligns with Hariguna and Ruangkanjanases (2024) and extends prior empirical streams by showing how satisfaction not only enhances performance but also strengthens decision-making effectiveness, thereby positioning our findings within established scholarly discourse. By linking these results to broader mechanisms such as routinization, institutionalization, and accountability, the study moves beyond descriptive explanation to theorization, offering insights that generalize beyond the manufacturing SME context.

7. Implications

7.1 Theoretical implications

This study makes a significant theoretical contribution to literature by examining the impacts of GenAI adoption in SMEs, with a particular focus on managerial job satisfaction. While ECM and UTAUT have frequently been applied separately to study technology adoption, relatively few studies have integrated these frameworks to examine post-adoption outcomes and their implications for managerial performance in SMEs. ECM focuses on post-adoption behavior through constructs such as expectation confirmation and perceived usefulness, whereas UTAUT incorporates broader determinants of technology acceptance including perceived value, social influence, and facilitating conditions. By integrating ECM and UTAUT, this study provides a more comprehensive framework to explain how post-adoption evaluations of GenAI shape managerial satisfaction, particularly in enhancing work quality and decision-making effectiveness. This integration builds on Bhattacherjee (2001) by extending ECM's post-adoption logic to AI-enabled organizational environments, where evaluation is increasingly outcome- and value-driven rather than expectation-driven alone.

Importantly, this study highlights that GenAI is not merely another IT system but a qualitatively distinct technological artifact. Its probabilistic outputs, iterative prompting, and cognitive load implications shift the locus of user evaluation from interface simplicity to cognitive interaction demands. This distinction establishes explicit boundary conditions for the explanatory power of UTAUT and ECM. The findings indicate that in post-adoption contexts where GenAI is embedded in organizational workflows, traditional drivers such as ease of use and social influence lose salience not only because of adoption stage, but because "ease of use" in GenAI is better understood as "ease of cognitive engagement." This requires a re-specification of technology acceptance logic in routine usage environments.

This refinement reweights the assumptions of UTAUT and ECM, elevating governance-related constructs such as ethical use and security considerations as dominant determinants of satisfaction. These findings suggest that technology acceptance models such as UTAUT and ECM may require contextual adaptation when applied to post-adoption managerial environments, where users interact with technologies that are dialogic, probabilistic, and cognitively demanding, and therefore evaluate them primarily in terms of trustworthiness, governance compliance, and operational support rather than interface usability.

In fact, the study extends the theoretical scope of technology acceptance research by incorporating underexplored constructs including security and privacy considerations, ethical use of GenAI, perceived GenAI value, and available organizational resources. The results demonstrate that these factors significantly influence managerial job satisfaction, which in turn enhances work quality and decision-making effectiveness. By introducing ethical and governance-related dimensions into the post-adoption analysis, this study contributes to emerging discussions on responsible AI adoption in organizational contexts. Specifically, the findings indicate that the ethical use of GenAI not only shapes users' confirmation of expectations but also supports sustainable and responsible technology practices within SMEs.

7.2 Practical implications

The findings of this study offer practical implications for SME managers, GenAI developers, and policymakers. Security and privacy are closely linked to job satisfaction because they play a significant role in building employees' trust in GenAI tools. SME managers can enhance job satisfaction by implementing strong data governance policies and providing cybersecurity training to ensure employees feel secure when using GenAI. Integrating robust security features such as encryption and clear privacy settings into GenAI tools can further strengthen user confidence. Transparent communication about data handling practices can also enhance trust. Policymakers can support these efforts by establishing comprehensive data privacy regulations and certification standards to ensure effective data protection.

The ethical use of GenAI is essential for long-term acceptance and responsible innovation. SMEs can develop internal ethical guidelines aligned with corporate values to promote transparency, accountability, and fairness. Training employees to address ethical dilemmas, algorithmic biases, and responsible AI use can further reinforce this culture. Developers can support these efforts by embedding fairness and explainability into GenAI systems and clearly communicating model limitations and risks. Policymakers can further strengthen ethical practices by introducing frameworks that require ethical audits, responsible AI certifications, and transparent reporting by SMEs using AI.

Perceived GenAI value is a key driver of adoption among SMEs. Managers can enhance perceived value by integrating GenAI into core workflows where it directly improves productivity, creativity, and decision-making, rather than treating it as an optional add-on. Highlighting internal success stories can further demonstrate tangible benefits. Developers can strengthen perceived value by offering solutions that are accessible, affordable, and tailored to

SME needs, ensuring measurable benefits without excessive investment. Policymakers can reinforce this value by offering incentives, grants, or tax benefits that encourage GenAI adoption and support SME competitiveness and innovation.

Available resources significantly influence an SME's ability to implement and benefit from GenAI tools. Managers should assess organizational resources, including technical expertise, financial capacity, and infrastructure, before adoption. Investing in employee training and collaborating with external partners can help address capability gaps. Developers can support resource-constrained SMEs by offering scalable, modular solutions and flexible pricing models that allow gradual adoption. Policymakers can further facilitate access by creating funding programs, public–private partnerships, and resource-sharing initiatives that reduce financial barriers.

Job satisfaction is critical for sustaining the effective use of GenAI tools within SMEs. Managers can position GenAI as a tool for professional growth by reducing repetitive tasks and enabling employees to focus on strategic and creative activities. Involving employees in feedback sessions during adoption can also make the transition more inclusive. Developers can contribute by designing intuitive interfaces, flexible customization, and context-aware features that simplify daily work. Policymakers can support workplace well-being by incorporating AI considerations into labor standards and providing funding for retraining and upskilling in AI-enabled environments.

Enhancing work quality through GenAI is another important objective for SMEs seeking to remain competitive. Managers can use GenAI to support higher-quality outputs by automating routine tasks, providing data-driven insights, and assisting creativity and problem solving. Training employees to effectively use GenAI features will further amplify these benefits. Developers should design systems that deliver reliable, contextually relevant, and accurate outputs, supported by built-in validation and quality assurance features. Policymakers can establish industry-specific standards for AI-supported work to ensure that GenAI adoption maintains or improves quality benchmarks.

Decision-making effectiveness is also influenced by GenAI integration in business processes. Managers can enable data-driven decision-making by ensuring employees have access to accurate and up-to-date data while encouraging critical evaluation of AI-generated insights. Developers can enhance decision support by designing systems that provide transparent reasoning behind recommendations, customizable parameters for different contexts, and scenario analysis rather than deterministic outputs. Policymakers can support responsible AI use by establishing guidelines that emphasize transparency, human oversight, and accountability in AI-assisted business decisions.

Although three hypotheses (ease of use, expectation confirmation, and social influence) were not supported, these findings still provide valuable insights. They indicate that GenAI adoption in managerial contexts is driven less by usability or social norms and more by ethical assurance, resource availability, and perceived value. Therefore, organizations should prioritize building trustworthy, well-supported AI ecosystems and equipping employees with appropriate training rather than relying primarily on user expectations or peer influence.

8. Conclusion

This study examines the factors influencing job satisfaction with GenAI tools in SMEs and its relation to work quality and decision-making, using UTAUT and ECM as guiding frameworks. The results revealed that security and privacy, ethical use of GenAI, perceived GenAI value, and available resources emerged as significant factors shaping job satisfaction and driving the continuous use of GenAI tools. On the other hand, the study found that GenAI ease of use, expectation confirmation, and social influence did not significantly impact job satisfaction in this context. Despite this, job satisfaction was positively linked with enhanced work quality and decision-making effectiveness, suggesting that job satisfaction plays an essential role in fostering better organizational outcomes.

Theoretically, this study refines UTAUT and ECM by showing that in post-adoption contexts, satisfaction depends less on usability or peer influence and more on organizational and ethical assurances. This insight advances understanding of GenAI adoption by highlighting the importance of trust, transparency, and resource adequacy in shaping managerial experiences. Empirically, the results demonstrate that job satisfaction with GenAI tools directly enhances work quality and decision-making effectiveness, underscoring its role in improving SME performance outcomes. Practically, the findings guide managers of small enterprises to invest in secure and ethical GenAI ecosystems, policy makers to develop clear data protection and ethical-use policies, and developers to design transparent, resource-efficient GenAI tools tailored to SME capacities. Overall, the study demonstrates that managerial job satisfaction from the use of GenAI in SMEs, which in turn enhances work quality and decision-making effectiveness, is driven primarily by available resources, security and privacy and the perceived GenAI value, rather than by ease of use or social influence.

9. Limitations and future directions

This research provides valuable insights; however, certain limitations should be considered. This study focused on specific factors impacting job satisfaction. Future research could explore the interaction and influence of these factors by examining their moderating or mediating effects, which would provide a more nuanced understanding of their relationships (e.g. how expectation confirmation may mediate managerial satisfaction and post-adoption outcomes in different organizational contexts). While this study addresses the role of ethical considerations in job satisfaction, future research could further explore the specific ethical challenges that SMEs face when integrating GenAI tools. Research could propose frameworks or guidelines for the responsible and ethical use of GenAI in different business environments, helping SMEs to build trust and minimize risks associated with AI-driven processes. The use of cross-sectional data limits the ability to establish causal relationships between variables, as the findings capture perceptions at a single point in time. In addition, reliance on self-reported measures may introduce perceptual and response biases, despite efforts to address common method bias statistically. In addition, the reliance on self-reported measures may introduce perceptual and response biases despite efforts to address common method bias statistically. Accordingly, the findings primarily reflect managers' perceptions rather than objectively measured organizational performance. Therefore, the reported improvements in work quality and decision-making effectiveness should be interpreted as perceived outcomes rather than verified changes in actual performance, and future studies should incorporate objective performance indicators where feasible.

Furthermore, although PLS-SEM is appropriate for exploratory and prediction-oriented research, it has inherent limitations in terms of model fit assessment and causal inference. Future research could address these limitations by employing longitudinal designs, incorporating objective performance measures (e.g. productivity levels, task completion time, or error rates), and applying complementary analytical techniques to strengthen causal interpretation.

Despite meeting the minimum recommended threshold for PLS-SEM analysis, the sample size of 163 may limit the statistical power and robustness of the findings. Furthermore, the combination of a relatively modest sample size and a comparatively complex research model warrants caution when interpreting and generalizing the results beyond the study context. Future research should validate these findings using larger and more diverse samples to enhance their generalizability. Additionally, the focus on Malaysian manufacturing SMEs may restrict the generalizability of the results to other sectors and geographical contexts. Future research is encouraged to employ larger and more diverse samples to enhance the reliability and external validity of the findings. Future studies could expand the sample to include organizations from different countries, industries, and sizes. This would allow for the examination of contextual factors, such as cultural differences, infrastructure, and market conditions, that may influence GenAI adoption and its impact on job satisfaction.

Lastly, this study relies on self-reported, GenAI-specific measures of work quality and decision-making effectiveness, which capture employees' perceived improvements rather than actual performance outcomes. As a result, the findings reflect subjective evaluations and may be influenced by individual biases or expectations. Future research should incorporate objective performance indicators (e.g. productivity metrics, error rates, or task completion times), multi-source data, or longitudinal designs to better assess the extent to which GenAI use translates into measurable improvements in work outcomes.

Appendix 1

Table A1. Questionnaire for data collection from the SME manufacturing side

Constructs	Definitions	Items	References
Security and privacy (SP)	"Protection of sensitive manufacturing data from unauthorized access and managing confidential information when using GenAI tools."	- I am confident that manufacturing data is protected when using GenAI - I trust GenAI tools to maintain the privacy of operational information - I take steps to secure sensitive data while using GenAI systems	Gupta *et al.* (2020)
GenAI ease of use (EOU)	"The degree to which using GenAI in manufacturing tasks is perceived as effortless and user-friendly"	- Learning to operate GenAI tools is easy for me - It is easy for me to become skillful at using GenAI for manufacturing - GenAI tools are easy to understand and interact with - Completing manufacturing tasks with GenAI requires little effort	Thong *et al.* (2006)
GenAI expectation confirmation (GEC)	"The degree to which actual performance of GenAI tools in manufacturing meets or exceeds initial expectations"	- GenAI in manufacturing performs better than I expected - My expectations about GenAI capabilities have been confirmed - Using GenAI in production has been more beneficial than anticipated	Thong *et al.* (2006)
Ethical use of GenAI (EUG)	"Adhering to responsible principles and ethical standards when deploying GenAI in manufacturing operations"	- I use GenAI tools ethically in my manufacturing tasks - I ensure compliance with ethical standards when applying GenAI. - I discourage unethical uses of GenAI in production activities - I promote awareness about the ethical use of GenAI among colleagues	Gupta *et al.* (2020)

(*continued*)

Table A1. Continued

Constructs	Definitions	Items	References
Perceived GenAI value (PGV)	"The degree to which using GenAI is seen as beneficial and value-adding to manufacturing activities"	- GenAI use improves my manufacturing productivity - GenAI provides significant value in manufacturing operations - GenAI helps optimize processes and reduce manufacturing costs - Overall, GenAI benefits my work performance in manufacturing	Thong *et al.* (2006)
Available resources (AR)	"The perceived availability of technical, financial, and human support for adopting GenAI in SMEs"	- My organization allocates sufficient resources for GenAI adoption - Technical support for GenAI use is readily available - We receive adequate training to use GenAI in manufacturing - There are enough skilled personnel to support GenAI projects	Gupta *et al.* (2020)
Social influence (SI)	"The impact of peers, supervisors, or industry trends on the adoption of GenAI in manufacturing SMEs"	- My peers encourage me to use GenAI in manufacturing tasks - Management expects us to adopt GenAI in production activities - Industry developments push me toward using GenAI. - People important to me support the use of GenAI at work	Isaac *et al.* (2019)
Job satisfaction (JS)	"The extent to which GenAI usage enhances personal fulfillment and satisfaction at work"	- Using GenAI makes my job more enjoyable - GenAI reduces my work stress by simplifying tasks - GenAI helps me achieve greater job satisfaction - GenAI allows me to focus on more meaningful manufacturing tasks	Thong *et al.* (2006)
Work quality (WQ)	"The perceived improvement in the quality and accuracy of manufacturing output through GenAI"	- GenAI improves the quality of my production work - GenAI tools help minimize errors in manufacturing operations - The consistency of my manufacturing outputs has improved with GenAI. - GenAI supports delivering higher standards in production tasks	Thong *et al.* (2006)

(*continued*)

Table A1. Continued

Constructs	Definitions	Items	References
Decision-making effectiveness (DME)	The extent to which GenAI helps in making faster, more accurate, and better manufacturing-related decisions	- GenAI enables me to make better production decisions - GenAI tools improve the speed of my decision-making - GenAI helps me make more data-driven operational decisions - Decision-making in manufacturing has become more effective due to GenAI	Kašparová (2023)

Appendix 2

Table A2. Cross-loading (CL) results

Item	AR	DME	EOU	EUG	GEC	JS	PGV	SI	SP	WQ
AR1	*0.970*	0.617	0.232	0.415	0.533	0.671	0.504	0.285	0.570	0.676
AR2	*0.892*	0.587	0.291	0.330	0.377	0.577	0.432	0.234	0.443	0.666
AR3	*0.948*	0.690	0.231	0.532	0.620	0.700	0.611	0.240	0.628	0.684
AR4	*0.833*	0.498	0.260	0.263	0.480	0.441	0.391	0.242	0.415	0.552
DME1	0.620	*0.850*	0.251	0.409	0.507	0.645	0.492	0.090	0.453	0.772
DME2	0.498	*0.876*	0.186	0.497	0.562	0.573	0.547	0.034	0.512	0.635
DME3	0.558	*0.731*	0.283	0.296	0.441	0.485	0.385	0.053	0.372	0.648
DME4	0.494	*0.820*	0.118	0.493	0.528	0.510	0.532	0.099	0.499	0.547
EOU1	0.234	0.200	*0.865*	0.037	0.107	0.180	0.151	0.170	0.124	0.344
EOU2	0.228	0.224	*0.874*	0.050	0.100	0.152	0.126	0.074	0.101	0.353
EOU3	0.212	0.179	*0.851*	0.078	0.140	0.172	0.089	0.067	0.144	0.346
EOU4	0.248	0.253	*0.825*	0.181	0.169	0.242	0.257	0.199	0.262	0.368
EUG1	0.398	0.380	0.145	*0.908*	0.459	0.564	0.635	0.115	0.567	0.400
EUG2	0.397	0.469	0.091	*0.932*	0.653	0.567	0.716	0.099	0.701	0.374
EUG3	0.419	0.559	0.145	*0.935*	0.597	0.651	0.710	0.069	0.626	0.479
EUG4	0.409	0.499	0.049	*0.948*	0.589	0.604	0.687	0.086	0.670	0.398
GEC1	0.490	0.579	0.145	0.427	*0.790*	0.466	0.499	0.126	0.462	0.444
GEC2	0.386	0.471	0.134	0.518	*0.881*	0.491	0.598	0.157	0.517	0.352
GEC3	0.526	0.528	0.121	0.615	*0.852*	0.524	0.668	0.129	0.637	0.430
JS1	0.592	0.659	0.140	0.649	0.616	*0.967*	0.693	0.110	0.605	0.640
JS2	0.513	0.547	0.164	0.511	0.395	*0.834*	0.538	0.117	0.486	0.577
JS3	0.641	0.658	0.230	0.644	0.638	*0.946*	0.672	0.130	0.633	0.685
JS4	0.678	0.603	0.289	0.518	0.463	*0.887*	0.525	0.209	0.520	0.712
PGV1	0.523	0.542	0.136	0.671	0.665	0.632	*0.934*	0.177	0.626	0.507
PGV2	0.361	0.447	0.104	0.686	0.590	0.480	*0.843*	0.058	0.585	0.345
PGV3	0.467	0.568	0.287	0.660	0.663	0.591	*0.897*	0.116	0.662	0.427
PGV4	0.569	0.584	0.169	0.673	0.631	0.688	*0.934*	0.096	0.652	0.535
SI1	0.267	0.100	0.157	0.091	0.184	0.175	0.116	*0.926*	0.263	0.161
SI2	0.154	−0.003	0.055	0.122	0.119	0.108	0.105	*0.757*	0.162	0.074
SI3	0.273	0.095	0.153	0.053	0.105	0.106	0.101	*0.858*	0.135	0.183
SI4	0.199	0.072	0.159	0.054	0.106	0.100	0.097	*0.755*	0.156	0.134
SP1	0.543	0.542	0.226	0.633	0.594	0.568	0.630	0.213	*0.911*	0.412
SP2	0.540	0.478	0.238	0.584	0.605	0.494	0.626	0.249	*0.911*	0.363
SP3	0.468	0.485	0.082	0.645	0.547	0.597	0.628	0.159	*0.873*	0.378

(*continued*)

Table A2. Continued

Item	AR	DME	EOU	EUG	GEC	JS	PGV	SI	SP	WQ
WQ1	0.624	0.765	0.280	0.473	0.543	0.706	0.512	0.158	0.440	*0.909*
WQ2	0.573	0.628	0.422	0.112	0.234	0.457	0.231	0.085	0.200	*0.786*
WQ3	0.570	0.632	0.387	0.420	0.372	0.598	0.461	0.139	0.372	*0.865*
WQ4	0.710	0.753	0.401	0.463	0.481	0.708	0.520	0.187	0.437	*0.930*

Note(s): AR = Available Resources; DME = Decision-Making Effectiveness; EOU = GenAI Ease of Use; EUG = Ethical Use of GenAI; GEC = GenAI Expectation Confirmation; JS = Job Satisfaction; PGV = Perceived GenAI Value; SI = Social Influence; SP = Security and Privacy; WQ = Work Quality. Values in italic indicate the highest loading for each indicator on its corresponding construct

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