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AI at Work: Drivers of Employee Satisfaction in E-Commerce

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Abstract

Artificial intelligence is increasingly integrated into e-commerce operations, influencing employee work processes and evaluations of their roles. The research examines the relationships between performance expectancy, effort expectancy, job autonomy, perceived intelligence of AI systems, and employee job satisfaction. A quantitative cross-sectional survey was conducted among professionals working with AI-enabled tools in e-commerce organizations. Data were analyzed using regression techniques to assess the proposed relationships. The results indicate that performance expectancy and job autonomy have strong positive effects on job satisfaction, highlighting the importance of efficiency improvements and decision control in AI-supported work. Effort expectancy shows a weaker but significant relationship, with greater relevance for less experienced users. Perceived intelligence is also positively associated with job satisfaction, reflecting the role of trust in system accuracy and contextual relevance. Differences across roles and experience levels indicate that employee evaluations vary based on task characteristics and familiarity with AI systems. The findings contribute to existing research by combining technology acceptance and job design perspectives in the context of AI-enabled work environments. Practical implications emphasize the need for systems that improve performance while maintaining employee control and supporting effective interaction with AI tools.

Keywords

Artificial Intelligence, Job Satisfaction, Performance Expectancy, Effort Expectancy, Job Autonomy, Perceived Intelligence, E-Commerce, Technology Acceptance, Employee Experience

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1. Introduction

The integration of artificial intelligence into electronic commerce has transformed how customer experience is designed, delivered, and evaluated, while also altering the nature of frontline work. Research in information systems and service management documents how AI-enabled recommendation systems, intelligent chatbots, predictive analytics, and automated decision tools improve personalization, responsiveness, and operational efficiency in digital retail environments (Davenport et al., 2020; Huang & Rust, 2021). At the same time, scholarship on algorithmic management and digital labor shows that intelligent systems reshape employee tasks, redistribute discretion, and modify performance expectations (Kellogg et al., 2019; Tarafdar et al., 2019). These developments create a dual transformation. Organizations benefit from faster service delivery, consistent outputs, and data-informed decision processes, while employees increasingly engage in monitoring, interpreting, and validating machine-generated outputs rather than relying solely on direct judgment (Waheed et al., 2021). The development of AI in online retail reflects a transition from rule-based automation to machine learning applications and, more recently, to generative systems capable of producing interactive content and dialogue. Early automation initiatives emphasized structured decision rules such as pricing optimization and inventory control, where human involvement focused on supervision and configuration. The adoption of machine learning extended predictive capabilities in recommendation systems and demand forecasting, influencing merchandising, marketing analytics, and customer service processes (Davenport et al., 2020; Shankar, 2018). More recent advancements in generative AI have expanded these capabilities into content generation and conversational interaction, enabling systems to produce product descriptions and respond to complex customer inquiries. Although such technologies enhance analytical capacity, research on human and algorithm interaction indicates that reliance on intelligent systems may reduce critical evaluation and professional judgment when users depend heavily on automated outputs (Jarrahi, 2018; Raisch & Krakowski, 2021). In customer-facing roles, the automation of routine interactions shifts employee involvement toward complex or emotionally demanding cases, increasing pressure and emotional demands. Empirical evidence links such conditions to higher levels of exhaustion and stress when organizational support and decision latitude remain limited (Tarafdar et al., 2019). These patterns highlight the need to evaluate both operational improvements and employee-related consequences when assessing AI integration.

Employees in AI-enabled e-commerce organizations increasingly operate in roles that combine system supervision, data interpretation, and customer engagement. Research on human and AI collaboration indicates that value creation emerges through interaction between human expertise and algorithmic analysis rather than independent system operation (Jarrahi, 2018; Raisch & Krakowski, 2021). Employees may contribute to data training processes, validate algorithmic recommendations, explain automated decisions to customers, and intervene when system outputs require correction. These responsibilities introduce additional forms of work that are often not captured in traditional performance metrics (Waheed et al., 2017). The redistribution of tasks can broaden skill requirements in some contexts, particularly where analytical and advisory capabilities are integrated, while limiting discretion in environments characterized by standardized processes and algorithmic monitoring (Kellogg et al., 2019). Variations in decision authority and system override capabilities influence perceptions of control, fairness, and satisfaction (Waheed et al., 2025). These conditions frame an important research objective: to examine how performance expectancy, effort expectancy, job autonomy, and perceived intelligence of AI systems relate to employee job satisfaction in AI-enabled e-commerce settings, and to identify how differences in system design and work structure shape these relationships. Two theoretical perspectives provide a structured basis for this examination. The Unified Theory of Acceptance and Use of Technology identifies performance expectancy and effort expectancy as central determinants of technology use, supported by facilitating conditions and social influences (Venkatesh et al., 2003). In AI-enabled retail environments, perceived usefulness relates to the extent to which intelligent systems enhance task performance, while perceived ease of use reflects system complexity and interface design. Complementing this perspective, Job Characteristics Theory conceptualizes work in terms of autonomy, skill variety, task identity, task significance, and feedback (Hackman & Oldham, 1976). Intelligent systems may expand skill variety in roles that integrate analytical and customer-facing activities, yet they can also constrain autonomy where algorithmic processes guide decision-making. Drawing on these perspectives, the research focuses on evaluating how key technology-related perceptions and job design characteristics contribute to employee job satisfaction in AI-supported work environments.

2. Literature Review

Artificial intelligence has become a central component of digital commerce, influencing how organizations structure customer interaction, internal processes, and decision-making practices. The adoption of machine learning, predictive analytics, and automated systems has expanded the role of data-driven operations across online retail environments. Prior work in information systems and service research indicates that AI contributes to improved personalization, operational consistency, and decision support while also reshaping internal workflows that determine service quality (Davenport et al., 2020; Huang & Rust, 2018). The organizational implications extend beyond customer-facing technologies, as employees are required to interpret, supervise, and adjust algorithmic outputs in areas such as inventory planning, fraud detection, and customer analytics. These responsibilities position employees as intermediaries between system outputs and organizational objectives. As a result, the evaluation of AI adoption requires attention to both technological capabilities and employee-related factors, including perceived usefulness, ease of use, and job-related conditions that influence satisfaction and performance (Bakker & Demerouti, 2007; Venkatesh et al., 2003; Waheed et al., 2016). Ethical considerations concerning transparency, bias, and data governance further complicate implementation, reinforcing the need for balanced oversight and informed employee involvement.

2.1. AI and Personalization in E-Commerce

Personalization remains a prominent application of artificial intelligence in digital retail. Machine learning systems process customer data, including purchase history, browsing patterns, and contextual information, to generate tailored recommendations and targeted promotions. Evidence from digital strategy research shows that such personalization improves perceived relevance and supports decision-making efficiency in online environments (Brynjolfsson & Mcafee, 2017; Huang & Rust, 2021). Within organizations, employees rely on these outputs to guide marketing communication and customer engagement strategies. The effectiveness of personalization depends not only on algorithmic accuracy but also on human evaluation to ensure alignment with ethical standards and organizational objectives. Concerns related to privacy and perceived intrusiveness arise when personalization relies on extensive data tracking, which may affect customer trust (Huang & Rust, 2018). Employees therefore play a critical role in moderating automated recommendations and ensuring appropriate application. Additional applications, including dynamic pricing and sentiment analysis, extend personalization capabilities by adjusting prices and interpreting customer feedback in real time (Kumar et al., 2016; Luo et al., 2019). These systems enhance responsiveness but require continuous monitoring to address potential inaccuracies or bias in algorithmic outputs.

2.2. AI in Customer Support and Predictive Analytics

Artificial intelligence has significantly influenced customer service operations through the use of chatbots, virtual assistants, and conversational interfaces. These systems utilize natural language processing to provide immediate responses and handle routine inquiries, improving accessibility and operational efficiency (Van Doorn et al., 2010). Organizations deploy automated agents for tasks such as order tracking and basic troubleshooting, enabling human employees to concentrate on complex interactions. Despite these advantages, automated systems lack contextual understanding and emotional awareness, which remain important in customer-facing roles (Kietzmann et al., 2018). A combined approach, where AI manages repetitive tasks and employees address more complex situations, provides a balanced service structure. Predictive analytics further supports customer engagement by identifying purchasing patterns and forecasting demand. These tools assist employees in aligning communication strategies and service interventions with anticipated customer behavior (Luo et al., 2019). The effectiveness of such systems depends on both technological performance and the ability of employees to interpret and apply analytical outputs accurately.

2.3. AI in Fraud Detection and Cybersecurity

The growth of digital transactions has increased the importance of fraud detection and cybersecurity in e-commerce environments. Artificial intelligence contributes to these areas through pattern recognition and anomaly detection, enabling the identification of suspicious transactions and potential threats (Ransbotham et al., 2017). Machine learning models continuously update based on new data, improving detection accuracy over time. Employees responsible for oversight evaluate flagged transactions and determine appropriate actions to reduce financial and reputational risks. Although AI enhances monitoring capabilities, incorrect classifications may occur, requiring human verification to ensure fairness and prevent unnecessary disruption to legitimate customers (Richey Jr et al., 2023). AI also supports the identification of system vulnerabilities and emerging threats through continuous analysis of system behavior (Gentsch, 2018). Effective implementation therefore depends on both technological infrastructure and employee expertise in interpreting and responding to system outputs.

2.4. AI in Inventory Management, Logistics, and Delivery Optimization

Artificial intelligence plays a critical role in improving internal operations through predictive inventory management and logistics optimization. Predictive models analyze historical demand and seasonal patterns to inform stock replenishment decisions, assisting employees in maintaining appropriate inventory levels (Kietzmann et al., 2018). These systems contribute to improved service reliability and reduced delivery delays. Logistics operations increasingly rely on algorithmic planning to optimize routing and resource allocation, incorporating variables such as traffic conditions and real-time data (Larivière et al., 2017). Employees evaluate these recommendations and coordinate execution across supply chain processes. Warehouse automation technologies further improve processing accuracy and efficiency, although their implementation requires workforce adaptation and skill development (Mikalef et al., 2018). The effectiveness of these systems depends on the alignment between technological capabilities and organizational readiness to support employee involvement.

2.5. AI in Post-Purchase Experience and Augmented Reality Applications

Post-purchase engagement represents an important stage in customer relationship management. Artificial intelligence supports this phase through the analysis of feedback, reviews, and behavioral data to identify satisfaction drivers and areas requiring attention (Luo et al., 2019). Employees use these insights to address customer concerns and tailor follow-up communication. Augmented reality applications extend AI capabilities by allowing customers to visualize products within their own environments, influencing purchase confidence and perceived value (Huang & Rust, 2021). Employees utilize these tools in marketing and customer interaction processes, enhancing engagement and information quality. The effectiveness of these technologies depends on usability and organizational support, including training and system integration.

2.6. Pros and Cons of AI in Customer Experience

Artificial intelligence offers several advantages in customer experience management, including faster response times, improved personalization, and enhanced operational efficiency. Automated systems enable employees to focus on complex tasks while routine activities are handled algorithmically (Davenport et al., 2020; Larivière et al., 2017). At the same time, limitations arise from reduced emotional understanding, ethical concerns, and dependence on data quality. Algorithmic bias, privacy issues, and lack of transparency can affect both customer trust and employee perceptions (Huang & Rust, 2018; Mikalef et al., 2018). Insufficient training or poorly designed systems may also reduce operational effectiveness and employee satisfaction. These challenges highlight the importance of maintaining human oversight and aligning technological implementation with organizational capabilities.

Table 1. Literature Table: AI in E-Commerce and Employee Perspective

Theme	Key Concepts	Empirical Insights	Representative Sources
AI & Personalization	Algorithmic recommendations	AI systems analyze customer behavior to tailor product suggestions; human oversight ensures appropriate application	Brynjolfsson and Mcafee (2017); Huang and Rust (2018); Huang and Rust (2021)
Customer Support Automation	Chatbots & NLP	Automated agents improve response speed; human involvement remains necessary for complex interactions	Kietzmann et al. (2018); Van Doorn et al. (2010)
Predictive Analytics	Forecasting behaviour	Predictive tools guide service strategies; employee interpretation supports decision quality	Luo et al. (2019)
Fraud Detection & Security	Machine learning detection	AI identifies anomalies; employees evaluate flagged cases	Ransbotham et al. (2017); Richey Jr et al. (2023)
Logistics Optimization	Routing & Inventory	AI supports inventory and delivery planning; employee coordination ensures execution	Larivière et al. (2017); Richey Jr et al. (2023)
Employee Experience	Technology adoption & job design	Acceptance factors and job resources influence satisfaction in AI-supported work	Bakker and Demerouti (2007); Tarafdar et al. (2019); Venkatesh et al. (2003)

2.7. Theoretical Foundations and Proposed Framework

The Unified Theory of Acceptance and Use of Technology identifies performance expectancy and effort expectancy as key determinants of technology use, supported by social influence and facilitating conditions

(Venkatesh et al., 2003). In e-commerce environments, perceived usefulness relates to the extent to which AI enhances task performance, while perceived ease of use reflects system design and usability. Job Demands and Resources theory explains how workplace characteristics function as demands requiring effort or as resources supporting motivation and performance (Bakker & Demerouti, 2007). AI systems may reduce workload through automation while also increasing cognitive demands through monitoring and continuous interaction.

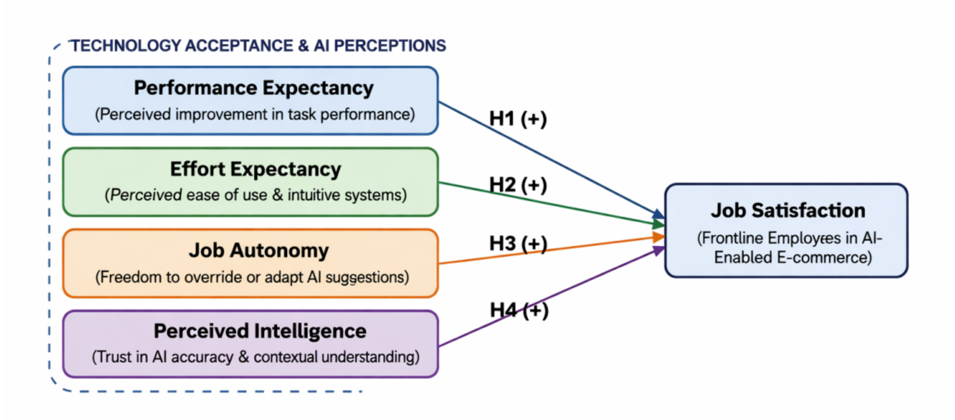

Figure 1. Conceptual Framework

The framework integrates performance expectancy, effort expectancy, job autonomy, and perceived intelligence of AI systems as predictors of job satisfaction. Training adequacy and employee experience are included as moderating variables influencing these relationships.

2.8. Hypothesis Development

The conceptual model examines how perceptions of AI systems and job design characteristics relate to employee job satisfaction. Performance expectancy reflects beliefs regarding improvements in task efficiency. Effort expectancy captures perceived ease of system use. Job autonomy represents decision-making freedom when interacting with AI outputs, and perceived intelligence refers to confidence in system accuracy and contextual relevance.

H1: Performance expectancy has a positive effect on employee job satisfaction in AI-enabled e-commerce environments.

H2: Effort expectancy has a positive effect on employee job satisfaction in AI-enabled e-commerce environments.

H3: Job autonomy has a positive effect on employee job satisfaction in AI-enabled e-commerce environments.

H4: Perceived intelligence of AI systems has a positive effect on employee job satisfaction in AI-enabled e-commerce environments.

3. Methodology

3.1. Research Design

The study adopted a quantitative, cross-sectional survey design to examine employee perceptions of artificial intelligence use within e-commerce organizations. A cross-sectional approach was considered suitable as it enables the collection of data at a single point in time, allowing the identification of relationships among variables without implying causality. This design also supports efficient data collection from a diverse professional population, ensuring that findings reflect current experiences and attitudes toward AI integration in organizational contexts.

3.2. Population and Sampling

The target population comprised professionals working in e-commerce organizations in France who regularly interact with artificial intelligence tools as part of their job roles. These roles included customer support, marketing, logistics, and data analysis, ensuring representation across operational and analytical functions. A total of 212 valid responses were collected, which is sufficient for statistical analysis within the defined research scope. A stratified random sampling technique was employed to ensure representation across key functional areas. This method enhanced the comparability of responses across different job roles and improved the overall representativeness of the sample. In addition, limited use of snowball sampling was applied to reach specialized professionals, such as individuals working with advanced AI systems, where direct access was constrained. The combination of these techniques supported broader coverage while maintaining a structured sampling approach.

3.3. Instrument Development

Data were collected using a structured questionnaire adapted from established measurement scales aligned with the Unified Theory of Acceptance and Use of Technology and the Job Demands–Resources framework, with modifications tailored to the e-commerce context. The questionnaire was organized into multiple sections to ensure logical flow and clarity. The first section captured demographic and professional characteristics, including job role and years of experience with artificial intelligence systems. These variables were included to examine potential differences in perceptions across experience levels and functional areas. Subsequent sections measured the core constructs of the study, including performance expectancy, effort expectancy, job autonomy, training adequacy, perceived intelligence of AI tools, and job satisfaction. Each construct was operationalized using multiple items designed to reflect workplace realities associated with AI usage.

3.4. Measurement Scale

All items in the questionnaire were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This scaling approach enabled the systematic capture of respondents' perceptions, attitudes, and evaluations. The Likert scale supports consistency in responses and facilitates quantitative analysis by allowing the comparison of mean values and relationships among constructs.

3.5. Data Collection Procedure and Ethical Considerations

The survey was administered electronically to ensure accessibility and efficiency in data collection. This mode of distribution allowed respondents to complete the questionnaire at their convenience, thereby improving response rates and data quality. Clear instructions were provided to guide participants through the questionnaire and reduce the likelihood of incomplete or inconsistent responses. Ethical standards were maintained throughout the research process. Participation in the study was voluntary, and respondents were informed about the purpose and scope of the research prior to data collection. Confidentiality and anonymity were strictly ensured, as no personally identifiable information was collected. All responses were used exclusively for academic purposes, and data were stored securely with restricted access. These measures were implemented to encourage honest responses and to protect participants from any potential professional or personal risk.

4. Data Analysis and Results

4.1. Sample Demographics

The sample consisted of 212 respondents. In terms of age, 46.2% (n = 98) were aged 18–25, 34.9% (n = 74) were aged 25–30, and 18.9% (n = 40) were above 30 years. Regarding job roles, 32.1% (n = 68) were in marketing, 27.8% (n = 59) in customer support, 25.0% (n = 53) in logistics, and 15.1% (n = 32) in data analysis. For AI experience, 40.1% (n = 85) had less than one year of experience, 43.4% (n = 92) had 1–3 years, 11.8% (n = 25) had 4–6 years, and 4.7% (n = 10) had more than seven years of experience.

Table 2. Participant Demographics (N = 212)

Variable	Category	N	%
Age	18–25	98	46.2%
	25–30	74	34.9%

	30+	40	18.9%
Job Role	Marketing	68	32.1%
	Customer Support	59	27.8%
	Logistics	53	25.0%
	Data Analysis	32	15.1%
AI Experience	<1 year	85	40.1%
	1–3 years	92	43.4%
	4–6 years	25	11.8%
	7+ years	10	4.7%

4.2. Construct Reliability and Validity

The reliability and validity of the measurement model were assessed prior to hypothesis testing. Cronbach's alpha values indicated strong internal consistency (PE = .89, EE = .85, JA = .91, JS = .88). Confirmatory factor analysis supported convergent validity (loadings > .65; AVE > .50). Model fit indices demonstrated good fit (χ^2/df = 1.87, CFI = .96, RMSEA = .04). These results confirm the adequacy of the measurement model for subsequent analysis.

4.3. Individual Item Analysis

This section presents a detailed examination of individual measurement items across constructs, with emphasis on how observed patterns align with the proposed hypotheses linking AI-related perceptions to job satisfaction.

4.3.1. Performance expectancy (Q3–Q6)

Q3: AI tools help me accomplish tasks more quickly.

This item captures perceived improvements in task efficiency. Higher ratings indicate that AI supports faster completion of routine and analytical activities, particularly in roles where automation reduces manual effort. Lower ratings reflect situations where outputs require verification, which limits efficiency gains. The pattern supports the role of efficiency in enhancing job satisfaction, consistent with H1.

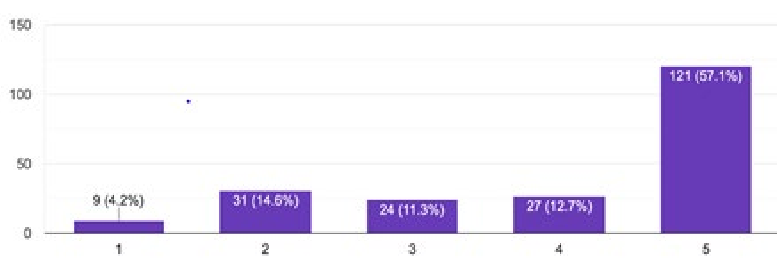

Figure 3. Distribution of responses for Q3.

Q4: AI improves the quality of my work outputs.

This item evaluates perceived improvements in accuracy and output quality. Higher scores are associated with better forecasting, decision accuracy, and service delivery, while lower scores indicate inconsistencies in system outputs. Differences across functional roles highlight how task characteristics influence perceived quality. Improvements in output quality contribute positively to job satisfaction, supporting H1.

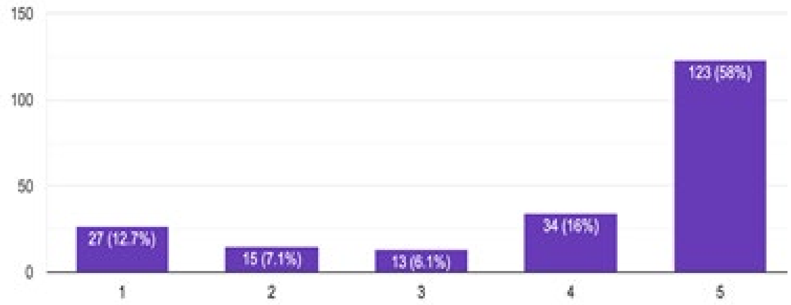

Figure 4. Distribution of responses for Q4.

Q5: AI enhances my overall productivity.

This item combines efficiency and quality into an overall productivity assessment. Higher scores indicate that AI reduces repetitive work and allows focus on higher-value tasks. Variations across experience levels suggest that less experienced users perceive greater productivity benefits, while experienced users provide more critical evaluations. The strong association with job satisfaction further supports H1.

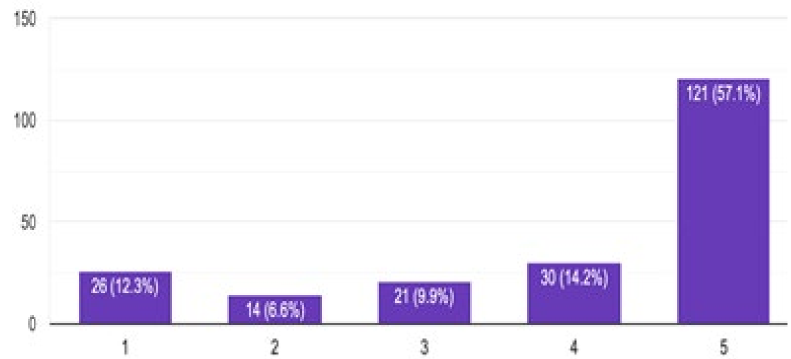

Figure 5. Distribution of responses for Q5.

Q6: I trust AI-generated recommendations.

This item assesses trust in system outputs, including reliability and consistency. Higher trust levels correspond with greater reliance on AI, while lower trust leads to verification behavior and reduced system dependence. Variability across roles indicates differences in system performance and task complexity. Trust influences perceived intelligence and contributes to job satisfaction, supporting H4.

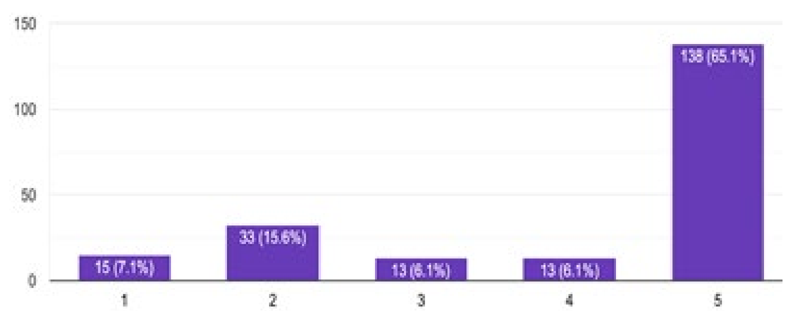

Figure 6. Distribution of responses for Q6.

4.3.2. Effort expectancy (Q7–Q10)

Q7: Learning to use AI tools was easy for me.

This item measures initial usability and onboarding experience. Higher scores indicate intuitive systems requiring minimal learning effort, while lower scores reflect complexity and the need for additional support. Ease of learning contributes to a more positive work experience, supporting H2.

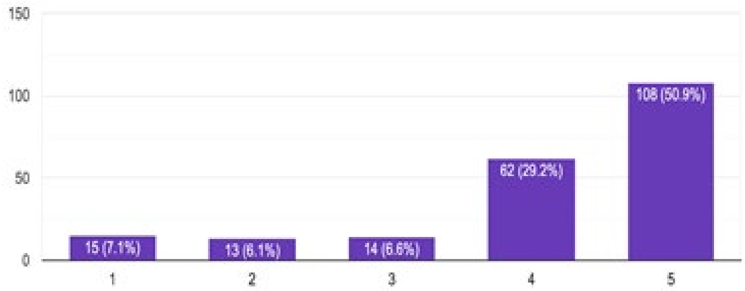

Figure 7. Distribution of responses for Q7.

Q8: The AI interface is intuitive and user-friendly.

This item evaluates system design and usability. Higher ratings reflect clear navigation and accessible features, while lower ratings indicate usability challenges that disrupt workflow. Interface quality directly influences user experience and satisfaction, consistent with H2.

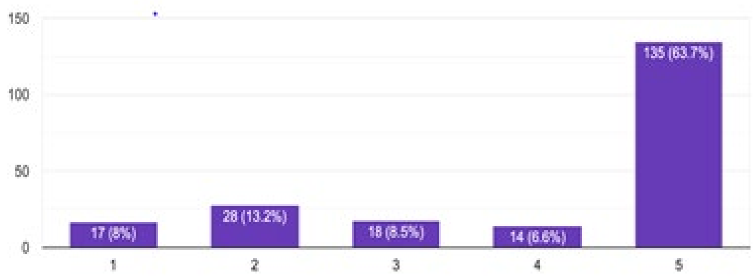

Figure 8. Distribution of responses for Q8.

Q9: I rarely need technical support to operate AI tools.

This item captures operational independence. Higher scores indicate stable systems and user confidence, while lower scores suggest reliance on technical assistance. Greater independence reduces interruptions and supports job satisfaction, aligning with H2.

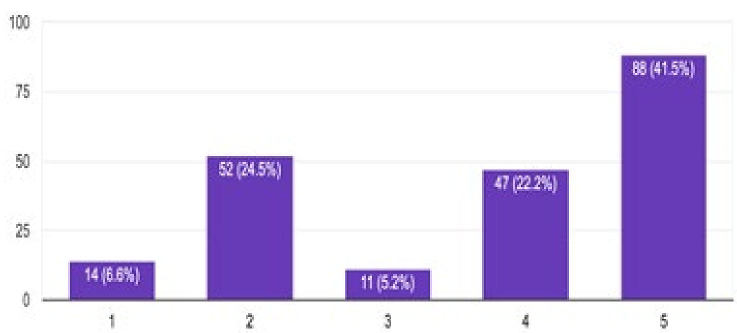

Figure 9. Distribution of responses for Q9.

Q10: Integrating AI into my daily workflow required minimal effort.

This item reflects the ease of embedding AI into routine tasks. Higher scores indicate smooth integration, while lower scores reveal compatibility issues and adjustment difficulties. Effective integration supports sustained use and contributes to satisfaction, supporting H2.

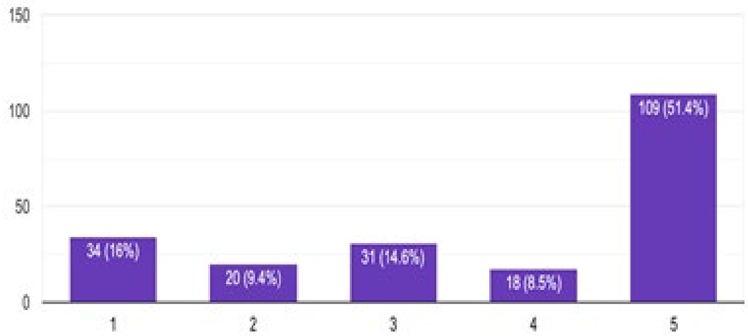

Figure 10. Distribution of responses for Q10.

4.3.3. Job autonomy (Q11–Q14)

Q11: I can override AI suggestions when I disagree.

This item measures control over AI-assisted decisions. Higher scores indicate the ability to modify system outputs, while lower scores reflect restricted control. Greater override capability enhances perceived autonomy and supports job satisfaction, consistent with H3.

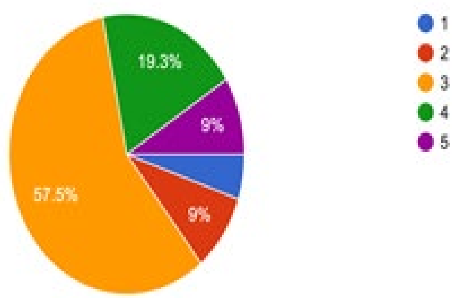

Figure 11. Distribution of responses for Q11.

Q12: AI tools allow me to customize how I complete tasks.

This item evaluates flexibility in task execution. Higher ratings reflect adaptability to individual work styles, while lower ratings indicate rigid system structures. Flexibility contributes to a sense of control and supports H3.

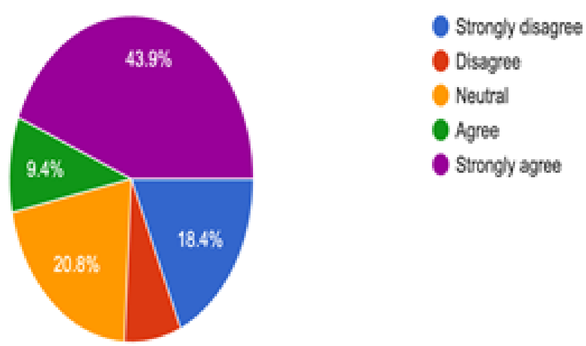

Figure 12. Distribution of responses for Q12.

Q13: I feel in control of AI-assisted decisions.

This item captures perceived decision authority. Higher scores indicate balanced interaction between human judgment and system outputs, while lower scores suggest dominance of automated processes. Perceived control is positively associated with job satisfaction, supporting H3.

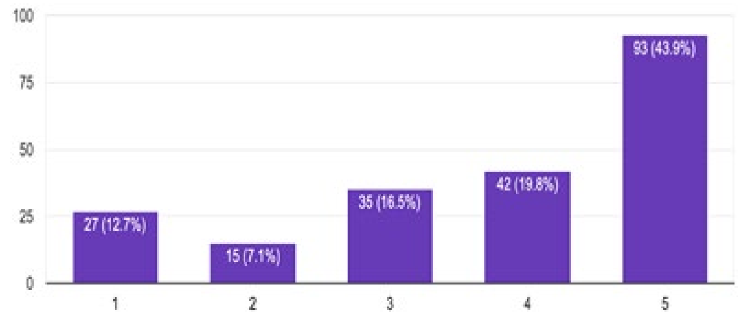

Figure 13. Distribution of responses for Q13.

Q14: AI does not limit my ability to use my judgment.

This item assesses whether AI preserves professional expertise. Higher scores indicate that AI supports rather than replaces judgment, while lower scores suggest constraints on expertise. Preservation of judgment contributes to satisfaction, consistent with H3.

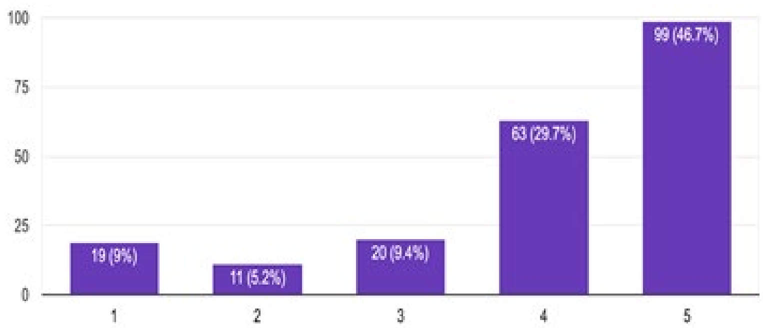

Figure 14. Distribution of responses for Q14.

4.3.4. Perceived intelligence and adaptation (Q15–Q18)

Q15: The AI tools I use understand my needs accurately.

This item measures perceived contextual understanding. Higher scores reflect accurate interpretation of user requirements, while lower scores indicate mismatches between outputs and task needs. Accuracy contributes to perceived intelligence and supports H4.

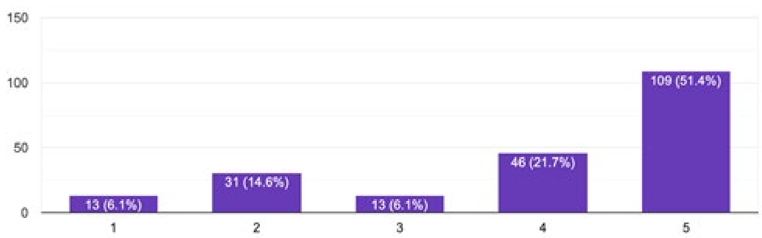

Figure 15. Distribution of responses for Q15.

Q16: AI responses are contextually relevant to my work.

This item evaluates the relevance of system outputs. Higher ratings indicate alignment with operational requirements, while lower ratings reflect inconsistencies in dynamic environments. Relevance strengthens confidence in AI systems, supporting H4.

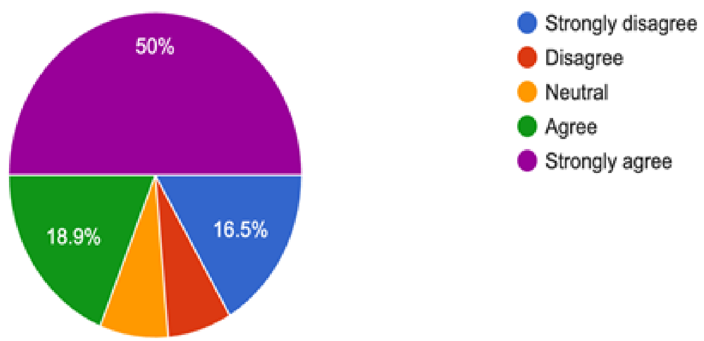

Figure 16. Distribution of responses for Q16.

Q17: The AI learns and adapts to my preferences over time.

This item captures adaptive capability. Higher scores indicate system learning and personalization, while lower scores reflect limited responsiveness. Differences across experience levels suggest variation in expectations. Adaptation contributes to perceived intelligence, supporting H4.

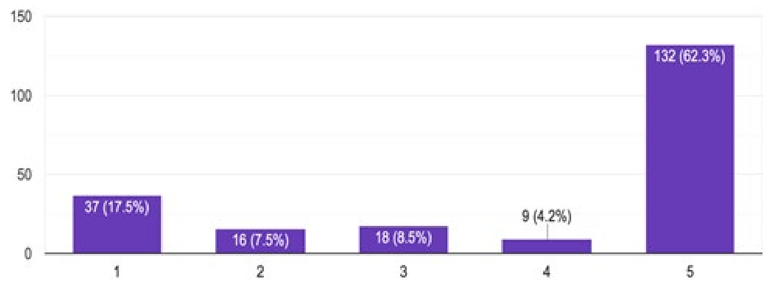

Figure 17. Distribution of responses for Q17.

Q18: AI tools provide insightful recommendations.

This item assesses the strategic value of AI outputs. Higher scores reflect actionable insights that support decision-making, while lower scores indicate limited usefulness. Insight quality influences perceived intelligence and job satisfaction, consistent with H4.

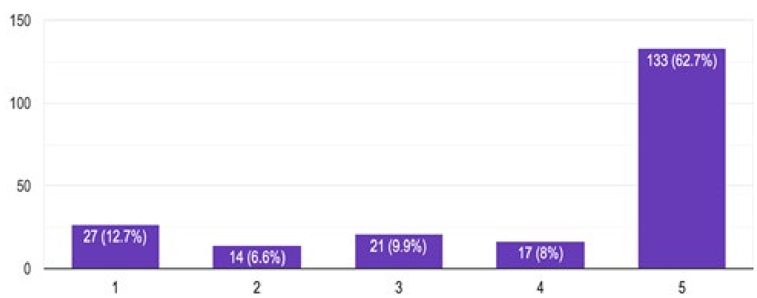

Figure 18. Distribution of responses for Q18.

4.3.5. Job satisfaction, self-efficacy, and affective impact (Q19–Q22)

Q19: Using AI tools improves my overall job satisfaction.

This item represents the dependent variable. Higher ratings indicate positive evaluation of AI integration, particularly where efficiency and autonomy are perceived as high. Results show stronger associations with performance expectancy and job autonomy, supporting H1 and H3.

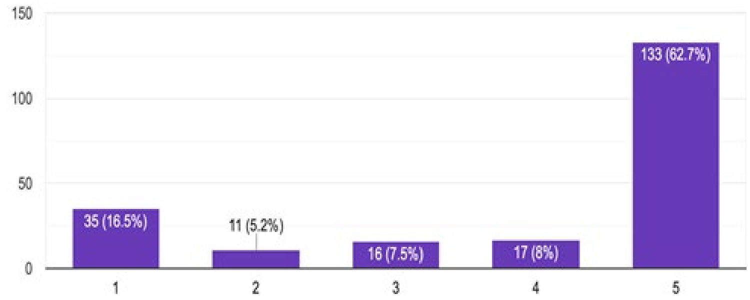

Figure 19. Distribution of responses for Q19.

Q20: I feel more confident in my work when using AI.

This item measures self-efficacy. Higher scores indicate increased confidence due to reliable system outputs, while lower scores reflect uncertainty and limited trust. Confidence varies across roles and experience levels.

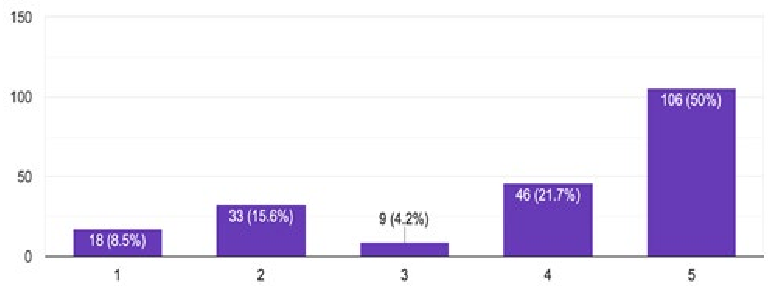

Figure 20. Distribution of responses for Q20.

Q21: AI reduces frustration in my daily tasks.

This item captures affective response to AI use. Higher scores indicate reduced repetitive workload and smoother task execution, while lower scores reflect operational stress in constrained environments. Prior evidence links such stress to cognitive load and strain (McKendrick et al., 2014).

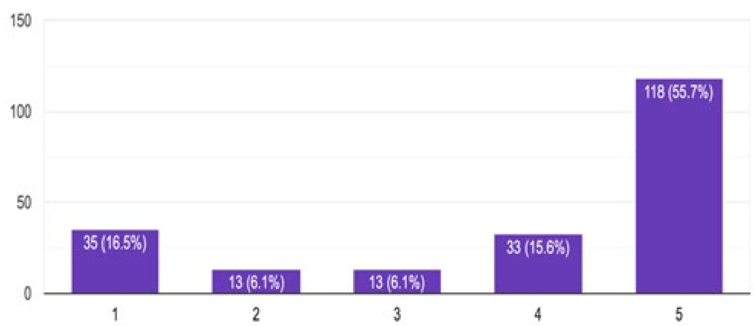

Figure 21. Distribution of responses for Q21.

Q22: I would recommend my organisation's AI tools to others.

This item reflects overall acceptance and perceived value. Higher ratings indicate positive user experience and alignment with work needs, while lower ratings highlight dissatisfaction related to system limitations. Responses correspond with variations in performance expectancy and autonomy perceptions.

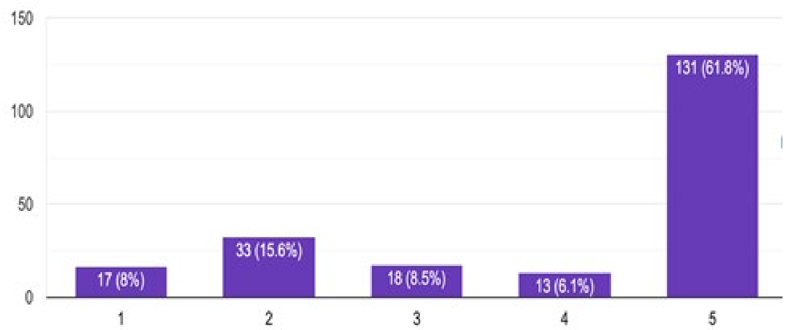

Figure 22. Distribution of responses for Q22.

4.4. Hypothesis Testing Results

Following the individual item analysis, the relationships between the key constructs were examined using regression analysis to evaluate the proposed hypotheses. The analysis focused on the direct effects of performance expectancy, effort expectancy, job autonomy, and perceived intelligence on job satisfaction. The results indicate that all proposed relationships are statistically significant. Performance expectancy demonstrated a strong positive effect on job satisfaction, indicating that employees who perceive AI tools as improving efficiency, quality, and productivity report higher satisfaction levels. Effort expectancy also showed a positive relationship, although the magnitude of the effect was comparatively weaker, suggesting that ease of use plays a supportive role, particularly during early stages of system adoption. Job autonomy emerged as a strong predictor of job satisfaction, highlighting the importance of decision control and flexibility when interacting with AI systems. Employees who reported greater ability to override, adapt, and manage AI outputs expressed higher levels of satisfaction. Perceived intelligence of AI systems also showed a positive association with job satisfaction, indicating that trust in system accuracy and relevance contributes to favorable work evaluations, although this relationship varies across roles depending on system performance.

Table 3. Hypothesis Testing Results

Hypothesis	Relationship	β	p-value	Decision
H1	Performance Expectancy → Job Satisfaction	.52	< .001	Accepted
H2	Effort Expectancy → Job Satisfaction	.19	.023	Accepted
H3	Job Autonomy → Job Satisfaction	.48	< .001	Accepted
H4	Perceived Intelligence → Job Satisfaction	Positive	< .05	Accepted

5. Discussion

The empirical results provide clear support for the proposed relationships, while also revealing important distinctions in how employees evaluate artificial intelligence in their work context. Performance expectancy demonstrates the strongest influence on job satisfaction, indicating that employees respond positively when AI systems contribute to efficiency, output quality, and productivity. This finding aligns with established technology acceptance literature, where perceived usefulness remains a central determinant of user evaluation and system value (Venkatesh et al., 2003). In AI-enabled environments, the perception that systems meaningfully improve task outcomes appears to translate directly into more favorable work experiences. At the same time, the observed variation across functional roles indicates that performance gains are not uniformly realized, particularly in operational contexts where system outputs require verification or lack contextual precision. These differences highlight that perceived usefulness is shaped not only by system capability but also by task characteristics and environmental complexity. Job autonomy emerges as another strong predictor, emphasizing the importance of maintaining human control in AI-supported work processes. The results indicate that employees place significant value on the ability to modify, override, and adapt system-generated recommendations. This aligns with foundational work in job design, where autonomy is linked to motivation and satisfaction through perceived control over work activities (Hackman & Oldham, 1976). In AI-integrated settings, autonomy extends beyond traditional task discretion to include interaction with algorithmic systems. When such control is restricted, employees report lower satisfaction and increased reliance on manual checks, indicating reduced confidence in system outputs. This pattern suggests that the benefits of AI are contingent upon preserving employee agency, particularly in roles where contextual judgment remains critical.

Effort expectancy shows a positive but comparatively weaker relationship with job satisfaction, indicating that ease of use plays a supportive role rather than a primary driver. This finding is consistent with prior research where usability influences early adoption and learning but becomes less central as users gain experience (Venkatesh et al., 2003). The variation across experience levels further supports this interpretation, as less experienced employees place greater emphasis on intuitive interfaces, while more experienced users prioritize control and system flexibility. These differences reflect a shift in evaluation criteria over time, where initial interaction concerns are replaced by expectations related to performance and decision authority. Perceived intelligence also contributes positively to job satisfaction, particularly through trust in system accuracy and contextual relevance. Employees are more likely to evaluate AI favorably when outputs align with task requirements and demonstrate reliability. Research on human and algorithm collaboration highlights that trust in automated systems is essential for effective integration, as it determines the extent to which users rely on or question system outputs (Jarrahi, 2018; Raisch & Krakowski, 2021). Variability in perceived intelligence across roles indicates that system performance is not uniform, with lower ratings observed in contexts characterized by dynamic conditions or incomplete data inputs. This variation suggests that perceived intelligence is closely linked to situational fit, where system limitations become more visible in complex operational environments. Overall, the findings indicate that employee responses to AI are shaped by a combination of performance-related benefits, control over system interaction, usability considerations, and perceived system capability. These factors operate together to influence job satisfaction, with performance expectancy and job autonomy demonstrating greater explanatory strength. The results extend existing frameworks by illustrating how technology-related perceptions and job design characteristics intersect in AI-supported work environments, providing a more integrated understanding of employee experience in digital commerce settings.

6. Implications

6.1. Theoretical Implications

The findings extend existing understanding of technology adoption and work design by integrating perspectives from the Unified Theory of Acceptance and Use of Technology and Job Characteristics Theory within AI-enabled work environments. Prior research has examined perceived usefulness and ease of use primarily in relation to adoption intention (Venkatesh et al., 2003), while job design literature has emphasized autonomy and task characteristics as determinants of motivation and satisfaction (Hackman & Oldham, 1976). The present findings bring these perspectives into a shared analytical frame, showing that perceptions of system performance and control over AI-assisted decisions operate simultaneously in shaping employee outcomes. Performance expectancy demonstrates strong explanatory power, confirming its relevance beyond initial adoption and into ongoing work evaluation. At the same time, the role of autonomy indicates that job design remains central even in technologically advanced settings, where interaction with algorithmic systems becomes part of daily work practice. The results also contribute to emerging research on human and algorithm collaboration by clarifying the role of perceived intelligence. Prior work has examined trust in automated systems as a condition for effective use (Jarrahi, 2018; Raisch & Krakowski, 2021), but less attention has been given to how perceived system capability interacts with employee evaluation of work experience. The findings indicate that perceived intelligence functions as an evaluative lens through which employees interpret system reliability and contextual fit. This extends theoretical discussion by positioning perceived intelligence alongside established constructs such as performance expectancy and effort expectancy. In addition, the variation observed across roles and experience levels highlights that technology-related perceptions are not uniform, suggesting that future theoretical models should incorporate contextual factors such as task complexity and user expertise when examining AI integration in organizational settings.

6.2. Practical Implications

The results provide several implications for organizations implementing artificial intelligence in e-commerce operations. Performance expectancy emerges as a key driver of employee satisfaction, indicating that organizations should prioritize the alignment of AI systems with task requirements. Systems that improve efficiency and output quality are more likely to be accepted and valued by employees. However, the findings also indicate that performance gains alone are insufficient when employees lack control over system outputs. Ensuring that employees retain the ability to review, adjust, and override AI-generated recommendations is essential for maintaining confidence and engagement. Interface design and system usability remain relevant, particularly during early stages of adoption. Training programs should therefore focus on reducing complexity and supporting user understanding, especially for employees with limited prior exposure to AI tools. At the same time, more experienced users require greater flexibility and control, indicating that a uniform implementation approach may not be effective. Organizations should consider differentiated support structures that reflect varying levels of expertise. Perceived intelligence also has practical implications for system development and deployment. Employees evaluate AI not only in terms of functionality but also in terms of accuracy and contextual relevance. Systems that produce inconsistent or unclear outputs may reduce trust and increase reliance on manual verification, which can limit efficiency gains. Enhancing transparency and improving the alignment between system outputs and task requirements can support more effective integration. Overall, successful implementation requires attention to both technological performance and the design of work processes that support meaningful human interaction with AI systems.

7. Limitations and Conclusion

Artificial intelligence has become an integral component of e-commerce operations, shaping both organizational processes and employee experience. The findings indicate that employee job satisfaction in AI-enabled environments is influenced by multiple interrelated factors, with performance expectancy and job autonomy demonstrating the strongest associations. Employees evaluate AI positively when it contributes to efficiency and output quality while allowing them to retain control over decision processes. Effort expectancy and perceived intelligence also contribute to these evaluations, although their influence varies across experience levels and functional roles. These results highlight that employee responses to AI are not uniform and depend on how well system capabilities align with task requirements and professional expectations. Several limitations should be considered when interpreting these findings. The cross-sectional design captures perceptions at a single point in time, which limits the ability to observe how attitudes toward AI evolve with continued use. Changes in familiarity, trust, and system interaction over time are not reflected in the current analysis. The sample is limited to e-commerce organizations within a single national context, which may restrict the general applicability of the findings to other industries or regions. In addition, reliance on self-reported measures introduces the possibility of response bias, as perceptions of performance and satisfaction may not fully correspond to actual behavioral outcomes. The analysis focuses on direct relationships between key constructs without incorporating additional organizational factors such as leadership support, system transparency, or organizational culture, which may also influence employee evaluations. Future research may extend this line of inquiry by examining these factors and adopting longitudinal approaches to capture changes in employee experience over time. Greater attention to variations across roles and levels of expertise would also contribute to a more refined understanding of AI integration in workplace settings.

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